Professional MBA
Entrepreneurship & Innovation

How Artificial Intelligence (AI) Innovators Profit From Innovation in Digital Platform Ecosystems: An Explorative Business Model Study

A Master's Thesis submitted for the degree of
"Master of Business Administration"

supervised by
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Vienna, July 2018

Affidavit

I, **SLOBODANKA DANA KATHRIN TOMIC**, hereby declare

1. that I am the sole author of the present Master's Thesis, "HOW ARTIFICIAL INTELLIGENCE INNOVATORS PROFIT FROM INNOVATION IN DIGITAL PLATFORM ECOSYSTEMS - AN EXPLORATIVE BUSINESS MODEL STUDY", 60 pages, bound, and that I have not used any source or tool other than those referenced or any other illicit aid or tool, and
2. that I have not prior to this date submitted this Master's Thesis as an examination paper in any form in Austria or abroad.

Vienna, 10.07.2018

Signature

Preface

The topic of this thesis stem from my interest in digital technologies and the role they play in creating new sources of competitive advantage and innovativeness for businesses and individuals. The rise of artificial intelligence with its projected immense impact on businesses and society and the success of digital platform businesses and ecosystems are interesting trends, which well deserve all the attention they receive from business scholars, managers, and public. These trends already shape the context for strategy and innovation management decisions across industries and geographies and will be of authoritative importance in the future.

The focus on business models of the artificial intelligence innovators and the selected explorative method based on e-research provided me with insights into the world of AI solutions endowed with remarkable present-day capabilities and future potential. The work on finding relevant patterns from published information and mapping them into the existing theories of strategic management proved challenging and at times overwhelming. The resulting analysis framework and business model typology emerged as simple but effective tools for mapping relevant issues and indicated some venues for further studies.

This thesis marks the end of my enriching and insightful MBA program. I am grateful to Dan and Tim for their loving patience, insights, and encouragement along that journey. I am also thankful to Wolfgang and Smartbow GmbH for inspiration and generous financial support.

Abstract

The topic of this thesis is the relationship between the business models (BMs) of the firms which create artificial intelligence (AI) solutions in complex digital platform ecosystems and their success in profiting from innovation.

The AI technology endows machines and processes with human-like communication and perception abilities, and with the capacity to learn from data and optimize at scale not accessible to humans. The AI technology solutions depend on the underlying digital solutions for access to data and computation resources. An AI solution is a digital product offered over a complex platform-based architecture that combines internal innovation with complementary assets some of which are controlled by other companies. According to theory, external complementary assets have substantial impact on how much a firm can profit from innovation. How key assets are allocated and controlled is part of a firm's business model. The aim of the thesis is to systematize BMs of AI innovators into a typology of patterns and to analyze how AI innovators of different types profit from their innovation.

The thesis adopts the qualitative content analysis of the information acquired in e-research. The particular focus of this study is on the AI innovators who are registered in the CrunchBase database, and who were acquired by other companies. The BM information is extracted from the websites of firms and the information about the acquisition. The hypotheses are: H1) Based on the collected data, a small number of distinct patterns can be identified; H2) The motivation for acquisition is to improve not only operational capabilities but also higher-order transformative capabilities, H3) The existing theory can be applied to BM patterns to reason about the emergence of the dominant design.

The result of the thesis is a typology of BM patterns and the underpinning analysis framework. The research prospects include verifying the typology and the analysis framework in both case studies and a larger sample of companies and conducting quantitative studies based on surveys and interviews with experts and managers to verify the findings.

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List of abbreviations

AGI	Artificial General Intelligence
AI	Artificial Intelligence
API	Application Programming Interfaces
B2B	Business to Business
B2C	Business to Consumer
BM	Business Model
BMI	Business Model Innovation
CC	Cloud Computing
DC	Dynamic Capability
GPT	General Purpose Technology
HR	Human Resources
IaaS	Infrastructure as a Service
ICT	Information and Communication Technologies
IoT	Internet of Things
IS	Information System
IT	Information Technology
ML	Machine Learning
PaaS	Platform as a Service
PFI	Profiting From Innovation Framework
R&D	Research and Development
RQ	Research Question
SaaS	Software as a Service
SDK	Software Development Kit

1. Introduction

In a global competitive environment, two business and technology trends are growing together: the evolution of digital platforms that underpin successful organizations and their business ecosystems, and the rise of artificial intelligence technology (AI) demonstrated by recent impressive practical success of machine learning (ML) and deep learning (DL) algorithms (Brynjolfsson & McAfee, 2017, IDC, 2016, 2017). Google, Amazon, Microsoft, Apple, IBM, Salesforce, Facebook, Uber, Netflix, Intel, and other digital platforms competing "at the digital frontier," are also the pioneers in advancing and adopting AI technologies (Bughin et al., 2017; Brynjolfsson & McAfee, 2017). Other companies, which currently experiment with embedding AI technology within their products and processes, perceive adoption of AI as a new source of competitive advantage; even companies presently lagging have realized the perils of not becoming AI adopters (Bughin et al., 2017).

One of the drivers of advancements in the AI technology is a globalized diffusion of knowledge, skills, and tools from the open source domain (e.g., Shafto, 2016, DZONE, 2017, Terdimann, 2018). The AI community refer to this trend as "democratization of AI" (Google, 2018, DELL, 2018, IBM, 2018, Microsoft, 2018). Due to a strong modularization trend (Yoo et al., 2010), the availability of components that can be used to orchestrate complex and scalable solutions is higher than ever before. The AI products and services are offered over "layered modular architecture" underpinning digital technology platforms (Yoo et al., 2010). This architecture and its "boundary resources" impact how AI innovators capture value in ecosystems and is of practical and theoretic importance (Yoo et al., 2010, Ghazawneh & Henfridsson, 2010).

Leveraging availability of data, algorithms and tools, the innovation ecosystem of companies that develop and commercialize AI solutions – the AI innovators, is growing. Three types of companies have impact on this ecosystem: 1) the digital incumbents, 2) startups, and 3) the companies from different sectors seeking to integrate AI innovation in their products or services. The group of digital incumbents include for example cloud providers, mobile platform providers, and social networks. The leading cloud providers, such as Amazon (AWS Cloud), Microsoft (Azure), Google (Google Cloud), IBM (IBM Cloud), have added AI development tools and AI algorithms to their vast offerings of cloud services, and are building partner networks to help other companies in using their cloud-based AI technology. Dominant mobile platforms, Apple (iOS) and Google (Android) are adding AI capabilities to their operating systems, software development kits (SDKs) and core applications to drive future user needs and network effects. Facebook has opened their internal AI tools for developers (Facebook, 2018). In parallel to these activities, the number of the AI startups founded by researchers or experienced industry experts, as well as the volume of investments in these ventures are on the rise (CB Insights, 2018, Card et al., 2017). The AI startups often tightly cooperate with corporations from different industries and sectors that search for AI solutions to enrich their products or processes. These belong to the third type of AI ecosystem influencers. To build up their assets and to innovate, these enterprises can select among a closed in-house research and development (R&D) and different open innovation governance strategies, the subject of intense academic inquiry (Felin and Zengler, 2014).

AI technology and AI skills are highly valued assets; therefore, the ecosystem of AI innovators have witnessed many mergers and acquisitions (M&A) (Card et at., 2017, CB Insights, 2018). These M&As are evidence of how companies “sense and seize opportunities” and “transform assets and business models” (Teece, 2007) to achieve better fit with their dynamic environment, that is, they are evidence of the so called “dynamic capabilities” (Teece & Pisano, 1994, Teece, 2007). As a result, embedded in “skills, processes, procedures, organizational structures, decision rules, and disciplines” – the “microfoundations” of these “dynamic capabilities” (Teece, 2007, p.1), AI technology may become a crucial source of competitive advantage.

1.1.Problem formulation

Reflecting the overwhelming expected benefits of the AI technology, the body of business knowledge is rapidly growing. Several business consultancies have conducted studies to assess opinions of experts and executives on the topics associated with the AI adoption, benefits, opportunities, and threats (Ransbotham et al, 2017, Bughin et al., 2017, Kolbjørnsrud et al, 2017), and have examined numerous use cases of the AI technology use (Chui et al., 2017). They have quantified the interest in the technology, the current level of implementation, and have identified perceived barriers of current and future adopters. Also, business intelligence agencies have started to publish findings about new entrants, investments and exists (CB Insights, 2017, 2018; Card, 2017), and business publications bring case studies of successful AI adopters (e.g., Economist, 2016, Sutton, 2018).

However, there is less evidence of research that systematically analyze the competition in the AI innovation ecosystem, the business models of AI innovators, and their strategies. The questions regarding the nature of complementary assets necessary for AI innovations, who owns and who controls them, have not been addressed sufficiently. The impact of platforms on the business models of AI innovators have also received less attention. From the perspective of the AI adopters, the linkage between the higher-order transformational capabilities - "dynamic capabilities" (Teece, 2007) and the AI solutions deserves better understanding, for example, understanding propensity of firms to subscribe for such capability when offered "as a service" by an AI innovator, as compared to propensity to acquire it or build a unique one. Finally, there is also less evidence of research that systematically analyze the issue of dominant designs in the AI innovation space. In many areas of AI development, there are challenges to be solved, such as improving efficiency and transparency, lowering the data need, and eliminating bias. As a result, existing solutions will potentially be replaced by new ones. The question is which companies, the established ones, or entrants will have the highest profit from these innovations.

1.2. Objective of the master thesis

This master thesis aims at advancing the understanding of the business models of the AI innovators, the specific nature of their value propositions, and the evolution of the AI innovation ecosystem. To this goal, the thesis postulates three research questions as guiderails for a qualitative study:

RQ1: Which significant business model patterns do AI innovators employ, and what factors influence their ability to profit from their innovation?

RQ2: Are there some AI offerings that could be microfoundations of dynamic capabilities for their users?

RQ3: Can existing theories of technology evolution and the evidence from the AI ecosystem be used to reason about the emergence of the dominant designs or winner-take-all outcomes?

1.3. Methodology overview and course of investigation

The methodology approach is the qualitative content analysis based on e-research and interpretative induction-based analysis of data. The research work combines 1) a review of relevant literature and elaboration of the evaluation approach, and 2) data collection, data analysis and systematization of results. In the theoretical part, a broader literature review was undertaken touching on concepts relevant for addressing the postulated questions. The publications analyzing the business aspects of the AI technology have also been examined. The literature analysis yielded an analysis framework for evaluation of selected companies. The object of the study was a sample of the AI technology companies filtered out from a commercial database (Crunchbase, 2018) that curates information about high tech businesses including their organisation profiles, and information about acquisitions and investments. The data for the analysis were collected from the companies' websites, as well as technology blogs.

1.4. Structure of the thesis

The thesis comprises five chapters. The first chapter has presented the motivating problem, the research questions and the methodology employed. Chapter 2 presents a review of selected literature on AI technology and its business-related issues, followed by a discussion of relevant concepts from the competitive advantage theories, dynamic capabilities theory and profiting from innovation framework, open innovation, and platform research, and business model research. Chapter 2 also describes the resulting analysis framework. Chapter 3 describes the methodology approach, explains how data collection and analysis were conducted and summarises the findings. Chapter 4 discusses the results. Chapter 5 concludes the thesis commenting on its limitations, and outlining its theoretical and practical contributions, and avenues for future research.

2. Literature part

2.1.Motivation for the theoretical scope

This chapter sumarizes a review of literature that provides conceptual underpinning for the inquiry into the business models of the AI innovators, their business offerings, and the AI market dynamics.

The review starts with the exploration of the extant literature that examines the business impact of AI on the global industry, as well as the characteristics of the AI innovation ecosystem in which the businesses emerge, innovate, develop their assets, cooperate, and compete. The dynamics of this vibrant ecosystem is driven by the process of democratisation of AI, by the strategies of large digital platforms which have an enabling role in bringing AI into operations, by strong investment activity and the resulting growing number of new entrants, and the constant line of mergers and acquisitions. For the companies developing their unique resources and unique business propositions within this competitive environment, the most essential strategic management question is how best to profit from innovation.

The competitiveness of the AI innovators can be analysed from different perspectives. The literature review touches upon the competitive advantage theories of the strategic management, the prominent “Dynamic Capabilities (DC) Framework” (Teece & Pisano, 1994) and “Profiting from Innovation (PFI) Framework” (Teece 1986). Accounting for the openness of the AI innovation ecosystem within which the evolution paths of the AI innovators unwind, and the significance of contributions coming from open challenges that attract independent data scientists, the concepts from the open innovation theory (Chesbrough, 2003) and crowdsourcing (Howe, 2006) have been briefly reviewed. Large digital platforms dominate the AI innovation environment; hence relevant findings from the platforms and ecosystem research have been revisited (Gawer, 2014; Adner, 2017), as well as the technology platform architecture concepts (Yoo et al., 2010). As the study of this thesis aims at identifying the business model patterns of the AI innovators, some approaches from the business model theory (Gassmann et al., 2016) intertwined with the DC and PFI frameworks (Teece, 2018) have also been reviewed. Finally, building upon the presented theoretical perspectives, an analysis framework has been proposed.

2.2.Business aspects of artificial intelligence technologies

2.2.1. Introduction

Artificial Intelligence (AI) has been recently described by Accenture (2017) as “a constellation of technologies that allow smart machines to extend human capabilities by sensing, comprehending, acting and learning thereby allowing people to achieve much more” (Accenture, 2017, p.2). AI consists of “multiple technologies that enable computers to perceive the world (such as computer vision, audio processing and sensor processing), analyze and understand the information collected (for example, natural language processing or knowledge representation), make informed decisions or recommend action (for instance, inference engines or expert systems) and learn from experience (including machine learning)” (Kolbjørnsrud et al., 2016). Some analysts claim that “when AI technologies are integrated, they can create a highly adaptable business capability” (Accenture, 2017).

AI is recognized to be “a new factor of production”, which will drive growth by “facilitating automation of complex physical world tasks that require adaptability and agility” (Purdy & Daugherty, 2016), by “complementing human capabilities, offering employees new tools to enhance their natural intelligence” (Purdy & Daugherty, 2016), and by “propelling new nnovation as it diffuses through economy” (Purdy & Daugherty, 2016). AI is expected to set the stage for economic transformation and disruption and will be the foundation for new competitive advantages (Rao & Verweij, 2017). Analysts point the importance for countries and businesses seeking to remain or become competitive to launch programs for development, adoption, and diffusion of AI technology and solutions (Bughin et al., 2017, Purdy & Daugherty, 2016, WWWF, 2017).

During its long history, the field of artificial intelligence has witnessed waves of optimism, overpromising and investment hikes and disappointing results followed by “AI winters” and investment stagnation; however, the AI research community continued to expand the field, recombine old and create new approaches, and experiment on an ever-growing body of available public and private data (Smith et al., 2006, Bughin et al., 2017). Finally, advancements, concentration, and integration of enabling technologies (e.g., fast graphical processors, the Cloud and Big Data technology) and the progress in machine learning and deep learning neural network algorithms have led to emergence of real-world AI solutions endowed with near human performance, or even super-human performance (AI Index, 2017, Eckersley et al., 2017). AI technology is a set of a wide variety of methods and algorithms, with machine learning being one subset of it. Deep learning, which brought breakthrough in natural language understanding and computer vision and image processing, is a subset of machine learning (Goodfellow, 2016). The number of innovations and the volumes of investment in AI technology are growing exponentially, and the projections of improvements in profitability amount to up to 40 percent by 2030 (Purdy and Daugherty, 2016, AI Index, 2017). This improvement will be attributed to robotics and automation, and cognitive systems working autonomously or in cooperation with human users (Kolbjørnsrud et al., 2016).

2.2.2. The AI technology systems and use cases

Artificial intelligence as summarised in (Economist, 2017): "refers to a set of computer science techniques that enable systems to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making and language translation" (Economist, 2017, p.4). From a more systemic perspective, AI refers to „IT systems that sense, comprehend, act and learn" (Kolbjørnsrud et al., 2016). However, „the definition of machine intelligence changes as people become accustomed to previous advances" (Minsky 1961, cited in Bughin et al. 2017). A famous definition equates intelligence with „whatever machines haven't done yet" (Tessler, 1979, cited in Bughin et al. 2017).

In their study on AI adoption Bughin et al. (2017) structured AI field into five dominant technology systems: "robotics and autonomous vehicles, computer vision, language, virtual agents (chatbots, conversational interfaces), and machine learning, which includes deep learning" (Bughin et al. 2017, p.6). The machine learning is a category that so far has received the largest investments (Bughin et al. 2017). An open machine learning platform DL4J (2018) maps a larger number of use cases and industries into different types of underlying data e.g. „sound/speech (e.g., voice recognition, search, sentiment analysis) time series (e.g., predictive monitoring based on sensor data, business analytics, recommendation engines based on web data, risk analytics based on logs access data), text (e.g., sentiment analysis, search, threat detection, fraud detection), image (e.g., facial recognition, image search, photo clustering, machine vision) and video (motion detection, threat detection)" (DL4J, 2018).

Chui et al. (2017) provides systematic mapping of AI algorithms to different industries, where travel, transport and logistics, retail, automotive and assembly, and high tech are identified as sectors to which AI brings highest performance improvements as compared to other techniques. Chui et al. (2017) also show how AI is used in different functional areas, where marketing and sales have the highest value potential, followed by supply chain management and manufacturing, risk, service operations, product development, finance and IT, and human resources. Chui et al. (2017) also elaborated a list of associated business problems and estimated their business impact. These business problems include for example customer acquisition/lead generation, predictive maintenance, hiring and retention, risk management, and others, which can all be more efficiently solved by embedding AI into the existing solutions (Chui et al., 2017).

While artificial intelligence techniques in the past focused on efficient codification of knowledge, storage and retrieval of knowledge concepts and features created by the domain experts, modern AI approaches - machine learning and deep learning – are based on training deep neural networks using large sets of training data (Goodfellow et al., 2016). Therefore, the capability to create and validate an AI algorithm is conditioned on the ability to access or create specialised data sets (data asset) of high quality training data. Accordingly, data harvesting and data aggregation are necessary first steps in creating the data asset. In the next step, an algorithm is trained on data. The algorithm can be specialised with additional data, and finally, it is used in action (Gerbert et al., 2017). In the dynamic environments when the data is continuously changing, the data asset need to renewed, and algorithms retrained. The algorithms differ depending on the need for data, to what level the output can be explained, the performance, the robustness, and the level of human intervention needed.

2.2.3. Future AI trends

While AI technology has already been used in large scale real-world applications, it has been continuously improved. Future trends in AI, as summarised in (PWC, 2018), are mostly lab developments of academic and corporate researchers that mark new generation of AI technology. These include: „1) deep learning theory 2) capsule networks 3) deep reinforcement learning (for strategic algorithms that learn by interacting with the environment) 4) generative adversarial networks (less human intervention, less data needed) 5) lean and augmented data learning 6) probabilistic programming (language with probability constructs) 7) hybrid learning models 8) automated machine learning, 8) digital twin 9) explainable artificial intelligence" (PWC, 2018) All these approaches seek to achieve better models, less data or synthetic data, autonomous and automatic learning with lower need for human intervention and improved explain-ability of inferences. The relevance of new trends is in the fact that they change the demand for some assets and indicate potential evolution paths towards the dominant designs.

2.2.4. AI adoption and expectations

A recent cross-industry study with managers and technology experts (Ransbotham et al., 2017), has revealed that at the time of study 23 percent of companies were conducting pilots ("the experimenters"), 18 percent have some technology deployed ("the investigators"), 5 percent extensively incorporates AI in their offerings (the pioneers"), and 54 percent of companies ("the passives") had no AI strategy. Companies strongly or somewhat agree to following reasons for adopting AI, (Ransbotham et al., 2017): 1) "obtain or sustain a competitive advantage (84%)" (p.9), 2) "move into new businesses (75%)" (p.9), 3) "organizations using AI will enter our market (75%)" (p.9), 4) "incumbent competitors will use AI (69%)" (p.9), 5) "pressure to reduce costs will require us to use AI (75%)" (p.9), 6) "suppliers will offer AI-driven products and services (61%)" (p.9), 7) "customers will ask for AI-driven offerings (59%)" (Ransbotham et al., 2017, p.9). These results show strong awareness that AI adoption is necessary for sustaining competitive advantage, and is an enabler for growth; however, there is also a perception that AI lowers entrance barriers for new entrants, that AI-powered companies achieve cost advantage, and that AI is vital for retaining the market share or critical suppliers.

Results presented in (Ransbotham et al., 2017) show that different paths towards sourcing innovation will be adopted. All segments report insufficient understanding of the development costs of AI products and services. The companies with higher adoption level of AI have higher willingness to develop skills by training or hiring. The others have higher propensity to outsource to consultants or other corporations.

2.2.5. What AI adopters desire from AI technology

In a study by Kolbjørnsrud et al. (2015) 1,770 front-line, mid-level and executive-level managers from 14 countries and 17 distinct industries were surveyed regarding their expected impact of the AI on their jobs, skills, and activities, and on the future of positions they held. Also, Kolbjørnsrud et al. (2015) conducted 37 interviews with executives from nine countries and seven industries on how to lead the digital enterprise. The results show a keen perception that "AI could absorb and accelerate routine work as well as provide powerful analytical support" (Kolbjørnsrud et al., 2015, p.4) but while (Kolbjørnsrud et al., 2015) "top managers relish the opportunity to integrate AI into work practices, mid-level, and front-line managers are less optimistic" (p.7). Less than 46% of top level, 26% of middle managers, and 17% of first line manager would "trust the advice of intelligent systems in making business decisions in the future", would "accept responsibility for an intelligent system's actions, or are "comfortable with an intelligent system monitoring and evaluating" their work (Kolbjørnsrud et al., 2015).

The reason for this is in a "drive to understand AI" or in more detail, as reported by Kolbjørnsrud et al. (2015) when asked "What would allow you to trust advice generated by an intelligent system?" (p.10). Respondents strongly or somewhat agree with the statement 1) "I understand how the system works and generates advice (61%)" (p.10), 2) "The system has proven track record (57%)" (p.10) 3) "The system provides convincing explanations (51%)" (p.10), 4) "People I trust use such systems (33%)" (p.10), 5) "Advice is limited to simple rule-based decisions (33%)" (p.10), and 6) "nothing (6%)" (p.10). The answers 1 and 3 indicate a strong need for explanations, which algorithms currently deployed generally do not offer. The answers 2 and 4, however, are indications of potential for network effects.

Another insight from (Kolbjørnsrud et al. 2015) identifies human advantage vs. machine advantage in an activity space of different levels of social and creative intelligence and matches "machine-based augmentation" (p.14) and automation to a routine work, and "machine augmented human" (p.14) to creative work requiring high level of social intelligence. Beyond transforming relationship between humans and machines, where machines take over routine tasks, significantly reducing the cost, Accenture (2017) suggests additional opportunities presented by AI: "Reimagine business models and processes" (p.2), where "smart machines will continually review end-to-end processes and apply 'intelligent automation of process change' to refine and optimize" (p.2).

2.2.6. Democratization of AI

The Webster dictionary defines the term "Democratize" as "to make (something) available to all people" (Democratize, 2018), "to make it possible for all people to understand (something)" (Democratize, 2018). "Democratization of AI" stands for opening AI tools, technologies, and education sources to be used, improved, and advanced by broad masses of experienced or nascent data sciences (Microsoft, 2018; Google, 2018, IBM, 2018, DELL, 2018; Terdimann, 2018). The open-source development underpins advancements and diffusion of AI and is perceived as of fundamental importance; "the industry logic", as pointed out by Shafto (2016) is that big companies "open-source their AI software because they wish to be the foundations on which other people innovate" (Shafto, 2016). Shafto (2016) suggests: "Any entrepreneur who does so successfully can be bought up and easily integrated into the larger parent. AI is central because it, by design, learns and adapts, and even makes decisions. AI is more than a product: it is a product generator" (Shafto, 2016), Finally, he implies: "In the near future, AI will not be relegated to serving up images or consumer products but will be used to identify and capitalize on new opportunities by innovating new products" Shafto (2016).

2.2.7. ICT and cloud computing as enablers for AI

The recent success of AI solutions has been attributed to the availability of enabling information and communication technologies (ICT): "advancements in ubiquitous computing, low-cost cloud services, new algorithms, data analytics and other technologies are now allowing AI to flourish." (Accenture, 2017). Bughin et al. (2017) found that the foundation of digitization is essential for generation of AI applications and that leading sectors in digital, such as high tech and telecom or financial services, tend to be leading growth sectors in AI. As reported in (SAS, 2017) a study conducted with respondents from a number of industries and sectors have assessed platform readiness issues. The results show that 53% of respondents report that their "internal platforms are not ready or have to be adapted for AI" (SAS, 2017); the other group already "made investments either in the cloud or using partners' infrastructure" (SAS, 2017). The organisations have argued that (SAS, 2017): "cloud is necessary… this type of multi-scalable architecture is necessary for AI adoption" (SAS, 2017), and "We think that cloud technology … is mandatory for its flexibility & speed" (SAS, 2017).

Information systems scholars have also argued that cloud computing (CC) radically altered the way firms access and use ICT for supporting their activities (e.g., Marston et al., 2011, Müller et al., 2015). Marston et al. (2011) define CC as "an information technology service model where computing services (both hardware and software) are delivered on-demand to customers over a network in a self-service fashion, independent of device and location." The benefits of CC include reduced cost of ICT ownership and operation costs, replacing capital investments by operating expenses, rapid deployment of new ICT services, and dynamic scaling to changing business needs (Müller et al., 2015); therefore CC-based architecture provides efficient and effective playground for product/service and process innovations (Müller et al., 2015). The business models currently offered by cloud providers – "the infrastructure as a service (IaaS), platform as a service (PaaS) and software as a service (SaaS)" (Marston et al., 2011) – have also been analyzed by researchers (e.g., Chang et al., 2010, Boillat & Legner, 2013, Labes et al., 2017, Gupta et al., 2013). Recently, the XaaS model, or "everything as a service" was coined (Deloitte, 2017, p70, OPENSOURCE, 2017, p37).

Information systems researchers have also studied the relationship between the propensity to use cloud technologies and the propensity to engage with other companies in "product and process innovation" (Loukis et al., 2017). The results from a study based on an e-Business survey of more than 600 companies in three less digitised sectors conducted by Loukis et al. (2017) showed that cloud technology is primarily considered a "cost-effective means of supporting inter-organizational collaboration with other firms for the design of innovations."; however, not so much for "implementation" of innovation (Loukis et al., 2017).

The major cloud computing providers, e.g., Amazon, Microsoft, Google, Alibaba, IBM, and others, have added to their storage and computation assets, cloud management capabilities, and cloud service marketplaces, also artificial intelligence development tools and algorithms in the form of AI-as-a-service products, over standardized application programming interfaces (APIs). Other providers of AI-as-a-Service often need to partner with cloud providers to create a scalable globally-accessible cloud-based solution.

2.2.8. AI as a general-purpose technology (GPT)

The term "general-purpose technology" (GPT) describes fundamental advances, such as steam, electricity, internal combustion, and information technology (IT) that change everyday life and how businesses operate (Rousseau, 2010). Exploitation of GPTs brings benefits to a broad range of sectors (Bresnahan and Trajtenberg, 1995; Youtie et al., 2008; Maine and Garnsey, 2006). Bresnahan and Trajtenberg (1995) suggested that GPT is characterised by spreading to most sectors (pervasiveness), continuous improvement driving continuous reduction in costs and prices, and spawning innovation by making it less complex to invent new products or processes. Jovanovic & Rousseau (2010) compared the evidence showing that electricity belongs to GPTs with the evidence for IT and showed that IT meets all three GPT conditions. GPT makes it easier to invent and produce new products or processes, often reflected by a surge in patenting (Rousseau, 2010). Youtie et al. (2008) propose that GPTs has positive impact on development of complementary technologies. GPTs require strong alliances with customers and partners to obtain complementary assets and financing as shown by Maine & Garnsey, (2006) for advanced material ventures.

Researchers, businesses, and politicians argue that AI may become, or already is a GPT (Teece, 2016, p7; Brynjolfsson and McAfee, 2017, p4; Trajtenberg 2017, EC, 2017). AI has already demonstrated to possess GPT characteristics (Trajtenberg 2017, Brynjolfsson and McAfee, 2017, Cocburn et al., 2018). Teece (2016) argues that because GPRs enable technological opportunities not only for inventors but also for many other agents, and so create "dynamic spillovers" the innovators may be able to extract only small fraction of the value. Teece (2016) suggests that from a business model standpoint capturing value from GPT and enabling technologies is more challenging as it "requires not only applying the technology but also driving the technology's path forward and into derivative applications, which inherently involves engaging with partners" (Teece, 2016). Cockburn et al. (2018) point out to a shift towards research that utilises "passively generated large datasets and enhanced prediction algorithms," and a potential race "to acquire and control large critical datasets and application-specific algorithms" (Cockburn et al., 2018). It has been observed that AI patents have been growing exponentially (Hoffman, 2007), that large companies (IBM, Microsoft, Google, and others) have already amassed large volume of AI patents either by filling or acquisition (Clarivate Analytics, 2017) and that Japan, Korea, USA, Taiwan, and China are leading countries in AI patents, while EU is lagging (OECD, 2017). As the technology advances in "inventiveness," the open issue of how to deal and whether to protect AI-created or machine-created inventions and patents has also attracted significant attention (WEF, 2018, Hattenbach & Glucoft, 2018, Somaya & Varshney, 2018).

2.3.Competitive advantage and dynamic capabilities

The researcher interest in competitive advantage that started in 1960s resulted in numerous strings of thoughts and strategic management theories, where the earlier stage of the theories development was dominated by the Market-Based View (MBV) (Wang, 2014). MBV considers external market orientation together with industry factors to be primary determinants of a firm's performance, the sources of value as resulting from competitive situation, and the strategic position as a "firm's unique set of activities that make it different from their rivals" (Wang, 2014). The most prominent analytical framework, the Porter five forces model (Porter, 1985) offers a structured way for analysing the current situation by identifying barriers to entry, threat of substitutes, bargaining power of suppliers and buyers, as well as level of rivalry among competitors. However, acknowledgAs systing that significant technological changes lead to dynamic markets and complex industries with multiple inter-relationships, MBV was criticised for assuming a perfect market and static market structure (Wang, 2014; Teece, 2007).

Moving away from the market-based perspective, the resource-based view of the firm (RBV) adopts "inwards-looking perspective" (Penrose, 1959 cited by Wang, 2014). It establishes the relationship between firm's competitive advantage and its "simultaneously valuable, rare, imperfectly imitable and imperfectly substitutable (VRIN)" intangible and tangible assets and capabilities (Barney, 1991). Capabilities and core competencies are firm-specific and systemic resources rooted in organisational processes (Barny, 2001). However, core competencies may stagnate and are recognised as not sufficient for the long-term success because they provide advantage based on contemporary circumstances (e.g., Helfat & Winter, 2011).

The Dynamic Capability (DC) perspective evolved from RBV as its dominant perspective attracting vibrant research community (Ambrosini & Bowman, 2009; Barreto, 2010). As systematized by Helfat & Winter (2011) researchers subscribing to the DC perspective explored the difference between the firm's operational and dynamic capabilities: while operational capabilities are a set of high-level routines guiding firms' activities towards a certain outcome, dynamic capability as defined by Teece & Pisano (1994) is "the subset of the competences/capabilities which allow the firm to create new products and processes and respond to changing market circumstances" (Teece & Pisano, 1994), "to create new resources, to renew or alter its resource mix" (Teece et al., 1997). DCs explain how competitive advantage arises from firms' capability to adapt to "market uncertainty and dynamic change", (Eisenhardt & Martin, 2000), however, as pointed out by Ambrosini & Bowman (2003) "dynamic capabilities do not equate with sustainable competitive advantage." For evaluating the performance of DCs evolutionary and technical fitness are proposed "distinguishing between 'doing the right things' (evolutionary fitness) and 'doing things right' (technical fitness)" (Ambrosini and Bowman, 2009).

Addressing the central question of how the dynamic capability evolves, Teece & Pisano (1994) and Teece et al. (1997) suggested three DC-building managerial processes: coordination/integration, learning, and reconfiguring. Zollo & Winter (2002) proposed learning mechanisms for the evolution of DCs: experience accumulation, knowledge articulation, and knowledge codification. Eisenhardt & Martin (2000) indicated how DCs are achieved in a process of obtaining, integrating, reconfiguring, and releasing resources for new resource configuration. Eisenhardt & Martin (2000) considered variation and selection as the crucial element in creating DCs suggesting that repetitions, past mistakes, and the pace of experience are the main mechanisms of evolution. Zahra et al. (2006) considered semi-automatic learning from experience as more relevant for established firms and trial and error, improvisation, and imitation mechanisms as more likely to be used by new ventures.

Teece (2007) elaborated an extensive integrated "sensing-seizing-reshaping" framework, that disaggregates dynamic capabilities into the capacity (a) to "sense and shape opportunities and threats", (b) to "seize opportunities", and (c) to "maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring the business enterprise's intangible and tangible assets" (Teece, 2007). Teece (2007) states that the "microfoundations of dynamic capabilities -the distinct skills, processes, procedures, organizational structures, decision rules, and disciplines—which undergird enterprise-level sensing, seizing, and reconfiguring capacities are difficult to develop and deploy" (Teece, 2007).

For all three DC blocks Teece (2007) have elaborated specific set of microfoundations, e.g., "Processes to identify target market segments, changing customer needs, and customer innovation" in "sensing", "Selecting enterprise boundaries to managing complements and control platforms" in "sizing", and "Knowledge Management" in "reconfiguration" (Teece, 2007).

Researchers have also studied specific DCs, e.g., IT DCs (Mikalef & Pateli, 2015, 2015) or DCs of e-business transformation (Daniel & Wilson, 2003). Mikalef & Pateli, 2015 (2015) proposed and verified a model that shows that "IT-enabled dynamic capabilities" are positively associated with "market capitalizing agility" and "operational adjustment capability" which themselves are positively associated with competitive performance. The model was verified based on the survey data from 274 international firms and by applying structural equation modelling (SEM), (Mikalef & Pateli, 2015). IT-enabled dynamic capabilities were measured by assessing how effective the firms were in using IT systems to support or enable routines associated with (1) sensing, (2) coordinating, (3) learning, (4) integrating, and (5) reconfiguring (Mikalef & Pateli, 2015). Using the same methodology, Ali et al. (2012) proposed factors of dynamic capabilities (integration, reconfiguration, renewal) and substantive capabilities and studied their significance and relationship. Substantive capabilities construct as used by Ali et al. (2012) enable firms to "perform operational activities such as logistics, marketing and sales or manufacturing" (Ali et al., 2012). Using the conceptualization of innovation capabilities (Lawson and Samson, 2001 cited by Daniel & Wilson, 2003) and dynamic capabilities (Eisenhardt & Martin, 2000) Daniel & Wilson (2003) used a case study approach of five companies to identify eight distinct dynamic capabilities in e-business transformation.

2.4.Profiting from Innovation Framework

The Profiting from Innovation (PFI) framework developed by Teece (1986), systematizes factors that determine how profit from innovation is distributed among the innovator, followers, and firms with assets that the innovator needs to commercialize innovation. The basic building blocks of the PFI framework (Teece, 1986) include the regimes of appropriability, the complementary assets, and the dominant design paradigm.

The regimes of appropriability, which may be "tight" or "week," are controlled by the efficacy of protection by means of patents, copyrights, and trade secrets, and the nature of technology, or the degree to which the knowledge is tacit, as opposite to codified (Teece, 1986). Teece (1986) further defines complementary assets as all generic, specialized, or co-specialized assets, which firms need to own/build (integrate) or asses (contract) to commercialize innovation. While generic assets can be used without adjustment, specialized assets are unilaterally dependent, and cospecialized exhibit bilateral dependence (Teece, 1986). The ownership of complementary assets is a critical factor in commercializing innovation (Teece, 1986). The owner of specialized assets either capture the largest share of innovation profit (in the weak appropriability regime) or share it with the innovator (Ceccagnoli and Rothaermel, 2013). Generic complementary assets in combination with the weak regime endow the customer with the most of the value, while in combination with the strong regime the innovator captures most of the value. (Ceccagnoli and Rothaermel, 2013). The third building block of the profiting from innovation framework (Teece, 1986), is the phase of the evolution of the product category. Building on the technology evolution theory of Abernathy and Utterback (1978, cited by Teece 1986) and Dosi (1982, cited by Teece 1986). Teece (1986) differentiates between two phases of development: 1) „the preparadigmatic stage" in which many designs compete against each other, and 2) "the paradigmatic stage" which starts with the emergence of the dominant design and is characterized with price-based competition, process innovation, importance of specialized and co-specialized assets, and innovation based on complementary products. Teece (1986) shows how a firm can select among costly integration and contracting (strategic partnering) accounting for appropriability regime and the type of needed assets, and how the outcome of the competition is determined by the appropriability regimes, the market powers of competitors, and the phase of the industry evolution. In weak appropriability regime as argued by Teece (1986) imitators can outperform innovators if they are better positioned with respect to complementary assets.

The refinement of PFI framework (Teece, 2006) adds timing, standards and installed base effects to the explicit drivers of the value appropriation. Teece (2010) points out that the PIF helps in selecting the appropriate business model based on the requirements and strategic options from the three business model types: the integrated business model, in which an innovating firm bundles innovation and product together, the outsourced business approach based on licensing, and different hybrid approaches in which selection and orchestration of the external assets become critical skills of management. Teece (2017) added understanding of business model design to capabilities that pioneers need for profiting from innovation.

Accounting for the changes that digital revolution exerts on the manner of innovation, Teece (2016) extended the applicability of the PFI framework in the presence of enabling technologies, e.g., information and communication (ICT) assets and standards. Teece (2016) argues that appropriability is particularly challenging when a firm develops and commercializes enabling technologies and/or general-purpose technologies, indicating the need for more granular view of standards, complementary assets, business ecosystem and business models.

As pointed out by Teece (2006, 2010) a merit of PFI framework is its predictive and normative power; however, while PFI framework predicts that profits will go to the bottleneck assets, these are not always easy to identify, and they may shift over time. Teece (2106) points out that pioneers of enabling and general purpose technologies have difficulty appropriating the fruits of their investment because 1) a single firm cannot control all complementary assets and technologies to internalize the spillovers, 2) the value of technology may not be understood, and it may be regulated, 3) technology is an intermediate input in the ("multi-innovation") value chain, hence pricing is an issue, 4) patents are costly to enforce, hence the appropriability regime is typically "weak", 5) reliance on external assets reduces market power of innovators (startups in particular) and requires building partnerships or joining ecosystems. In a case of multi-technology innovation Teece (2016) argues that the bottleneck is often a technology that must be sourced externally. Teece (2016) shows how within connected business ecosystems (e.g., the one emerged in the mobile data revolution) characterized with complexity and interdependence of the technologies the set of drivers of a PFI framework is to be extended with the "ecosystem strength."

2.5.Open innovation and crowdsourcing

In modern economies, firms increasingly base their innovation activities on a combination of internal and external knowledge resources, skills, and production capabilities (Chesbrough, 2003, 2006; Huizingh, 2011). Uncertainty in the environment and the complexities of innovation problem lead to "increased permeability of organizational boundaries" in the process of the solution search, and this openness influences how firms innovate and appropriate benefits of innovation (e.g. Chesbrough, 2003a; Laursen & Salter, 2006).

A two-dimensional analytical framework proposed by Dahlander & Gann (2010) classifies open innovation into inbound or outbound based on the direction of the innovation in respect to the focal firm, and pecuniary and non-pecuniary based on the type of exchange. The four resulting types of openness (Dahlander & Gann, 2010) are: 1) revealing (outbound, non-pecuniary) 2) selling, e.g. licensing (outbound, pecuniary), 3) sourcing (inbound, non-pecuniary) and 4) acquiring (inbound, pecuniary), have their distinctive characteristics, advantages, and disadvantages, which strongly depend on the appropriability regime (Dahlander and Gann, 2010). Revealing or selling as outbound innovation requires emphasizes the value of formal IPRs (Dahlander & Gann, 2010). Inbound innovation requires efficient searching, absorptive capacity, avoiding over-search or high similarity of external and internal knowledge (Dahlander & Gann, 2010). "Absorptive capacity" as the ability of the focal firm to recognize the importance, absorb, and use external knowledge which is required for open innovation, is the result of R&D which crates new knowledge and increases absorptive capacity (e.g., Cohen & Levinthal, 2000; Zahra & George, 2002)

Addressing the question of search for open innovation, Felin and Zengler (2014) classifies the search methods based on the level (high/low) to which the knowledge is hidden to the managers of the focal firm, and the complexity (high/low) of the problem. They suggest that in the regime of a high level of hidden knowledge the open, theory-guided search and self-selection is best suited for high complexity problems, and directional, trial and error search – self-selection, best for simple, decomposable problems (Felin and Zengler 2014). When the level of hidden knowledge is low, Felin and Zengler (2014) suggest that well understood simple problems can be solved resorting to centralized selection, directional, trial and error search, and that difficult ill-defined problems can be best solved by centralized selection, theory guided search. Felin and Zengler

(2014) positioned six innovation governance approaches within the search space: two closed innovation approaches: authority based and consensus-based hierarchy, and four groups of open innovation governance: 1) markets or contracts (simple problems, self- or centralized- selection) 2) partnerships, alliances or corporate venture capital (CVC) (moderately complex problems, centralized selection), 3) contests, tournaments, and platforms (simple problems, self-selection) 4) users and communities (complex problems, self-selection). Felin and Zengler (2014) point out to different outcomes of different forms of open innovation: the sourcing based on markets/contracts results in the exchange of property rights that allow for access to externally owned technology, knowledge, or solutions; partnerships, alliances, and CVC yield solutions to problems of intermediate complexity achieved in open exchange of knowledge, or creation of theories to guide solution search for complex problems; contests, tournaments, and innovation platforms match firms that offer "decomposable problems" with firms or individuals with potentially relevant knowledge or complete solutions. Felin and Zengler (2014) argue that the open innovation benefit from fruitful investments in theories for decomposing previously complex problems, from availability of technologies and platforms that lower costs of search, and from network externalities that arise on these innovation platforms.

One of the mechanisms of the open innovation paradigm is crowdsourcing which refers to an act in which a company outsources a problem to a crowd (Howe et al., 2006) The crowdsourcing platforms use Web and communication technologies to manage the interactions among solution seekers and a self-designated crowd (Prpic et al. 2015). A stream of research has addressed the relation among the attributes of the crowdsourced problem and the determinates of the problem solvers; as found pointed out by Jeppesen and Lakhani (2010) the problem solvers at a lager dommain distance from the field of the problem were more likely to solve the problem. Afuah and Tucci (2012) argued that with crowdsourcing firms benefit from turning the distant search into the cost-efficient local search.

Prpic et al. (2015) analyzed "crowd capital" in different types of crowdsourcing, such as crowd-voting, idea crowd-sourcing, micro-task crowdsourcing, or solution crowdsourcing. One example of a "tournament-style" crowdsourcing platform is Kaggle (acquired by Google in 2017), a platform for predictive modelling and analysis where companies, such as GE, NASA, Deloitte and Allstate (Weldon, 2013) can address a global online community of more than 500,000 registered statisticians and data miners, by posting a challenge with all the necessary data and a description of the problem, a prize pool, and a deadline (Waters, 2017). One example of a winning algorithm was crowdsourced by GE and achieved a 12 percent improvement in efficiency over actual situation (Bughin et al., 2017). Thereby, the incentive for problem-solvers is often not monetary but the desire for "access to interesting data sets and interesting problems" (Bender, 2016). Kohler & Nickel (2017) analyzed business models of two successful business crowdsourcing platforms and extracted as the factors of their success: 1) effective value creation 2) crowd recognition, 3) ensuring quality 3) sharing value captured, 4) fully aligned business model, and 5) engaging crowd in the evolution. Simon (2016) showed how user generated content model of social media, blogging and content platforms have added users as a new source of production and co-creation and have created opportunities for companies to engage with communities for brand promotion, advertising, and sourcing talents.

2.6. Platforms and ecosystems

2.6.1. Platforms

Managers and scholars use the term platform indifferent technological and organizational contexts. Platforms are popularized as business that can achieve exponential growth or create innovative data-driven business models (Parket et al., 2016, van Spijker, 2011, Ismail, 2014). Some of the strongest companies are digital platforms or platform-mediated networks which facilitate compatibility and interaction, and compete for their dominance (Eisenmann et al., 2006; 2011). Strong Internet platform owners such as Microsoft, IBM, Google, Amazon, Facebook, Alibaba, Baido and others, carefully manage their platforms and ecosystems of value co-creators, and compete for customers in various areas of their business activity (Economist, 2014).

Scholars have studies different economic, technology or organizations aspects of platforms and ecosystems, and several studies provide classifications and systematizations of the research field (e.g., Gawer, 2014, Gawer & Cusumano 2014, McIntire 2017, Thomas et al., 2014). Based on a structured literature review, Gawer & Cusumano (2014) extracted platform typology that differentiate between the internal or company-specific platforms, and "external or industry platforms" Gawer & Cusumano (2014). Internal platforms are as "set of assets organized in a common structure from which a company can efficiently develop and produce a stream of derivative products" (Gawer & Cusumano, 2014), and external platforms as "products, services, or technologies that are similar in some ways to the former but provide the foundation upon which outside firms (organized as a "business ecosystem") can develop their own complementary products, technologies, or services" (Gawer & Cusumano, 2014). While an internal platform supports a focal firm with its close suppliers in developing families of products by reusing or redeploying assets, industry platforms facilitate large number of complementary innovations generated by "an a priori unconstrained set of external actors" (Gawer & Cusumano, 2014). As suggested by Gawer & Cusumano (2014) on innovation management of a technology platform requires special consideration in which "open or modular architecture, vibrant coalition, mutually beneficial ecosystem relationships, continuous evolution of the platform, the ecosystem and the business models all play crucial role."

Gawer (2014) further extended this typology to account for internal, supply-chain and industry platforms. According to Gawer (2014) platforms "federate and coordinate constitutive agents who can innovate and compete" (Gawer, 2014); "create value by generating and harnessing economies of scope in supply or/and in demand" (Gawer, 2014); and "entail a modular technological architecture composed of a core and a periphery" (Gawer, 2014). This model, as argued by Gawer (2014) connects two dominant perspectives of platform research: the industrial economics perspective and engineering design perspective. The former is concerned with platforms as two-sided or multi-sided markets, their role as matchmakers, the "network effects," direct or same-side network effects, or indirect network effects among different sides, and the "lock-in" effect which may result in a "winner-take-all" outcome (Gawer, 2014). The latter understands platforms as hierarchical, modular, and decomposable architectures shared across a family of products, where innovation results from making design choices on re-using common assets on architecture structured into the core and the complements (Gower, 2014).

In an integrative model Gawer (2014) expresses new quality of industry platforms along for dimensions: 1) constitutive agents flexibly adopt user/provider roles, 2) interfaces are open, 3) accessible innovation capabilities are unlimited pool of external innovators, and 4) coordination mechanisms – is ecosystem governance controlling competition among platform complementors and protecting the core of the platform (Gawer, 2014).

Related to the product architectures, Yoo et al., (2010) argued that a new type of product architecture, "the layered modular architecture", extends the "modular architecture of physical products", and "instigates profound changes in the ways that firms organize for innovation" (Yoo et al., 2010). Defining the architecture as "loosely coupled layers of devices, networks, services, and contents created by digital technology" (Yoo et al., 2010), he propose a concept of "doubly distributed network", where distributed refers to "the unbounded mix-and-match capability of heterogeneous resources across layers" in the process of value-creation, and "doubly distributed" refers to the fact that "the control over product components is distributed across multiple firms, and the product knowledge is distributed across heterogeneous disciplines and communities" (Yoo et al., 2010). This theoretical concept connects the "key strategic resources that the firm can control" which are the "design of technical boundary resources such as APIs and SDKs (Ghazawneh and Henfridsson, 2010) and "social boundary resources such as incentives, intellectual property rights, and control" (Ghazawneh and Henfridsson, 2010). The theory of the boundary resources in software platforms (e.g., Ghazawneh, 2012) strongly focuses on the boundary resources that stimulate innovation of complementors, which are APIs and SDKs. Yoo et al., (2010) argues that "a firm's ability to attract heterogeneous and unexpected firms to build various components" using these technological resources, "has become strategically important" (Yoo et al., 2010).

Thomas et al., (2014) extracted from the extant research on platforms four streams: organizational (platform stores an organization's resources and capabilities), product family (the platform facilitates development of product families and variants for market niches), market intermediary (the platform controls a marketplace) and ecosystem stream (the platform equates to shared core technologies/standards for value co-creation of complementary products) (Thomas et al., 2014). Thomas et al., (2014) suggests that common for all streams are "the theoretical logic of leverage and openness". Leverage is attained in a process of creating shared assets, designs, and standards, and their coordinated recombination, and can be production, innovation, and transaction leverage (Thomas et al., 2014). The architectural openness is according to Thomas et al.,

(2014) related to modularization, information disclosure and open interfaces, and can range from “closed” to “many-to-one” in case of a supplier chain or “many-to-many” configurations of industry platforms (Thomas et al., 2014). The concept of “architectural leverage” combines types of leverage and openness together to help differentiate among different platform logics from internal, to supply chain, to markets to ecosystems, and their evolution strategies.

McIntyre & Srinivasan (2017) identified three dominant views within the platform research: the market dynamics view, the strategic management view, and the technology management view. Within the market dynamics perspective McIntyre & Srinivasan (2017) see research of economists on network effects, the impact of the platform’s installed base, and the “winner-take-all outcomes” (McIntyre & Srinivasan, 2017). According to McIntyre & Srinivasan (2017) the strategic management view includes research that moves from explanation to effectuation (actions) that influence the outcome (McIntyre & Srinivasan, 2017). The studied factors include timing of entry, firm size, platform features, quality, pricing, competition among platforms, and management of complementors (McIntire & Srinivasan, 2017). Within the technology management view, McIntire & Srinivasan (2017) positioned research on technical architectures aspect. McIntire & Srinivasan (2017) suggest that focus on improving understanding of the “interplay between the strength of network effects” and “platform design choices” may help answer “why some industries tend to converge on a single platform, while others foster the emergence of multiple competing platforms.” Similarly, McIntire & Srinivasan (2017) emphasize the role of the firm’s ability to leverage its existing network, complementor attributes, and incentives, on competitive advantage.

2.6.1. Ecosystems

To describe different types of non-hierarchical governance among multiple companies that align and cooperate to jointly create value, researchers have come up with the concept of ecosystem (e.g., Adner, 2017). Adner (2007) argued the thought “the ecosystem construct is related to business models, platforms, coopetition, multisided markets, networks, technology systems, supply chains, value networks” (Adner, 2017), it brings new insights for the strategy literature. Adner (2017) classifies ecosystem theory into two mutually consistent viewpoints: “ecosystem-as-affiliation”, which sees “ecosystems as communities of associated actors defined by their networks and platform affiliations" (Adner, 2017).; and (b) "ecosystem-as-structure", which views "ecosystems as configurations of activity defined by a value proposition" (Adner, 2017). Adner (2017) argued that in the "affiliation view" companies in the ecosystem align their roles and capabilities with the openness strategies and the directions set up by one or more central companies, and he pointed out that this perspective can be explained with the platform construct. The ecosystems-as-structure, as proposed by Adner (2017) considers value creation grounded in a value proposition, and it seeks to identify which actors must interact to implement the proposition. Hence, the ecosystem, as defined by Adner (2017) is the alignment structure of the partners that need to multilaterally interact for a focal firm's value proposition to materialize, which also accounts for divergence in interests, perspectives, and business models of the ecosystem partners. Adner (2017) defined four elements of the ecosystem: activities (actions to be undertaken), actors (or roles that undertake the activities), positions ("who hands off to whom"), and links (multilateral connections among partners that show transfers of information, material, money). Adner (2017) also further argues that "If the heart of traditional strategy is the search for competitive advantage, the heart of ecosystem strategy is the search for alignment" Adner (2017), and he warns that in extant research "the constructs of complements, complementors, and complementary assets" (e.g., Milgrom & Roberts, 1990; Teece, 1986, cited in Adner, 2017) have "suffered from a conceptual blending" Adner (2017), and that "distinctiveness of these distinctions has remained underexplored" (Adner, 2017).

Jacobides et al. (2018) explored different types of complementary assets in ecosystems, which as they argued are enabled by modularity that allows interdependent organizations to coordinate without full hierarchical agreement. Jacobides et al. (2016) analyzed modularity and coordination of multiple firms and proposed three types of systems for value creation: the hierarchy-based, the ecosystem-based, and the market-based value system. Jacobides et al. (2016) analyzed different type of complementarities – generic (can be used without change), unique (requires coordination), and super-modular (when coordination yields less costly production, or more ad value in consumption - the network effect). Jacobides et al. (2018) showed how depending on the type of complementarities needed in production and consumption, different coordination structures emerge. Jacobides et al. (2018) posit that ecosystems emerge if there are non-generic complementarities and if roles of partners are well specified with special rules.

In his extended PFI framework Teece (2016) argue that the ecosystems are driven by “a value-creating form of complementarity” and necessitate addressing new types of complementary. A “multi-level PFI” framework introduced in (Teece 2016) addresses competition in multi-layer technology ecosystems, where layers are interdependent. In case of the mobile innovation analyzed by Teece, (2016) the communication chips layer, infrastructure equipment and terminal devices (primarily handsets), mobile carriers and handset makers layer, and Google and Android ecosystem for independent software developers, and Internet can all be viewed as ecosystems and grouped to incorporate interactions (Teece 2016). Accordingly, companies compete in multiple ecosystems, across many layers of this layered architecture, for which as Teece (2016) points out “architectural innovation is often desirable and especially difficult.” Teece (2016) pointed out how modulation lies at the core of the conflict among the autonomous and the systemic innovation: 1) the impact of autonomous innovation enabled by modularization could be curtailed without architecture system-level innovation, 2) modularity may reduce the ability of the ecosystem to generate systemic (or architectural) innovation.

2.6.2. Dominant design and winner take all outcomes

The emergence of the dominant design has been studied in the context of industry evolution and as already mentioned in the context of “Profiting from Innovation (PFI)” framework Teece (1986, 2006, 2016). The dominant design marks the end of „the preparadigmatic stage” in which many designs compete against each other, the result of which is an accepted design, which gets further incrementally improved in the so called “paradigmatic stage” (Teece, 1986). How the dominate design emerges and who wins the innovation battle towards the dominant design has been studied by many researchers, as systematized in (Srinivasan et al., 2016).

Studying the money market mutual fund industry Makadok (1998) showed that in the industry where the barriers to entry generally low and imitability of new products high, first or early movers can achieve sustainable pricing advantage and a moderately sustainable market share advantage. Analyzing the US bicycle industry, Dowel & Swaminathan (2006) show that “firms that are founded with a technology more proximate to the dominant design are more likely to develop a product that is based upon the dominant design", and hence profit in the innovation battle. Dowel & Swaminathan (2006) argue that companies should observe developments in an industry and enter just before the dominant design happens to emerge, or enter early but be flexible in transitioning "from one technological trajectory to another", eventually transitioning to the dominant design. Helfat and Lieberman (2002) showed that the companies with resources that better match what is required by a particular industry at the time of entrance are more likely to enter and more likely to survive and prosper. To better address "timing of entrance", Suarez et al. (2015) introduced the concept of "the dominant category" and showed that the right window of opportunity for entry is between the points in time at which 1) the dominant category emerges and 2) the dominant design becomes apparent. Suarez et al. (2015) argue that dominant category emerges when the understanding and crystallization of categories converge, and there is a shared understanding about the meaning of categories and product characteristics.

The winner-take-all (WTA) is related to the dominant design research but in the context of platform evolution, network effects, and platform competition. Srinivasan et al. (2016) analyzed determinants of the time and probability of the emergence of the dominant design. Srinivasan et al., (2016) showed that weak appropriability (difficult or low protection of IPRs), weak network effects, high R&D costs, low product radicalness make dominant design more likely to emerge, and emerge sooner in case of weak appropriability, larger value net, de facto standards, and low product radicalness. In the platform economy winner-take-all (WTA) is often considered a result of the "installed base advantage", "network effects" and the "lock-in" effects. Chen et al. (2017) studied the outcomes from the dominant technology designs competition among startups and diversifying entrants in platform-based and non-platform-based technologies. They examined the "relative risk of technological exits" by "relating the exit to the focal firm's pre-entry experience and the characteristics of the dominance battle" (Chen et al., 2017). Based on evaluation of 134 technologies involved in 31 dominance battles in the information technology industry from 1979 to 2007, they show that platform technology-based dominance battles more likely lead to the exit of technologies of startups, while this relation cannot be observed in non-platform technology-based dominance battles, or after the emergence of dominant designs

(Chen et al., 2017). Consequently, Chen et al. (2017) suggested that a startup must consider whether the technology is a platform or non-platform, and understand the stage of industrial evolution, that is whether the dominant design has emerged. Chen et al. (2017) points out that exit for startups is related to lack of organizational legitimacy, missing complementary assets, and low integrative capabilities.

Zhu & Iansiti (2012) developed a theoretical model to examine the relative importance of platform quality, indirect network effects, and consumer expectations on the success of entrants in markets based on platforms. They modelled three regions in the platform evolution, the quality-based region, the installed-base region, and the user expectation region. General result of Zhu & Iansiti (2012) is that in markets with significant indirect network effects, an installed base advantage does not shield the first mover from entrants if the market is in the quality driven region; hence, the incumbent needs to achieve quality levels at least comparable to those of the entrant. However, when the installed-base advantages or consumer expectations are the main drivers, the first movers may win even with inferior quality. Accordingly, Zhu & Iansiti (2012) suggest that in markets with statistically significant indirect network effects, no single strategy will always work to achieve WTA, arguing that for this reason findings from previous work often fail to explain market dynamics in different settings. Evans & Schmalensee (2016) argue that the WTA analysis should account for the correct "installed base" and indirect network effects.: while Google and Facebook are each considered WTA in their own category (Google in search and Facebook in social networking) they both share advertiser segment, where there is no evidence of WTA (Evans & Schmalensee, 2016).

Henkel et al. (2015) studied competition in the ecosystem and suggested that new entrants to a market tend to outperform incumbents in originating radical innovations and proposes explanation based on markets for technology. Henkel et al. (2015) argue that this apply in all in industries where entrants develop technologies and bid to be acquired by incumbent as they cannot survive by their own, while in turn, incumbents select to acquire a startup that developed the project of highest realized value and then commercialize their innovation. Henkel et al. (2015) have focused their study on industries where start-ups have access to limited funding, R&D require modest upfront investments, radicalness does not depend on R&D funds, and the targeted outcome is acquisition. The results indicate new entrants always produce more radical innovation than the incumbent, which they conferred to be applicable in the EDA industry.

Cozzolino & Rothaermel (2018) provide insight into competition between incumbents and entrants in different appropriability regimes following the "core-knowledge discontinuity." They show two dominant strategies of incumbents: allying with entrants when the appropriability regime is strong or acquiring entrants when the appropriability regime is weak (Cozzolino and Rothaermel, 2018). In addition, by considering "complementary-asset discontinuities" Cozzolino & Rothaermel (2018) come up with a model where incumbents tend to cooperate among themselves either cooperating with entrants in case of the strong appropriability regime or competing against the entrants in the weak regime.

2.7.Business Model

Business Model (BM) is a strategy framework and a management tool that entrepreneurs and established businesses alike, use to create and share a structured, holistic, and coherent picture of value proposition, value creation and value capture of their firms (Magretta, 2002, Chesbrough and Rosenbloom, 2002, Zott & Amit, 2010). The BM concept has high significance both in scientific research and in practice, as it can be related both to strategy and securing and expanding competitive advantage (Johnson et al. 2008) and to a process of creative "business ideation" often equated with the Business Model Canvas (BMC) of Osterwalder & Pignauer (2010).

The interest in the role of business models started with companies focusing on Internet-based value chains and revenue models of 1990s (Timmers, 1998). The BM research created a plethora of different conceptualizations, empirical studies, and reviews providing systematization of different research streams and identification of gaps and future research directions (e.g., Baden-Fuller and Mangematin, 2013, Gassman et al., 2016, Wirtz et al., 2016,)

Gassman et al., (2016, 7) showed how the BM research field is structured into seven dominant schools of thoughts: 1) "the activity system school" (e.g., Zott and Amit, 2010) understanding a business model "as a set of interdependent activities spanning firm boundaries" 2) "the process school" (e.g., Demil and Lecocq, 2010), conceptualizing a business model as "a dynamic process of balancing revenues cost organization and value" 3) "the cognitive school" (e.g., Baden-Fuller and Morgan, 2010) understanding a business model as “a ‘model’ or ‘logic’ of how firms do business” 4) “the technology-driven school” (e.g., Teece 2010, Chesbrough and Rosenbloom, 2002, Osterwalder & Pignauer, 2010) defining a business model as “a way to commercialize new technology” 5) the “strategic choice school” (e.g., Casadesus-Masanell & Ricart, 2010b) seeing a business model as “a result of strategic choices”, 6) “the recombination school” (e.g. Gassmann et al., 2014) understanding a business model as a “recombination of patterns for answering who-what-how” questions of the business, and 7) “the duality school” (e.g., Markides, 2006) that posit that “a business model does coexist with competing business models and requires ambidextrous thinking” (Gassman et al. 2016).

Gassman et al. (2016) points out to different degrees of abstraction that different “schools of thought” have adopted: from “narratives” of the cognitive school, to “archetypes” of the recombination school, to “key components” of the technology driven school, to “firm-level choices and meta-models” of process, duality and strategy choice school, to “activity system” of the activity school (Gassmann, 2016). In their use case analysis, Gassman et al. (2016) demonstrate how different business model conceptualizations allow for different types of business model analysis or business model innovation considerations.

Baden-Fuller and Mangematin (2013) created a typology of the business model classification with elements “customer sensing,” “customer engagement,” “monetization” and “value chain and linkage,” pointing out to the fact that multi-sided model platform model has received too little attention. Baden-Fuller and Mangematin (2013) addressed the “perceived status ordering among business models” and raised the question of what motivates investors to support a business model “fashion or logic”? (Baden-Fuller and Mangematin, 2013).

Wirtz, et al. (2016) analyzed the BM research and put three identified research standpoints: the “technology-oriented view”, the “organization-theory oriented view”, and “the strategy-oriented view”, into the historic perspective, arguing that while separated at the origins, these views were converging together, allowing for increasingly uniform (activity-based) business model understanding to emerge (Wirtz et al., 2016). A unifying definition proposed by Wirtz et al. (2016) posits: “A business model is a simplified and aggregated representation of the relevant activities of a company” (Wirtz et al., 2016). “It describes how marketable information, products and/or services are generated by means of a company's value-added component" (Wirtz et al., 2016). In addition to the architecture of value creation, strategic as well as customer and market components are taken into consideration, in order to achieve the superordinate goal of generating, or rather, securing the competitive advantage" (Wirtz et al., 2016). "To fulfil this latter purpose, a current business model should always be critically regarded from a dynamic perspective, thus within the consciousness that there may be the need for business model evolution or business model innovation, due to internal or external changes over time" (Wirtz et al. 2016).

Based on a comparison of sixteen dominant published business models Wirtz et al. (2016) proposed following constituent components for the integrated model: strategy, resources, network, customers, market offering (value propositions), revenues, service provision, procurement, and finance. Of these nine components, the business model of Osterwalder et al. (2010) covers seven organized within the Business Model Canvas (BMC): Key Resources (KR), Key Partners (KP), Customer Segments (CS), Value Proposition (VP), Customer Channels (CC), Customer Relationships (CR), Revenue Streams (RS), Key Activities (KA), and Cost Structure (CS). Their business model does not explicitly include strategy, as they consider business model to be "a missing link between strategy and processes" (Osterwalder, 2010). The relationship between the business model and strategy is a controversial topic as reviewed by Bukhard et al. (2011). For example, Casadeus-Masamell & Ricart (2010) argue that "a firm's business model is a reflection of its realized strategy," and in their business model conceptualization, they conceptualize "choices" (regarding assets, policies, governance) and consequences of choices (Casadeus-Masamell & Ricart, 2010). Teece (2018) points out to closely entwinned relationship and argues that "once in place, a business model shapes strategy," and in turn "strategy dictates business model design" (Teece, 2018).

While BMC of Osterwalder (2010) facilitates analysis based on components and technology, an activity-based business model conceptualization proposed by Zott & Amit (2010) establishes relationship between a BM and strategic decisions. Their BM is as a system of interdependent activities that spans the boundaries of the focal firm and shows how "value is created, appropriated, and shared among the focal firm and its partners, suppliers, and customers" (Zott & Amit, 2010). The activity system is described in terms of the so-called design elements – "content (what), structure (how) and governance(who)", and the sources of the value creation are described in terms of strategic decisions or the "design themes" – "novelty (adopt innovative content, structure or governance)" (Zott & Amit, 2010), "lock-in (build in elements to retain business model stakeholders)" (Zott & Amit, 2010), "complementarities (bundle activities to generate more value" (Zott & Amit, 2010) and "efficiency (reorganise activities to reduce transaction costs)" (Zott & Amit, 2010). Reporting about an empiric study aimed at verification of the model Zott & Amit (2007) pointed out to an inherent challenge of identifying strategic decisions from the business model realization, and telling novelty and performance apart.

Due to its general applicability for many different business model configurations, the Business Model Canvas (Osterwalder, 2010) have found broad adoption both in research studies (e.g., Boillat and Legner, 2013) and in practical application in business model design and business model innovation activities of stratus and enterprises. Inspired by the business model canvas (BMC) of Osterwalder (2010), several other canvases were proposed by practitioners: 1) the Lean Canvas (Canvanizer, 2012) with categories: problem, solution, unique value proposition, unfair advantage, customer segments, cost structure and revenue streams, 3) the Platform Canvas (GoetzPartners, 2016) with the components: platform owners, platform stakeholders, enabling technologies, empowering services, core value proposition, data sources, exchanges, channels and contexts, partners, and peers, 4) the Digital Platform Canvas (DPC, 2018) with components: producer segments, producer journeys, pricing, funnel, value proposition, tools and services, partners, filters, rules, core interactions, customer segments, customer journeys, cost structure and revenues, the Platform Business Model Canvas (PBMC, 2018) with components: consumers, producers, partners, owner, value proposition, transactions and core mission, and even the Machine Learning Canvas (Dorard, 2018) with components: value proposition, data sources, features, collecting data, building models, live evaluation and monitoring, ML task, offline evaluation, making predictions and decisions.

A "non-canvas" approach towards business model analysis and creation is proposed by Board of Innovation (BOIN, 2016). It introduces design elements to model different types of stakeholders in the value-network and to capture the relationships and transactions between them. The model proposed by BOIN (2016) has been tested in analyses of fifty business models of successful platforms and industry disruptors.

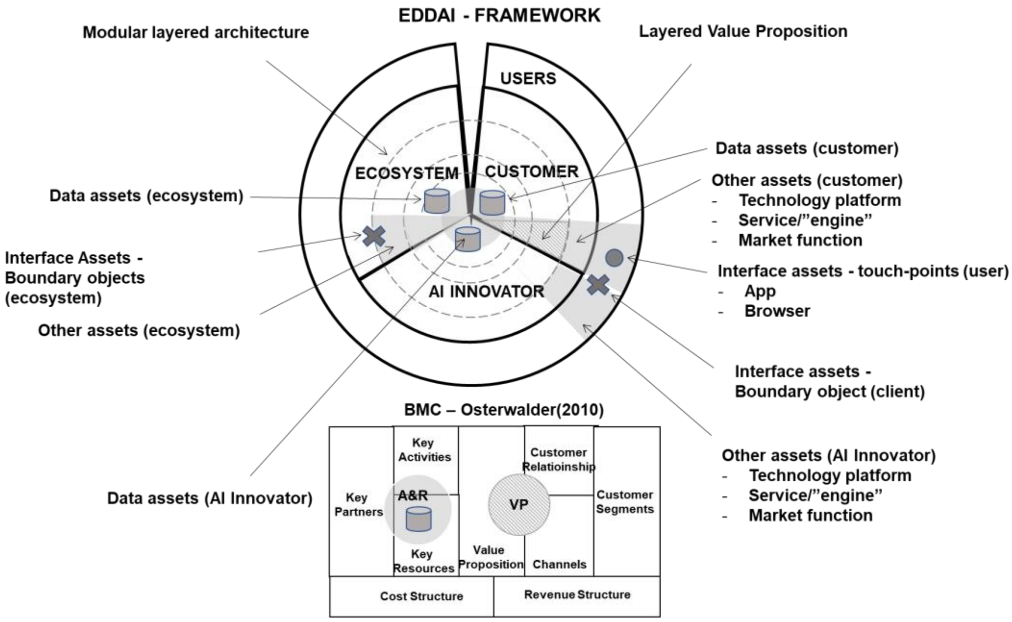
2.8.The analysis framework

This section describes the framework for analysis of the offerings and business models of the AI innovators. It integrates theoretical viewpoints presented in previous sections to facilitate in answering the research questions of the thesis. Inspired by the platform and ecosystem theory (Gawer et al., 2014, Thomas et al., 2014, Adner, 2017, Jacobides et al., 2018, Teece, 2016) and "doubly-distributed" framework of Yoo et al. (2010) the framework attempts to represent relationships among four significant domains of control: 1) AI Innovator, 2) Ecosystem, 3) Customers, and 4) Users. As the framework deals with ecosystems over doubly-distributed architecture (Yoo et al., 2010) we refer to it as EDDAI Framework.

The AI Innovator is the focal firm with value-proposition that motivates the ecosystem alignment (Adner, 2017). The Ecosystem stands for firms that align strategies and assets that AI Innovator need for the commercialization of its offering. On the other hand, the companies of the ecosystem also have their own perspectives and strategies beyond the AI Innovator VP. The Customers are the firms that benefit from the AI Innovator's offering and integrate them into their own processes or products. They typically serve (end)users, who benefit from AI-powered (end)product or service. The EDDAI Framework is general: users can be consumers, e.g., benefiting from a chatbot interface, or data scientists developing algorithms an AI Platform, or employees of the Customer who use an AI enabled solution in their business functions, e.g., an AI-powered tool for marketing analytics. If a focal firm provides offerings for (end)users, then AI Innovator and Customers denote two business units of the same business, e.g., an R&D and operations.

2.8.1. Graphical framework representation and BMC

Error! Reference source not found. gives a graphical representation of the EDDAI framework and its relationship to the Business Model Canvas (BMC) of Osterwalder (2010). The AI innovator creates a solution that delivers a value proposition to its B2B Customer. The VP is created over layered architecture by connecting complementary assets available in the Ecosystem (e.g., Cloud services, mobile platforms), owned by the Customer (e.g. existing tools), or owned by users (e.g., Smartphone), and the focal firm innovation (e.g., an



analytics tool of deep learning algorithms for computer vision)

Figure 1 The concept of the EDDAI framework and mapping to BMC

The AI Innovator builds and organizes its internal resources and activities, and aligns with partners (Ecosystem), Customers and Users to implement Value-Proposition. Which complementary assets the AI Innovator needs is determined by the nature of the AI innovation that in general requires data and computational capabilities. Complementary assets may be owned or controlled by the companies in the Ecosystem (e.g., data storage, cloud computing resources), but also by the Customers (e.g., specific company internal data) or by Users (e.g., a smartphone, or a smart home assistant). The EDDAI Framework differs from the general-purpose nature BMC, as it aims at accounting for a special nature of the AI innovation (VP) and is stronger aligned with the theory of ecosystems and platform architectures (Adner, 2017; Gawer et al., 2014). The AI Innovator maintains a technology platform: either internal or external. Some of the AI Innovators are industry platforms open for complementors' innovation, and some are also multisided markets.

The EDDAI Framework is also aligned with the concept of hierarchical modular architecture (doubly-distributed) of digital technology platforms providing digital products (Yoo et al., 2010, 2012), As illustrated in Figure 1, the domains of control of the Ecosystem, AI Innovator and Customer are represented as layers and "boundary resources" (Yoo et al., 2010, 2012) interconnecting the modular components of different companies and layers. The layered conceptualization can be used to represent innovation and different technology-based types of assets which can be distributed in different domains of control: 1) the data assets, 2) the components, 3) the engines, 4) the markets, and 5) the boundary objects. The data assets are needed to train the AI algorithms. The components are needed to deploy algorithms or store data. The markets represent the matching capability in case of the multi-sided platform. The engines provide access to algorithms. The boundary objects, open APIs, and SDKs, (Ghazawneh and Henfridsson, 2010) are the points of integration and flexibility. In the context of the digital innovation If the company controls assets of the boundary type it may be considered as an external technology platform that support open-end, flexible platform-based innovation; the boundary resources describe the technology but also governance in terms of contracts and incentives (Ghazawneh and Henfridsson, 2010) that developers (of Ecosystem partners or Customer) use to implement complementary product on the focal firm platform. The AI Innovator solution is therefore a layered solution comprised of internal technology (e.g., engines) and complementary assets of partners populating different layers.

While instrumental for representing inter-firm integration, the "boundary resources" construct (Ghazawneh and Henfridsson, 2010) do not fully account for user domain of control, and user-facilitated innovation. The users do not use boundary resources; however, they sometimes create content, they leave traces of use (Web Data) and they may provide feedback over the service interface.

The EDDAI Framework therefore extends the existing architecture view with the "touch point" construct, as the interface between the User domain of control and other domains of control. In the business model of Osterwalder (2010) the constructs of customer relationship (interaction facilitating the service/ product provision) and the channel (over which the service/product is delivered) describe to some extent the capabilities of the "touch point" resource. The "touch point" integrates three common or emerging capabilities on this interface: the co-creation capability, the sensing capability, and reconfiguration capability. The relevance of explicitly modelling touch points is in increased technological and governance modularization. A touch point can be an externally controlled asset monetized as a service. The aim of the EDDAI Framework is to capture the complexity of relationships between the Ecosystem, AI Innovator and Customers and Users which are not explicitly accounted for in a business model of AI Innovator.

2.8.1. Dynamics in the ecosystem and dynamic capabilities

The assumption of the EDDAI framework is that the companies represented as Customers, Ecosystem companies or AI Innovator, use open innovation strategies and can use different approaches to source innovation including cooperation projects to test whether the dominant design is emerging, renting complementary assets, acquiring startup innovators, or partnering with more established companies that acquires a startup innovator. The perspective of the Customer also focuses the lens of enquiry on the benefits that these companies derive from the focal firm's AI offering. The solution can aim at improvement of operational capabilities, e.g., by enabling optimization of processes hence saving time, or reducing cost (Teece, 2007). However, accounting for the general-purpose nature of AI, its ability to foster innovation, its human-like conversational and inferential abilities, and its ability to learn, the solution can also target improvement of dynamic capabilities - sensing, seizing, transforming (Teece, 2007), or substantive capabilities (Zahra et al., 2002) or DC microfoundations (Teece, 2007). Offering value proposition that is tailored to improve operational capabilities, or the one that belongs to microfoundations of dynamic capabilities, may have different implications for the AI innovator, e.g., being able to commercialize the service alone or be acquired.

From the technological perspective, distinctive features of deep learning technology make it a candidate for underpinning dynamic capabilities are the following. Firstly, with deep/machine learning the knowledge (the inference / decision making model) is learned (codified) automatically based on experience (raw labelled data) which can be collected automatically. The model can be used in the solutions facing the customer, or instructing the human decision maker, or in an automated process. Secondly, the algorithms are not only capable to classify objects (such as documents, parts of conversation, images or sequences of videos) based on the learned model, but can also autonomously create new objects, e.g., summaries of document, proposals of complex contracts, proposals for new drugs, new pieces of code, new strategies in playing games, trading strategies, meaningful dialogues, images or sequences of videos, patents, and can automatically deploy and test new strategies. Thirdly, these algorithms will improve in time, and business analysts already argue that AI solutions would be capable of even designing business models, and even managers and consultants might face replacement by AI solutions.

Accordingly, it can be expected that some AI solutions may evolve into very powerful microfoundations of a firm' dynamic capabilities. For each company it will be important to define whether such solution can be contacted or needs to be owned and integrated. This will also very much depend on what type of the asset is this complementary asset: the generic or specialized or co-specialized (Teece, 1986) or based on (Jacobides et al., 2018), generic, unique or supra-modular in consumption (demand) or in production (supply).

2.8.2. The analysis dimensions

The business model components defined within the BMC of Osterwalder et al. (2010) and the concepts underpinning the proposed EDDI Framework provide the basis of the business model analysis. The cross-section study, the content analysis approach, and the nature of information published on the companies' websites as selected object of analysis all impose constraints on the level of detail of the analysis, hence it can be assumed that components of the business model such as cost structure, or customer relationship could not be comprehensively assessed.

A deeper analysis of some dynamic aspects of the business model evolution would necessitate a case-study approach, the cross-sectional study based on a content analysis of the web pages can only assess a snapshot of information available at a specific moment in time. Moreover, the analysis in this study may be more based more on "signals" rather than grounded in objective facts.

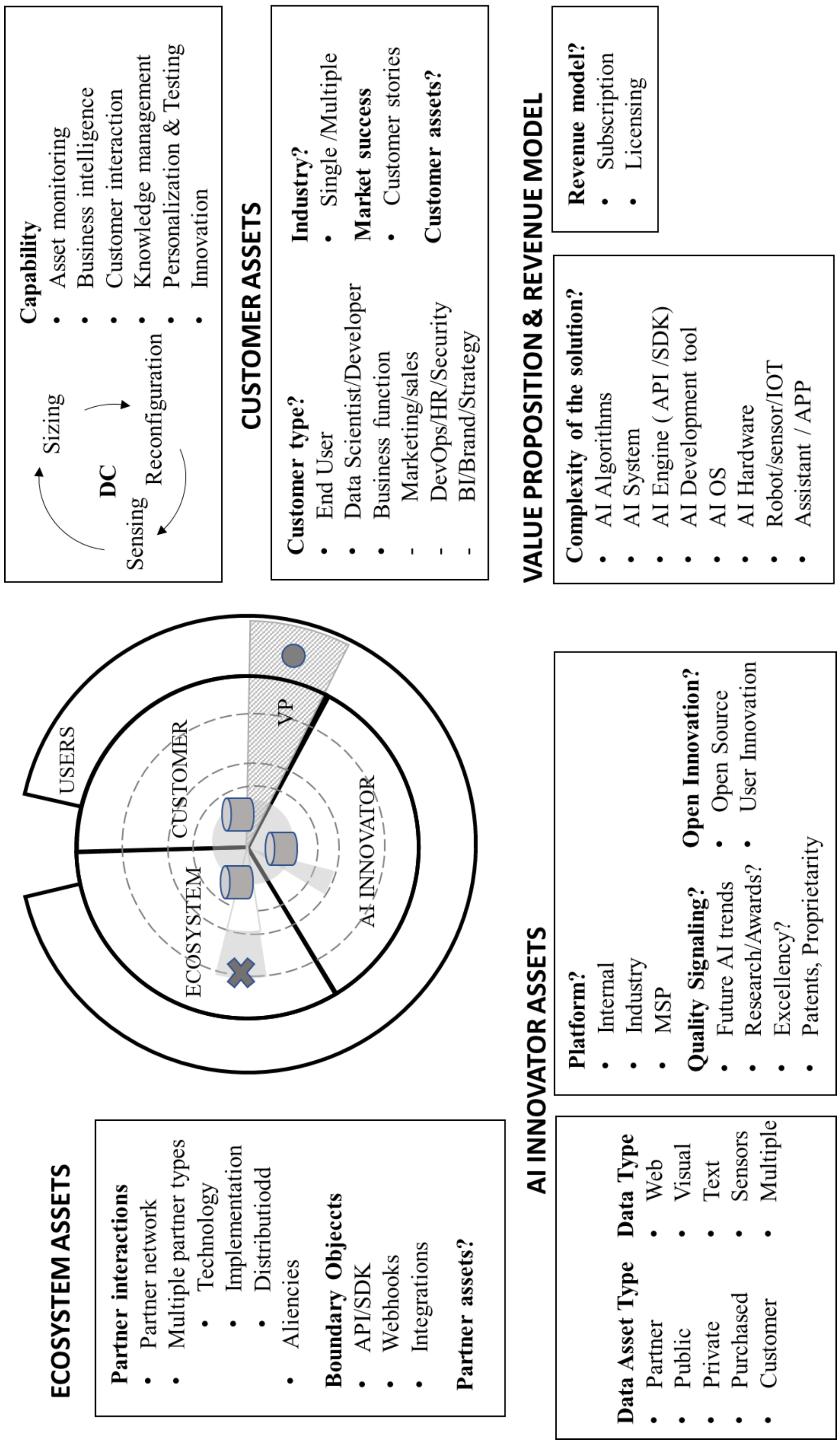


Figure 2 Analysis dimensions of the EDDAI framework

3. Empirical study

3.1. Methodology

3.1.1. The purpose

The purpose of this empirical study is to develop understanding for the business models of the AI innovators, to elicit specific determinants of their offerings, and to identify the aspects of the competitive ecosystem that have impact on how AI innovators appropriate profit form their innovation, and on the emergence of the dominant design. The research questions are:

RQ1: Which significant business model patterns do AI innovators employ, and what factors influence their ability to profit from their innovation?

RQ2: Are there some AI offerings that could be microfoundations of dynamic capabilities for their users?

RQ3: Can existing theories of technology evolution and the evidence from the AI ecosystem be used to reason about the emergence of the dominant designs or winner-take-all outcomes?

3.1.2. Design of the study

The research strategy of this explorative study is qualitative research. Bryman & Bell (2015) argue that a typical approach of qualitative data analysis is searching for themes which can be "discerned in many if not most approaches to qualitative data analysis, including grounded theory, critical discourse analysis, qualitative content analysis, and narrative analysis" (p.578)

The method selected to answer the research questions is the qualitative content analysis approach. Bryman & Bell (2015) suggest that qualitative content analysis as a strategy is at the core of coding approaches, which are used in the analysis of qualitative data, such as grounded theory (Bryman & Bell, 2015). Bryman & Bell (2015) explain grounded theory as (Bryman & Bell, 2015): "theory that was derived from data, systematically gathered and analysed through the research process" (p.541).

Krippendorff (2013, p. 49, cited by Mayers, 2013) defines content analysis is "an unobtrusive technique that allows researchers to analyse relatively unstructured data in view of the meanings, symbolic qualities, and expressive contents they have and of the communicative roles they play in the lives of the data's sources" (Krippendorff, 2013, p. 49, cited by Mayers, 2013).

As pointed out by Duriau et al. (2007) based on their comprehensive study of literature using content analysis, this method has several advantages over other approaches: 1) it provides methodology that can be replicated, and which can access profound structures of individual or collective types (Duriau et al., 2007): "such as values, intentions, attitudes, and cognitions" (p.6), 2) it allows the analytical flexibility making both statistical analysis of text, as well as interpretation of the latent content and deeper meaning embodied in the text valid approaches, 3) is applicable for both inductive and deductive research, and 4) allows rendering the "rich meaning associated with organizational documents combined with powerful quantitative analysis" (Duriau et al., 2007, p.7). However, as highlighted by Bryman & Bell (2015, p.315), content analysis also have limitations: 1) validity of results critically depends on the quality of the documents which authenticity, representativeness, and credibility need to be assessed; 2) the interpretation on the side of the coders is inevitable 3) when the aim is to impute latent rather than manifest content the potential for invalid readings increases 4) "why" questions are difficult to address, and 5) accent is often placed on what is measurable instead on what is theoretically significant. The study of this thesis relies of the information published by companies on their websites in the Internet. Basing analysis on documents is acceptable as documents can be viewed as "windows onto social and organizational realities" (Bryman & Bell, 2015, p.568). However, the caution is needed. Atkinson & Coffey's (2004: 58, cited by Birman and Bell) argue that "documents need to be recognized for what they are—namely, texts written with distinctive purposes in mind, and not as simply reflecting reality, and should be viewed as a distinct level of 'reality' in their own right", as "they are written in order to convey an impression" (Atkinson & Coffey's, 2004, p.58, cited by Birman & Bell).

The design of the study of this thesis accounts for the nature of the adapted approach. As pointed out by Bryman & Bell (2015) the process of qualitative content analysis "is iterative or reverse meaning that data collection and analysis proceed in tandem, repeatedly referring back to each other" (Birman and Bell, 2011, p.585). Bryman and Bell (2015) also suggest that content analysis reveals latent content within a certain topic and as such discovers meaning beneath the dominant content (Birman and Bell, 2015). Accordingly, this study started with defining the research questions, followed by the literature analysis, collection of initial data and elaboration of the coding scheme. Thereafter the main data collection and analysis was conducted and synthesized, as illustrated in Figure 33.

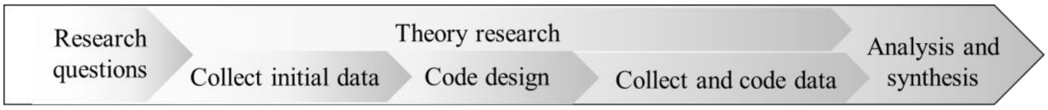


Figure 3 The research process

One of the requirements for the content analysis, as noted by Bryman & Bell (2015) is that the researcher's personal biases should be avoided and rules strictly followed so that the data collection can be automatized and repeatable. In this study the initial data collection showed high heterogeneity of the websites, which resulted in adaptation of the analysis framework to remove codes that were impossible to instrument.

3.1.3. The object of analysis

The primary source of information for the study were websites of the AI companies. This study, therefore, belongs to e-research, and as pointed out by Birman & Bell (2015) in e-research, websites and web pages are virtual documents and legitimate sources of data for content analysis of quantitative and qualitative type. However, pointed out by Bryman & Bell, (2015) being sensitive to challenges regarding the webpages' authenticity, credibility, representativeness, and their dynamic and ephemeral nature is necessary. On the other hand, as maintaining effective online presence can be considered as one of the strategic activities of firms, this study started with the assumption that websites will reveal and signal the most relevant characteristics of offering, value creation, the partner programs, the customer case studies, history, team, the products, and the pricing. However, as focus of the study shifted from active to acquired innovators, in which case the website information may be reduced or missing, also the acquisition and the company-related articles have been consulted.

In e-research, determining the population of websites to sample from, is another problem which can be approached by using a search engine such as

Google, or a combination of search engines (Birman & Bell, 2015), which filter out results depending on the keywords that used in the search process.

For this study the sample of the companies was extracted from the directory published by the online database Crunchbase (www.crunchbase.org), which as reviewed by Feldman (2016): is “a crowd-sourced database started in 2007 by Michael Arrington, (which) provides news, events, and funding data on over 800,000 startup companies including on pre-IPOs (initial public offerings) and acquisitions” Feldman (2016, p.1). The information available in this catalogue includes basic information such as headquarters, description, date of founding, company websites, funding rounds, investors, team, total funding, size of the company, news, and more. The directory also calculates for each of the companies the internal rank which considers signals such as the level of community engagement, funding events, news articles, and acquisitions. The companies self-describe themselves with as many categories as they wish, including categories such as “Artificial Intelligence”, “Machine Learning”, “Software”, and others.

3.1.4. Sample selection

The companies selected for the study were sampled from the group of the companies that self-describe themselves as Artificial Intelligence companies by using “Artificial Intelligence” as one of their categories. We refer to these companies as “AI innovators.” The total number of “AI innovators in the Crunchbase database is 4256, and the total number of firms from United States is 1740 (last query on 28.06.2018). However, the information in the database is not complete. For example, the category “Headquarters Location” is missing for 412 firms. The information about total funding is missing for 2376 firms. While initially a sample from population of active AI innovators was considered for the study, it was not clear how to filter out a relevant sample. The categories are not used in a structured way, and for some that were created by analysts, such as mentioned in CB Insights (2018) the selection motivation was unclear.

Therefore, this study focused on acquired firms that self-declare as Artificial Intelligence companies. There are 185 acquisitions of AI companies (as of 28.06.2018). After analysis the 5 of acquired companies were disqualified as their self-identification within the “Artificial Intelligence” category was not relevant. The 180 analyzed acquisitions are listed in the Appendix 1. Two pure consultancies were also not analyzed. In addition to collecting the information about business model of the acquired company the information relevant to the acquisition from the perspective of the acquiring firm was also collected, such as motivation and purpose. The acquiring companies were analyzed to identify and describe a high-level role of the Customer, from EDDAI framework.

In addition to acquired and acquiring companies, a set of AI Incumbents has been analyzed to identify some determinants of their role within the AI Ecosystem. An AI Incumbent is a company that creates and commercializes AI solutions and cooperate and compete with AI innovators (startups). These companies are integrated companies with a broad set of owned complementary assets. For this study, a group of major AI incumbents from the Cloud Service Provider group has been evaluated. This included Amazon (AWS Cloud), Google (Google Cloud), Microsoft (Azure), and IBM (IBM Cloud). It can be argued that there are other companies that belong to this group, and that for each of these companies a specific strategic focus and approach could be identified. However, this analysis aimed at assessing their high-level common strategy which can be used to define a role of the AI Incumbent within the Ecosystem of EDDAI Framework.

3.2.Findings

The analysis revealed several different business model patterns of analyzed companies. Following the EDDAI framework, the findings reveal insights into three roles - AI Incumbent (from the Ecosystem), Customer, and AI Innovator. This study did not directly analyze the User role and other potentially significant roles from the Ecosystem, which could be, e.g., the role of the Innovation Intermediaries, Investors, etc.

3.2.1. AI incumbents

The AI Incumbents are characterized with technological leadership, commitment to AI democratization and community support. Their value proposition is a full spectrum of digital solutions and professional services, and their strategy is continuous renewal of assets, including AI assets. They demonstrate strong research presence in areas perceived as AI, such as machine translation, speech processing, natural language processing, machine intelligence, machine perception, natural language understanding, Quantum A.I., robotics, and areas underpinning and facilitating AI, such as software engineering and systems, human-computer interaction and visualization information retrieval and the Web, mobile systems, networking, hardware and architectures, data management, mining and modelling, distributed systems, parallel computing, economics and electronic commerce, education innovation, security, privacy and abuse prevention. They contribute to research via their labs which publish papers and open source. AI solutions are also offered as pay-per-use commercial cloud services. These companies benefit from AI internally, reducing costs and improving their own processes. AI democratization is an important aspect of the AI incumbent strategy. For example, Google publishes on its website that it brings "benefits of AI to everyone", conducts "research that advances the state-of-the-art in the field", applies "AI to products and to new domains", and develops "tools to ensure that everyone can access AI" (Google, 2018). Al incumbents offer tools for AI development, application development, algorithms design tools, test infrastructure, and education to the developer and AI scientists community. They support opensource developer communities, foster open source alliances, and offers open source libraries and platforms, which qualify for de facto standards, such as a de facto standard deep learning platform Tensorflow (Tellicherry, 2018).

AI incumbents offer a broad suite of digital products to enterprises and startups. Some digital products are already enhanced with AI, e.g., the Android development platform. They recognize the categories that the other incumbents introduce and offer solutions for the same categories. The pretrained AI algorithms are offered as pay-for-use cloud services over the Cloud infrastructure. The managed clouds host storage, computational and AI resources of numerous businesses. Some incumbents set up a venture fund for the support of startups.

Regarding the assets, AI incumbents see data scientists as one of their main assets. Furthermore, they create blueprints of end-to-end solutions, train algorithms, amass publicly available data, compete in the number of filed patents and de-facto standards related to software and hardware, and have abundancy of financial resources. Another type of assets are their partnering arrangements with companies who are capable creating solutions based on the incumbent technology.

3.2.1. Acquired AI Innovators

Related to the group of the acquired companies it was observed that typically after the acquisition the information about the acquired companies available on their website was reduced, and many websites have been discontinued. This is in accordance with the motivation for the merger and acquisition, and the nature of the integration process that typically follows M&A. Particularly when the acquiring company was one of the AI incumbents or big platforms, the team and the technology were integrated within the acquiring organization and product architecture. The companies that retained their presence were those acquired by equity managing companies or innovation intermediaries, those that had strong product brands and a broad customer base, and which M&A had more characteristics of a merger.

Based on the available information, the analysis of companies focused on the significant factors of what is the value proposition and what is needed to create it, and these factors were used to factors to classify acquired companies within six types of the typology. The factors were described in the EDDAI framework. The designations for the types of companies reflect the dominant benefit of the value proposition. The acronyms of types are used in Appendix 1 to associate the type to each of the analyzed company. The type description is high level and for each type an example company is mentioned.

A) Data harvesting, modeling and analytics (HARV)

The analysis discovered 33 (out of 185) firms of this type (18%).

Own Assets and Activities: The companies of this type drew their advantage from their deep understanding and knowledge of a specific customer segment pertaining to a specific industry (e.g., a health service provider) or business function (e.g., marketer, advertiser, HR) across different industries. These AI innovators have demonstrated high level of expertise in building effective models that underpin the data asset and have the technical ability to identify the sources of relevant data and build the system to harvest them. By means of machine learning, deep learning or other AI approaches these data were used to bring model to life. As systematically pulling, integrating, and analyzing data, are the activities that result in creating a data asset, this type of companies can be characterized as “data asset builders”. These innovators have demonstrated a combination of two types of expertise and skills: 1) a deep understanding of the customer domain and 2) the knowledge about the data management and analytics technology.

Value Proposition: These firms aim at satisfying the need of their potential customers to improve based on specific new knowledge, e.g., about a physical or social process that is costly to acquire, maintain or analyze. This include for a deep knowledge about end users, their product preferences, spending patterns, or behavior. Similarly, the missing knowledge can be related to internal processes, employees or prospect employees, the health status of some physical assets, the security of the IT systems and components, and similar. The AI innovators in this group leveraged the AI technology to discover the missing knowledge from available data and make it assessable. A data asset they create for this purpose can be understood as a digital representation of a specific physical asset (process, equipment, software system) or market determinants (customers, competitors, products). A part of value proposition are tools for analytics, for inspecting the digital model along different dimensions, e.g., to detect anomalies (asset monitoring), or to identify best leads or partners (customer base monitoring).

Ecosystem Assets (Generic): The companies in this group create closed solutions, for which they mostly use generic assets. Firstly, cloud services of cloud service providers are used to deploy the model and have a running internal platform. Some also explore the multihoming approach where their solution can run on different underlying infrastructure. Secondly, the published information available from the web is harvested and integrated within the data asset.

Customer Assets: This companies also use customers assets, particularly in solutions where data assets are specific to the company. Such customer information available from customer projects is aggregated within a sector-relevant data asset and the algorithms that are trained on customer data are improved with each instance and become sector relevant internal asset.

Market Success: The companies within this group have been able to attract significant customer interest prior to acquisition. Companies focused on different sources of data characteristic for different industries / business functions. Similarly, while some companies needed customer data for their service other have harvested public data or have established partnership with data owners and have integrated this data in an integral asset.

Example: Accompany, acquired by Cisco, leveraged AI to harvest information including tweets, articles, biographies, etc. to profile business influencers. Accompany offered profiles of business decision makers with their partnering propensity. The product offered a network model of relationships, etc.

B) Predictive personalization (PERS)

The analysis discovered 11 (put of 185) firms of this type (6%).

Own Assets and Activities: The companies of this type drew their advantage from their deep understanding and knowledge of AI, user experience and user behavior tracking, and software reconfiguration technology to create solutions that offer highly automated data-driven user recommendations and product reconfigurations solutions. This cluster comprises companies that offer solutions that are concerned with measuring and improving consumer engagement, by leveraging AI capabilities to understand behavior and personalize content. Personalization is identified as one of the most compelling functions for the companies who have direct channel towards the customer. The technology underlying personalization includes 1) harvesting data that customer traces, 2) understanding customer behavior, 3) reconfiguring user interfaces. These companies have built internal platforms that can facilitate monitoring of the ROI of personalization. These companies are internal platforms, but have

Ecosystem Assets: These companies typically combine several different functionalities to achieve thorough understanding of the user behavior and they therefore also purchase data form ecosystem partners, data-as-a-service providers to reach required quality. These companies also harvest public user information, e.g., from blogs and social networks (user “touch points”)

Customer Assets: These solutions use customer assets that are customer APPs, Websites, or systems that customers use to face end-user (user “touch points”). The type of co-specialization is the one that requires the customer to enhance its solution with additional code that syphon the relevant data to the AI innovator. Solutions are tightly integrated so that the re-configurations can happen in a data driven process triggered by the platform of the AI innovator.

Market Success: The companies had relevant customer success

Example: AddStructure acquired by Bazaarvoice, leveraged machine learning and natural language processing expertise to offer a solution that improves search and create landing pages optimized for search, to leverage user generated content which is otherwise difficult and time-consuming to find or use.

C) Algorithms from the technology frontiers (ALG)

The analysis discovered 40 (put of 185) firms of this type (22%).

Own Assets and Activities: The companies in this cluster have competed strongly on the leading-edge research and component-based implementation of innovation, rather than on concrete product E2E offerings. Based on the information collected about these companies, which is often very scares, it can be suggested that firms select to solve severe problems, create radical solutions, and compete in the market for technologies, like those described in (Henkel et al., 2014) where they need exit as they cannot commercialize their solutions alone

Value Proposition: The crucial determinant of these offerings is their newness/high level of radicalness, and at the same time their demonstrated viability.

Ecosystem Assets: The use of ecosystem assets is typically only for viability demonstration purposes.

Customer Assets: The use of customer (data) assets, is also typically only for viability demonstration purposes.

Market Success: Typically, these solutions have attracted some customers but have not achieved market relevance prior to the acquisition.

Example: Aimatter acquired by Google, provided SDK with their proprietary advanced image processing technology which runs DL models in real time on smartphones.

D) Hardware from the technology frontiers (HW)

The analysis discovered 3 (put of 185) firms of this type (1%).

Own Assets and Activities: Excellence in hardware design, capability to conceive and demonstrate new ideas.

Value Proposition: New categories of hardware design removing existing performance barriers.

Ecosystem Assets: The use of assets for viability demonstration purposes.

Customer Assets: No customer assets

Market Success: Typically, these solutions receive significant interest of customers; however, they lack sustainable commercialization assets.

Example: Movidius, acquired by Intel designed and manufactured computer vision processors for drones and virtual reality (VR) devices and benefits from large scale deployment made possible through acquisitoion.

E) Robots and autonomous driving (ROBO)

The analysis discovered 2 (put of 185) firms of this type (1%).

Own Assets and Activities: These are highly specialized companies. Potentially there are far more robotic companies that were acquired and whose profile is in the CrunchBase, potentially they did not self-identified “Artificial Intelligence” as the relevant category. The AI technology in focus is computer vision, and context understanding of driving situations. The sample is very small and generalization provided here may not have relevance on a larger sample.

Value Proposition: Improved perception capabilities but also human – robot or car interface. Novel approaches to autonomous driving and robot handling.

Ecosystem Assets: These companies critically depend on the car as an asset, or robotic platforms and establish ecosystem partnerships to implement their solutions.

Customer Assets: The customer assets are visual data that characterize customer physical environment and requirements on usability or special needs.

Market Success: These companies demonstrated viability and have successfully tested their solutions in some niche.

Example: Auro, acquired by Ridecell, offered driverless shuttles for a niche category of last mile public transportation such as campus areas, team parks, industrial sites, etc.

F) AI design tools and AI components (DT&API)

The analysis discovered 42 (put of 185) firms of this type (23%).

Own Assets and Activities: The companies in this cluster have demonstrated thorough understanding of needs of data scientists or developers, both very experienced and unexperienced or nascent. They have strong expertise in AI, creating user friendly tools and moderating communities of users.

Value Proposition: The companies in this cluster offered tools for data scientists, such as workbenches for algorithm design with simplified deployment of the same in the cloud, and tools for developing AI solution based on components and interfaces to services or engines, including tools for building chatbots or conversional assistants. These solutions are industry technology platforms with interfaces for external co-creators, and the companies belong to a group of developer platforms. All the acquired platforms have first found acceptance of large numbers of developers.

Ecosystem Assets: These companies often had their own services running in the cloud (the ecosystem assets) and have offered API-based access to their services. Important ecosystem assets are messenger platforms (such as WhatsUp (Facebook), slack, digital home assistants such as Echo/Alexa (Amazon) or Google Home (Google). Other assets include integrations with or support for tools already used by data scientists. These companies offer interconnections to all platforms (multi-homing).

Customer Assets: These companies do not need customer assets; however, they offer integrations with other tools and platforms that their customers use. They create co-specialized assets (of the type boundary resources) where the co-specialization is on their side. These integrations prove instrumental for creating credibility and linking own product to the various market leaders.

Market Success: All companies in this cluster have demonstrated significant market success by obtaining significant installed base. However, most of the tools are offered bot as an enterprise and as a community version which is free to use.

Example: Dialogflow, acquired by Google, have served a community of 60,000 developers who used it to build AI-powered voice and text-based conversational interfaces (voice apps, chatbots) powered by AI. It offered connection to all popular platforms (website, mobile app, the Google Assistant, Amazon Alexa, Facebook Messenger),

G) APPs and AI Assistants (APP/AI)

The analysis discovered 18 (put of 185) firms of this type (10%).

Own Assets and Activities: The companies in this cluster have created unique and specialized AI-based user interfaces such as chatbots / virtual assistants, and APPs with AI-powered user engagement, e.g., based on images. They have demonstrated strong expertise in AI (such as designing algorithms for natural language understanding, image understanding), ability to create a general data asset for training conversational interfaces, ability to integrate sector specific conversational data to improve and specialize the interface, and create software that engage users, track user behavior, or help user create content ("touch points"). These companies have developed internal platforms for monitoring of their APPs and AI Assistants, and offer integrations with other platforms with relevant user "touch points" that their customers use.

Value Proposition: APPs and AI Assistants that enable the customer to offer better services to users, better understand users, better engage user with the brand. The value proposition includes integration of the conversational or image/video interface with the customer knowledge base. However, these companies can provide offers directly to end users via their own APPs or assistants. Their offer essentially is an AI-powered “touch point”.

Ecosystem Assets: Data assets (mostly general) based on public and private data, and mobile development platforms for APP development, and underlying AI Assistant development platforms, or social network development platforms. The solutions critically depend on these underpinning platforms, as the AI innovators act in a role of co-creator. They are therefore impacted by platform governance and strategic moves.

Customer Assets: Customers data assets cospecialized by integration in the AI Innovator’s solution are critical for the solution creation.

Market Success: Those offering to the business customer suffered from their need for co-specialized assets of the customers which constrained them to specific industry or sector (e.g., health) and relatively low number of users. Some of those offering to the end user have experienced significant network effects.

Example: Face acquired by Facebook, leveraged their unique facial recognition technology in an application for Facebook and end-users. By offering their own API they departed from a clear co-creator role and were acquired.

H) Sector and BM Innovators and Partnerships (SIP)

The analysis discovered 27 (put of 185) firms of this type (15%).

Own Assets and Activities: The companies in this cluster all share distinctive capability to create strong partner networks, implementing integrations with sector-relevant platforms and tools, and offer market governance as the part of their innovation. They are all technology platform, some with multisided platform capabilities. They use network effects

Value Proposition: The companies offer solutions to multiple customer segments where AI technology may play different roles. For example, AI technology can help establish better match between multiple segments.

Ecosystem Assets: These companies use ecosystem assets (e.g., generic - cloud, mobile platforms, data sellers) in a sustainable business model.

Customer Assets: These companies use assets of their customers in a sustainable business model.

Market Success: These companies have already large market shares.

Example: Automated Insights, acquired in the portfolio of the Vista Equity Partners, provides natural language generation as a Platform and APIs. It generates summaries for investors (3,000 articles each quarter) based on earnings reports. It is on the technology frontier, it pursues extensive integration and partner program strategy, as well as customization of solutions

3.2.1. The Typology of the Acquiring Companies

The study found evidence that some of the companies that acquired AI Innovators have done after either successfully partnering with the AI innovator, some were the customers of the AI innovator, some were the platform where AI Innovator created complementary solutions, and some perceived the AI Innovator as potential new entrant and threat. The acquiring companies have been analyzed with the aim to understand the characteristics of the "Customer" role and the "Ecosystem" role of the EDDAI framework which could not be assessed by studying solely the value propositions of the innovator. Based on the information collected about the acquisitions the acquiring companies have been clustered within five clusters, based on the perception of their main motivation for the acquisition. The motivations include:

A) Accelerating AI Advancements

The motivation was to invest in the future technology trends and solutions by acquiring high reputation teams that develop them. The goal was to provide the acquired teams the most fungible type of assets (financial), together with easy access to other complementary assets. In return the acquiring company adds flexibility to develop technology on many different technological trajectories towards the dominant design.

B) Renewing capabilities with AI, or platform governance

Here motivations fall into several categories: 1) acquiring a critical asset created by the AI innovator (with sector-wide impact) and securing it for internal use, 2) integrating acquired AI solution within an internal platform architecture to enhance the existing functionality or add the missing capability with a new base of users. For platform owners, additional motivation is: 1) acquiring an AI solution of a complementor which competes with the core function, 4) acquiring an AI solution that could enrich the core of the platform beyond the current scope.

C) Leveraging complementarities and scaling up

The companies in these cluster have acquired / merged with the AI innovator who demonstrated a sustainable business model, have attracted an end-user segment which will extend the user base of the acquiring company, and has established a strong brand. The AI innovator benefits from the data assets of the acquiring company and can improve solution based on these assets.

D) Adopting new business models

The companies in this cluster can be characterized by their motivation to create a new ecosystem based on the AI innovator's solution.

E) Innovation Intermediation

The companies in this cluster invest in high potentials or high performers. The study found evidence for acquiring companies investing in growth towards a successful IPO, and evidence for helping companies to grow by helping them get access to assets of the companies of the same investment portfolio.

4. Discussion

4.1. Interpretation of Results

The analysis to what extent the findings manage to answer the research questions is systematized in the following subsections.

RQ1: Can significant business model patterns of AI innovators be extracted, and what factors influence their ability to profit from their innovation?

The major assumption of the study was that the analysis of the information that companies have revealed on their websites can provide a groundwork for interpretative systematization of the business models. However, the study encountered the problem of missing information, for example, specific information such as the revenue model, or completely unavailable information. This did not allow for fully characterizing business models of the companies based on the component-based Business Model construct of Osterwalder (2010). On the other hand, the theoretical frameworks of platforms and ecosystem and the profiting from innovation framework (Teece, 1986, 2006, 2016) offered rich constructs and typologies of platforms and complementary assets which can help in analyzing the competitive positions and success of innovators. Therefore, the analysis narrowed the focus on the different types of assets that are needed for the implementation of the value proposition of the focal company - in line with the definition of the ecosystem proposed by Adner (2017).

The analysis helped to identify several different types of companies competing with a broad variety of value propositions and having different dependencies on the ecosystem assets and the customer assets.

For some clusters of companies, the customer assets are not necessary, others critically depend of co-specialized customer assets. The level of co-specialization depends on how data are collected from the customer, and on the uniqueness of the customer data. The need for co-specialized data and component assets puts AI innovators who mostly compete in the week appropriability regime in a challenging position. Nevertheless, when innovators manage to turn customer data assets into their own assets via sector-wide platform approach, and with each customer improve their solution for all other customers they can create network effects and lock-in effects.

Some ecosystem assets are of a generic type as they can be used without specialization and need no coordination. This study classifies cloud-based resources that AI innovators need to implement their solutions as typical generic assets. The technology evolution of the cloud services has already reached paradigmatic stage, the technology is standardized or driven by de-facto standards. On the other hand, while cloud services could be generic resources, the companies providing them also offer AI technologies via their cloud platforms and are therefore sensitive to AI solutions of other companies. The innovators from the sample of studied companies that achieved sustainable growth have typically created multi-homing solutions for generic resources to escape lock-in.

Other ecosystem assets can be characterized as co-specialized assets; however, the specialization is on the side of the focal firm. These assets are integrations with well-established software/platform products that AI innovators create to have deeply integrated solution for their customers who already use other companies' solutions. By doing so AI innovators achieve higher level of integrations and improve their credibility and competitive position.

The conclusion regarding the RQ1 is that the analysis based on the collected data was not able to extract complete business model pattern classifications due to missing information. However, the analysis has yielded a typology of companies, where similar companies have been clusters together based on the value propositions and the assets that they need to implement it. Based on the extant theory the profiting from innovation framework (e.g., Teece, 1986, 2006, 2016) it can be argued that these assets together with the appropriability regime, the network effects, the stage of the industry development, and the strength of the ecosystem are critical determinants of the firms' ability to profit from innovation.

RQ2: Can some AI offerings ne identified that could be microfoundations of dynamic capabilities for their users?

Teece (2007) explains DCs are difficult-to-replicate source of competitive advantage development over time, that facilitates adaption to changing customer and technological opportunities. Teece (2007) asserts that DCs assist in achieving evolutionary fitness and entrepreneurial fitness; hence an enterprise possessing DCs is capable to implement new products, processes, viable business models, and even shape its own environment (Teece, 2007).

However, Teece (2007) also suggests that identifying what the microfoundations of dynamic capabilities are must be "incomplete, inchoate, and somewhat opaque" (Teece, 2007, p.1321) and/or "their implementation must be rather difficult" (p.1321). Teece (2007) further argues that sustainable competitive advantage would be reduced with the "effective communication and application of dynamic capability concepts" (p.1321). Moreover, Teece (2007) also posits that ownership of DCs is of special relevance in (Teece, 2007): "business environments with well-developed markets for goods and services, but poorly developed markets in which to exchange technological and managerial know-how" (p.1325). While managerial actions and knowledge are central to DCs, Teece (2008) does not exclude the technology solutions as constituents of the microfoundations. This study found indication that AI solutions have focus aligned with several microfoundations described in the "sensing" DC block (Teece, 2007). A microfoundation defined under "Processes to identify target market segments, changing customer needs, and customer innovation" (Teece, 2007, 1326) shows some similarity with the definition of benefits that personalized solutions with high level of re-configurability offer, or promise to offer to their adopters.

For an AI innovator the success with which it can commercialize a solution that could be a microfoundations of DCs, depends on whether enough customers would select contracting instead of integration model (Teece 2006) particularly for a solution offered by a startup (low credibility). The analysis of acquired companies show that some the inherent replicability of solution when it is offered as a service to a broad range of the customers. In other words, this AI solution becomes a general asset that companies can contract.

The analysis of the companies provided insights into type of the capabilities that a particular-value proposition address. The literature on dynamic capabilities makes a distinction between the operational capabilities which are the processes that are set into place satisfy the needs of the current customers by providing existing products or services in a cost-efficient way. Also, the operational capabilities are related to incremental improvement. The dynamic capabilities include the capabilities of the firms to “sense new opportunities” – new needs, new customers segments, new partners, to “size opportunities” – design new products, new business models, new pricing schemes, and to “reconfiguration” – knowledge management. While AI solutions are already used for improving processes (e.g., energy consumption optimization in a data center, optimal scheduling in the customer care center) the question what AI has to offer in dynamic capabilities.

As the answer to the RQ2 question it could be argued that the offerings of the AI innovators show that AI technology has something to offer in obtaining DC, which is indicated by the motivations of the acquiring companies. It could be argued that some of the motivations for the acquisition were 1) obtaining radically new technology which offers the acquiring company flexibility on the way towards dominant design 2) acquiring large user base that creates for the acquiring company the jump-start for growth based on network effects, 3) securing unique dynamic data assets that are digital, observable representations of customers, potential competitors, competitors, prices, internal knowledge, market influencers, and similar, which acquiring companies integrated in their internal systems to improve their understanding of the market and internal challenges, 4) obtaining radically new personalization capability which acquiring company expects to automatically create new digital product (on the “touch points” to the customers), and present and test them with the customers. Number 3 & 4 could be characterized as a motivation for obtaining dynamic capability.

RQ3: Can existing theories of technology evolution and the evidence from the AI ecosystem be used to reason about the emergence of the dominant designs or winner-take-all outcomes?

The theory of dominant design makes clear difference between the strategic positions of firms that have critical complementary assets and the companies that do not. Teece (1986) suggested that firms well positioned in respect to critical assets can wait, while those that are not are in a bad position. Teece (1986) recommends a winning strategy of staying flexible until the dominant design emerges and then investing heavily once a design looks like it can become the winner. The acquisition of companies that offer radically new technologies offer the acquiring companies this flexibility. As mentioned previously construct of the dominant design is related to the construct of the dominant categories. It can be argued that some dominant AI categories have emerged, which means that the understanding of these categories/product features is becoming well established. The AI incumbents and successful AI innovators have contributed to the emergence of these categories due to their strong support for AI democratization, based on “revealing” as an open innovation approach. The question whether the dominant design has already emerged in some categories is open. For example, while the quality of the conversational interface has been significantly improved within short time, the computational and data needs are still high and require new approaches. Regarding RQ3 it could be argued that the AI innovators with strong IP protection will be in a better position than the other startups, but weaker position than AI Incumbents. Based on results of Chen et al. (2017) and considering 1) that the competition is platform-based for innovators of APP/AI and DT&API type, and 2) that dominant design still did not emerge in these categories, strong incumbents/platforms have better cards. For the other types, while platforms may exit also there, the importance of ability to establish legitimacy, ability to build-up complementary assets, as well as create strong integrations may benefit AI Innovators, which is evident considering the success of the SIP type of AI innovators. Adopting the asset typology of Jacobides et al. (2018) it could be argued that SIP and PRES innovators are associated with super-modular assets in production, ALG and HW with generic assets in production and all other types of this study with unique assets in production.

5. Conclusions and prospects

Presented study systematized the evidence of the business model patterns of the AI innovators, and have proposed a typology which primary focus is on value proposition and assets needed to create it. Adopting the perspective of the ecosystem (Adner, 2017) the thesis have analyzed what types of solutions have been created by AI innovators and how they use resources of ecosystem companies bundling mobile, big data, cloud and Internet of Things technologies into a “doubly distributed” architecture for digital product innovation (Yoo et al., 2010) Researchers and practitioners attribute the upsurge in the artificial intelligence innovations to the fact that only recently all the necessary technology components have come together – the abundancy of multifaceted data, the accessibility of the high-performance computing infrastructure, and the improvements of tools which facilitate AI algorithms, components and system design, deployment, testing, and evolution. Viewed through the lens of the strategic research related to profiting from innovation, platform, and ecosystem theory, these three identified AI facilitators stand for major complementary assets that AI innovators need for innovation and commercialization of their solutions. These assets are controlled by different companies who are all involved in the AI innovation race in which dominant design may emerge. This thesis aimed to connect the dots of different theoretical viewpoints, and it added to the understanding of the role of the assets in how AI innovators profit from innovation in digital platform ecosystems.

5.1. The limitations of the study

The study of this thesis has some limitations. Firstly, the companies to be analyzed were sampled from a database which data is crowdsourced and incomplete. The information about the acquisitions does have details of the deal; however, this information is often concealed from public. Secondly, the analysis depended solely on the e-research data. The information that about the acquired companies that was the object of the content analysis was limited so that the full assessment of business models was not possible. Understanding the value proposition of many acquired companies and the motivation for acquisitions required consulting and interpreting press releases and news articles. Extracting structured data from this information was tedious, and in many cases not possible

While the study managed to extract high-level analysis for the whole sample of the acquired companies, some deeper analysis of each of the acquisition was also not viable. The structured coding of information without imputations was attempted but was of a limited success. The analysis method was qualitative and interpretative which restricted the argumentative power of results.

5.2. Practical contribution

Practical contribution of this work is in the typology of the analyzed companies, and in the EDDAI framework which is proposed as a template for structured analysis of questions such as “What are the critical assets that AI innovator needs?”, “Who owns and controls these assets?” and “What are the implications of different types of assets?”, “What layer functionalities, components, and boundary objects are implemented by which partner in the ecosystem?”.

The framework and the typology can help entrepreneurs entering the AI field understand different evolution paths of innovations and make decisions regarding their offers based on their own assets, and their own selected determinants of success, e.g., early exit or sustainable commercialization. While EDDAI framework needs further verification and honing in practical use, its intention is to build practical awareness of the distribution of critical assets and the impact of different types of assets on the success of the venture. The EDDAI framework does not attempt to replace the Business Model Canvas but to offer an additional multifaceted perspective on assets that the AI innovators can use to better understand the role of assets in their business models.

5.3. Theoretical contribution

This framework draws from a broad variety of theoretical viewpoints, with the aim to look for missing connections between different theoretical constructs. The theoretical contribution is in anchoring the AI technology innovation, albeit based on analysis of a small sample of companies to the constructs of the theories of business model, ecosystems, platform architectures and profiting from innovation framework.

5.4. Prospects for future research

The study presented in this thesis can be extended in several directions, related to the width and depth of analysis, the methodology, and research questions. For more nuanced insights the sample of the analyzed firms should be enlarged. An extracted typology can be tested for completeness and usefulness on a sample of active AI innovators, e.g., from the CrunchBase dataset. However, in such a study the manual work of content analysis should be automatized. Automatic data collection and AI-powered data analysis would make such a study more efficient and allow for more insights. A long-term study may start with initial analysis of the complete population which will help have more information at the event of exit of eventually acquired companies. The follow-up study could also study similarities and differences between the business models across regions to gain insights on how different data privacy regulations impact creation and distribution of the critical assets, ecosystem partnering and business models.

Furthermore, the proposed EDDAI framework need to be honed and verified in practice. The assumption underpinning the EDDAI framework is that by using it a firm can better understand the value and constraints of different types of assets. This should be verified by testing the EDDAI framework in the creative process of the business model ideation. The EDDAI framework does not replace the Business Model Canvas and would be used as a complementary construct in the business model analysis. The EDDAI framework has introduced the construct of a "touch point" which is a boundary object that aims at accounting for user innovation. A deeper analysis of touch points in different AI innovation approaches can also be a topic for further inquiries. Further studies could also refine the research questions related to the dynamic capabilities and the emergence of the dominant categories and designs. Such study could start with hypothesis about the relationship between different approaches to creating AI innovation and the company success, propose a model of relevant factors and subfactors, and measure the loading based on interviews with experts and managers from the AI companies. Similar approach can be used to test hypothesis that some AI solutions underpin dynamic capabilities, and that this have impact on the innovators ability to profit from innovation. The question of the emergence of the dominant design also deserves continued research effort and a longitudinal study. Assessing how experts and innovators perceive the emergence of the dominant design can be the basis for case studies and further quantitative studies.

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Appendices

Appendix 1 – Analyzed Companies

The complete URL format: https://www.crunchbase.com/organization/URL

#	TYPE	YEAR	Acquired URL	Acquiring URL	#	TYPE	YEAR_	Acquired URL_	Acquiring URL_
1	ALG	2012	/vivint	/blackstone-group	1	DT&API	2006	/kiwilogic	/artificial-solutions
2	ALG	2013	/dnnresearch	/google	2	DT&API	2010	/acumem	/rogue-wave-software
3	ALG	2013	/lookflow	/yahoo	3	DT&API	2010	/enkia	/sentiment360
4	ALG	2014	/dark-blue-labs	/google	4	DT&API	2011	/yap	/amazon
5	ALG	2014	/deepmind	/google	5	DT&API	2012	/face-com	/facebook
6	ALG	2015	/perceptio	/apple	6	DT&API	2013	/indisys	/intel
7	ALG	2015	/granata-decision-systems	/google	7	DT&API	2013	/iq-engines	/yahoo
8	ALG	2015	/timeful	/google	8	DT&API	2014	/jetpac	/google
9	ALG	2015	/conyak	/gravity4	9	DT&API	2014	/vision-factory	/google
10	ALG	2015	/compellon	/hoist-finance-ab	10	DT&API	2014	/cognea	/ibm
11	ALG	2015	/saffron-technology	/intel	11	DT&API	2014	/madbits	/twitter
12	ALG	2016	/emotient	/apple	12	DT&API	2015	/xange-private-equity	/groupe-siparex
13	ALG	2016	/graphlab	/apple	13	DT&API	2015	/alchemyapi	/ibm
14	ALG	2016	/spikenet-technologies	/brainchip-inc	14	DT&API	2015	/whetlab	/twitter
15	ALG	2016	/itseez	/intel	15	DT&API	2016	/appforma	/algomizer-2
16	ALG	2016	/touchtype	/microsoft	16	DT&API	2016	/angel-ai	/amazon
17	ALG	2016	/2338-technologies	/predictive-inc	17	DT&API	2016	/tuplejump	/apple
18	ALG	2016	/metamind	/salesforce	18	DT&API	2016	/blackbird-technologies-2	/etsy
19	ALG	2016	/viv-labs	/samsung-electronics	19	DT&API	2016	/api-ai	/google
20	ALG	2016	/magic-pony-technology	/twitter	20	DT&API	2016	/moodstocks	/google
21	ALG	2016	/geometric-intelligence	/uber	21	DT&API	2016	/versus-io	/menschdanke-group
22	ALG	2017	/micampaÃ±a-com	/adext	22	DT&API	2016	/prediction-io	/salesforce
23	ALG	2017	/body-labs	/amazon	23	DT&API	2017	/regaind	/apple
24	ALG	2017	/graphiq	/amazon	24	DT&API	2017	/raven-tech	/baidu
25	ALG	2017	/harvest-ai	/amazon	25	DT&API	2017	/augur	/bounce-exchange
26	ALG	2017	/skry-2	/bloq-inc	26	DT&API	2017	/ozlo	/facebook
27	ALG	2017	/mindmeld	/cisco	27	DT&API	2017	/aimatter	/google
28	ALG	2017	/pv-cube	/element-data	28	DT&API	2017	/motion-ai	/hubspot
29	ALG	2017	/outsideiq	/exiger	29	DT&API	2017	/wrapidity	/meltwater
30	ALG	2017	/brighterion	/mastercard	30	DT&API	2017	/apprento	/m-files
31	ALG	2017	/maluuba	/microsoft	31	DT&API	2017	/sailendra	/pharmagest-interactive
32	ALG	2017	/orbital-atk	/northrop-grumman	32	DT&API	2017	/wise-data-media	/whitesmoke
33	ALG	2018	/dreambit	/facebook	33	DT&API	2018	/sigmento	/akeneo
34	ALG	2018	/autonomic	/ford	34	DT&API	2018	/otosense	/analog-devices
35	ALG	2018	/semantic-machines	/microsoft	35	DT&API	2018	/bloomsbury-ai	/facebook
36	ALG	2018	/matrix-mill	/nianticlabs-google	36	DT&API	2018	/bonsai-ai	/microsoft
37	ALG	2018	/voicebox-technologies	/nuance	37	DT&API	2018	/chattypeople	/mobilemonkey-inc
38	ALG	2018	/evolution-ai-corp	/recall-studios	38	DT&API	2018	/datascience-inc-	/oracle
39	ALG	2018	/thread-genius	/sothebys	39	DT&API	2018	/parlo	/service-now-com
40	ALG	2018	/deepui	/walkme	40	DT&API	2018	/converse-2	/smartsheet-3
1	HW	2015	/intelligent-automation	/changyuan-group	41	DT&API	2018	/chatbotph	/sterling-paper-group-of-companies
2	HW	2016	/movidius	/intel	42	DT&API	2018	/empirical-systems	/tableau
3	HW	2016	/nervana-systems	/intel	1	SIP	2013	/clara	/jive-software
1	PERS	1998	/firefly-network	/microsoft	2	SIP	2014	/brainstation	/konrad-group
2	PERS	2010	/social-kinetics	/redbrick-health	3	SIP	2014	/equivio	/microsoft
3	PERS	2014	/scarab-research	/emarsys	4	SIP	2015	/vocaliq	/apple
4	PERS	2014	/medio	/here-technologies	5	SIP	2015	/convertro	/davinci11
5	PERS	2015	/tellapart	/twitter	6	SIP	2015	/wit-ai	/facebook
6	PERS	2016	/expertmaker	/ebay	7	SIP	2015	/portware	/factset
7	PERS	2017	/halli-labs	/google	8	SIP	2015	/automated-insights	/vista-equity-partners
8	PERS	2017	/gotripl	/trivago	9	SIP	2016	/opera-software-as	/golden-brick-capital
9	PERS	2018	/addstructure	/bazaarvoice	10	SIP	2016	/nexidia	/nice-systems
10	PERS	2018	/replyyes	/nordstrom	11	SIP	2017	/sophia-search	/aiqudo
11	PERS	2018	/jetlore	/paypal	12	SIP	2017	/resnap	/albelli
1	ROBO	2013	/industrial-pereception-inc	/google	13	SIP	2017	/realas-com	/anz
2	ROBO	2017	/auro-robotics	/ridecell	14	SIP	2017	/restore-eu	/centrica
1	HARV	2009	/delver	/sears-holdings-corporation	15	SIP	2017	/acrolinx-gmbh	/genui-partners
2	HARV	2013	/cognitive-security	/cisco	16	SIP	2017	/neokami-2	/relayr
3	HARV	2013	/netbreeze	/microsoft	17	SIP	2017	/zensight	/seismic-software
4	HARV	2013	/causata	/nice-systems	18	SIP	2017	/codiant	/yash-technologies
5	HARV	2014	/tripboard	/nokia	19	SIP	2017	/bright-box	/zurich-insurance-group
6	HARV	2015	/infoprice-2	/b2w-digital	20	SIP	2018	/quickhelp-5281	/1001-squared-artificial-intelligence
7	HARV	2015	/aihit	/frontier-market-intelligence	21	SIP	2018	/pulpix	/adyoulike
8	HARV	2015	/explorys	/ibm	22	SIP	2018	/mezi	/americanexpress
9	HARV	2015	/footfall	/tyco-retail-solutions	23	SIP	2018	/textrecruit	/icims
10	HARV	2016	/salespredict	/ebay	24	SIP	2018	/poltergeist	/loft-management-gmbh
11	HARV	2016	/kifi	/google	25	SIP	2018	/a2ia	/mitek-systems
12	HARV	2016	/crosswise	/oracle	26	SIP	2018	/leadspace	/radius-intelligence-inc
13	HARV	2016	/apprity	/oracle	27	SIP	2018	/recast-ai	/sap
14	HARV	2017	/meta	/chan-zuckerberg-initiative	1	APP/AI	2005	/algorx	/corgentech
15	HARV	2017	/perspica	/cisco	2	APP/AI	2013	/skyphrase	/yahoo
16	HARV	2017	/fdi-compass	/conway-data-inc	3	APP/AI	2014	/emu-chat	/google
17	HARV	2017	/uppoints	/embraco	4	APP/AI	2014	/incredible-labs	/yahoo
18	HARV	2017	/gazaro	/market-track	5	APP/AI	2015	/orbeus	/amazon
19	HARV	2017	/arimo	/panasonic	6	APP/AI	2015	/lendmn-nbfi	/and-global-and-systems
20	HARV	2017	/datarpm	/progress-software	7	APP/AI	2015	/storysense-computing	/dianhuabang
21	HARV	2017	/intelligentsia-ai	/quartz	8	APP/AI	2015	/zoyo-ai	/magictiger
22	HARV	2017	/argo	/tableau	9	APP/AI	2015	/http-www-fitho-in	/practo-technologies-pvt-ltd
23	HARV	2017	/dextro	/taser-international	10	APP/AI	2015	/tempo-ai-sri-spin-off-m	/salesforce
24	HARV	2017	/vbrand	/the-nielsen-company	11	APP/AI	2016	/expert-personal-shopper-x	/ibm
25	HARV	2017	/next-it	/verint	12	APP/AI	2016	/mentio	/lendified
26	HARV	2017	/the-robot-report	/wtwh-media-llc	13	APP/AI	2016	/genee	/microsoft
27	HARV	2018	/heavywater-inc	/black-knight-financial-service	14	APP/AI	2017	/ernest-2	/moneyfarm
28	HARV	2018	/accompany	/cisco	15	APP/AI	2017	/giaran-inc	/shiseido-company-limited
29	HARV	2018	/idinvest-partners	/eurazeo-com	16	APP/AI	2017	/loyalblocks	/wix
30	HARV	2018	/altocloud	/genesys	17	APP/AI	2018	/lyke-3	/jollychic-com
31	HARV	2018	/zenatix	/hero-electronix	18	APP/AI	2018	/building-robotics	/siemens
32	HARV	2018	/viewsy	/ipsos-retail-performance	1	CONS	2016	/data-prophet-pty-ltd-	/yellowwoods
33	HARV	2018	/talkwalker	/marlin-equity-partners	2	CONS	2018	/evolusys-sa	/bechtle