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University industry collaborations in AI development

Understanding the motivations of Swedish researchers

by

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Abstract: Artificial Intelligence is an expansive topic that is receiving considerable amounts of attention and funding for research, as it has the potential to have a wide-ranging effect on work, business, and society. Following from this, actors of all types, universities, companies, and others are conducting research into AI, and investigating how they can make the best use of the technology and develop it as quickly, and efficiently as possible. As such, this thesis seeks to explore the motivations and drivers of university researchers collaborating with the private sector in AI work. This is a qualitative study relying on in-depth interviews and surveys of individual researchers to unveil motivations and impacts of collaborating with the private sector. The literature suggests a range of motivating factors for researchers to engage in collaboration, including access to resources and inspiration, which corresponds to the core findings of this study.

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1 Introduction

1.1 Research problem

Innovating is a loosely defined practice which involves the process of bringing new inventions to the market (Fagerberg, 2005). To create the invention that serves the foundation for an innovation generally requires some amount of research and novel ideas to be combined and realized, with many different types of actors conducting the research, from public universities and the military, to private companies and individual inventors (Nelson & Rosenberg, 1993). There is a selection of different components that are neccesary for the innovation process, in particular an appropriate combination of skills, knowledge, and resources from those who are innovating. While it is possible that the same actor holds all the neccesary skills and resources to create an innovation, some form of collaboration is a common approach to be able to better innovate and acquire other neccesary components rather than doing it independently.

Universities and their researchers hold a considerable amount of research skills and knowledge that can be useful for innovation, particularly in the context of highly technical topics that many companies lack the ability to fully conduct research on within their organization. Meanwhile, universities often lack the ability or mandate to engage directly in innovation themselves given their position as publicly funded, and with other overarching directives (Seashore Louis et al., 1989). As such, collaborations between universities and other actors can aid the innovation process by linking new crucial developments from the universities to others who know where, and how to successfully turn that knowledge into a successful innovation.

Artificial Intelligence is a broad concept that covers research within several different topics, ranging from foundations in philosophy to necessary components of mathematics, statistics, and computer science (Buchanan, 2005). Artificial Intelligence, abbreviated as AI, refers to technologies that can emulate intelligent thought, and act upon this. This can be applied in a very wide variety of ways and settings, and some expect that artificial intelligence innovations will have a considerable impact on the ways people live their lives, work, and do business (Brynjolfsson & McAfee, 2017; Wang & Siau, 2019). To realize such a future where AI driven innovations have a considerable impact on the life and work of a large share of the population, developments need to continue happening in the technology, as well as within the applications of it for society. Conducting effective research into artificial intelligence requires a variety of skills, and in particular access to neccesary data and staff that has the appropriate knowledge to be able to use and apply it, often with knowledge of machine learning and algorithms (Yu, Liang & Wu, 2021). As a topic with a wide range of neccesary components for successful research, collaborations between actors of different types can be an appropriate way to ensure access to everything necessary for successful innovation.

1.2 Aim and scope

While there is an extensive body of literature on collaborations between universities and the private sector, both globally as well as specifically in Sweden, it is still a topic that warrants further, more detailed exploration. There is a small range of literature on collaborations between universities and the private sector on specific topics, including software development, which overlaps with artificial intelligence to some extent. However, artificial intelligence research is a broader topic that spans across the boundaries of hardware and software research, and there have been no detailed studies, in the Swedish context or elsewhere examining university industry collaborations in AI research, which is the aim of this thesis.

In particular, the goal of this study is to gain descriptive and qualitative insight into the motivating factors for university researchers working with artificial intelligence to participate in collaborations with the private sector. This includes their personal motivations, as well as how collaborating with the private sector can help their existing research projects and departments. More specifically, this thesis aims to examine how researchers associated with Lund University perceive this. This will help fill the considerable research gap into AI Innovation research, which exists despite the large and growing attention that work with AI is attracting from all sectors of society (Furman & Seamans, 2019).

1.3 Outline of the thesis

This thesis is split into four sections following this introduction. Firstly, a literature review which considers theories of innovation, motivations for collaborations between universities and private sector actors, and the specificities of innovation in the field of artificial intelligence. This is followed by a section of methods which further explains the qualitative approach of this thesis, and the case selection. This is followed by the findings, which expand on the motivations to collaborate that have been observed in this study. Finally, the conclusion of this thesis provides an overview, and considers the limitations and implications of this study.

2 Literature review

2.1 Key theories of innovation and their relevant details

The study of how innovation happens has a long history of different theories that highlight particular aspects of innovation and may be useful in different contexts. This literature review considers the key factors of a small number of selected theories that have been deemed to be relevant for this thesis. These different theories of innovation can all be useful heuristics to explain and analyse why innovation happens in the way that it does, and these theories are additive rather than competing theories to explain innovation. While some theories of innovation are foundational and explain some of the most basic components of why innovation happens the ways it does, others are novel and may only be suitable for a small number of cases. Abrahamson (1996) warns of new models of innovation, as fads and fashions that distract the innovation practitioners from their important work.

2.1.1 Linear Innovation

In studies of innovation, the conventional linear or closed innovation model remains central to understanding other more contemporary theories of how innovation happens, because the newer approaches are meant to either compliment, or replace this. While different authors may have notable differences in their descriptions of the traditional model of innovation, for the purpose of this thesis they will be treated as one, as they are not at the centre of the relevant literature.

In the closed, linear innovation model, the principal actors are the firm, and the market is the only actor it interacts with. The firm conducts research and development, and is also responsible for marketing the ideas, and receiving feedback through market mechanisms (Kline, 1985). At either end of this model is either a push from novel research, or a pull from market demands, the question of which is more dominant has occupied scholars of innovation for a long time (Kline, 1985).

2.1.2 Innovation Systems

The innovation systems framework is one of the most popular and widely used alternatives to linear models of innovation. In this understanding of innovation as a system, one includes and considers all actors, both public and private, who develop, use, modify, and import new innovations through their actions and interactions with others (Alkemade, Kleinschmidt & Hekkert, 2007).

To be more specific in the analysis of a system of innovation, qualifiers regarding the geographic area, as well as regarding the technologies that are innovated on. Grandstand and Holgersson (2020) note that national, regional and sectoral systems of innovation are the most commonly used units of analysis. A sectoral system of innovation refers to the actors who produce or use technologies that are relevant to one specific sector of the economy, and is often limited to one or a very small set of technologies that the innovations happen within (Malerba & Nelson, 2011). The geographic delineators are instead focused on the institutions and economic factors which exist in a region. This is a useful tool for analysis not only because institutions tend to be limited to a region or country, but also because of the geographic proximity which is an important factor that impacts how innovations are diffused in society.

2.1.3 Open innovation

Open innovation emerged as a concept within innovation studies to better capture the interactive reality of innovation with a focus of flows of knowledge, as a contrast to the closed and linear model of innovation (Bogers, 2011). Chesbrough, Vanhaverbeke, and West (2006) note that the openness in open innovation comes in two domains. Firstly, they claim that knowledge is transferred and flows with purpose from one actor to another, in multiple directions, both in and out in the innovation process. Secondly, there is an openness to how innovations can be brought to market, both internally in through the core organization as in the closed innovation model, but an innovation can also be brought to the market with collaboration through external actors, with agreements like licensing to another firm's market, spin-offs and more. These two aspects of openness are the core of an open innovation framework, which can be useful for understanding the reality of how interactions and collaborations happen in the innovation process. The focus on purposive flows in the open innovation framework is useful for separating spillovers which are without intent.

Flows of knowledge in open innovation

In open innovation, knowledge flows with purpose both in and out from an organization. Purposeful inflows of knowledge have been well understood for a longer time, where firms attempt to capture value from knowledge that others have produced. Rosenberg (1994) argued that companies conduct internal research and development partly in order to better be able to capture knowledge from outside the firm. They conducted research to develop their absorptive capacity. This mechanism helps understand how in-flows of knowledge interact with internal research.

Purposive outflows of knowledge may be more complex and less intuitive to understand. Traditionally, spill-overs from research have been studied extensively, where proximity to research leads to unintentional, often positive spill-overs (Meagher & Rogers, 2004). In the open innovation, it is instead intentional, purposive outflows of knowledge that are of interest. This means that knowledge is leveraged outside the organization, as external actors may be more strategic alternatives to bring knowledge to the market given their geographic location, or establishment in the market (Naqshbandi, Kaur & Ma, 2015). These purposive outflows can take the shape of licensing or selling intellectual property rights.

The innovation process includes other flows of knowledge, beyond the explicitly purposive sharing that is centred in the open innovation framework, namely spillovers. While spillovers are generally considered to be unintentional creation of knowledge that cannot be directly brought to the market, they still serve a role in an open innovation paradigm. Licencing of internal spillovers to another actor serves as a conventional way to send knowledge outwards, and profit off of it in open innovation (Christensen, 2006). Furthermore, through ties to the market and other organizations, an organization may find spillovers from other actors that they can licence and leverage into an innovation internally, as an inbound flow of knowledge (Christensen, 2006). The creation of spillovers might be incidental, but the use of them in the innovation process is intentional, and connects different actors and organizations, which therefore fits in the open innovation framework.

Open innovation centres connections between actors, and utilizing resources, skills, and spillovers form others in the innovation process. The linkages between the different actors can range from informal to fully formalized, and still fit within the open innovation framework. Formal ties between actors are contractually agreed upon collaborations, which have clear divisions of what is shared such as a strategic alliance or a licencing agreement that is entered into because of a specific identified gap in their knowledge that they could fill (Simard & West, 2006). Informal ties in innovation exist between the individuals of different organizations, and can take many forms, but are common among members of the same industry networks and social circles.

Pathways to market and profitability in open innovation

The outbound flows of knowledge in open innovation are tightly connected to the ways by which profitability and pathways to the market look in an open innovation paradigm. The previously mentioned pathways of using property rights externally are one pathway. There are however several other pathways to the market that retain more openness, within open innovation. Freel and Robson (2017) explored formal or institutional, and informal or strategic appropriation strategies to help capture value on the market in the context of open innovation. They suggest that SMEs are more likely to work through strategic appropriation strategies, where they work with secrecy, shorter lead-times, and relatively high complexity to capture profit from ideas that were developed through an open innovation process. The alternative, to work with institutional appropriation strategies is relatively time-consuming, and costly to register and especially defend patents and trademarks from competitors who had access to many of the same sources of knowledge. Given these costs, Freel and Robson (2017) suggest that large companies are more likely to rely on these types of mechanisms to capture value. While these different ways of appropriating value from the innovation process mirror formal and informal relationships, where formal relationships and institutional approaches correspond to each other, as an alternative to informal relationships and strategic appropriation strategies, they are not neccesarily linked in these pairs. Instead, even if the relationship between the parties is largely informal, there may be a formal contract to deal with the legalities of sharing information and profits.

2.1.4 Why actors collaborate in innovation

Bogers (2011) argues that there are two main theoretical explanations for why organizations choose to collaborate in innovation, transaction costs economics, and the resource-based view of the firm. These two can be analysed in isolation, or they can be integrated into one unified understanding of the choice to collaborate or not.

In the resource-based view of the firm, there is a focus on what the firm has and what it can do as determinants of success and collaboration, rather than an emphasis on the external forces and market conditions determining success (Mowery, Oxley & Silverman, 1998). Skills and capabilities that the firm has can be both tangible such as production designs or techniques, or intangible such as brand recognition or market knowledge. According to this view, collaborations take place to use and exploit complementarities with others to make better use of the capabilities that either party has.

To understand collaboration through a transaction cost economics perspective can be simplified to a firm's choice of to make or buy new technologies (Remneland-Wikhamn & Knights, 2012). The choice is determined by transaction costs and the risk of opportunism from your collaborative partner. In this context, transaction costs are everything that is incurred from working on a market, rather than working internally and can involve the cost of searching for information or coordinating and enforcing collaboration contracts. Meanwhile, opportunism in this context stems from the information asymmetry that may exist between the partners.

Moving from interfirm collaboration to university industry collaboration

These theories of collaboration have their foundations in collaborations between multiple firms, but they can help us understand the dynamics of collaboration also in industry-academic-collaborations. In collaborations between two firms, the different parties may choose to collaborate because they can provide different things. Mowery, Oxley, and Silverman (1998) suggest that a common dynamic is one firm with technical abilities, where the other firm has good market knowledge, potentially in a new location or market segment that the other partner is not familiar with. This dynamic where one partner is technical, and the other provides market knowledge mirrors collaborations between the private sector and academia. In those cases, the university partners and its representatives would be expected to contribute significant amount of specific technical knowledge on a topic that lays the foundation for an innovation. Meanwhile, the private sector partner would be expected to contribute knowledge on how the innovation works in real life, what is needed and desired on the market. While these different abilities of the private sector partner and the university would complement one another, Mowery, Oxley, and Silverman (1998) highlight the importance of a degree of technical overlap in order for collaborations to be successful. Their study highlighted this in the context of interfirm collaborations, but the dynamic in university-industry collaborations may be different. As the partners are further separated than two collaborating companies, the parts they play in the collaboration may be more different than expected. For two companies that aim to collaborate, too great a distance in their expertise may be detrimental. However, academic, and private sector partners will have different motivating factors that go beyond the profit interests that drive collaboration between two private companies, as such they may be successful under circumstances that would not suit collaboration between companies.

2.2 Innovation in Artificial Intelligence

Artificial Intelligence has a selection of characteristics that differentiates innovation on this topic from innovation in other domains. Artificial Intelligence is an expansive, loosely defined concept within disciplines ranging from philosophy to mathematics and statistics (Buchanan, 2005). Artificial Intelligence refers to technologies that can do, or emulate intelligent thought, and act upon that emulated thought. Currently, it is within machine learning that the majority of AI innovation happens, which refers to the ability to learn rules from a set of data, rather than specifying rules for action in advance (Howard, 2019).

To better understand a new and emerging technology, Curry (2016) suggests that using tools from the business community, value chains and ecosystems to better understand the environments and relationships that are relevant to the technology. The ecosystem approach is useful to understand the context of the technology and how the different stakeholders relate to each other. Meanwhile, the value chain allows us to explore the information flow in the system, to better model the system and steps that underly the generation of value and insights through the technology.

Yu, Liang, and Xue (2022) notes that the AI value chain is still in its formative stage, but through inspiration of the big-data value chain which is both thematically and practically connected to the AI value chain they suggest a structure by which we can start to understand the AI value chain. In the industry, they identify infrastructure providers such as sensors and computer chips, technology developers such as those working with algorithms for computer vision and voice recognition, and finally application scenarios such as smart healthcare and autonomous driving which is the step of the AI value chain closest to the end consumer (Yu, Liang & Xue, 2022). Yu, Liang, and Xue (2022) selected core components that are AI specific, from the more widely used, and more well-defined big data value chain, as examined by Curry (2016).

Figure 1 Basis of the AI Value Chain, adapted from Yu, Liang, and Xue (2022)

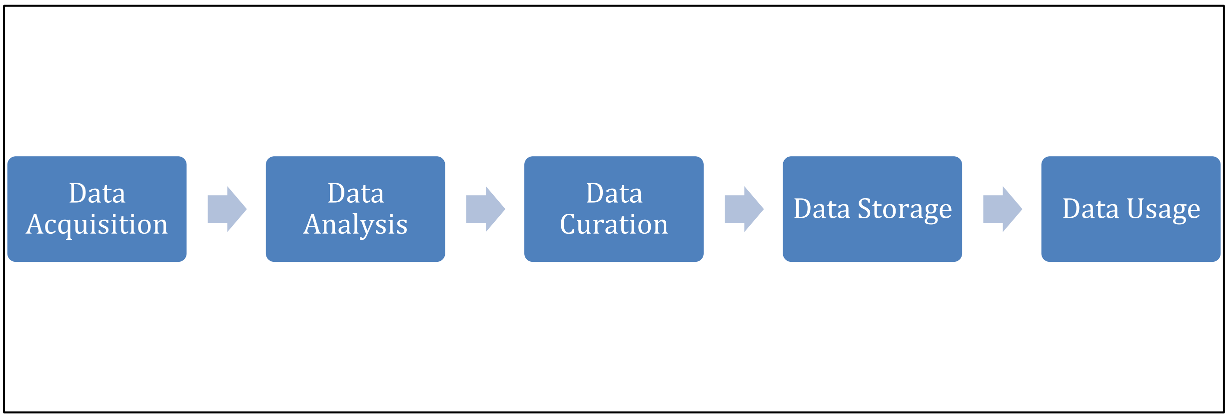

Figure 2 The Big Data Value Chain, adapted from Curry (2016)

Through examining the different activities described in the big-data value chain, it is possible to gain a better understanding of different types of actors that are present there, and the relationships which link them together. The infrastructure providers in the AI Value chain create sensors and computer chips that are used to gather data from the real world and needed to process it with machine learning. These activities are present across the Data Acquisition, Data Analysis, and Data Storage steps of the Big Data value chain (Curry, 2016). These crucial pieces of infrastructure are innovations in their own right, but while they are useful for Artificial Intelligence, they are not neccesarily innovations that are driven by artificial intelligence. The technology developers on the AI Value chain work with algorithms for vision and voice recognition. The development of this would primarily fall under Data Usage in the Big Data value chain described by Curry (2016), as the creation and adaption of these algorithms and the machine learning is driven by the data. Finally, the Application Scenarios would also come under the category of Data Usage in the Big Data Value Chain, or perhaps go beyond it. For these application scenarios take the algorithmic knowledge from the Technology Developers and apply it to a real-world scenario, develop a solution to make it useful for actual end-users. This would produce an AI driven product on the market.

University researchers can come in at different stages and have different roles across the AI Value Chain. Academic research is likely very important for the infrastructure development, but as the pieces of infrastructure are widely applicable beyond AI scenarios, the academic work conducted there is likely not specific to AI, but rather in general to the engineering of software chips and sensors. Meanwhile, among the technology developers a strong involvement of researchers working with AI would be expected. In particular given that different variations of topics such as pattern detection, the second most common use case for AI applied in the real world (Davenport & Ronanki, 2018). Finally, Application Scenarios entails the development of final products that can make use of AI driven solutions and adapting them into final products on the market. Here, involvement from academic researchers is expected to be limited in comparison to previous stages of the AI Value Chain. This as application scenarios is likely to require less AI specific knowledge to develop applications, but rather general software development knowledge

2.2.1 Artificial Intelligence research and innovation

Research into artificial intelligence takes a wide variety of shapes given the broad scope of the technology and the fact that AI is being applied in a wide range of settings and sectors. All of these settings and particular areas of AI may require both applied research, and related basic research. Furthermore, along different stages of the AI value chain, research may look different, and tightly connected to the concept of the AI Value chain are the steps from basic research to applied research, and onwards to application development.

Basic research in the domain of Artificial Intelligence research entails work on foundational issues such as mathematics, algorithms, linguistics and an understanding of how thinking learning works, and how all this fits together to make intelligence (Wu & Feng, 2018; Z. Li et al., 2020). The basic research manages and solves general problems that are needed to progress. Meanwhile, applied research in artificial intelligence builds upon the foundational, basic research that has been done, and is often meant to explore a specific, potentially practical issue, and in the case of artificial intelligence research, explore different ways in which artificial intelligence can be applied in order to solve a particular, real-world issue (Z. Li et al., 2020).

Application development uses the insights from the applied research to make products, innovations for the market that use artificial intelligence to solve a practical issue in the real world, for end users. It entails the development of intelligent products and adapting it into something functional and useful in real world situations, accessible to a wider mass of people than the direct results of applied research (Z. Li et al., 2020).

2.2.2 General Purpose Technologies

There has been considerable academic debate and discussion on the question of whether Artificial Intelligence can be considered a General Purpose Technology, a GPT. In particular, the debate questions whether it is appropriate to categorize AI as a GPT at this time. In their extensive work on GPTs, Lipsey, Carlaw, and Bekar (2005) highlight two aspects of GPTs in their definition of the term, “ what distinguishes GPTs from other technologies is a matter of degree. So there will always be technologies that on our definition are almost, but not quite, GPTs. Second, any definition of a GPT must be historical in nature” (p. 97). Given these two components of how to define a GPT, it is challenging to define a currently emerging technology as a GPT, when it is just beginning to have a wide impact on society and may still continue to change considerably. Nonetheless, considering AI as a GPT in the making, or a potential GPT may allow for a deeper understanding of how it is developing, and the impact it has on society. Crafts (2021) explored the impact past GPTs have had on productivity and contrasts it with the impacts that AI has so far had on productivity and society. He argues that Artificial Intelligence has the potential of being the foundation for a fourth industrial revolution, since it may be a GPT that raises productivity of research and development activities. Other authors are more sceptical of AI’s ability to have a wide impact on society, and its status as a GPT. Haenlein and Kaplan (2019) note that scientists have regularly expected AI to have a wide impact on society in only a few years ever since the 1950s. As such, AI's promise as a GPT remains alive, but continues to not be fulfilled.

The GPT like characteristics of AI nonetheless have an impact on how innovation within the field happens and how one can appropriate value from innovation in this field. Yang, Chesbrough, and Hurmelinna-Laukkanen (2021) argue that it is challenging to appropriate value from innovation in GPTs in general, and AI in particular. They argue that an open innovation framework can help solve some of the issues that come with innovating in GPTs that stem from the wide range of fields they can be applied in. At the early stages of innovating in a GPT, it is still unknown which applications will be the best suited for it, and in particular which ones are best suited for appropriating financial gains (Yang, Chesbrough & Hurmelinna-Laukkanen, 2021). With openness in the innovation process, the innovator's search in the market can be wider and faster, and they can make better use of their patents and appropriation strategies than if they limit their search to a more conventional, closed innovation process. This is the case, because as they share more information about their innovation and the process of creating it, widely with the world, more potential users attain information about it, and may have their own use cases for applying it.

Gambardella et al. (2021) further explored the closely connected question of how companies may profit from enabling technologies. They note that enabling technologies are similar to GPTs, as they can be applied across multiple domains, but they differ from GPTs as they do not have wide impact on society's economic structure. As such, insights on enabling technologies ought to be applicable to studies of AI as a GPT, as the societal impact of AI is still largely pending. Gambardella et al. (2021) found that the conventional framework on profiting from innovation (PFI), which was been developed by Teece (1986), is only applicable to innovations with applications in specific domains. Gambardella et al. (2021) expand on this and shows that the innovation process is different for a wide variety of reasons. In particular two trade-offs, firstly between design cost and applicability, where additional fine tuning is needed for a setting, increasing costs of the innovator. Secondly, and closely connected is the value and applicability trade-off, where the more general applicability leads to additional costs of adaptation to the specific setting, reducing the profitability. The insights from Gambardella et al. (2021) show that innovation in an enabling technology is different, more uncertain and complex compared to innovations in specific domains. They found that there are often fewer avenues for legal appropriability, which has an impact on the potential ways to profit. Other authors have found similar issues of profiteering, appropriability, and patentability, specifically with innovations relating to Artificial Intelligence (Bisoyi, 2022; Greenberg, 2020). Regardless of if Artificial Intelligence is better categorized as an enabling technology, or as a GPT that may be in the making, both tightly connected concepts of innovation give insights into how we study innovation in artificial intelligence. These concepts are joint in their focus on technologies that can be applied in a wide variety of ways and settings, which is a quality that Artificial Intelligence has.

2.2.3 Intellectual Property Rights

Protecting intellectual property rights when the innovation is intangible, such as software in general, and AI in particular is not as simple as with more tangible innovations. The issue stems from algorithms, which are considered to be discovered not invented, and as such they would not be patentable, but it is in combination with tangible aspects, they can become a patentable innovation (Vasylyeva, Zelisko & Zinych, 2018). Greenberg (2020) specifically explored to what extent AI innovations are eligible for patents under law in the United States. Greenberg (2020) further notes that there are some issues for patenting AI innovations in the US, as they occasionally are too abstract to be patentable according to the courts. Nonetheless, there is a specific category of patent intended for AI data-processing inventions, which indicates that AI innovations could be patentable, even if there is some ambiguity as to which aspects of AI this applies to. Vasylyeva, Zelisko, and Zinych (2018) further compared patentability of AI innovation between the United States and some of the largest EU countries, which unfortunately did not include Sweden. They highlight that the EU has adopted legislation to help regulate the innovative practice and use of AI in the union, but it does not specifically cover patentability. Furthermore, they note that the German patent office has been relatively stringent in recognizing patentability of AI innovations in comparison to other EU countries in their study. While there may be specific differences that prevent the insights from these studies from being applicable in Sweden, Greenberg's (2020) exploration of US patent law, and Vasylyeva, Zelisko, and Zinych's (2018) exploration in Europe are still relevant as professors and other actors in Sweden are likely to desire protection of their innovations in the US, and the rest of the EU as well, not only Sweden.

In Sweden specifically, intellectual property rights for university professors differ compared to most other countries given a "teacher's privilege". This allows university professors to claim intellectual property rights from their university research in a similar manner to any other researcher or individual (Stenvik, 2009). In practice, this applies broader than just patentable inventions and professors have legal rights to most of their work products, unless otherwise has been agreed upon (Nordin Bartlett, 2021). Legislation like the Swedish teacher's privilege used to be more common in Europe, but following the adoption of the Bahy-Dole act in the USA in 1980, that grants the intellectual property rights to the university institution itself, many other European countries have followed suit since (Stenvik, 2009). The fact that Sweden is nearly unique in retaining this privilege for professors makes it especially important to study university-industry relations in this context, as insights regarding individual motivations are likely more complex here than in other countries where they retain less legal rights.

In University-Industry collaborations, there is yet another actor beyond the university and the researcher who may have an impact on the distribution of intellectual property rights that in turn changes the motivations to collaborate. There is a wide range of different specific legal arrangements, but rather than providing a complete taxonomy it appears more relevant to examine the agreements on scales regarding questions such as contract formality, degree of shared governance, and IP ownership aggressiveness (Gretsch, Tietze & Kock, 2020). Factors like these help understand how each individual collaboration structures ownership of the intellectual property that is produced. Goldfarb and Henrekson (2003) argue that the Swedish system which grants intellectual property rights to the university professors means that the university as an organization is less likely to promote collaborations to industry, as it the professors themselves are the ones who see any eventual profit, rather than the university and its departments. They further argue that this means that the Swedish system of university-industry collaborations is characterized by a bottom-up approach, where individual motivations are an important driver for collaboration. This further supports the focus on individual researchers of this thesis, as they are especially important to study in the Swedish context.

2.2.4 Complementarities and resources

To develop any innovation in order to hopefully bring it to the market is a long process that requires a variety of resources and funding that differ (Lindgaard Christensen, 1992). To understand the importance of resources and complementarities as a driver for collaborations, one first needs to understand how important they are for conducting the different types of research. With AI being applied in a range of different fields, the resource intensity and selection of different resources will differ slightly across the areas of research. Software development is a common component of multiple different fields of AI innovation. In this field, both financial and human capital resources are important to the process, as we can see that small firms in software development are limited in their innovative activity by resource constraints (Munir, Wnuk & Runeson, 2016). Meanwhile, Garousi et al. (2019) explored resource related challenges in collaborations between industry and academia in software engineering. They highlight issues of a lack of human resources and man hours to do all the necessary aspects of innovating while maintaining the project and collaboration. Meanwhile, Garousi, Petersen, and Ozkan (2016) observed resource related issues in a quarter of industry academia collaborations in software engineering. However, the prevalence of the issue is only a weak proxy for how resource intensive innovating in this manner is.

The use of artificial intelligence is also especially prevalent in innovation in medicine, ranging from the development of medical robots to diagnosis and medical statistics (Hamet & Tremblay, 2017). The amount of resources needed and precisely which ones are important will differ across these different areas of innovation, and that is even within the bounds of AI innovation in medicine, which helps us understand that the range and breadth of required resources differs even more when considering AI innovation in general.

Regardless of which resources are especially important for a type of innovation, access to them is a well-studied motivation for collaborating to innovate. This in particular as different actors may have complementary resources (Bogers, 2011). In the domain of AI innovation, resource complementarities are especially prominent given some types of resources that are important for innovating in this field. In particular, Yu, Liang, and Wu (2021) argue that data for machine learning is a neccesary resource for many innovations in the AI sphere. In particular, this data needs to be in large sets, and ideally well-structured to be useful. They go as far as claim that data may be considered the “new oil” (Yu, Liang &

Wu, 2021, p.1) to truly highlight how crucial data is in order to innovate within artificial intelligence. This is the case as data as a resource has qualities as a resource which sets it apart from many other resources. Firstly, it is challenging or impossible for another actor to imitate or replicate a dataset, as it is the result of a real-world situation, often captured by sensor or individuals (Yu, Liang & Wu, 2021). Furthermore, data is in theory both infinite and non-competitive, meaning that it could be shared an infinite number of times without degrading its quality. Given this nature of data as a resource, Yu, Liang, and Wu (2021) note that large and incumbent companies often gather, accumulate and hold large amounts of data that have been captured from different aspects of their operations, as an additional spillover from other aspects of their business. Furthermore, Rikap and Lundvall (2020) argue that large, powerful companies in tech work hard to acquire, and go as far as monopolize knowledge and data, and that they gain a powerful bargaining position where they are able to extract rents because of the data they that hold. With such a powerful position held by some actors in the innovation system, it may be unbalanced and cause issues with collaboration because of the power imbalance.

2.3 Previous studies on University Industry Collaborations

How university researchers work with industry actors has been studied extensively, with different studies emphasizing various academic disciplines, geographic locations, or more general motivations studies of how and why they work with industry. Etzkowitz, Asplund, and Norman (2001) argue that collaborations in the past were centred around the exchange of trained personnel who would conduct research for the companies, within the well-defined bounds of the company. More recently, they note that the forms of interaction between universities and the private sector have become increasingly diversified, with a variety of different types of collaborations. As such, it is important that we have a good understanding of how this range of interactions happen, and what characterizes them.

In their examination of university industry collaborations, Perkmann and Walsh (2007) note that a large amount of past studies have focused on patent data to explore patterns of university-industry collaborations. They argue that this data is relatively thin and flawed, as it does not uncover motivations, and may not fully capture collaborations that do not result in patent applications, or misrepresent collaborations where patents are not a primary goal. As such, they observe that many of the more recent studies in the field either use surveys specifically for this purpose, or qualitative data that can yield richer insights. The importance to cover a variety of different forms of collaborations is uncovered by Perkmann et al. (2013) in their systematic review of studies on university industry collaborations, which note that there is a wide range of different models for collaboration. They primarily highlight activities in the following six categories, collaborative research, consulting, sponsored research, contract research, patenting, and academic entrepreneurship. While there is room for additional nuance to characterize specific relationships, this list provides a high-level overview of the different ways collaboration can happen. Their review further provides an overview many of the commonly examined variables that have an impact on likelihood to engage in collaboration, and likelihood to commercialize research findings. As their review covered 36 identified studies they provide an expected sign of the type of relationship, such as positive, negative, or neutral, but no detailed exploration of the reasons for why these relationships are expected.

Seashore Louis, Blumenthal, Gluck, and Stoto (1989) explored a selection of five different types of different university industry collaborations through a survey life scientists, to understand why they are undertaken and how they are experienced by the researchers. In their study, they found that researchers still very much prioritize their academic work, and that there was little or no risk that they shift their focus to entrepreneurial activities. Instead, they suggest that researchers balance their involvement with industry as it is not an either/or involvement. This they explain with the types of involvement, and distribution between them are similar for researchers, regardless of if they are involved in many collaborations or not.

Iorio, Labory, and Rentocchini (2017) expanded on other studies of university industry collaborations, by separating the breadth and depth of knowledge transfer in the collaborations. They conceptualize knowledge transfer breadth as the number of unique collaborations that a researcher is engaged in and is commonly studied. Knowledge transfer depth instead refers to the frequency through which an activity is repeated. This indicates a stronger tie between the researcher and the industry actor. Stronger ties are in turn linked to both better collaborations in the present time through additional trust and reciprocity, but also has an impact on how both organizations develop going forward, as they become more likely to develop complementarities to actors they have a strong link with. Their study showed that researchers tended to either have wide breadth or deep depth in their knowledge transfer activities, but not both. Furthermore, their study uncovered that the mission of furthering research and improving society was an important driver for many academics to collaborate with industry. As such, they argue that programmes to promote university industry interactions should focus on furthering and disseminating the research in addition to the financial incentives.

Etzkowitz, Asplund, and Nordman (2001) explored the emergence of academic entrepreneurship in Sweden. They argue that the relationships between university researchers and the industry actors are especially characterized by personal relationships. Furthermore, they claim that Swedish universities at the time primarily worked with large or medium-sized actors, as they were the ones who could make use of the specific knowledge from the universities. Interactions with small companies was only relevant if they were highly specialized and able to fully benefit from insights from academia. Furthermore, they note that academics in computer science were especially tightly connected to industry, but that universities suffered from loss of personnel who were attracted by the higher salaries in the private sector. In regards to the intellectual property rights of the academics, Etzkowitz, Asplund, and Nordman (2001) found that most academics were quite happy with the Swedish system, but that some found it confusing or challenging when it came to larger collaborations.

However, they also note that most professors have little interest in actively commercializing their research, at least little interest in spending time on those activities.

Åstebro, Braguinsky, Braunerhjelm, and Broström (2019) compared academic entrepreneurship in the USA and Sweden. They found that academics are less likely than the rest of the population to engage in entrepreneurship in both countries and that Swedish academics are somewhat more likely to become entrepreneurs than their American counterparts. They argue that this supports the notion that the Swedish “teacher’s privilege” works to incentivize individual academics to become entrepreneurs and in industry in that way. Furthermore, entrepreneurship gives little or no financial benefit to the academics, especially after adjusting to the risk. However, this does not address compensation that academics receive through other forms of collaborations with industry, which are likely more predictable and agreed beforehand, as well as carrying less risk for the individual.

Motivations

In a systematic review of previous studies of university-industry collaborations, Ankrah and Al-Tabbaa (2015) group the motivations of academics to enter and partake in collaborations in five main categories: necessity, reciprocity, efficiency, stability, and legitimacy. These categories of motivation capture the general motivations and can be useful to categorize more specific statements. Necessity in this context refers to an institutional context which requires or strongly emphasizes collaboration, reciprocity and efficiency are tightly linked, with reciprocity in Ankrah and Al-Tabbaa’s (2015) definition referring to interpersonal benefits, while efficiency is linked to improve abilities to conduct work and research, to exploit each other’s resources. Stability refers to a reduction in risk, for example when entering a new area of research or market segment. Finally, legitimacy refers to prestige on a personal level as an academic, as well as for the university as an institution whose reputation benefits from research ties to industry.

D’Este and Perkmann (2011) explored the various motivations for academics to engage with industry in a study of British researchers. In general, they found that academics were primarily motivated to work with industry by the prospects of furthering their research rather than commercialization of their knowledge. However, when examining the different modes of engagement with industry, they uncovered that the different ways of working with industry are characterized by different motivations from the researchers. In particular, the academics who were interested in commercializing their work tended to engage more in consulting, spin-offs, and patenting. Meanwhile, learning more was the main motivation associated with contract research, joint research, and also consulting. D’Este and Perkmann (2011) argue that there is a tension between commercialization as a motivation, and motivations to further research. In particular, more collaborative forms of engagement are driven by a desire to further their research. Meanwhile, the more individual forms of collaborating are driven by commercial prospects and potential financial gain.

These observed reasons for participating in university industry collaborations appear to be understood primarily through a resource based view of the firm, as was explored by Mowery, Oxley, and Silverman (1998) and discussed in the earlier section. In particular, the study by D'Este and Perkmann (2011) centres the resources and capabilities that are held by the university and the companies respectively, and it is an intuitive way to understand the collaboration between two actors. Furthermore, the different categories of reasons to collaborate presented by Ankrah and Al-Tabbaa (2015) also primarily correspond to an understanding of collaboration through a resource based view, rather than transaction based economics. This is understandable as these reasons to collaborate are from the view of the university or academic, and the transaction-based economics view of collaborations highlights risks undertaken on a market and in the search process. While a university and its representatives may be subject to certain types of "risks" from this perspective, such as coordination costs, and issues with enforcing contracts properly, they may not have the same option of producing an innovation without collaboration, which is the traditional option in a transaction cost economics view of collaboration (Remneland-Wikhamn & Knights, 2012). As such, the focus on motivations rather than risks in the resource-based view of the firm makes it somewhat more applicable to understanding the motivations for collaboration by universities when they partner with the private sector.

University industry collaboration in software engineering

While there are no published studies on collaborations between universities and the private sector in the context of AI, there is a body of literature which examines collaborations in software engineering, which is a necessary component of AI work. In a review of 101 individual collaborations, Garousi et al. (2019) notes that the level of collaboration between universities and industry in the field is relatively low. Furthermore, the research that universities undertake is disjointed from the software engineering that companies engage in, even if both parties conduct considerable amounts of research on the topic (Garousi et al., 2019). This shows that while both universities and the private sector value research on the topic, their work and priorities does not seem to be aligned or coordinated.

Through a structured literature review, Garousi, Petersen, and Ozkan (2016) uncovered ten themes which the most prevalent challenges can be grouped into. Most of these mirror challenges that have been observed in other studies of university-industry collaborations and relate to topics such as issues with the university research that it, or the practitioners does not match the industry needs, issues with communication, project management and expectations, as well as contractual rights and resource related issues. Awasthy, Flint, Sankarnarayana, and Flint (2020) highlight that the motivations to collaborate differ between industry and universities in this sector. Furthermore, they note that the private sector might not see the full potential of benefits from collaborating with universities, with a general view that the companies can do equivalent research internally just as well. The issues faced in collaborations around software engineering are not unique, the frequency by which they occur and the best practices to manage them may differ from other fields, which could help explain why collaborations in this field are relatively rare.

According to Chimalakonda, Reddy, and Shukla (2015) the most conventional structure for collaborations between universities and companies collaborate in software engineering is that universities supply novel ideas that they want to realize, while their private sector partners contribute with financing to enable the project. This would follow a very conventional view of why universities and the private sector collaborate, much like in other disciplines where the private sector enables more research. However, Chimalakonda, Reddy, and Shukla (2015) also note that not all collaborations in software engineering follow this conventional structure. Instead, the researchers may collaborate because they need novel inputs for teaching, or they have attained vast funding from other sources.

3 Methods

3.1 Methodological Approach

3.1.1 Correction from quantitative to qualitative enquiry

As the work on this thesis started, the original intention was to conduct a quantitative study where survey data would be the basis for analysis. This was originally chosen as in the vast majority of studies on university-industry collaborations, surveys are used to collect data given their ability to gain insight on a the actions and motivations in a large population (Perkmann et al., 2013).

This survey was distributed together with AI Lund, an open university network collecting and organizing work relating to AI in the different departments of the University. It was sent to the mailing list of all academic University staff who followed AI Lund, a group of 667 individuals. This was the first time that AI Lund had sent out a survey of this type to their followers, as such it was very unclear what the response rate would be. The survey was sent out on April 6th, 2022, with a stated deadline for responses on April 30th. Given the broad applicability of artificial intelligence to different areas of academia, this list of people is expected to include people to whom this survey is not relevant, as their work with AI for example does not involve industry or private sector actors, which further put the expected response rate into question.

As the deadline had passed, only 7 responses to the survey had been received, only four of which had responded to a significant number (<80%) of the questions. This highlighted the need for an alternate source of data, to collect sufficient amounts of valuable information to analyse and gain insights from. As such, interviews were planned to be the main source of data for this thesis to attain deeper insights into the practices and motivations of the university researchers. With a qualitative approach, the information gathered from the completed surveys can be analysed in tandem with the interviews.

Among the four relevant responses, there were three women and one man. One of these were associated with the faculty of medicine, whereas the remaining three were associated with the faculty of engineering.

3.1.2 Survey

A survey was constructed with multiple-choice questions regarding the researcher's background. The sections on motivations, achievements, and characteristics of the collaborations that the researchers had conducted mainly used 5-point Likert scales, as appeared to be common from observations of other similar studies. The use of Likert scales provides ordinal data and is relatively easy for the respondents to answer and is common in other studies on university-industry collaborations. Norman (2010) highlights that there are some issues with using Likert scales, but that they can still provide very valuable insights if there is caution in the methods of analysis, and generalizability of the data. There was one question on the main challenges that were faced in collaborations that was asked as an open text question, where the answers are intended to be coded by the researchers afterwards.

3.1.3 Interviews

A selection of semi-structured, in-depth interviews were conducted with individuals who were researchers with an association to Lund University. These participants are required to have artificial intelligence as part of their academic work and have participated some sort of university-industry collaborations to speak to their own experiences and motivations.

The questions in the interview guide were constructed with the original survey as a basis. This was to gain insights that follow the original intentions of the study, as well as the ability to gain insights that can be qualitatively analysed in tandem with the survey answers. The interview guide is available in Appendix A.

Before each interview the participants were asked to give their informed consent about participation in the study, and explicitly informed about the possibility to leave the study at any time without giving a reason or receiving any negative consequences. Furthermore, they were informed of the rights they hold regarding any personal information they share in accordance with Swedish data protection law, GDPR, and were given contact details to the Lund University Data Protection officer. All interviewees were asked to confirm that they had read through the information provided.

The participants were found through convenience and snowball sampling. The Lund University Research Portal is a catalogue of researchers affiliated to the university, which captures their published work, both titles and abstracts, as well as their cataloguing the participation in research networks. This database was used to identify potential participants through searches for keywords including "Artificial Intelligence" and "Machine Learning". The discovered profiles who had two or more matches on the keywords were screened for relevance, identifying 57 researchers. In this stage, researchers whose work only tangentially relates to artificial intelligence were filtered out, such as researchers in the humanities who consider AI in a philosophical sense, or researchers working specifically with ethics of artificial intelligence and similar associations to AI. This excluded 7 individuals. The remaining 50 academics were sent an interview request by email which specified the aims of this research project and invited them to participate in an interview. The choice to rely on convenience, or nonprobability sampling means that the findings from this study are not strictly generalizable to a wider population. Given the structure of this study, and the qualitative nature of the insights that it seeks to find, non-generalizable findings are deemed to be valuable, nonetheless. Of the 50 academics that were contacted, ten responded and were either willing to be interviewed themselves or suggested that we interview another person they work with who had not already been covered in the 50 interview requests which were sent out. After all these individual researchers had been followed up with, eight potential subjects were willing to be interviewed, and a suitable time and location could be found to conduct all these eight interviews. Others who responded primarily indicated that they did not have time to participate, whereas two people who were contacted indicated that they do not work together with the private sector. Seven of the interview subjects were men, whereas one was a woman. Two interviewees were associated with the faculty of medicine, whereas the remaining six were all associated with the faculty of engineering.

Semi-structured interviews were deemed the most appropriate for this study to allow for a deeper exploration of the thoughts, opinions, and motivations of the study participants. The semi-structured nature allowed the participants to fully continue streams of thought referring to individual projects, allowing for a more natural conversation, and hopefully richer insights than fully structured interviews.

The questions in the interview guide, like the survey questions aimed to first establish an understanding of the position of the researcher, the types of research they conduct, in what settings, and to what extent and in what manner it relates to artificial intelligence. This is followed by a section exploring how the researcher has worked with the private sector, covering both the types of different partnerships, what types of partners, frequency of collaboration. More specifically, this section seeks to explore motivations for entering partnerships and what makes them critically question participating other partnerships or collaborations. The final section contained questions regarding knowledge sharing and knowledge flows in the collaborations, as well as the how the participant views intellectual property. This group of questions is meant to explore views on open innovation, and how it happens in practice for this group of researchers.

The interviews were conducted in the period between May 2nd, and July 1st, 2022.Five of the interviews were conducted remotely over Zoom, to enable more flexible scheduling while three were conducted in person in Lund. Since consent for recording audio had been acquired, all interviews were recorded and later transcribed, and these transcripts serve as the main source of data for this thesis.

3.1.4 Qualitative Case study

A qualitative case study design was chosen to be able to fully utilize the variety of different types of data that had been collected from different sources. The survey responses which would conventionally be analysed statistically, examining associations and frequencies are instead analysed qualitatively in combination with the interview transcripts as a unified set of insights. The survey responses and interview transcripts were coded and analysed in Nvivo

12, which allows them to be coded together despite their varying file-types. As the data was approached without specific previous themes, Open coding was used to generate categories that the data would fit into. The notable themes uncovered in this process are the ones presented in section four, findings.

3.2 Data

3.3 Case Selection

3.3.1 Choice of researchers affiliated with Lund University

The two core factors that make up the case selection in this study, the choice of examining the perspective of researchers, and specifically researchers associated with Lund University was a choice made in tandem. In particular, as collaboration with AI Lund allowed access to reach out to their network of researchers, the choice was made to select this particular case.

3.3.2 Reliability and validity

In the context of research, validity refers to how accurate the findings are, and how well they represent the reality of the phenomenon or case that is being studied (Kirk & Miller, 1986). Meanwhile, reliability is instead concerned with the methodology and repeatability of the work that has been conducted. This means the ability to follow the steps laid out in the description of the methodology and being able to find similar findings if the work is repeated. This ensures that there are no accidents or spurious findings. When doing research on a social topic, Yin (2003) claims that it is crucial to assess both these aspects in order to ensure quality of the work that is being conducted.

In qualitative research, Creswell and Creswell (2018) suggest that there is a variety of ways to approach and ensure validity. One strategy they suggest triangulation of different types of data sources. This study uses a combination of interviews and their transcripts, as well as a small set of questionnaire responses. This allows for some exploration of how the themes correspond to one another depending on the type of collected data. Furthermore, the study could have been expanded upon with additional data on collaborations in this context, such as a study of patent data. While Perkmann and Walsh (2007) suggest that there are several issues with using patent data for studying university industry collaborations, it could still serve a valuable role in increasing the validity of this study. Creswell and Creswell (2018) further suggest presenting contradictory evidence as a method to increase validity in qualitative work. By the nature of this study, and the themes along which the findings are presented, contradictory statements from individual interviews or survey answers is presented where relevant.

Yin (2003) suggests an extensive documentation of the undertaken procedures as a way to manage and ensure reliability. Furthermore, it is crucial that codes used in the analysis remain constant in the way they are defined and used across all data (Creswell & Creswell, 2018). In the methodology section of this thesis, the steps taken for analysis are described with an appropriate level of detail to ensure this. Furthermore, to ensure that the analytical definitions and themes are interpreted correctly they are kept as simple as possible. In addition, the codes that were developed and defined were re-examined after all material had been coded to ensure that their definitions had not drifted, which Creswell and Creswell (2018) suggest is a useful method to improve reliability of qualitative research.

4 Findings

4.1 Motivations for working with the private sector

As explored earlier in this thesis, previous studies have highlighted a range of different factors and motivations that drive academics to engage with private sector actors. The range of quantitative studies have highlighted common associations that can help explain the general phenomenon of university-industry collaborations. To some extent, the same factors that were highlighted in the previous literature appeared in this qualitative study, and the specific motivations expressed by the researchers are explained further in the following sections. This not only examines what factors are important for collaboration among researchers working with Artificial Intelligence but gives a deeper understanding as to why. This can in turn be connected to the specificities of AI research, to better explain how, and to what extent research and innovation on the topic of AI is unique.

4.1.1 Researchers along the value chain and their characteristics

Nearly all researchers surveyed and interviewed in this study indicate that working with industry and the private provides them with valuable resources for conducting research that would be hard or impossible to access from other sources. This sentiment was explicitly shared by all four questionnaire respondents, 3 of whom said that industry provides resources that are nearly impossible to replace, and the last indicating that they resources would be challenging to replace. Among the eight interviewees, five directly indicated that they get access to resources that would be hard or impossible to replace in other manners. The remaining interviewees also shared similar sentiments, showing that they value what industry provides but did not indicate as clearly that it was imperative to work with private sector for access to what they received from them. Precisely what resources and inputs from the industry the different researchers value depends on what is important for their specific research. The joint characteristic is that they are hard, or impossible to replace from other sources.

4.1.2 Financial and other resources

Financial resources to conduct research was mentioned by several researchers as an important factor for collaborating with the private sector. In particular, two researchers working with artificial intelligence in the context of robotics both indicated that working with industrial partners was neccesary for the financial resources to support the expenses associated with robotics research, which requires considerable amounts of hardware. One of these researchers is involved in a robotics lab that is run jointly between two university departments. He highlighted that finding funding for this lab is a constant struggle. Working with the private sector is one necessary way to secure enough funding to keep this lab running and competitive.

While working with the private sector can provide neccesary financing for projects like these, it is unsurprising that the private sector primarily wants to finance projects that are to their own benefit. One senior researcher and project manager highlighted that the private sector financing is especially allocated to applied research, in projects that are meant to solve a problem that the private sector is facing. However, he indicated that they “sneak in” some basic research also in projects with the private sector. This he argued was possible as the projects were still controlled to a large degree by the university and its representatives who could provide very valuable insights into AI and research to the private sector which they in turn cannot easily develop in other ways.

One researcher at the faculty of engineering highlighted that multi-party collaborative projects are an important source of financial resources. In particular, he pointed out that collaborations between the university and companies may often have other parties involved as well, who provide funding to ensure that the university can conduct interesting research, on a topic that is mutually interesting for the company and industry partner as well. Different interview subjects have mentioned projects with national research support from organizations such as Vinnova the Swedish innovation agency, or EU financing. One medical researcher brought up a Vinnova financed project in the context of independence in collaboration with the private sector. As he wanted to remain as independent as possible from the private companies he worked with, whose AI solutions he conducted research on, external financing from a third party allowed them to undertake more interesting projects, while retaining a layer of separation from the private sector, keeping the research independent from private sector interests.

Meanwhile, other researchers working primarily in software-oriented research relating to AI did not emphasize the strain of resources to the same extent as their counterparts who worked with AI in settings that include a lot of hardware. One interviewee working in medicine, with clinical research, indicated that indicating that they do not want money to exchange hands with companies in order to remain completely independent. Much of the work they were conducting with the industry was with development and validation of AI software for use in the clinic. Their desire for independence went as far as they paid licences for the software which that they were conducting research on. While they did pay a licence fee to the company to use the software as one layer of independence, they got access other human and technical resources from the company that helps them conduct their research properly. Here, financial resources were not a strain on the ability to do the neccesary research, but the researchers were fully dependent on the private sector to continue developing novel AI solutions.

While the interviewees have a mix of relationships with the industry as a source of financial resources for conducting research, no interviewee or survey respondent indicated that personal financial profit was a notable factor for engaging with the private sector or not. One survey respondent, and several interviewees indicated that they had however seen personal financial gain from working with the private sector, even if this is not what they seek out. One interviewee who indicated this had also turned down other paid positions with a company they had closer academic ties to, and was co-publishing with, to retain stronger independence for the sake of work that they were co-publishing together. By doing this they put their research interests above their personal interests, or the company's interests. Meanwhile, an interviewed professor at the engineering faculty who had participated in the creation of a university spin-off company highlighted that the likelihood of personal financial gain from that kind of work is very uncertain. As such, academic entrepreneurship and financial gain was not a motivating factor for him to engage with spin-offs or the private sector, but rather the desire to see knowledge come to use, and the process of solving interesting, real-world problems. Personal financial gain in this context was simply a bonus.

Previous studies indicated that access to data has the potential of being a strong reason to collaborate when innovating within artificial intelligence, with an expectation that companies hold a large amount of valuable data for machine learning (Yu, Liang & Wu, 2021). None of the interviewees in this study appear to highlight this specific reason for collaboration. Among the researchers working at the faculty of engineering, none of them indicated that it was a constraining factor. In particular, one researcher at the faculty of engineering highlighted that the data held by companies is rarely as valuable as may be desired, not being fully annotated and organized to the point where it is useful. Furthermore, he said "If a company comes to me and has data than they want help with machine learning, I might not be very excited unless the company is called Google and they have a bunch of researchers who are working on this project with [existing] financing". Meanwhile, among the researchers working in medicine, the relationship is reversed compared to what may be expected from the literature. Here, the university holds the neccesary medical imaging data, and the private companies want to work with the university for access to this. Rikap and Lundvall (2020) indicated that the power in collaborations would be held by the companies with large amounts of relevant data. Among the interviewed medical researchers, they control the neccesary and relevant data, and they also have a considerable amount of power in their relationships with external partners. As such, the notion that access to data yields power in the relationship may be true, but in this case that power lies with the university.

4.1.3 The private sector as a source of inspiration

Choosing to work with the private sector for the sake of inspiration and a connection to real world issues is a sentiment that was explicitly shared by most researchers in this study, six of the eight interviewees. It was unfortunately not explicitly covered by any survey question and is therefore hard to guise from the survey responses.

The researchers in this study all indicate that they have considerable knowledge of AI and the application of it their particular areas of research, as would be expected. When there is a nearly endless list of possible, theoretical applications, real world problems provided by the industry can serve as a reason to choose one topic over another and to give relevance to the work that is undertaken.

The problems faced by industry provides input and inspiration to the researchers in a variety of ways, guiding both their specific collaborations to solve a complicated issue, but also in how the researchers work with their students. One researcher who is also a course convener linked the problems faced by companies to a range of his work with his students and sees that the private sector is an important source of inspiration for all types of work he conducts with students. He explained that a problem faced by one company can serve as the inspiration for a small course for students, and if the collaboration works well and the findings along the way are interesting, the project can continue to develop, serving as inspiration or guidance for graduation theses that he supervises as well. This interviewee indicated that the process of seeing an idea that would solve a real problem grow and develop was his primary motivation to work with the private sector. This because real world problems to solve and investigate provide a more dynamic ability to continue than hypothetical issues for the sake of academia.

Beyond simply seeing a problem and idea grow, other researchers emphasized the necessity of balance when working with companies, as the real-world problems they receive from them need to match interesting, ideally publishable research. In particular, one researcher noted that he does not only want to deliver a finished project for the benefit of a company, but it should be an interesting process and serve as a foundation for publishing so that his work can benefit the wider world. The same researcher also linked this notion of benefit for a wider world to risks and academic entrepreneurship, where companies have a connection to the market and have better knowledge of what is needed. In this particular context, the researcher is emphasizing the need for inputs from any external party, that a wider understanding of the market and problems are is needed in order to understand what would work as an innovation, and what would not.

This motivation to work with the private sector matches what Chimalakonda, Reddy, and Shukla (2015) hypothesized happens when software developers work with the private sector, in a manner that does not correspond to the most traditional patterns. However, in their consideration they expected the university actor to have sufficient financial resources from other sources already, and then they may seek out collaborations that take other shapes which was not observed here. Instead, inspiration is often sought after in tandem with financing. This indicates that the power relations may be different, as the university researchers can ask for more when working with AI.

4.1.4 The private sector as a source of skills and software

Researchers in this study who were working in medicine all highlighted another important reason to work with private sector actors, access to their software solutions and accompanying knowledge. The research that is done by the interviewees working in medicine is based on accessing, evaluating, and further developing AI driven solutions for use in the clinic.

For this type of research, access to the appropriate AI driven solutions is at the very centre of being able to conduct the research, the transfer of software and skills to adapt it from the companies to the researchers. One researcher indicated that there is a variety of potential companies to work together with and that they chose their partners carefully, on the basis of their reputation as a company, and personal relationships with those responsible. Their motivations in these collaborations were both the possibility to improve work with cancer imaging for the sake of patients, as well as their own ability to publish work related to their research.

Researchers working with AI in this context cannot freely develop their own AI driven solutions and implement them for the patients in the clinic. One of the interviewees claimed that for legal and patient safety reasons they need to work with companies who provide the software solutions and get them CE marked. One researcher highlights this not as a constraint, but as an advantage, as it saves them from the hassle of certification, and allows them to focus on conducting the neccesary research that ensures the success of the solutions, and the benefit for clinicians and patients. The collaborations in this theme are highly reciprocal, but the exchange is not research work for resources, but rather research in exchange for better solutions to the clinic and its patients.

4.1.5 Outward knowledge transfer

The sections above have covered some of the primary components of what the private sector provides to university researchers, and how that relates to the individual researcher’s motivations. While this study does not examine the view of the companies, it can still show what academics provide and transfer to their partners when collaborating with the private sector.

The interviewees generally indicate that their main contribution to collaborations with companies is specific knowledge of the topics of the collaborations. Among the interviewees associated with the faculty of engineering, they indicate that they provide specific topic knowledge of artificial intelligence to the companies, which they need to create and develop their products. Similarly, three out of the four survey respondents indicated that they contribute “a significant amount of specific knowledge” in collaborations with the private sector. This shows that when they work together with the private sector, the detailed knowledge of artificial intelligence, engineering and algorithms is what the private sector actors need from the skilled academics and allows them to innovate and solve problems that are faced in the real world.

Several of these interviewees indicated that there is a tension between the desires of the companies and the interests of the researchers in these collaborations. The researchers indicate that they are happy to work with the private sector actors and apply their skills and knowledge, as long as they are allowed to publish work to the general world based on the work they have done together. Here, the interviewees argue that the companies want to retain private access to the knowledge and information as long as possible, and ideally not ever see much of it publicly available. Meanwhile, the priority of the researchers is being able to share interesting findings with a group that is as wide as possible. Several interviewees, both at the faculty of engineering and medicine indicated that they prefer to work with companies that have a strong research background, often university spin-off companies because they have a better understanding for the desire of the academics to share with the wider world, allowing for knowledge to flow more freely in these collaborations, from the researchers to the companies in addition to a wider audience.

Despite some tensions between the desires of the companies, the university researchers interviewed universally indicated that they were in high demand from the companies. Thanks to this, the researchers could generally find collaborators that they were happy with. This deviates from the findings in software engineering by Awasthy et al. (2020), which claimed that companies perceived themselves to be able to do research of comparable value internally. This highlights that work and research on the topic of AI differs from general software engineering, potentially that there is a stronger sense of urgency to innovate, or that companies to an extent lack the specific knowledge required for work with AI.

Students as outward knowledge transfer

Three of the interviewees who all conduct a significant amount of teaching in addition to their research all made references to their students as what they contribute outward, to the private sector. Rather than spending time on research directly for and with companies, one researcher explained that he much prefers to spend that time teaching, sending out about a hundred skilled graduates who can be hired to conduct skilled work and research for the companies. Similarly, another researcher made similar references to his past PhD students, who were highly sought after and headhunted by companies after they had completed their defence. In these cases, the interviewed researchers provide the companies with what they need and desire in an indirect manner, not through collaborating with them, but by teaching another generation of skilled staff for them to hire. All three interviewees who highlighted their roles as supplying the private sector with skilled staff also indicated that they see the private sector as a source of inspiration, both for their research, but also specifically for their teaching topics.

Teaching students that can be hired by private sector companies would traditionally not be expected to fall within the open innovation paradigm. It traditionally centres the innovation process and development of new knowledge and innovations such as academic consulting, joint projects and collaborative research (Perkmann & Walsh, 2007). However, in this case, the academics specifically teach topics inspired by problems faced in the private sector, embedding skills into many new students, which are then sought after by the same companies who inspired the teaching. As such, the knowledge embedded in the students can be considered a spillover from the collaboration between the company and the professors who were inspired by them to plan their teaching. This notion of skilled students as a spillover has been noted by Saxenian (1996), who emphasizes the geographic, regional aspect of it, as the graduates are still somewhat spatially sticky.

4.1.6 Personal relationships and private sector partner selection

The specific, AI related skills that are held by the researchers interviewed as part of this study are in high demand from the companies and private sector actors who are looking to expand their innovation work with artificial intelligence. As such, the AI researchers have a great deal of agency in choosing what projects to take on, and to shape them in a way that they desire. This can be seen, for instance in how one of the researchers indicated that he was able to choose components to include funding for basic research when needed. With this high desire for the specific skills held by researchers working with artificial intelligence, personal relationships, and a high degree of respect for the potential partners become the ultimate deciding factor according to three of the eight interviewees. Considering that the structure of these collaborations often contains a large amount of direct work together with the other actors and their representatives, for practical and collaborative reasons, the emphasis on interpersonal relationships as a deciding factor is very understandable.

In their study of academic entrepreneurship in the USA and Sweden, Etzkowitz, Asplund, and Nordman (2001) observed a similar, strong reliance on close personal relationships among Swedish academics when working with industry, in particular in comparison with the USA. They emphasize this stronger connection as a result of the personal rights to intellectual property that are held by Swedish academics, as they are personally invested in the outcome of their collaborative work. This is in contrast to other systems, where the university as an institution holds the intellectual property rights, and therefore takes a bigger part in mediating the collaborations with private sector actors. Among the interview subjects in this study, mediation from the university came in the form of assistance dealing with intellectual property, and assistance for creating contracts to work with external parties.

The literature on patentability of innovations with Artificial Intelligence indicated that the AI aspects may be challenging to patent in practice, as discussed in the earlier section on intellectual property rights. The interviewees who had dealt with these sorts of discussions to allocate intellectual property from university-industry collaborations did not have any hesitations that once the contracts are in place that their rights would be appropriately protected. However, only two interviewees mentioned patents that had been applied for and acquired because of their collaborative works. As such, patentability is likely not a major concern.

4.2 Synthesis and comparison of themes

Examining the presented themes, it is clear that academics have a wide variety of reasons to engage with industry, and for each individual collaboration, different ones will be particularly important. Returning to the five categories of reasons to participate in university industry collaboration presented by Ankrah and Al-Tabbaa (2015), necessity, reciprocity, efficiency, stability, and legitimacy, their definition of efficiency corresponds well to the most commonly noted reason to collaborate, according to the interviewees, that they highlight the ability to utilize resources from the private sector partner. No interviewee indicated a strong necessity to participate in collaboration, at least not in accordance with the definition by Ankrah and Al-Tabbaa (2015), which considers organization policies that require collaboration. Similarly, while legitimacy directly stemming from the act of collaborating with the private sector was not an indicated factor by any of the interviewees, the importance of publishing was very clear from three of the interviewees, which in turn is strongly linked to the individual legitimacy and reputation, even if this link was not made explicit by the interviewees. Stability was not explicitly noted as a reason to collaborate by any of the researchers, but it was considered as one of the reasons why they were not interested in academic entrepreneurship themselves. Reciprocity and interpersonal benefits appears to be a strong reason, not neccesarily for participating in collaborations in general, but in regards to partner choice.

The researchers examined in this study are associated with two different faculties, the faculty of medicine, and the faculty of engineering. The types of research related to Artificial Intelligence that is conducted in university industry collaborations among the interviewees differs along the lines of these faculties. The researchers at the faculty of engineering work primarily with applied, and some basic research where they contribute with knowledge of the algorithms and software aspects of Artificial Intelligence. Meanwhile, the researchers working with medicine mostly work with application development and adaptation, where they examine

These differences can also be understood as having different places on the AI value chain. The academics from the faculty of engineering provide knowledge needed before an application can be developed by the companies. Their expertise lies primarily is in the algorithms and machine learning that enable AI driven solutions, at the Technology Developers stage of the AI value chain. Meanwhile, the medical researchers are working with existing solutions, to validate their functionality and better adapt them for use in a clinical setting. This work places them either at the last stage of the AI Value chain presented by Yu, Liang, and Xue (2022), Application Scenarios.

5 Conclusion

5.1 Research aims and objectives

The aim of this thesis was to gain descriptive and qualitative insights into the motivations of university researcher working with AI to collaborate with the private sector. Including personal motivations, and how collaborations link to their existing projects.

Researchers working with AI appear to in general be driven by the same categories of factors that apply across different disciplines. This study has shown that along the AI value chain, the researchers have different needs which in turn are associated with different motivations for engaging in collaboration with the private sector.

Two themes that were frequently noted by the researchers considered in this study which diverge from commonly cited themes across other studies and disciplines are; the private sector as a source of inspiration, and the importance of students' knowledge as a spillover. While embedding knowledge in students is not a unique or surprising factor to be highlighted by professors, how the interview subjects link it to their collaborations with the private sector is. Inspiration from the private sector as a motivation to collaborate did appear in the literature from previous studies of university industry collaborations, it was however never a primary or commonly cited reason for collaborations. There are many potential hypotheses for why this reason stood out in this context, ranging from specificities with AI research, to the local, geographical context.

5.2 Limitations

Given the nonprobability, convenience sampling that were used in this study, the findings of this study would never be strictly generalizable to a broader population. Further contributing to this issue is the relatively small sample of 12 relevant participants in this study, eight of which were interviewed. This limited the ability to reach saturation of the themes, as well as the ability to draw trends across a population.

While this study attempted to isolate the work that is conducted specifically in relation to artificial intelligence, the interview subjects nonetheless included mentions of work and projects that fall outside of the scope of artificial intelligence. While the study still accomplishes insight into the motivations of researchers working with AI, it does not necessarily isolate innovation activities on the topic of AI. As such, it is harder to draw conclusions that explain how this AI is or is not unique in comparison to other technologies.

5.3 Future research

The findings of this study indicate a variety of pathways to continue future work that would help ensure a better understanding of the topic with more detail, and in particular a better understanding to what extent artificial intelligence is a unique aspect. A first avenue for research is to examine collaborations between universities and the private sector across all parts of the AI Value chain. This can help gain a better understanding of how the different actors work, and where university research plays a considerable part, or not. This would also serve as useful insight to help expand on precisely what actors and actions ought to be included in the AI value chain, as it is still a developing concept.

This study considered collaborations between universities and the private sector from the view of the university and its researchers. Given the importance of companies in the innovation process, it would be useful to examine their motivations and views in more detail, as a contrast to the findings from this study. When considered in combination, this could help facilitate better collaborations between universities and the private sector in AI innovation. Ensuring that all actors have a better understanding of each other may help resolve some of the frictions and enable richer results.

5.4 Practical Implications

This thesis has contributed to the study of how work is conducted on emerging innovations in general, and innovation on the topic of AI in particular. Specifically, it has highlighted what drives university researchers across multiple disciplines to work with the private sector in further development of AI innovations. As such, this work can be of assistance to those who are planning new collaborations between the private sector and universities in this field, in particular third-party facilitators or private sector actors, who may not have specific insight into the motivations of university researchers.

References

Abrahamson, E. (1996). Management Fashion, *The Academy of Management Review*, vol. 21, no. 1, pp.254–285.

Alkemade, F., Kleinschmidt, C. & Hekkert, M. (2007). Analysing Emerging Innovation Systems: A Functions Approach to Foresight, *International Journal of Foresight and Innovation Policy*, vol. 3, no. 2, pp.139–168.

Ankrah, S. & AL-Tabbaa, O. (2015). Universities–Industry Collaboration: A Systematic Review, *Scandinavian Journal of Management*, vol. 31, no. 3, pp.387–408.

Åstebro, T., Braguinsky, S., Braunerhjelm, P. & Broström, A. (2019). Academic Entrepreneurship: The Bayh-Dole Act versus the Professor's Privilege, *ILR Review*, vol. 72, no. 5, pp.1094–1122.

Awasthy, R., Flint, S., Sankarnarayana, R. & Jones, R. L. (2020). A Framework to Improve University–Industry Collaboration, *Journal of Industry-University Collaboration*, vol. 2, no. 1, pp.49–62.

Bisoyi, A. (2022). Ownership, Liability, Patentability, and Creativity Issues in Artificial Intelligence, *Information Security Journal: A Global Perspective*, vol. 0, no. 0, pp.1–10.

Bogers, M. (2011). The Open Innovation Paradox: Knowledge Sharing and Protection in R&D Collaborations, *European Journal of Innovation Management*, vol. 14, no. 1, pp.93–117.

Brynjolfsson, E. & McAfee, A. (2017). The Business of Artificial Intelligence, *Harvard Business Review*, Available Online: https://hbr.org/2017/07/the-business-of-artificial-intelligence [Accessed 2 January 2021].

Buchanan, B. G. (2005). A (Very) Brief History of Artificial Intelligence, 4, *AI Magazine*, vol. 26, no. 4, pp.53–53.

Chesbrough, H., Vanhaverbeke, W. & West, J. (2006). Open Innovation : Researching a New Paradigm, Oxford: OUP Oxford.

Chimalakonda, S., Reddy, Y. R. & Shukla, R. (2015). Moving Beyond: Insights from 1st International Workshop on Software Engineering Research and Industrial Practices (SER&IPs 2014), *SIGSOFT Softw. Eng. Notes*, vol. 40, no. 2, pp.28–31.

Christensen, J. F. (2006). Whither Core Competency for the Large Corporation in an Open Innovation World?, in H. Chesbrough, W. Vanhaverbeke, & J. West (eds), *Open Innovation Researching A New Paradigm*, Oxford, NY: Oxford University Press, pp.35–61.

Crafts, N. (2021). Artificial Intelligence as a General-Purpose Technology: An Historical Perspective, *Oxford Review of Economic Policy*, vol. 37, no. 3, pp.521–536.

Creswell, J. W. & Creswell, J. D. (2018). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches, 5th edition., Los Angeles, CA: SAGE Publications, Inc.

Curry, E. (2016). The Big Data Value Chain: Definitions, Concepts, and Theoretical Approaches, in J. M. Cavanillas, E. Curry, & W. Wahlster (eds), *New Horizons for a Data-Driven Economy*, Springer, Cham, pp.29–37.

Davenport, T. H. & Ronanki, R. (2018). Artificial Intelligence for the Real World, *Harvard business review*, vol. 96, no. 1, pp.108–116.

D'Este, P. & Perkmann, M. (2011). Why Do Academics Engage with Industry? The Entrepreneurial University and Individual Motivations, *The Journal of Technology Transfer*, vol. 36, no. 3, pp.316–339.

Etzkowitz, H., Asplund, P. & Nordman, N. (2001). Beyond Humboldt: Emergence of Academic Entrepreneurship in the U.S. and Sweden, Working Paper, 27, Umeå: Umeå University, Available Online: https://www.diva-portal.org/smash/get/diva2:227334/FULLTEXT01.pdf.

Fagerberg, J. (2005). Innovation: A Guide to the Literature, in *The Oxford Handbook of Innovation*, Oxford, NY: Oxford University Press.

Freel, M. & Robson, P. J. (2017). Appropriation Strategies and Open Innovation in SMEs, *International Small Business Journal*, vol. 35, no. 5, pp.578–596.

Furman, J. & Seamans, R. (2019). AI and the Economy, *Innovation Policy and the Economy*, vol. 19, pp.161–191.

Gambardella, A., Heaton, S., Novelli, E. & Teece, D. J. (2021). Profiting from Enabling Technologies?, *Strategy Science*, vol. 6, no. 1, pp.75–90.

Garousi, V., Petersen, K. & Ozkan, B. (2016). Challenges and Best Practices in Industry-Academia Collaborations in Software Engineering: A Systematic Literature Review, *Information and Software Technology*, vol. 79, pp.106–127.

Garousi, V., Pfahl, D., Fernandes, J. M., Felderer, M., Mäntylä, M. V., Shepherd, D., Arcuri, A., Coşkunçay, A. & Tekinerdogan, B. (2019). Characterizing Industry-Academia Collaborations in Software Engineering: Evidence from 101 Projects, *Empirical Software Engineering*, vol. 24, no. 4, pp.2540–2602.

Goldfarb, B. & Henrekson, M. (2003). Bottom-up versus Top-down Policies towards the Commercialization of University Intellectual Property, *Research Policy*, vol. 32, no. 4, pp.639–658.

Granstrand, O. & Holgersson, M. (2020). Innovation Ecosystems: A Conceptual Review and a New Definition, *Technovation*, vol. 90–91, p.102098.

Greenberg, A. (2020). Protecting Virtual Things: Patentability of Artificial Intelligence Technology for the Internet of Things, *IDEA: The Law Review of the Franklin Pierce Center for Intellectual Property*, vol. 60, no. 2, pp.328–351.

Gretsch, O., Tietze, F. & Kock, A. (2020). Firms' Intellectual Property Ownership Aggressiveness in University–Industry Collaboration Projects: Choosing the Right Governance Mode, *Creativity and Innovation Management*, vol. 29, no. 2, pp.359–370.

Haenlein, M. & Kaplan, A. (2019). A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence, *California Management Review*, vol. 61, no. 4, pp.5–14.

Hamet, P. & Tremblay, J. (2017). Artificial Intelligence in Medicine, *Metabolism*, vol. 69, pp.S36–S40.

Howard, J. (2019). Artificial Intelligence: Implications for the Future of Work, *American Journal of Industrial Medicine*, vol. 62, no. 11, pp.917–926.

Iorio, R., Labory, S. & Rentocchini, F. (2017). The Importance of Pro-Social Behaviour for the Breadth and Depth of Knowledge Transfer Activities: An Analysis of Italian Academic Scientists, *Research Policy*, vol. 46, no. 2, pp.497–509.

Kirk, J. & Miller, M. (1986). Reliability and Validity in Qualitative Research, [e-book] Newbury Park, California: SAGE, Available Online: https://methods.sagepub.com/book/reliability-and-validity-in-qualitative-research.

Kline, S. J. (1985). INNOVATION IS NOT A LINEAR PROCESS, *Research Management*, vol. 28, no. 4, pp.36–45.

Lindgaard Christensen, J. (1992). The Role of Finance in National Systems of Innovation, in *National Systems of Innovation: Toward a Theory of Innovation and Interactive Learning*, London, UK: Pinter Publishers, pp.146–168.

Lipsey, R. G., Carlaw, K. I. & Bekar, C. T. (2005). Economic Transformations: General Purpose Technologies and Long-Term Economic Growth, Oxford, NY: Oxford University Press.

Malerba, F. & Nelson, R. (2011). Learning and Catching up in Different Sectoral Systems: Evidence from Six Industries, *Industrial and Corporate Change*, vol. 20, no. 6, pp.1645–1675.

Meagher, K. & Rogers, M. (2004). Network Density and R&D Spillovers, *Journal of Economic Behavior & Organization*, vol. 53, no. 2, pp.237–260.

Mowery, D. C., Oxley, J. E. & Silverman, B. S. (1998). Technological Overlap and Interfirm Cooperation: Implications for the Resource-Based View of the Firm, *Research Policy*, vol. 27, no. 5, pp.507–523.

Munir, H., Wnuk, K. & Runeson, P. (2016). Open Innovation in Software Engineering: A Systematic Mapping Study, *Empirical Software Engineering*, vol. 21, no. 2, pp.684–723.

Naqshbandi, M. M., Kaur, S. & Ma, P. (2015). What Organizational Culture Types Enable and Retard Open Innovation?, *Quality & Quantity*, vol. 49, no. 5, pp.2123–2144.

Nelson, R. R. & Rosenberg, N. (1993). Technical Innovation and National Systems, in *National Innovation Systems*, Oxford, NY: Oxford University Press, pp.3–22.

Nordin Bartlett, M. (2021). Lärarundantaget, *KTH*, Available Online: https://www.kth.se/samverkan/samverka-med-forskar/lararundantaget-1.967774 [Accessed 21 April 2022].

Norman, G. (2010). Likert Scales, Levels of Measurement and the “Laws” of Statistics, *Advances in Health Sciences Education*, vol. 15, no. 5, pp.625–632.

Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D’Este, P., Fini, R., Geuna, A., Grimaldi, R., Hughes, A., Krabel, S., Kitson, M., Llerena, P., Lissoni, F., Salter, A. & Sobrero, M. (2013). Academic Engagement and Commercialisation: A

Review of the Literature on University–Industry Relations, *Research Policy*, vol. 42, no. 2, pp.423–442.

Perkmann, M. & Walsh, K. (2007). University–Industry Relationships and Open Innovation: Towards a Research Agenda, *International Journal of Management Reviews*, vol. 9, no. 4, pp.259–280.

Remneland-Wikhamn, B. & Knights, D. (2012). Transaction Cost Economics and Open Innovation: Implications for Theory and Practice, *Creativity and Innovation Management*, vol. 21, no. 3, pp.277–289.

Rikap, C. & Lundvall, B.-Å. (2020). Big Tech, Knowledge Predation and the Implications for Development, *Innovation and Development*, vol. 0, no. 0, pp.1–28.

Rosenberg, N. (1994). Exploring the Black Box: Technology, Economics and History, Cambridge: Cambridge Univ. Press.

Saxenian, A. (1996). Regional Advantage, [e-book] Harvard University Press, Available Through: JSTOR http://www.jstor.org.ludwig.lub.lu.se/stable/j.ctvjnrsqh [Accessed 13 August 2022].

Seashore Louis, K., Blumenthal, D., Gluck, M. E. & Stoto, M. A. (1989). Entrepreneurs in Academe: An Exploration of Behaviors among Life Scientists, *Administrative Science Quarterly*, vol. 34, no. 1, pp.110–131.

Simard, C. & West, J. (2006). Knowledge Networks and the Geographic Locus of Innovation, in H. Chesbrough, W. Vanhaverbeke, & J. West (eds), *Open Innovation Researching A New Paradigm*, Oxford, NY: Oxford University Press, pp.220–240.

Stenvik, A. (2009). University Employee Inventions in Scandinavian and Finnish Law, in W. P. zu W. und Pyrmont, M. J. Adelman, R. Brauneis, J. Drexl, & R. Nack (eds), *Patents and Technological Progress in a Globalized World: Liber Amicorum Joseph Straus*, [e-book] Berlin, Heidelberg: Springer Berlin Heidelberg, pp.339–351, Available Online: https://doi.org/10.1007/978-3-540-88743-0_24.

Teece, D. J. (1986). Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing and Public Policy, *Research Policy*, vol. 15, no. 6, pp.285–305.

Vasylyeva, V. A., Zelisko, A. V. & Zinych, L. V. (2018). Peculiarities of Patenting Artificial Intelligence in the United States and Countries of the European Union, *Journal of Advanced Research in Law and Economics (JARLE)*, vol. 9, no. 8, pp.2854–2860.

Wang, W. & Siau, K. (2019). Artificial Intelligence, Machine Learning, Automation, Robotics, Future of Work and Future of Humanity: A Review and Research Agenda, *Journal of Database Management (JDM)*, vol. 30, no. 1, pp.61–79.

Wu, Y. & Feng, J. (2018). Development and Application of Artificial Neural Network, *Wireless Personal Communications*, vol. 102, no. 2, pp.1645–1656.

Yang, J., Chesbrough, H. & Hurmelinna-Laukkanen, P. (2021). How to Appropriate Value from General-Purpose Technology by Applying Open Innovation, *California Management Review*, p.00081256211041787.

Yin, Robert. K. (2003). Case Study Research Design and Methods, 3rd edn, Thousand Oaks, California: Sage Publications.

Yu, Z., Liang, Z. & Wu, P. (2021). How Data Shape Actor Relations in Artificial Intelligence Innovation Systems: An Empirical Observation from China, *Industrial and Corporate Change*, [e-journal] no. dtaa063, Available Online: https://doi.org/10.1093/icc/dtaa063 [Accessed 31 March 2021].

Yu, Z., Liang, Z. & Xue, L. (2022). A Data-Driven Global Innovation System Approach and the Rise of China's Artificial Intelligence Industry, *Regional Studies*, vol. 56, no. 4, pp.619–629.

Z. Li, Y. Wang, Y. Ji, & W. Yang. (2020). A Survey of the Development of Artificial Intelligence Technology, in *2020 3rd International Conference on Unmanned Systems (ICUS)*, 2020 3rd International Conference on Unmanned Systems (ICUS), 27 November 2020, pp.1126–1129.

Appendix A – Interview guide

Background

- Tell me about your position here at the university
  - What is your main area of research, and how does AI come in to it?
  - How much of your academic work relates to AI?
  - Do you expect the amount of time you spend working on AI related research to change? In what way?

Work with the private sector

- You work with artificial intelligence both in your individual research, and in collaborations with the private sector, correct?
  - Do you mostly work on AI with the private sector, or mostly in research that is only university work?
- What types of projects do you work in where the private sector is also included?
  - Big collaborations with a third party like WASP/AI Sweden?
  - Consulting/contract research?
  - Human resource transfer?
  - Are you an entrepreneur yourself?
  - Using your Intellectual Property Rights?
- How often does this happen?
- When you entered into THIS partnership, why was that?
  - I am thinking of reasons like solving problems in society, furthering your research, access to resources or people, reputation
  - Did the collaboration you fulfil your original motivations? Or have you gotten something else out of it?
  - Have you actually produced something in these collaborations?
    - More or less than if you would not have been part of the collaborations?
  - If you would give one main challenge that you faced after you entered the collaboration, what would that be?

- What motivates or hinders you from participating in other partnerships with the private sector?

Knowledge sharing & Intellectual property in projects that involve AI

- When working with the private sector – do you provide a lot of specific/scientific knowledge?
- And what about the private sector partner? Do they provide knowledge, or other things?
  - And how much?

- Are intellectual property rights important to you when working in collaborations?
  - Do you hold any patents yourself?
- Is there anything the private sector provides that is hard to replace in other ways?