This paper was presented at ISPIM Connects Bangkok – Partnering for an Innovative Community, Bangkok, Thailand on 1-4 March 2020.

The capability approach to innovations: How AI can enhance the innovation potential of ecosystems

Sami P. Rusthollkarhu*

Tampere University, Korkeakoulunkatu 10, 33720 Tampere, Finland.
E-mail: sami.rusthollkarhu@tuni.fi

Leena Aarikka-Stenroos

Tampere University, Korkeakoulunkatu 10, 33720 Tampere, Finland.
E-mail: leena.aarikka-stenroos@tuni.fi
* Corresponding author

Abstract: Artificial intelligence (AI) carries great expectations for future business potential. Among other disciplines, the disruptive potential of AI to innovation ecosystems has been widely recognized. As innovation ecosystems have a high reliance on data solutions that enable the efficient utilization of resources, technologies, and capabilities and the disruptive potential of AI is based on the ability to handle vast data masses, the complementary condition between AI and innovation ecosystems seems obvious. However, no research on the intertwinement of AI and innovation ecosystems have yet been published. In this paper, we elaborate on this topic. Based on interviews conducted in two IT consulting companies we present three categories of benefits (information standardization, competence matching, and forecasting) of AI and two categories of barriers (technical and organizational), organizations must overcome to successfully utilize AI solutions in the context of innovation ecosystems.

Keywords: Artificial intelligence; innovation ecosystem; innovation; capabilities

1 Introduction

Increasingly interdependence, co-evolutionary and more contemporary business processes have shifted the focus of B2B literature towards the ecosystem approach (Aarikka-Stenroos and Ritala, 2017). The adoption of the approach is crosscutting covering disciplines such as strategic management (e.g. Ansari, Garud and Kumaraswamy, 2016; Adner, 2017; Dattee, Alexy and Autio, 2018)), industrial and B2B marketing (e.g., Möller, 2013; Wilkinson and Young, 2013; Vargo, Wieland and Akaka, 2015) and innovation and technology management (e.g., Ritala *et al.*, 2013; Clarysse *et al.*, 2014; Gawer and Cusumano, 2014). In this paper, our focus is on the latter. We approach innovation ecosystems from the view of capabilities within ecosystem actors and focus to examine the effects of artificial intelligence to enhance the efficiency of utilization of these capabilities.

Innovation ecosystems, as well as other ecosystem streams, emphasize the idea of co-creation and collaboration, but instead of other possible goals focus to examine the innovation as an outcome of co-creation and collaboration. Innovation ecosystems emphasize the high reliance on efficient knowledge flows between actors as well as effective utilization and linking of different capabilities and technologies of ecosystem actors (Gobble, 2014). AI has the great potential to enhance the efficiency of the capability linking process on the platform and thus increase the platform's total innovation potential. The current literature already recognizes the power of AI in handling vast data masses (Paschen, Kietzmann and Kietzmann, 2019), the strength of ecosystem models in combining the resources of multiple actors (Basole and Karla, 2011; Gawer and Cusumano, 2014) and the importance of capabilities in creating the innovations (Weerawardena and Mavondo, 2011). However, the research of intertwinement of these aspects yet remains underrepresented in the academic field.

In this paper, we aim to answer the question of how AI can enhance the innovation potential of the ecosystem. We focus to examine the question from the view of the capabilities of individual human actors in the ecosystem. In order to reach our goal, we have conducted a total of 18 interviews with two different Finnish IT consulting companies, both of which are developing their own technological platform consisting also of AI tools to coordinate collaboration with their customers and subcontractors. The purpose of the collaboration in ecosystems of two for mentioned companies is not in all cases directly linked to creating innovations but includes a wider variety of activities related to co-creation and fulfilling customer expectation (e.g. more mundane activities required in delivering backend developers for customers teem). However, the way the interviewees described the challenges related to for example gathering the right team for the customer, revealed similarities to innovation ecosystems (e.g. high reliance on efficient knowledge flows).

We continue our paper by elaborating on the concept of artificial intelligence (AI) as well as defining it from the viewpoint of this study. In addition, we shortly introduce the concept of machine learning (ML) while it's intrinsic to the functioning of AI. We also shortly elaborate on our approach to capabilities and innovation ecosystems. Second, we present our research design and reasoning behind our methodological choices. Third, we present the results of our interview study and finally present a conclusion of the theoretical and practical implications of our findings.

2 Background

2.1 Artificial intelligence

Traditionally intelligence is perceived to be the property of mind and tightly linked to consciousness. In this human context, intelligence is defined as an ability to learn, to understand abstract concepts, to deal with new situations and use previously gained knowledge to manipulate one's environment (Legg and Hutter, 2007; Stenberg, 2017). Paschen, Kietzmann and Kietzmann (2019) defined intelligence in more general terms as follows: "the ability to perceive and process data, transform data into information and ultimately knowledge and use this knowledge towards goal-directed behavior." The word artificial separates the linkage between consciousness and intelligence. According to Nilsson (2010), artificial intelligence includes all activities which aim is to make machines intelligent. Like Paschen, Kietzmann and Kietzmann (2019) with intelligence

Nilsson (2010) refers to properties that enable an entity to interact with its' surroundings and modify its behavior in a goal-oriented way. In this paper, we follow the reasoning of Paschen, Kietzmann and Kietzmann (2019) and Nilsson (2010) and refer artificial intelligence as the computational agents which can learn and use previously gained knowledge to adapt to new situations.

Machine learning (ML) is a concept tightly linked to artificial intelligence. In general terms, machine learning means that instead of preprogrammed rules, the machine learns to perform a task by examining previous examples (Louridas and Ebert, 2016). Referring to (Murphy, 2012), machine learning is a way to automatically find patterns from the data. Whereas the concepts of artificial intelligence focus more on the abilities of an entity or outcome of the process (e.g. learning, adapting, pattern recognition, language understanding), machine learning describes the way the outcome was obtained. Here we illustrate this with a simple imagined cat classifier example. The machine learning model can, for example, use the information on each pixel of the cat image as an input, analyze the relations of the information in input pixels and at the end guess whether the picture presents a cat. If after the initial guess the right answer (whether there is a cat in the picture or not) is told to the model, the model can change the parameters it used in analyzing the relations of information in input pixels to match the answer. If this process of showing images and telling the right answer is repeated many times enough with a diverse set of cat images, we will end up having AI-system specialized to recognize images presenting cats. Because of this more thorough way of presenting the thinking process of AI, machine learning has also been referred to as the brains of artificial intelligence (Chatterjee *et al.*, 2019).

2.2 The role of capabilities in innovation ecosystems

Gobble (2014) draws together the definitions of innovation ecosystems gathered by Autio and Thomas (2014) as follows:

> "Innovation ecosystems are dynamic, purposive communities with complex, interlocking relationships built on collaboration, trust, and co-creation of value and specializing in exploitation of a shared set of complementary technologies or competencies"

According to Jackson (2011), innovation ecosystems consist of two weakly linked economies: research economy, driven by the fundamental research where resources are invested and commercial economy, driven by the marketplace, where resources are derived. In the context of our paper, the link between commercial and research economies is rather clear. The role of both IT consulting companies participated in this study is to offer different capabilities to their customers in exchange for commercial benefit. By doing so they simultaneously participate in the exchange in both economies. As we explore the benefits of AI to capability utilization in the research economy through the capabilities of individual consults, our approach to capabilities in this paper is human-centric rather than organization-centric.

3 Methodology

The empirical material for this paper consists of primary and secondary data. The primary data are a part of a wider research project focusing on B2B sales ecosystems and the use of AI and software robots. From a total of 40 interviews, 18 were analyzed for this paper. Those 18 interviews consisted of executive-level directors, consults, salespeople and platform developers of two Finnish IT-consulting companies both of which are developing their open platform for increasing the efficiency of collaboration with their customers and subcontractors. In the results section of this paper, those companies are referred to as company A and company B. Most of the interviews were conducted face-to-face and took place in the premises of for mentioned companies with few exceptions of remote interviews conducted using Microsoft Teams meetings. We chose to use semi-structured interviews as these gave the possibility to investigate issues that emerged as the interviews progressed. Interviews were structured around the questions of digital tools applied within the organization as well as customer projects and the current state of platform development and future plans for the platform. Interviews lasted about 90 min, were recorded and later transcribed in Finnish. The quotes presented in this paper were translated into English after the analysis phase.

The transcribed texts were analyzed by first creating a general understanding of the benefits of the platform. The roles of AI tools in the platform were then categorized according to the benefits they provided. A total of three categories of benefits were observed to be consistently repeated in interviews. In addition to benefits, one broad category of barriers related to human behavior was identified during the analysis of interview transcriptions. As our aim in this paper was rather to understand the potential of AI in the context of innovations ecosystems than describe the current state of AI implementations, we didn't put special emphasis to categorize whether the mentioned benefits were already implemented in the platform or planned to be implemented in near future.

The primary data were complemented with secondary data. Secondary data consisted of the documented process descriptions of two companies as well as documented development plans for the platforms. In addition to company documents, we utilized extant literature describing the technological requirements to utilize AI methods. Extant literature on AI ended up forming a second, technical barrier, in utilizing AI tools in innovation platforms.

We considered the interviews conducted on the field of IT-consulting to represent well the utilization of multiple capabilities of different actors. The way how the know-how of different consults is brought together to solve the problem of the customer, shares similarities with the utilization of competencies innovation ecosystems rely on. For example Gobble (2014) describes innovation ecosystems as follows: " – – innovation ecosystems rely on flows of knowledge to power collaboration and co-creation." The similar reliance on flows of knowledge was also brought up by interviewees when describing the process of finding the right team for the project. We considered similarities between the process of finding the right consults to customer project and capability flows in innovation ecosystems to justify the separation of the sample of 18 interviews and analyzing them from the view of innovation ecosystems.

4 Results

To show our results we selected some quotations and observations from our interviews. With a quotation, we provide a short context or description of our analysis considering the topic discussed in the quote. We start by describing the general purpose of platforms as well as the challenges companies are hoping to overcome with an ecosystemic model of operating. Secondly, we present the three categories of benefits of AI for innovation ecosystems and finally present the barriers for AI implementations.

The reasoning for platform development for both companies was to enable and enhance the large-scale collaboration with both the customers and subcontractors. Society sector lead of company A describes the need for platform solutions as follows:

> "Earlier when we were a lot smaller, I knew people. I was, in my head, able to think who would be most suitable for each project. I knew, who had the right capabilities, and who wanted to do what. During our growth, we have had an increasing number of tools we have used to organize this, and now we hope that our platform will provide a solution. "

The CEO of Company B describes the complexity within the projects followingly:

> "In approximately 80% of our cases, we use the experts from our network of around 4000 people (i.e. professionals who are not employees of Company B). Typically at the end of the project, there can be actors from tens of organizations."

He continues by emphasizing the need for dialog between different actors and the solution they hope to achieve with their platform:

> "Usually questions and adjustments emerge during the projects, the need for dialogue between actors is huge. We are in the middle of it, sometimes as contributors, sometimes as bottlenecks. Organizations do have systems for capability management, but interfaces outside are barely existing. Every time you need an e-mail or a phone and a lot of manual work. With our platform, we aim to simplify and automate things."

Both Company A and B share a similar challenge to coordinate the capabilities in an environment consisting of multiple different actors. The platform is hoped to function as an enabler of interaction as well as automate the capability linking process (i.e. the actions needed to get the professionals from multiple different organizations to work together to form a solution requiring the capabilities of all actors involved). The level of complexity in customer requirements differ vastly within both the Company A and B. Both companies provide consultation for creating new IT solutions for customers as well as act as consultant brokers finding experts for tasks defined by the customer. The former of which can be seen to fulfill the definition of innovation (see e.g. Baregheh, Rowley and Sambrook, 2009) while it requires mixing different technologies and implementing them in customers organization. However, the complexity and aims of customer requirements differ, the actual process of finding the right capabilities follows similar patterns. CEO of Company B elaborates the differences as follows:

> "" Selling the professionals" is more straight forward as the guidance of work happens from the customer's initiative. In more complicated projects most of the customer's interests lie on key professionals. However, the process of finding the right people is quite similar"

4.1 Benefits

We found three categories of benefits of how AI can improve the capability utilization in ecosystems. The first category of information standardization relates to the ways how AI can be used to improve the understandability of information describing certain capabilities for human observers. The second category, competence matching lists benefits directly affecting the process of matching capabilities of different actors together. The last category of benefits, forecasting, relates to ways how AI can be used to forecast the need and utilization of certain capabilities. Table 1 presents benefits in each category as well as example observations of this benefit based on gathered research data.

Table 1 Categories of benefits of the AI in capability linking process in ecosystems

Category	*Benefit*	*Observation/ finding/ quote*
Information standardization	AI can be used to standardize the format of information describing the capability	The documented plans for AI-enhanced CV tools which standardize the way how different capabilities are described, automatically gather the information related to capabilities published in Linkedin and update the capability information in CVs as well as send reminders when user input or validation of information is required. (Documented development plans of Company B)
		In addition to capability information in CVs interviewees also highlighted the need to link references to earlier projects to illustrate value provided by the capability. (Sector Leads of Industry and Business in Company A)
	AI can be used to gather and standardize the information describing the need for the capability	” We usually need to ask at least about 20 elaborating questions to the customer before informing partners. With AI bots we could reduce the number of questions to maybe one or two.” (Company B CEO)
Competence matching	Allocating right capabilities to right projects	All interviewees brought up the benefit of AI to be linked in analyzing the expressed needs and capabilities and automating the process of matching capabilities to innovation needs.
	Utilization of AI in team formation	In addition to right capabilities, the perspectives of analyzing personality traits (Resource Manager and Head of Sales of Company B) and motivation (Company A Head of Innovation and Product Owner of Platform)
	Data provided on working methods could be utilized in competence matching	Interviewees (CEO, Head of Sales and Resource manager of Company B) described how different actors could provide information on their

		working methods (e.g. scrum, agile, waterfall, working remotely or in shared office) or information on these could be automatically gathered from outside sources (e.g. job ads or company web pages). This information could then be used to find professionals who could provide the most value regarding the working methods.
Forecasting	AI was seen to drastically improve the forecasting efficiency of availability of capabilities	The amount of manual work needed in order to track and forecast the availability of capability at a certain moment was brought up by almost all interviewees. Especially this concerned sales personnel currently mainly responsible for finding available persons. Both companies expressed the plans to utilize AI tools to both improve forecasting accuracy and efficiency of the forecasting process.
	Improved forecasting efficiency was also discussed from the viewpoint of customers.	"Customer can gain understanding on capabilities available and can already plan own actions accordingly, excess manual work will decrease" (Company A Industry Sector lead)

In addition to benefits presented in table 1 interviewees brought more general benefits of utilizing AI tools in their processes. E.g. the use of bots was described also from the broader context of general managerial tasks:

> "Currently we use about twenty different bots with different managerial capabilities. For example, bots send reminders and are responsible for mundane activities like checking for working hours or handling ticket bookings and traveling expenses. We do not have middle management, so our bots carry the most of the mundane managerial tasks" (Head of Innovation of Company A)

Next, we present the barriers organizations may face in the utilization of AI tools.

4.2 Barriers

Barriers presented include observations made based on our interviews as well as secondary data from extant literature describing a general challenge in applying AI tools. Table 2 presents the barrier as well as our observation based on research data. Two categories of barriers include organizational barriers focusing on the ways individuals within organizations interact with technology and technical barriers related to the level of technological prerequisites needed in order to utilize AI technologies.

Table 2 Barriers in implementing AI solutions

Category of barrier	*Barrier*	*Observation/ finding/ quote*
Organizational barriers	Engagement barrier	"The biggest challenge is to get people to use the tool." (Industry Sector Lead in Organization A) Most interviewees brought up the challenge to get people to use the tool and provide data on their capabilities. E.g. The head of Sales of Company A describes the challenge related to employee-generated data as follows: "The biggest thing is, how we can get the data. These technologies would enable so much, but if the data isn't in check you can't trust anything."
	Structural barrier	In four interviews the need for structural change in organizations to gain benefit for new tools were brought up. E.g. The Product Owner of Platform in Company A described this as follows: "The whole organization needs to change. When we produce an MVP (minimum viable product) and start to use it, we also need to do the minimum viable organizational change to actually gain benefit from the tool. Otherwise, we end up in a situation that we're doing things just like before, but with the tool not supposed to be used in that way. It always starts with the organization, not the tools."
	Expertise barrier	Organizations may have limited access to data scientists or other expertise needed to implement AI and data solutions (Hew *et al.*, 2015).
Technical barriers	Disunity of data	Data can be spread throughout multiple corporate applications sharing no interface. This may prevent the efficient use of AI tools. (Chatterjee *et al.*, 2019)
	The computing power	The high cost of appropriate computing systems and on-premise hardware can prevent organizations from efficiently implement AI solutions (Chan and Chong, 2013). However, cloud computing has forecasted to lower this barrier (Chatterjee *et al.*, 2019).

Quality of data	An irregular, heterogeneous mixture of data depending on the mixture of on-premise systems and of cloud can lead to soil the quality of data AI systems use (Chatterjee *et al.*, 2019).

5 Conclusion

In this paper, we have presented three categories of benefits of artificial intelligence to the innovation ecosystem from the approach of capabilities of individual professionals takin part of the innovation ecosystem. In addition to benefits, we have found two categories of different barriers hindering the AI implementations.

This study benefits the practitioners mainly in two ways. Findings help companies that take part in innovations ecosystems to (1) understand the potential of AI in enhancing the innovation in the ecosystem and (2) help ecosystem builders to highlight critical issues that need to be addressed when implementing AI solutions and platform-type structures to business processes. In addition to practical implications, the research contributes to the literature stream of innovation ecosystems by creating an understanding of the role of AI from the view of the capabilities of individuals.

Acknowledgments

This paper was conducted within ROBINS research project funded by Business Finland (7885/31/2018). ROBINS studies the value creation potential for AI and intelligent software robots in B2B sales ecosystems.

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