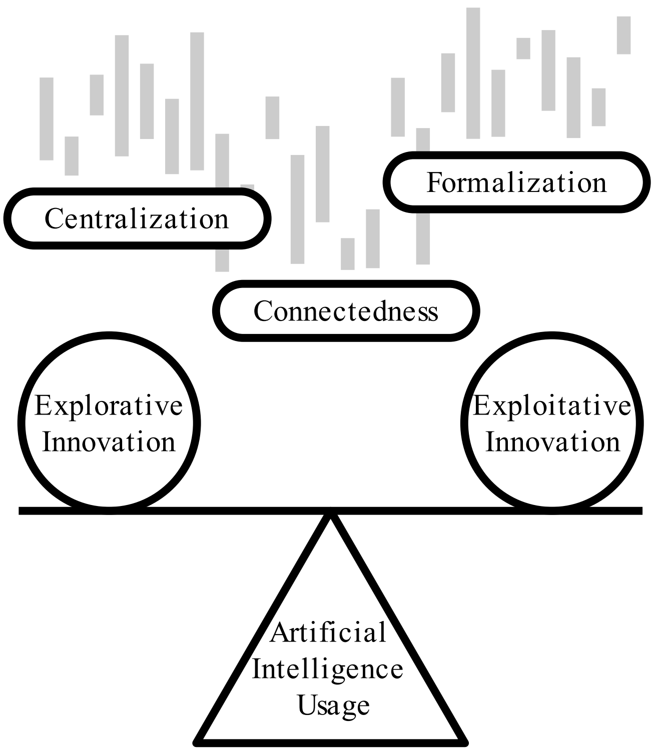
Thesis Joint MSc Entrepreneurship

TOWARDS INNOVATION AMBIDEXTERITY IN THE ERA OF ARTIFICIAL INTELLIGENCE: EXPLORING THE ROLES OF ORGANIZATIONAL COORDINATION MECHANISMS



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MSc Entrepreneurship (Joint Degree)

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1st of July 2021 Supervisor: Prof. Dr. Wouter Stam

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Simon van Luik

ABSTRACT

This research built upon existing literature in the field of artificial intelligence (AI) and innovation ambidexterity (i.e., simultaneously facilitating exploration and exploitation) while examining the importance of the organizational coordination mechanisms of centralization, formalization, and connectedness. It answered the following research question: *What is the relationship of artificial intelligence usage between both explorative innovation and exploitative innovation, and what are the moderating roles of the organizational coordination mechanisms of centralization, formalization, and connectedness in these relationships?* Data has been collected through an online survey distributed amongst managers specialized in artificial intelligence, business analytics, innovation, and general activities working for European organizations. Hypotheses were developed based on prior literature and tested with a sample of 123 respondents. Statistical support was found for a positive relationship between AI usage and explorative innovation, and a positive relationship between AI usage and exploitative innovation. However, no statistical support was found for centralization, formalization, and connectedness as being of influence in the aforementioned relationships. Hereby, it suggests future research to examine the effect of other organizational and/or environmental factors that influence the impact of AI usage on both explorative and exploitative innovation. Although many studies have highlighted the importance of AI in innovation practices, AI was still to be investigated in the light of innovation ambidexterity. Besides, prior literature fails to highlight the importance of organizational coordination mechanisms when such new technologies are used for innovation purposes.

CONTENTS

1 INTRODUCTION

In today’s rapidly changing global and digital markets, organizations are required to adapt and innovate to not become obsolete. Two heavily discussed types of innovation are explorative innovation and exploitative innovation (March, 1991; Benner & Tushman, 2003; Gabriel Cegarra-Navarro, Sánchez-Vidal, & Cegarra-Leiva, 2011; Im & Rai, 2014). While explorative innovation focuses on entering new markets, disrupting industries, and developing novel products and services, exploitative innovation builds upon existing processes, knowledge, products, and services. Scoring high on both exploration and exploitation has a positive impact on firm performance (Birkinshaw & Gibson, 2004a; He & Wong, 2004). Therefore, an organization must achieve a balance between both flavors of innovation (Benner & Tushman, 2003; March, 1991), which can be referred to as innovation ambidexterity (Chang, Hughes, & Hotho, 2011; Soto-Acosta, Popa, & Martinez-Conesa, 2018).

While the firm’s environment plays an important role in achieving innovation ambidexterity (Chang, Hughes, & Hotho, 2011; Prajogo & Mcdermott, 2014; Soto-Acosta, Popa, & Martinez-Conesa, 2018), organizations must facilitate it internally (Raisch & Birkinshaw, 2008; Birkinshaw & Gibson, 2004b; Tushman & O'Reilly III, 1996). Prior literature has suggested that both the formal coordination mechanisms consisting of the centralization of decision-making (i.e., centralization) and the documentation of standards (i.e., formalization) and the informal coordination mechanism of interdepartmental connectedness (i.e., connectedness) are managed internally achieve ambidexterity (Chang, Hughes, & Hotho, 2011; Jansen, Van Den Bosch, & Volberda, 2006).

Besides formal and informal coordination mechanisms, information technology (IT) has caught interest in the field of innovation ambidexterity (Soto-Acosta, Popa, & Martinez-Conesa, 2018; Ko & Liu, 2019; Ouyang, Cao, Wang, & Zhang, 2020). It is suggested that an organization’s IT capabilities are positively associated with innovation ambidexterity (Soto-Acosta, Popa, & Martinez-Conesa, 2018). Besides IT capabilities in general, big data analytics capability is suggested to have a positive impact on both explorative innovation and exploitative innovation (Rialti, Marzi, Caputo, & Mayah, 2020). Developments in big data technologies (Duan, Edwards, & Dwivedi, 2019) and the increase of computational power (Brynjolfsson & McAfee, 2016, pp. 40-56) has supported a gain of momentum in the field of even more advanced analytics (Anthes, 2017). Artificial intelligence (AI) is one of these developments and has been reviewed in light of society (Marr, 2020) and business (Ransbotham, Gerbert, Reeves, Kiron, & Spira, 2018). In NVP’s 2021 annual executive survey, among eighty-five senior executives from Fortune 1000 corporations show that 96% of the executives declare yielding results from big data and AI investments. Besides, 81% notices that they are positive about the future of these technologies (Bean, 2021).

Technologies such as AI have been investigated in terms of innovation (Lou, Lou, & Hitt, 2019; Haefner, Wincent, Gassmann, & Parida, 2021; Kakatkar, Bilgram, & Füller, 2020) and supply chain activities (Chen, Preston, & Swink, 2015; Zhu, Song, Hazen, Lee, & Cegielski, 2018; Dubey, et al., 2018). For instance, it is suggested that supply chain efficiency and stability have a positive impact on a firm's innovation output (Modi & Mabert, 2010). Moreover, a firm's supply network is an important source of innovation (Bellamy, Ghosh, & Hora, 2014). The supply network generates a fast amount of data and information that firms can integrate and share with partners for better innovation (Zimmermann, Ferreira, & Moreira, 2018). Despite the intensive use of AI in supply chain activities (Baryannis, Validi, Dani, & Antoniou, 2019; Riahi, Saikouk, Gunasekaran, & Badraoui, 2021; Toorajipour, Sohrabpour, Nazarpour, Oghazi, & Fischl, 2021) and its interest in innovation practices (Botega & da Silva, 2020; Muhlroth & Grottke, 2020; Verganti, Vendraminelli, & Iansiti, 2020), research is lacking about how firms should coordinate themselves internally to leverage the use of AI in the context of supply chain management (SCM) for innovation. Therefore, this research aims to investigate the moderating roles of centralization, formalization, and connectedness in the relationships of artificial intelligence usage between both explorative innovation and exploitative innovation. It does so by answering the following research questions: (1) *What is the relationship of artificial intelligence usage between both explorative innovation and exploitative innovation, and* (2) *what are the moderating roles of the organizational coordination mechanisms of centralization, formalization, and connectedness in these relationships?*

The next section presents a literature overview to establish an understanding of the theories and definitions concerning the topics of AI, innovation ambidexterity, coordination mechanisms, and the relationships between them. Based on the literature overview, a conceptual framework will be presented, and hypotheses will be developed. The third section will cover the research methodology used to answer the research questions. This section will justify and explain the methodology behind sampling, data collection, and measurements. The fourth section presents the analysis of the data where a detailed presentation of the procedures and results for hypotheses testing will be provided. After the hypotheses are tested, a discussion and conclusion about the findings will be provided in the final section. This section concludes research limitations, practical implications, and future research directions.

2 LITERATURE OVERVIEW AND HYPOTHESES DEVELOPMENT

2.1 Innovation Ambidexterity

Firms evolve through periods of incremental change interrupted by discontinuous changes (Tushman & O'Reilly III, 1996). These discontinuous disruptions are suggested to be caused by environmental factors (Raisch & Birkinshaw, 2008) such as new technologies (Tushman & Anderson, 1986; Christensen, 1997). Successful short-run performance requires firms to increase strategic alignment, cultural fit, and efficiency, while long-run performance requires flexibility towards disruptive changes (Birkinshaw & Gibson, 2004a; Tushman & O'Reilly III, 1996). To manage this implication of short and long-run survival, firms must be ambidextrous. An ambidextrous organization masters both the activities of exploration and exploitation (March, 1991; Birkinshaw & Gibson, 2004a).

March (1991) proposes that the activities of exploration and exploitation differ from each other in terms of organizational learning. While exploration relates to "search, risk-taking, discovery, and experimentation," exploitation is more concerned with "efficiency, implementation, and refinement" (March, 1991, p. 71). Both exploration and exploitation are important for a firm's performance. However, over-engaging in either of the two has an adverse effect (Birkinshaw & Gibson, 2004a). March (1991) suggests that when firms pursue exploration at the expense of exploitation, short-run performance is likely to suffer through cost-intensive new product development, R&D, and experimentation. In other words, it takes too much risk. On the other hand, firms that over-engage in exploitation face the threat of inertia and obsolescence due to technological disruptions (Christensen, 1997) or become trapped too much in today's business and markets (March, 1991). Overcoming these adverse effects demands a suitable balance between the two (Raisch & Birkinshaw, 2008; Tushman & O'Reilly III, 2004; He & Wong, 2004).

Birkinshaw & Gibson (2004a) propose two distinct forms of ambidexterity: structural ambidexterity and contextual ambidexterity. Structural ambidexterity is concerned with establishing structures that deal with the tensions between exploration and exploitation. For instance, organizational units can continuously alternate between exploring new opportunities or exploiting the existing business (Raisch & Birkinshaw, 2008). Contextual ambidexterity is concerned with the dedication of time employees spend on either exploration or exploitation (Birkinshaw & Gibson, 2004a). Here, the context is designed to allow individuals to alternate between the two (Raisch & Birkinshaw, 2008). Chang & Hughes (2012) extend the distinction of structural and contextual ambidexterity by adding leadership-based characteristics.

Leadership-based ambidexterity is concerned with the trade-offs top management makes about the allocation of resources for either explorative or exploitative purposes. Often within the scope of ambidexterity, the distinction between structural, contextual, and leadership-based ambidexterity is made (Raisch & Birkinshaw, 2008).

Tushman & O'Reilly III (1996) argue that ambidextrous organizations are ones that "both execute today's strategies and create capabilities to innovate for tomorrow's competitive demands" (p. 20). While some articles use the term organizational ambidexterity (Andriopoulos & Lewis, 2009; Cao, Gedajlovic, & Zhang, 2009; Raisch & Birkinshaw, 2008), others use innovation ambidexterity (Chang & Hughes, 2012; Soto-Acosta, Popa, & Martinez-Conesa, 2018), and others just ambidexterity (Tushman & O'Reilly III, 1996; Birkinshaw & Gibson, 2004a). This research uses the term innovation ambidexterity to define an organization's extent to which it facilitates both explorative innovation and exploitative innovation simultaneously.

2.1.1 Differences Between Explorative and Exploitative Innovation

Within the field of ambidexterity, different opposites are used to describe the paradox. Birkinshaw & Gibson (2004a) use 'alignment' to describe a firm's capability to create value for the short run and 'adaptability' to describe a firm's capability of taking advantage of new opportunities. Tushman & O'Reilly III (1996) talk about evolutionary and revolutionary change when discussing ambidextrous organizations. They refer to evolutionary change as the practice of strategic, cultural, and structural fit when operating in an environment of incremental innovation. Revolutionary change is what they refer to as the practice of drastically altering the organization to cope with an environment of disruptive innovation. March (1991) and many others (e.g., (Chang & Hughes, 2012; Jansen, Van Den Bosch, & Volberda, 2006; He & Wong, 2004)) use 'exploration' and 'exploitation' to discuss innovation ambidexterity.

Despite the differences in terminology, there are similarities in the definitions used to discuss innovation ambidexterity. Recalling this research's definition of innovation ambidexterity, the terms explorative innovation and exploitative innovation will be used to examine the phenomenon. Within this research, explorative innovation (ERI) is defined as the type of innovation where organizations search for new knowledge, opportunities, and markets to develop new products, services, and processes through risk-taking, discovery, and experimentation. Conversely, exploitative innovation (ETI) is defined as the type of innovation where organizations build upon existing competencies by enhancing current products, services, and processes through refinement, implementation, and making them more efficient.

2.2 Artificial Intelligence

The term artificial intelligence (AI) was introduced at the Dartmouth Summer Research Project in 1956 (Solomonoff, 1985). The mathematician and computer scientist Alan Turing organized the Turing Test in 1950 which is well-known in the field of data science (Turing, 1950). This test was designed to assess whether a machine was capable of performing human-like tasks such as natural language processing; knowledge representation and reasoning; and vision (Russell & Norvig, 2010). A machine passed the test when it was capable of replacing a human in a conversation without the ones in the conversation noticing any difference (Turing, 1950). In March 2016, the phenomenon of AI gained worldwide attention when the AI-driven program AlphaGo, developed by Google DeepMind, defeated the 18-time world champion Lee Sedol in a Go game. That game is extremely difficult to play due to its infinite possibilities. According to Chen J. X. (2016), a professor of computer science, "The huge number of options in Go (361!) is still beyond computing power; ordinary human players can see just a few moves ahead … a professional human player can make relatively easier judgments compared to a machine due to instincts that algorithms can't capture, but AlphaGo might have broken this barrier" (p. 6). The machine managed to perform human-like thinking by AI and won four out of five games from the world champion.

There are some recent developments in AI technologies such as machine learning and deep learning. These developments in AI have gained momentum due to the exponential growth in the computational power of machines, which is generally known as Moore's Law (Denning & Lewis, 2017). Jakhar & Kaur (2020) define machine learning as a subset of AI that "includes all the approaches that allow machines to learn from data without being explicitly programmed," and deep learning is a subset of machine learning that "incorporates computational models and algorithms that imitate the architecture of the biological neural networks in the brain" (p. 131). The remainder of this research uses the following definition for AI, which extends the definition from Duan, Edwards, & Dwivedi (2019): artificial intelligence is a machine's capability to learn from data through algorithms, computational models, and statistical models to possess, or even exceed, human-like capabilities to achieve a certain goal.

2.2.1 Artificial Intelligence Usage

Senior executives declare positive benefits from AI and find its future promising (Bean, 2021). Many companies have taken advantage of the opportunities generated by AI (Brynjolfsson, Rock, & Syverson, 2019). For example, Alphabet Inc. invests in AI developments and considers it as a driver of its innovations (Alphabet, 2020); Unilever uses AI to allow people to search for job opportunities internally (Unilever, 2019); Walmart launched an 'Intelligent Retail Lab' that leverages AI to seek the firm's opportunities in AI-enabled retail (Walmart, 2019); and General Electric is deploying it for predictive maintenance purposes (Duan, Edwards, & Dwivedi, 2019).

Artificial intelligence is considered to be a general-purpose technology (Brynjolfsson, Rock, & Syverson, 2021) which implies that the technology spreads throughout the economy and society with similar intensity; improves over time; and enables innovation as a consequence (Bresnahan & Trajtenberg, 1995). Despite the broad adoption of AI in business and management (Ransbotham, Gerbert, Reeves, Kiron, & Spira, 2018; Iansiti & Lakhani, 2020), minor productivity growth is visible yet (Brynjolfsson, Rock, & Syverson, 2019). This is generally known as the Solow (1987, p. 36) paradox: "You can see the computer age everywhere but in the productivity statistics." Brynjolfsson, Rock, & Syverson (2019) suggest that it is difficult to measure the full impact of AI on productivity because implementing AI in an organization is time-consuming and cost-intensive, which causes low productivity rates. Over time, this results in a J-shaped curve of productivity: the measured productivity reduces due to unmeasurable intangible investments at the early stages of AI adaption and rises when these intangible investments start to contribute to measurable factors such as financials and capital – forming a hockey stick curve of productivity (Brynjolfsson, Rock, & Syverson, 2021).

Despite the broad interest, it is yet to be discovered how a firm should coordinate itself to leverage AI for innovation purposes. As AI is widely used in supply networks, which are substantial sources of innovation (Bellamy, Ghosh, & Hora, 2014), this research examines the extent to which a firm deploys AI in supply chain activities to investigate its association with innovation. Within supply chain activities, this research, therefore, defines artificial intelligence usage (AIU) as the extent to which a firm deploys and uses artificial intelligence.

2.2.2 Artificial Intelligence Usage and Innovation Ambidexterity

Haefner, Wincent, Gassmann, & Parida (2021), suggest that AI has the potential to generate ideas inexpensively. This can be achieved by breaking traditional search routines within an organization and overcoming information processing barriers. Also, emerging trends and technologies can be identified early due to AI's capability to analyze large amounts of data in for example customer behavior, publications, and patents (Muhlroth & Grottke, 2020). Organizations could benefit from using AI in their innovation processes as it captures value from large amounts of data; empower employees by giving creative insights that they would otherwise miss out on; and ask better questions about the process itself (Kakatkar, Bilgram, &

Füller, 2020). In terms of product and service design, AI offers possibilities to better understand the customer, enhance creativity, and speed up the rate of innovation (Verganti, Vendraminelli, & Iansiti, 2020). And, as a general-purpose technology, it enables innovation as a consequence (Bresnahan & Trajtenberg, 1995; Brynjolfsson, Rock, & Syverson, 2021).

Explorative innovation (ERI) requires the absorption of new knowledge (Božič & Dimovski, 2019) which can be achieved by ensuring an external orientation (Festa, Safraou, Cuomo, & Solima, 2018). Marvel (2012) suggests that knowledge acquisition through customer problems and market information is positively associated with explorative innovation. Besides, a firm's capability to share knowledge throughout the organization enhances radical product innovation (Maes & Sels, 2014), which can be considered as explorative innovation. Because AI is capable of complementing human-centered tasks in the innovation process (Haefner, Wincent, Gassmann, & Parida, 2021) by detecting emerging technologies and trends (Muhlroth & Grottke, 2020); empowering employees in their creative efforts (Kakatkar, Bilgram, & Füller, 2020); enhance customer-centricity (Verganti, Vendraminelli, & Iansiti, 2020); and new product development through self-innovating AI (Hutchinson, 2021), it enhances one's capability to search for novel ideas to generate new offerings (Haefner, Wincent, Gassmann, & Parida, 2021; Muhlroth & Grottke, 2020).

Supply chain networks are important sources of innovation (Bellamy, Ghosh, & Hora, 2014). Likewise, buyer-supplier networks generate knowledge for explorative innovation (Hao & Feng, 2016) and it generates fast amounts of data and information that firms can integrate and share with partners for better innovation (Zimmermann, Ferreira, & Moreira, 2018). Similarly, sharing knowledge throughout the organization enhances radical product innovation (Maes & Sels, 2014). As ERI is the type of innovation where organizations search for new knowledge, opportunities, and markets to develop new products, services, this research hypothesizes a positive relationship between AIU and ERI. Hence,

H1. Artificial Intelligence Usage (AIU) is positively related to Explorative Innovation (ERI).

Exploitative innovation (ETI) is the type of innovation where organizations build upon existing competencies by enhancing current products, services, and processes through refinement, implementation, and making them more efficient. AI and machine learning have enabled organizations to automate their business processes and speed up transportation (Canhoto & Clear, 2020). Besides, it is suggested to be more cost-efficient and less error-prone than humans (Castelli, Manzoni, Popovič, & Sanei, 2016). AI embedded into devices continuously track information, enabling personalization of processes, services, and products, and continuously improving their performance. The AI-embedded devices are capable of problem-solving, autonomously providing personalized solutions to a problem, making refinements, and improve efficiency (Verganti, Vendraminelli, & Iansiti, 2020). With the rise of the fourth industrial revolution (i.e., industry 4.0), AI is increasingly embedded into supply chain devices as well, which affects every aspect of the business (Koh, Orzes, & Jia, 2019). Here, supply chain activities are made more efficient and refined, enabling a firm to offer enhanced versions of current products, services, and processes. It can therefore be hypothesized that AIU, within supply chain activities, is positively related to exploitative innovation. Hence,

> *H2.* Artificial Intelligence Usage (AIU) is positively related to Exploitative Innovation (ETI).

2.3 The Moderating Role of Organizational Coordination Mechanisms

Van de Ven (1986) proposed four central problems that arise when innovating within organizations: (1) human attention is directed towards existing practices; (2) mismanagement of ideas; (3) organizational structures that discourage the spread of ideas; and (4) institutionalized leadership. Three organizational coordination mechanisms are often examined in the light of innovation and can be derived from the problems described by Van de Ven (1986). These three organizational coordination mechanisms are the centralization of decision-making; the formalization of rules, procedures, and instructions; and interdepartmental connectedness (Jansen, Van Den Bosch, & Volberda, 2006; Prajogo & Mcdermott, 2014).

Zmud (1982, p. 1422) explains that “organic organizations, i.e., those more open to individual initiation and discretion, are more likely to experience innovation than mechanistic organizations.” Centralization and formalization are often used to examine this “organic-mechanistic distinction,” and can be considered as formal coordination mechanisms (Jansen, Van Den Bosch, & Volberda, 2006). In other words, they are concerned with the formal hierarchical structure of an organization. Connectedness, however, is more concerned with the social relations within an organization. Connectedness is therefore considered to be an informal coordination mechanism.

2.3.1 Centralization of Decision-Making

Centralization of decision-making refers to the extent to which a small group of people in an organization is involved in decision-making, generally at the higher levels of the organization. Decentralization of decision-making, conversely, refers to “the extent to which decision-making discretion is pushed down to lower levels of the organization" (Lin & Germain, 2003). This research defines centralization (CEN) as the extent to which decisions are made at the top levels of the organization within a small, centralized group of individuals. In terms of innovation, it is suggested that centralization is negatively related to employees' innovative behavior (Dedahanov, Rhee, & Yoon, 2017). Conversely, decentralization of decision-making is positively related to a firm's service innovativeness (Daugherty, Chen, & Ferrin, 2011).

Jansen, Van Den Bosch, & Volberda (2006) show that a high extent of centralization within an organization is negatively related to explorative innovation. Similarly, Prajogo & Mcdermott (2014) found the same relationship. Sheremata (2000) suggests that individuals at the heart of a problem are the ones that are most capable of finding the right solution. And, as information about a problem loses accuracy when it moves to higher levels in the organization, centralized decision-making is based on poor information, reducing explorative innovation (Chang, Hughes, & Hotho, 2011). As AI enhances an individual's capability to generate novel ideas (Haefner, Wincent, Gassmann, & Parida, 2021) by detecting new market trends and technologies (Muhlroth & Grottke, 2020), it might be suggested that having centralization reduces AI's capability to complement individuals for explorative innovation. Therefore, this research hypothesizes that centralization (CEN) negatively moderates the relationship between AIU and ERI (Hypothesis 3a).

Centralization is suggested to speed up idea generation and allow organizations to make decisions quickly as consensus is achieved sooner when fewer people are involved in the decision-making process (Sheremata, 2000; Atuahene-Gima, 2003). Likewise, Ettlie, Bridges, & O'Keefe (1984) suggest that decentralized organizations engage in more incremental innovation and Germain (1996) found that decentralization is positively related to exploitative innovation as this type of innovation is generally low in costs, requires minimum new knowledge, and involves low risks. Hereby experiencing minimum resistance from supervisors. As AI is more cost-efficient and less error-prone than humans (Castelli, Manzoni, Popovič, & Sanei, 2016) and capable of problem-solving, refining, and improving efficiency (Verganti, Vendraminelli, & Iansiti, 2020), having centralization might reduce the positive effect that AI has on ETI. Hypothesizing that centralization (CEN) negatively moderates the relationship between AIU and ETI (Hypothesis 3b). Hence, the following hypotheses will be tested:

H3. Centralization (CEN) (a) negatively moderates the relationship between artificial intelligence usage and explorative innovation, and (b) negatively moderates the relationship between artificial intelligence usage and exploitative innovation.

2.3.2 Formalization

Formalization can be referred to as “the extent to which rules, procedures, instructions, and communications are written” (Pugh, Hickson, Hinings, & Turner, 1968, p. 75). While this definition is widely used, Bodewes (2002) argues that it causes inconsistencies within the literature and therefore proposes the following definition: “Formalization is the extent to which documented standards are used to control social actors’ behaviors and outputs” (p. 221). This research uses that same definition for formalization. In general, formalization is suggested to harm innovation as organic organizations are more suitable for innovation than mechanistic organizations (Aiken & Hage, 1971; Zmud, 1982).

Kang & Snell (2009) suggest that documented standards that use existing knowledge and organizational routines establish a common frame of reference among employees that biases an organization’s problem-solving skills towards already known patterns. It is therefore suggested that formalization reduces explorative innovation (Jansen, Van Den Bosch, & Volberda, 2006). According to Haefner, Wincent, Gassmann, & Parida (2021), two barriers are faced when a firm pursues idea generation and development: incapability to process and absorb information, and existing search routines. The latter implies that firms must search beyond existing domains to be more explorative – a constraint AI might overcome as it searches for patterns humans are biased for. However, while AI can overcome familiar search routines, having formalized documentation in place might downgrade its potential in doing so. Considering the above, this research hypothesizes that formalization (FOR) negatively moderates the relationship between AIU and ERI (Hypothesis 4a).

In contrast to explorative innovation, exploitative innovation is suggested to benefit from formalization as the common frame of reference causes organizations to decide previously proven successes resulting in small refinements and improvements (Kang & Snell, 2009). In line with that suggestion, Ettlie, Bridges, & O'Keefe (1984) conceptualizes that formalization is part of the incremental innovation process and is inherited to the organizational structure. A mechanistic structure speeds up decision-making as less discussion is required due to a standardized, reliable set of rules and procedures. AI accelerates this decision-making process (Haefner, Wincent, Gassmann, & Parida, 2021) and continuously tracks information that enables refinement of processes, products, and services (Verganti, Vendraminelli, & Iansiti, 2020). Having documented standards in place (i.e., formalization) is therefore likely to leverage AI for exploitative innovation. Accordingly,

H4. Formalization (FOR) (a) negatively moderates the relationship between artificial intelligence usage and explorative innovation, and (b) positively moderates the relationship between artificial intelligence usage and exploitative innovation.

2.3.3 Interdepartmental Connectedness

As already mentioned, organic organizations are more likely to be more innovative than mechanic ones (Zmud, 1982). Interdepartmental connectedness is one of such characteristics that contribute to an organic organization (Chang & Hughes, 2012). Interdepartmental connectedness (hereafter, connectedness) enhances a firm's capability to absorb and leverage current and newly acquired knowledge (Atuahene-Gima, 2005). Besides, it promotes the spread of knowledge through informal communication channels across functional departments which in turn lead to improved market orientation (Jaworski & Kohli, 1993). In this research, connectedness (CON) is defined as the degree to which the functional departments of an organization interact, communicate, and coordinate with one another to collect, process, and share knowledge.

Regarding explorative innovation, a low degree of connectedness reduces explorative innovation as it diminishes the creation of new and diverse social relations within the organization (Kang & Snell, 2009). In general, connectedness promotes explorative innovation through social relations that develop new knowledge (Jansen, Van Den Bosch, & Volberda, 2006). Besides, a more connected structure allows expansion, acquisition, and absorption of new knowledge that promotes explorative innovation (Kang & Snell, 2009). As already mentioned, explorative innovation requires the absorption of new knowledge (Božič & Dimovski, 2019; Marvel, 2012).

AI is capable of spotting trends, acquire knowledge, search for novel ideas, and generate solutions that contributee to the creation of new knowledge within an organization. In terms of explorative innovation, it is therefore important that organizations structure themselves so that this knowledge can be disseminated throughout the organization. Connectedness is therefore likely to strengthen the relationship between AIU and ERI. Hence, this research hypothesizes that connectedness positively moderates the relationship between AI usage and explorative innovation (Hypothesis 5a).

Similarly, high degrees of connectedness enhance the efficiency of problem-solving as individuals have more internal connections for feedback and intervention (Atuahene-Gima, 2005; Sheremata, 2000). It deepens the understanding of existing knowledge through connections across different functions which promotes refinement of existing processes, products, and markets (Jansen, Van Den Bosch, & Volberda, 2006). Through AI, existing knowledge could be enriched by deploying algorithms to the firm's internal data and visualizing unchartered areas of improvement and refinement. It breaks the barriers of routine search, thereby increasing the speed of innovation (Haefner, Wincent, Gassmann, & Parida, 2021). Whereas connectedness deepens the understanding of existing knowledge, AI does the same through algorithmic thinking. It can therefore be hypothesized that connectedness positively moderates the relationship between AIU and ERI (Hypothesis 5b). Considering the above, the following hypotheses were developed:

> *H5.* Connectedness (CON) (a) positively moderates the relationship between artificial intelligence usage and explorative innovation, and (b) positively moderates the relationship between artificial intelligence usage and exploitative innovation.

The developed hypotheses resulted in the conceptual model represented in Figure 1. To summarize, it is expected that AIU has a positive associated with both ERI and ETI (H1 and H2 respectively), where centralization negatively moderates both the AIU-ERI and AIU-ETI relationships (H3a and H3b respectively); formalization negatively moderates the AIU-ERI relationship (H4a), and positively moderates the AIU-ETI relationship (H4b); and where connectedness positively moderates both the AIU-ERI and AIU-ETI relationships (H5a and H5b respectively).

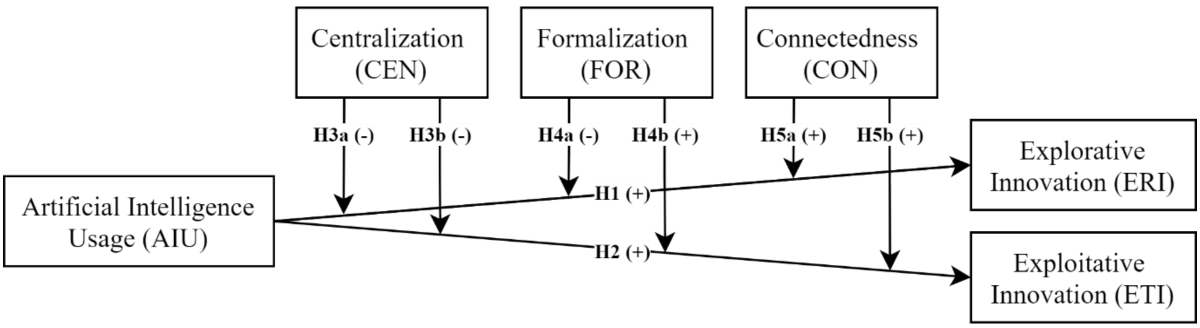


Figure 1. Conceptual Model. Control Variables: Industry, Firm Size, Firm Age, and Previous AI Experience

3 RESEARCH METHODOLOGY

3.1 Research Philosophy & Approach

"The Research-Practice Continuum" described by Trochim, Donnelly, & Arora (2016, pp. 6-7) gives a conceptual perspective on how an initial research idea translates into an influential phenomenon in our daily lives. On the left end of this continuum, research is conducted to discover an idea. As we move to the right of this spectrum, research is conducted to assess the broad effects of the discovery on society. Moving from the left to the right of the continuum requires many individual research projects that contribute to making a true impact. At the middle of the continuum, there is a type of research that the authors refer to as "implementation and dissemination research" (Trochim, Donnelly, & Arora, 2016, p. 7). This type of research aims to examine how well something "can be implemented in and disseminated to a broad range of contexts" (p. 7). This research can be considered as this type of research as it examines how well AI can be implemented in and disseminated to the context of organizations and innovation practices.

In line with this research-practice continuum, Edmondson & McManus (2007) propose a framework that directs decision-making on what research methodologies to use. They make a distinction between nascent, intermediate, and mature research archetypes. Here, nascent research relates to subjects where little to no previous literature exists and where qualitative approaches fit best. Intermediate research "draws from prior work – often from separate bodies of literature – to propose new constructs and/or provisional theoretical relationship" (Edmondson & McManus, 2007, p. 1165) and is suitable for hybrid use of qualitative and quantitative designs. Finally, mature research builds upon extensive existing literature to further develop these theories and is mostly suitable for quantitative approaches that test hypotheses.

As this research builds upon extensive prior literature about ambidexterity (Birkinshaw & Gibson, 2004a; March, 1991; Tushman & O'Reilly III, 1996) and organizational coordination mechanisms (Jansen, Van Den Bosch, & Volberda, 2006; Van de Ven, 1986; Zmud, 1982) while using the less develop literature about AI and innovation (Haefner, Wincent, Gassmann, & Parida, 2021), it can be located in between intermediate and mature designs. Therefore, using a quantitative approach. Besides, it uses a deductive approach of reasoning where hypotheses are developed and tested based on prior literature (Trochim, Donnelly, & Arora, 2016, p. 22). After testing the hypotheses, a contribution to the literature is made. Due to time limitations in the context of this MSc thesis, a cross-sectional design serves as the basis for conducting this research as all observations are taken at a single point in time (Trochim, Donnelly, & Arora, 2016, p. 14).

3.2 Data Collection and Sampling

The population from which the sample has been drawn consists of managers working for organizations located in European countries who are responsible for activities such as innovation, business intelligence, big data analytics, artificial intelligence, machine learning, or general management of the organization. The respondents were recruited by using a combination of LinkedIn and RocketReach. LinkedIn is a professional networking platform that connects professionals and creates professional relationships. RocketReach is an online screening software that mines publicly available contact information of professionals (including ones registered on LinkedIn) with certain expertise, skill, or profession (RocketReach, n.d.). This form of sampling can be referred to as expert sampling which involves the assembly of a sample consisting of people with specific knowledge or expertise (Trochim, Donnelly, & Arora, 2016, p. 88).

RocketReach provides the possibility to automatically generate lists of email addresses based on preferred characteristics. These characteristics, or 'search settings,' permit the user to search through large amounts of contact details and automatically generate lists. Drawing the sample for this research was done by querying *innovation managers*, *business intelligence managers*, *artificial intelligence managers*, and *managing directors* working for firms in the Netherlands, Germany, Belgium, France, Spain, Switzerland, Denmark, Sweden, and Norway. This resulted in a total of 2,741 verified email addresses.

The data collected for testing the hypotheses was done by distributing an online survey. This questionnaire was distributed to all 2,741 collected email addresses. An invitation to participate was sent to all 2,7141 email addresses followed by a weekly reminder during the following three weeks. At the end of that period, 273 respondents finished the questionnaire resulting in a 9.96% response rate. However, two questions were asked at the start of the survey controlling for eligibility to participate. Eligibility was ensured when the respondent was managing or working on either innovation, AI, or general activities; and when the organization uses or plans to use AI in at least one of its activities. Eligibility was ensured for 133 respondents, resulting in a 4.85% effective response rate.

3.3 Measurement and Validation of Constructs

The constructs of innovation ambidexterity and organizational coordination mechanisms have been measured multiple times in prior research (Chang, Hughes, & Hotho, 2011; Jansen, Van Den Bosch, & Volberda, 2006; Prajogo & Mcdermott, 2014). Mikalef & Gupta (2021) conceptualized an instrument for a firm's capability to leverage AI. Besides, big data analytics capabilities, as a precursor of AIC, have been measured frequently (Mikalef, Krogstie, Pappas, & Pavlou, 2020; Rialti, Marzi, Caputo, & Mayah, 2020; Gupta & George, 2016). This research builds on these constructs and translates the measurement used by Chen, Preston, & Swink (2015) for big data analytics usage to artificial intelligence usage. All measures and constructs utilized for this study can be found in Appendix A.

The measurements for the dependent variables *explorative innovation* (ERI) and *exploitative innovation* (ETI) were adopted from Jansen, Tempelaar, van den Bosch, & Volberda (2009). Both *explorative innovation* and *exploitative innovation* were measured on a 7-point Likert scale ranging from 1 = *strongly disagree* to 7 = *strongly agree* each having 4 items. While ERI shows questionable reliability by a Cronbach's alpha of 0.67 ($\alpha = .67$), ETI shows acceptable reliability as Cronbach's alpha is 0.74 ($\alpha = .74$).

Measuring the independent variable *artificial intelligence usage* (AIU) was done on a 5-point Likert scale ranging from 1 = *none at all* to 5 = *a great deal.* It measures the extent to which an organization uses AI in its supply chain activities such as logistics improvements, sourcing analysis, and inventory optimization. The scale was adopted from Chen, Preston, & Swink (2015) who used the technological-organizational-environmental (TOE) framework to examine the driving forces of big data analytics usage within a firm's supply chain activities. This study uses the same scale but with big data analytics usage being replaced by AIU. This 10-item scale proved Cronbach's alpha of 0.88 ($\alpha = .88$) indicating good reliability.

The moderating variables *centralization*, *formalization*, and *connectedness* were measured by constructs adopted from Jansen, Van Den Bosch, & Volberda (2006). All three moderation variables were measured on a 7-point Likert scale ranging from 1 = *strongly disagree* to 7 = *strongly agree* with each having 5 items. Centralization shows good reliability with a Cronbach's alpha of 0.87 ($\alpha = .87$). Formalization shows a questionable Cronbach's α of $.68$ ($\alpha = .68$) due to the reversed item "Employees in our organizational unit are hardly checked for rule violations" (even after reverse-coding). Excluding this item from the measurement result in acceptable reliability with a Cronbach's alpha of 0.73 ($\alpha = .73$). Connectedness proves acceptable reliability by a Cronbach's alpha of 0.70 ($\alpha = .70$).

The control variables in this study are *industry* (measured on a nominal scale), *firm size*, *firm age*, and *previous AI experience* (measured on ordinal scales). Previous AI experience measures how many years the organization has been investing in AI. Firm size is measured in terms of the number of employees the organization counts. Firm age is measured in the number of years since the organization was founded.

With this cross-sectional research design, all data has been collected using the same questionnaire during the same period. Therefore, variance might be associated with the measurement method rather than the variables themselves. This is generally known as common method bias (Podsakoff & Organ, 1986). To account for this bias, Harman's one-factor test will be performed which tests whether one factor is explanatory for the variance associated with the measurements. Harman's one-factor test shows that 18.32% of the variance is explained by the methods used (Appendix B5, Table M) meaning that 81.68% of the variance is associated with the variance in the variables.

3.4 Statistical Procedure

All data analyses and transformations are performed using IBM SPSS, version 27. To test the conceptual model presented in Figure 1 statistically, a hierarchical regression analysis will be performed. Two separate hierarchical regression analyses will be performed, one for each dependent variable (ERI and ETI). Each of these two analyses consists of six models: models 1a-1f examining paths directed to the dependent variable ERI and models 2a-2f examining paths directed to ETI.

The models of both the hierarchical regression analyses are built up similarly. Model 1a and 2a consist of just the control variables (industry, firm size, firm age, and previous AI experience) and aims to investigate the impact of those on the two dependent variables. The nominal control variable industry was dummy coded first to be included in the analysis. Here, the group '*Others*' served as the baseline group as it represents the highest percentage of respondents (Table A). Model 1b and 2b introduce the independent variable AIU to the regression analysis. Here, Hypothesis 1 and 2 will be tested. Model 1c and 2c include the moderators CEN, FOR, and CON to the regression analysis.

To test for moderation, interaction terms had to be created. To do so, the predictor variables (dependent and moderators) had to be centered before including in the analysis. Centering is done by subtracting the grand mean from each observation. Centering variables make the results from the regression analysis interpretable when dealing with cases of score zero (Field, 2018, pp. 486-487). After centering the variables AIU, CEN, FOR, and CON, the interaction terms were created and included in the regression analysis. By including these terms in the analysis, it will be tested if any significant moderation effect is observed. Firstly, the centered interaction term between AIU and CEN was introduced through models 1d and 2d.

Secondly, the centered interaction term between AIU and FOR was introduced through models 1e and 2e. And finally, the interaction term between AIU and CON was introduced through models 1f and 2f. When models 1d-1f and 2d-2f found significant moderation effects, the magnitude of the effects has to be interpreted. This will be done graphically by a simple slope analysis (Field, 2018, p. 489) and statistically with the Johnson and Neyman (1936) approach. By doing so, Hypotheses 3, 4, and 5 will be tested. Figures 2 and 3 represent the two hierarchical regressions in the form of a statistical model. Figure 2 shows the regression model predicting ERI and Figure 3 shows the regression model predicting ETI.

Figure 2. *Statistical Model Predicting Explorative Innovation (ERI). Control Variables: Industry, Firm Size, Firm Age, and Previous AI Experience.*

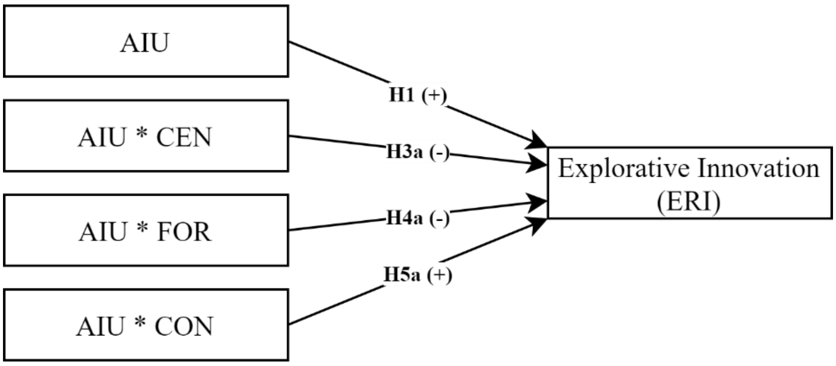
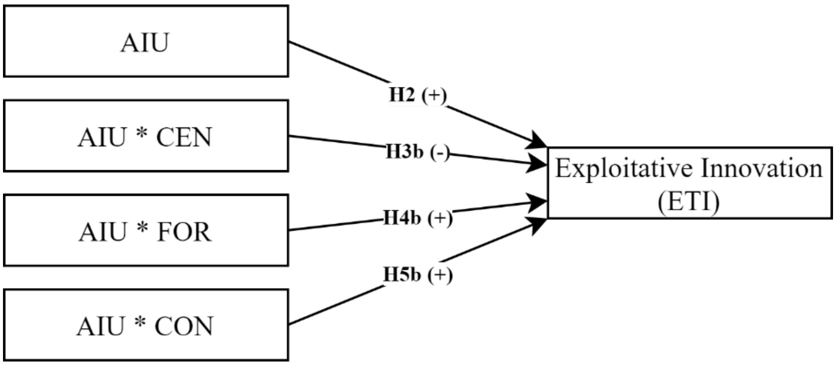


Figure 3. *Statistical Model Predicting Exploitative Innovation (ETI). Control Variables: Industry, Firm Size, Firm Age, and Previous AI Experience.*



4 RESULTS

4.1 Data Preparation

After all responses were collected, data had to be cleaned to establish the sample for effective analysis. Respondents outside the population region (Europe) were deleted from the sample (3 in total). Besides, two responses from duplicate companies were deleted and three more responses were excluded as a result of short duration (less than 4 minutes) for completing the questionnaire.

For the dependent, independent, and moderator variables, outliers were removed from the sample. Outliers are considered to have an absolute standard score (or z-score) of higher than 3.29 meaning that the outlier falls outside the 99.9% of the observations (Field, 2018, p. 39). One outlier was spotted in the AIU variable with an absolute z-score of 3.83, and one in the CON variable with an absolute z-score of 4.51. Together, this resulted in an established sample size of 123.

Table A. *Sample Descriptives* [a]

Variable	Frequency	Percentage	Cumulative Percentage
Industry			
Technology	23	18.7	18.7
Bank & Financials	7	5.7	24.4
ICT & Telecommunications	10	8.1	32.5
Consulting Services	21	17.1	49.6
Consumer Services	2	1.6	51.2
Media	5	4.1	55.3
Health Care	15	12.2	67.5
Consumer Goods	6	4.9	72.4
Others	34	27.6	100.0
Firm Size			
1-9 employees	9	7.3	7.3
10-49 employees	19	15.4	22.8
50-249 employees	25	20.3	43.1
More than 250 employees	70	56.9	100.0
Firm Age			
0-20 years	35	28.5	28.5
21-40 years	31	25.2	53.7
41-60 years	16	13.0	66.7
61-80 years	4	3.3	69.9
More than 80 years	37	30.1	100.0
Previous AI experience			
Less than 1 year	33	26.8	26.8
1-3 years	58	47.2	74.0
3-6 years	21	17.1	91.1
More than 6 years	11	8.9	100.0

[a] $N = 123$

4.2 Descriptive Analysis

Table A shows the characteristics of the sample. As visible, 56.9% of the respondents work for organizations with more than 250 employees, 35.7% for SMEs (10-249 employees), and 7.3% for organizations with less than 10 employees. Regarding previous AI experience, the majority (74.0%) has AI experience up to 3 years and 26.0% more than three years. Regarding industries, 18.7% are operating in the technology industry, and 17.1% in consulting services. The highest percentage of respondents (27.2%) work for organizations operating in industries not proposed in the questionnaire.

To further analyze the data, variables that consist of items measured on a Likert scale (AIU, ERI, ETI, CEN, FOR, and CON) had to be transformed and combined. This was done by calculating the means of the aggregated item scores of these variables. Table B presents an overview of the means, standard deviations, and correlations of the dependent, independent, moderator, and control variables. Besides, it shows the reliabilities of the six main variables on the diagonal.

As visible in Table B, AI usage is significantly positively correlated to both ERI ($p = .013$) and ETI ($p < .001$). From the moderators, only connectedness shows a significant ($p < .05$) positive correlation with ERI. The control variable firm size is significantly ($p < .01$) positively correlated to firm age, previous AI experience, centralization, and formalization, while significant ($p < .01$) negatively correlated to connectedness. Firm age shows a positive significant correlation with previous AI experience, centralization ($p < .05$), and formalization ($p < .01$), while negatively correlated to connectedness ($p < .01$). Previous AI experience is significantly positively correlated to AI usage ($p < .01$).

Table B. *Means. Standard Deviations, and Correlations*

Variable	*M*	*SD*	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Industry [a]	5.2846	3.06359										
2. Firm Size [b]	3.2683	.97571	.177*									
3. Firm Age [c]	2.8130	1.61626	.301**	.604**								
4. Previous AI experience [d]	2.0813	.89253	-.068	.295**	.209*							
5. Artificial Intelligence Usage	1.8439	.77429	-.013	.156	.109	.387**	(.875)					
6. Explorative Innovation	4.9472	.97628	-.176	-.097	-.169	.083	.224*	(.674)				
7. Exploitative Innovation	5.5061	.83560	-.125	-.055	-.045	.021	.346**	.448**	(.742)			
8. Centralization	2.3252	1.10865	.305**	.275**	.193*	.202*	.278**	-.154	-.070	(.871)		
9. Formalization	4.1037	1.29506	.207*	.412**	.284**	.136	.286**	.038	.127	.163	(.729)	
10. Connectedness	6.1740	.63760	-.041	-.273**	-.317**	-.039	-.120	.223*	.094	-.334**	-.046	(.698)

Notes. *N* = 123. Cronbach's alphas are presented in parentheses on the diagonal. [a] Industry is coded as 1 = Technology, 2 = Bank & Financials, 3 = ICT & Telecommunications, 4 = Consulting Services, 5 = Consumer Services, 6 = Media, 7 = Health Care, 8 = Consumer Goods, 9 = Others. [b] Firm Size is coded as 1 = 1-9, 2 = 10-49, 3 = 50-249, 4 = More than 250. [c] Firm Age is coded as 1 = 0-20 years, 2 = 21-40 years, 3 = 41-60 years, 4 = 61-80 years, 5 = More than 80 years. [d] Previous AI experience is coded as 1 = Less than 1 year, 2 = 1-3 years, 3 = 3-6 years, 4 = More than 6 years.

* Correlation is significant at the level of 0.05 (2-tailed)

** Correlation is significant at the level of 0.01 (2-tailed)

4.3 Justifying the Model

Before testing the hypotheses, it must be is justified to run the hierarchical regression analyses. This should be done by testing assumptions that ensure testing the hypotheses is done in a justified way. Violating these assumptions indicate that interpreting tests statistics should be done with caution, otherwise leading to false conclusions. For running the regression models described in Section 3.5, assessing the following assumptions are important: linearity; homoscedasticity; normally distributed errors; no influential outliers; and no multicollinearity.

Linearity. This assumption assesses whether the relationship between the dependent variables and the independent variables (including the moderators) are indeed linearly related. As shown by the scatter plot matrix in Appendix B1 (Fig. 6), all dependent, independent, and moderator variables show linear relationships between each of them. Thus, it can be assumed that linearity is assured (i.e., not violating the assumption).

Homoscedasticity. This assumption relates to the variance of the dependent variables. It assumes that changes in the independent variables, do not change the variance in the dependent variables. In other words, the residuals at each level of the dependent variables (including moderating variables) have the same variance. To test this statistically, the Breusch & Pagan (1979) test was performed which tests for heteroscedasticity in the linear regression model. Here, a linear regression including all moderating variables and independent variables predicting the squared residuals of the dependent variables is performed. So, one linear regression predicting the squared residuals of ERI, and one linear regression predicting the squared residuals of ETI. The linear regression predicting the squared residuals of ERI (Appendix B2, Table G) does not significantly predict the residuals in ERI ($F(15, 107) = 1.094, p = 0.370$) failing to reject the null-hypothesis of the Breusch-Pagan test and indicating homoscedasticity. The linear regression predicting the squared residuals of ETI (Appendix B2, Table H) does not significantly predict the residuals in ETI ($F(15, 107) = 1.153, p = .320$), failing to reject the null-hypothesis of the Breusch-Pagan test and indicating homoscedasticity. Therefore, homoscedasticity can be assumed (i.e., not violating the assumption).

Normally distributed errors. To test for normally distributed errors, the Kolmogorov-Smirnov test, and Shapiro-Wilk (Appendix B3) test will be performed (Field, 2018, p. 249). These tests allow comparing the residuals in the sample with a normal distribution. If the test shows significance ($p < .05$), it is suggested that the distribution is different from a normal distribution. For both the linear regression predicting ERI and ETI, the tests are performed. The Kolmogorov-Smirnov test indicates that the residuals in ERI follow a normal distribution, $D(123) = .064, p = .200$. Besides, the Shapiro-Wilk test showed no significant deviation from normality, $W(123) = .982, p = .097$ (Appendix B3, Table I). For ETI, the Kolmogorov-Smirnov test indicates that the residuals do not follow a normal distribution, $D(123) = .085, p = .031$. However, the Shapiro-Wilk test showed no significant deviation from normality, $W(123) = .983, p = .121$ (Appendix B3, Table J). In addition, for both the dependent variables the normal P-P plots (Appendix B3, Fig. 7 and Fig. 8) show normality. Therefore, normally distributed errors can be assumed (i.e., not violating the assumption).

No influential outliers. Testing for influential outlier observations is done by computing the Cook's distance for each case. The Cook's distance measures the overall influence of a single case on the model (Field, 2018, p. 383). The highest value for the Cook's distance is $.137$ for the linear regression predicting ERI (Appendix B4, Table K). For the linear regression predicting ETI, the highest Cook's distance is $.269$ (Appendix B4, Table L). Cases with a Cook's distance of greater than 1 are considered to be an influential outlier. Therefore, it can be assumed that no influential outliers exist in the models (i.e., not violating the assumption).

No multicollinearity. Multicollinearity exists when two or more predictor variables have a strong correlation between them. To test for this, the variance inflation factor (VIF) is computed which indicated whether a strong correlation between one predictor variable and other predictor variables exists. From the regression analyses that will be performed in the next section, it is visible that from all the VIF values none exceed 10 and the average of the VIF values is 1.565 which not substantially higher than 1 (Appendix C). Therefore, it can be assumed that there is no multicollinearity in the models (i.e., not violating the assumption).

4.4 Hypotheses Testing

To test the impact of the control variables on both ERI and ETI, the hierarchical regression analyses started with just the control variables (Table C, Model 1a and Table D, Model 2a). None of the control variables show significant relationships with either ERI or ETI. However, as indicated by R^2 in both models, 11.4% of the variance in ERI is accounted for by the control variables (Table C, Model 1a), and a low 4.5% of the variance in ETI is explained by the control variables (Table D, Model 2a).

To test for a positive relationship between AIU and ERI (Hypothesis 1), AIU was introduced to the hierarchical regression analysis predicting ERI. Doing so, 14.8% of the variance in ERI is explained by both the control variables and AIU, indicated by an R^2 of $.148$ (Table C, Model 1b). Moreover, introducing AIU to the model increased the explained variance (R^2) with 0.034 with a significant ($p = .039$) F-statistic of 4.345. In other words, adding AIU to the model significantly increases the explained variance in ERI. The standardized coefficient

β of AIU in Model 1b (Table C) is $.207$ and significant ($se = .125,\ t = 2.085,\ p = .039, 95\%\ CI[.013,\ .509]$). The β of $.207$ indicates that as AIU increases one standard deviation ($.894$), ERI increases by $.207$ standard deviations. In other words, AIU is positively related to ERI, thus supporting Hypothesis 1.

Testing Hypothesis 2 (a positive relationship between AIU and ETI) required a similar procedure but with ETI as the dependent variable. When introducing AIU to the hierarchical regression analysis of Table D (Model 2b), 18.0% of the variance in ETI is explained by AIU and the control variables which is indicated by an R^2 of $.180$. Moreover, introducing AIU to the model increased the explained variance (R^2) with $.135$ by a significant ($p < .001$) F-statistic of 18.133. In other words, adding AIU to the model significantly increases the explained variance in ETI. Besides, the linear regression model introducing AIU (Table D, Model 2b) significantly predicts ETI with $F(12, 110) = 2.013, p = .029$). The standardized coefficient β of AIU in Model 2b (Table D) is $.415$ and significant ($se = .105,\ t = 4.258$, $p < .001, 95\%\ CI[.239,\ 656]$). The β of $.415$ indicates that as AIU increases one standard deviation ($.894$), ETI increases by $.415$ standard deviations. In other words, AIU is positively related to ETI, thus supporting Hypothesis 2.

To test for Hypotheses 3, 4, and 5, the moderating variables CEN, FOR, and CON were included in the regression analyses (Table C, Model 1c and Table D, Model 2c). Including the moderating variables to the model predicting ERI made the model explain 21.2% of the variance in ERI (Table C, Model 1c). This inclusion of the moderating variables to the model increased the explained variance (R^2) with $.064$ by a significant ($p = .038$) F-statistic of 2.899. Hence, adding CEN, FOR, and CON to the model that predicts ERI significantly increased the explained variance of that model. Besides, the linear regression model introducing the moderating variables (Table C, Model 1c) significantly predicts ERI with $F(15, 107) = 1.918, p = .029$.

Predicting ETI by including the moderating variables in the regression analysis made the model explain 21.0% of the variance in ETI (Table D, Model 2c) indicated by an R^2 of $.210$. Adding the moderating variables to the model predicting ETI did not significantly increase the explained variance in ETI. However, the linear regression model that introduces the moderating variables significantly predicts ERI ($F(15, 107) = 1.892, p = .032$).

To test Hypothesis 3a (a negative moderating effect of CEN on the relationship between AIU and ERI) and Hypothesis 3b (a negative moderating effect of CEN on the relationship between AIU and ETI). The interaction term of AIU and CEN had to be included in both analyses (Table C, Model 1d and Table D, Model 2d). To do so, the interaction terms had to be centered first (Section 3.4). Including the centered interaction term did not have a significant effect on the explained variance in either ERI or ETI. Results of including the centered interaction term (Table C, Model 1d) found no support for Hypothesis 3a as there was no significant interaction effect of AIU and CEN on ERI ($b = .053, se = .093, t = .569, p = .570, 95\%\ CI = [-.131, .237]$). Thus, rejecting Hypothesis 3a. Additionally, results of including the centered interaction term (Table D, Model 2d) found no support for Hypothesis 3b as there was no significant interaction effect of AIU and CEN on ETI ($b = .040, se = .079, t = .509, p = .612, 95\%\ CI = [-.117, .198]$). Thus, rejecting Hypothesis 3b.

Table C. *Results of Hierarchical Regression Analyses with ERI as the Dependent Variable*

	1a			1b			1c			1d			1e			1f		
	B	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*
Model 1a																		
Industry: Technology	.331	.273	.133	.317	.269	.127	.290	.281	.116	.292	.282	.117	.286	.284	.115	.318	.286	.128
Industry: Banks & Financials	.150	.406	.036	.276	.404	.066	.063	.404	.015	.079	.406	.019	.073	.409	.017	.026	.412	.006
Industry: ICT & Telecomm.	.099	.377	.028	.181	.374	.051	.089	.386	.025	.116	.390	.033	.105	.395	.029	.166	.400	.047
Industry: Consulting Services	.546	.282	.211	.520	.278	.201	.459	.276	.178	.477	.279	.185	.476	.280	.184	.486	.280	.188
Industry: Consumer Services	-.320	.713	-.042	-.296	.703	-.038	-.489	.698	-.064	-.476	.701	-.062	-.484	.705	-.063	-.482	.705	-.063
Industry: Media	.419	.466	.085	.494	.461	.100	.320	.463	.065	.319	.465	.065	.315	.467	.064	.306	.467	.062
Industry: Health Care	-.184	.300	-.062	-.080	.300	-.027	-.094	.294	-.032	-.074	.297	-.025	-.086	.302	-.029	-.073	.303	-.025
Industry: Consumer Goods	.645	.428	.143	.636	.421	.141	.782	.416	.173	.742	.423	.164	.724	.432	.161	.777	.435	.172
Firm Size	-.020	.117	-.020	-.027	.115	-.027	.013	.120	.013	.030	.124	.030	.031	.125	.031	.034	.125	.034
Firm Age	-.078	.074	-.129	-.082	.073	-.136	-.061	.073	-.100	-.062	.074	-.103	-.062	.074	-.102	-.061	.074	-.101
Previous AI Experience	.134	.109	.122	.040	.117	.037	.060	.115	.055	.054	.116	.049	.055	.117	.050	.074	.118	.068
Model 1b																		
Artificial Intelligence Usage				.261	.125	.207*	.307	.131	.243*	.293	.133	.232*	.298	.135	.236*	.277	.137	.220*
Model 1c																		
Centralization							-.155	.092	-.176	-.169	.096	-.192	-.168	.096	-.191	-.180	.097	-.204
Formalization							.035	.080	.046	.034	.081	.044	.030	.082	.040	.053	.086	.070
Connectedness							.259	.152	.169	.265	.153	.173	.272	.157	.178	.244	.159	.160
Model 1d																		
AIU × CEN (Centered)										.053	.093	.057	.057	.095	.062	.005	.110	.006
Model 1e																		
AIU × FOR (Centered)													-.023	.100	-.022	-.004	.102	-.004
Model 1f																		
AIU × CON (Centered)																-.222	.233	-.107
R^2		.114			.148			.212			.214			.215			.222	
$F\ (df)$		1.301 (11,111)			1.590 (12,110)			1.918* (15,107)			1.807* (16,106)			1.689 (17,105)			1.644 (18,104)	
ΔR^2		.114			.034			.064			.002			.000			.007	
$\Delta F\ (df)$		1.301 (11,111)			4.345* (1,110)			2.899* (3,107)			.324 (1,106)			.054 (1,105)			.909 (1,104)	

Notes. N = 123. ** $p < .01$, * $p < .05$ (two-tailed)

Similarly, to test Hypothesis 4a (a negative moderating effect of FOR on the relationship between AIU and ERI) and Hypothesis 4b (a positive moderating effect of FOR on the relationship between AIU and ETI). The interaction term of AIU and FOR had to be included in both analyses (Table C, Model 1e and Table D, Model 2e). Including the centered interaction term did not have a significant effect on the explained variance in either ERI or ETI, indicated by low and insignificant changes in R^2. Results of including the centered interaction term $AIU \times FOR$ (Table C, Model 1e) found no support for Hypothesis 4a as there was no significant interaction effect of AIU and FOR on ERI ($b = -.023, se = .100, t = -.232, p = .817, 95\%\ CI = [-.221, .175]$). Thus, rejecting Hypothesis 4a. Additionally, results of including the centered interaction term (Table D, Model 2e) found no support for Hypothesis 4b as there was no significant interaction effect of AIU and FOR on ETI ($b = .024, se = .086, t = .283, p = .777, 95\%\ CI = [-.145, .194]$). Thus, rejecting Hypothesis 4b.

Table D. *Results of Hierarchical Regression Analyses with ETI as the Dependent Variable*

	2a			2b			2c			2d			2e			2f		
	B	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*	*B*	*SE (B)*	*β*
Model 2a																		
Industry: Technology	.221	.242	.104	.197	.226	.092	.174	.241	.082	.175	.241	.082	.182	.244	.085	.188	.246	.088
Industry: Banks & Financials	.351	.361	.098	.567	.340	.158	.430	.346	.120	.442	.348	.123	.449	.351	.125	.439	.355	.122
Industry: ICT & Telecomm.	-.026	.335	-.008	.114	.314	.037	.074	.331	.024	.095	.334	.031	.107	.339	.035	.120	.345	.039
Industry: Consulting Services	.143	.251	.065	.099	.233	.045	.061	.237	.028	.075	.239	.034	.077	.240	.035	.079	.241	.036
Industry: Consumer Services	-.696	.634	-.106	-.653	.590	-.099	-.787	.598	-.120	-.777	.601	-.118	-.769	.604	-.117	-.768	.607	-.117
Industry: Media	-.156	.414	-.037	-.028	.387	-.007	-.112	.397	-.026	-.112	.398	-.027	-.108	.400	-.026	-.110	.402	-.026
Industry: Health Care	-.115	.267	-.045	.064	.252	.025	.046	.252	.018	.061	.254	.024	.074	.259	.029	.076	.261	.030
Industry: Consumer Goods	.172	.380	.045	.157	.354	.041	.244	.357	.063	.214	.363	.055	.232	.370	.060	.243	.375	.063
Firm Size	-.031	.104	-.036	-.043	.097	-.050	-.028	.103	-.032	-.014	.106	-.017	-.015	.107	-.018	-.015	.107	-.017
Firm Age	-.014	.065	-.027	-.021	.061	-.041	-.012	.063	-.024	-.013	.063	-.026	-.014	.064	-.027	-.014	.064	-.026
Previous AI Experience	.043	.097	.046	-.117	.098	-.125	-.102	.099	-.108	-.106	.100	-.113	-.107	.100	-.114	-.103	.102	-.110
Model 2b																		
Artificial Intelligence Usage				.448	.105	.415**	.467	.112	.433**	.457	.114	.423**	.452	.116	.419**	.448	.118	.415**
Model 2c																		
Centralization							-.103	.079	-.136	-.113	.082	-.150	-.114	.082	-.151	-.116	.083	-.154
Formalization							.038	.069	.059	.037	.069	.058	.041	.071	.063	.045	.074	.070
Connectedness							.114	.130	.087	.119	.131	.091	.111	.134	.085	.105	.137	.080
Model 2d																		
AIU × CEN (Centered)										.040	.079	.051	.036	.082	.045	.025	.095	.032
Model 2e																		
AIU × FOR (Centered)													.024	.086	.027	.028	.088	.032
Model 2f																		
AIU × CON (Centered)																-.046	.201	-.026
R^2	.045			.180			.210			.212			.212			.213		
$F\ (df)$	.475 (11,111)			2.013* (12,110)			1.892* (15,107)			1.778* (16,106)			1.664 (17,105)			1.560 (18,104)		
ΔR^2	.045			.135			.030			.002			.001			.000		
$\Delta F\ (df)$	.475 (11,111)			18.133** (1,110)			1.336 (3,107)			.260 (1,106)			.080 (1,105)			.053 (1,104)		

Notes. *N* = 123. ** $p < .01$, * $p < .05$ (two-tailed)

And finally, to test Hypothesis 5a (a positive moderating effect of CON on the relationship between AIU and ERI) and Hypothesis 5b (a positive moderating effect of CON on the relationship between AIU and ETI). The interaction term of AIU and CON had to be included in both analyses (Table C, Model 1f and Table D, Model 2f). Including the centered interaction term did not have a significant effect on the explained variance in either ERI or ETI, indicated by low and insignificant changes in R^2. Results of including the centered interaction term $AIU \times CON$ (Table C, Model 1f) found no support for Hypothesis 5a as there was no significant interaction effect of AIU and CON on ERI ($b = -.222, se = .233, t = -.953, p = .343, 95\%\ CI = [-.685, .240]$). Thus, rejecting Hypothesis 5a. Additionally, results of including the centered interaction term $AIU \times CON$ (Table D, Model 2e) to the model predicting ETI found no support for Hypothesis 5b as there was no significant interaction effect of AIU and CON on ETI ($b = .046, se = .201, t = .230, p = .819, 95\%\ CI = [-.444, .352]$). Thus, rejecting Hypothesis 5b.

Figures 4 and 5 show the statistical models for both regression analyses with the corresponding test results. Note that Hypotheses 3, 4, and 5 are not supported (ns.). To summarize, results show that Hypothesis 1 (a positive relationship between AIU and ERI) is supported due to the significance of the relationship. In addition, the results show significant support for Hypothesis 2 (a positive relationship between AIU and ETI). Unlike hypothesized, the results showed that none of the moderators (centralization, formalization, and connectedness) show a significant moderation effect on either the AIU-ERI relationship or the AIU-ETI relationship. Hereby, rejecting H3-H5. It can therefore be concluded that none of the moderators significantly strengthen nor weaken the relationships of artificial intelligence usage between both explorative innovation and exploitative innovation.

Figure 4. *Statistical model of AIU and the interaction terms predicting ERI. b = Unstandardized Coefficient,* $\boldsymbol{\beta}$ = *Standardized Coefficient, * p < .05, ** p < .01,* ns. = *not supported.*

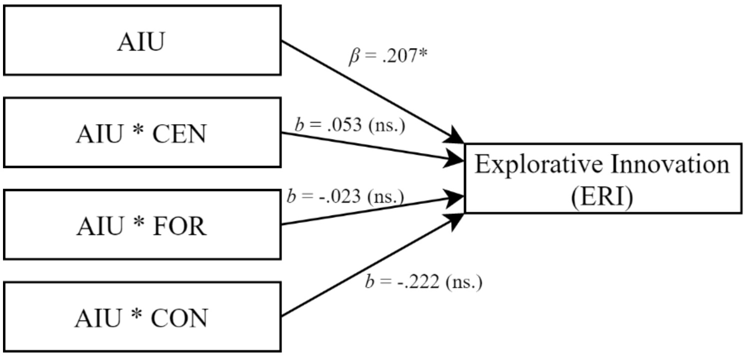
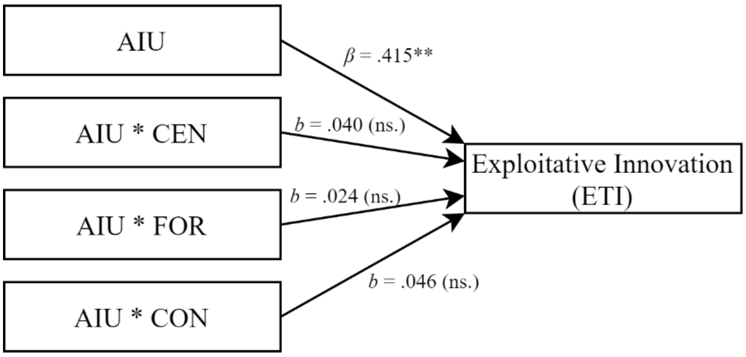


Figure 5. *Statistical model of AIU and the interaction terms predicting ETI. b = Unstandardized Coefficient,* $\boldsymbol{\beta}$ = *Standardized Coefficient, * p < .05, ** p < .01,* ns. = *not supported.*



5 DISCUSSION & CONCLUSION

5.1 Findings

This research examined the relationship between artificial intelligence (AI) usage and explorative innovation, and the relationship between AI usage and exploitative innovation. Besides, it examined the moderating effects of the organizational coordination mechanisms of centralization, formalization, and connectedness on both relationships. Hereby answering the following research questions: (1) *What is the relationship of artificial intelligence usage between both explorative innovation and exploitative innovation, and* (2) *what are the moderating roles of the organizational coordination mechanisms of centralization, formalization, and connectedness in these relationships?*

The results showed that AI usage is positively related to both explorative innovation and exploitative innovation. In other words, when an organization uses AI to a higher degree in its supply chain activities, it enhances its explorative innovativeness and exploitative innovativeness. Regarding the organizational coordination mechanisms of centralization, formalization, and connectedness, none of these variables moderate the aforementioned relationships. In other words, neither centralization, nor formalization, nor connectedness strengthens or weakens the relationship of AI usage between explorative innovation or exploitative innovation.

5.2 Literature Contribution

Comparing the results with other studies in the field of innovation ambidexterity, there are some differences and similarities. As prior literature has suggested a positive impact of AI on an organization's innovativeness (Botega & da Silva, 2020; Haefner, Wincent, Gassmann, & Parida, 2021; Hutchinson, 2021; Kakatkar, Bilgram, & Füller, 2020; Lou, Lou, & Hitt, 2019), this research showed similar results. Regarding innovation ambidexterity, prior literature suggests that information technology has a positive impact on both explorative innovation and exploitative innovation (Božič & Dimovski, 2019; Im & Rai, 2014; Ko & Liu, 2019; Soto-Acosta, Popa, & Martinez-Conesa, 2018), including big data analytics (Rialti, Marzi, Caputo, & Mayah, 2020). As an extended arm of IT, AI showed to have a positive impact on both explorative innovation and exploitative innovation. Hereby enriching existing literature through this research.

Especially regarding the impact of organizational coordination mechanisms on both types of innovation, the results show differences from prior literature. For instance, both Jansen, Van Den Bosch, & Volberda (2006) and Prajogo & Mcdermott (2014) found that centralization is negatively related to explorative innovation; formalization is positively related to exploitative innovation; connectedness is positively related to exploitative innovation. For the other relationships (e.g., centralization-exploitation, formalization-exploration, and connectedness-exploration) no statistical support was found, which shows similarity with the results of this research. However, as this research examines the moderating effects rather than the direct effects, the differences might be caused by the inclusion of AI usage as the independent variable.

Firstly, this research found no statistical support for centralization as a moderator. In other words, the centralization of decision-making neither strengthens nor weakens the relationships. This is in contradiction with Vendrell-Herrero, Bustinza, & Opazo-Basaez (2021) who found support for centralization as a positive moderator in the relationship between information technology and innovation. In terms of explorative innovation, AI is suggested to complement humans in generating novel ideas (Haefner, Wincent, Gassmann, & Parida, 2021) which requires decentralized decision-making (Sheremata, 2000). This research failed to comply with this suggestion and showed that the use of AI in supply chain activities positively relates to explorative innovation but is not weakened through centralization. Regarding exploitative innovation, Ettlie, Bridges, & O'Keefe (1984) argue that centralization increases exploitative innovation while Germain (1996) suggests that centralization reduces exploitation. This research found no support for centralization being a moderator in the relationship between AI usage and explorative innovation. These findings might be an effect of AI being a problem-solver and decision-maker itself (Duan, Edwards, & Dwivedi, 2019; Russell & Norvig, 2010). As AI complements or even replaces decision-making in organizations, using it in supply chain activities for different orientations of innovation might not be influenced by (de)centralization of decision-making as the technology masters it by itself.

Secondly, prior literature has suggested that the documentation of standards (i.e., formalization) is negatively related to an organization’s innovativeness (Aiken & Hage, 1971). Similarly, this research hypothesized a negative influence of formalization on the relationship between AI usage and explorative innovation. However, no support was found for this. As Haefner, Wincent, Gassmann, & Parida (2021) suggest that existing search routines facilitated by formalization negatively influences explorative innovation, this research suggests that formalization does not influence the relationship between AI usage in supply chain activities and explorative innovation. Just as Muhlroth & Grottke (2020) suggest because AI itself allows searching for non-existing patterns so that formalization does not impact it. Additionally, no support was found for formalization as a negative moderator in the relationship between AI usage and exploitative innovation. This could be explained by AI’s capability to accelerate decision-making (Duan, Edwards, & Dwivedi, 2019) whereby documented standards may be bypassed and thus having no influence on the relationship between AI usage in supply chain activities and exploitative innovation.

Finally, the results show that the extent to which different organizational functions, departments, and/or units collaborate does not positively influence the relationships of AI usage between explorative innovation and exploitative innovation. This is not consistent with Prajogo & Mcdermott (2014) who found that connectedness is positively related to both explorative innovation and exploitative innovation. In terms of explorative innovation, it could be suggested that AI so much utilizes algorithms to deepen the understanding of existing organizational-wide knowledge for innovation purposes so that it mimics the creation of cross-functional human social interaction. Wilson & Daugherty (2018) suggest a similar proposition saying that “human-machine collaboration enables companies to interact with employees and customers in novel, more effective ways.”

Looking at the organizational coordination mechanisms of centralization, formalization, and connectedness in retrospect with AI usage and explorative innovation and exploitative innovation in general, this research showed no significant influence of these mechanisms. While prior literature showed these mechanisms having an impact on innovation ambidexterity (Chang & Hughes, 2012; Jansen, Van Den Bosch, & Volberda, 2006; Prajogo & Mcdermott, 2014) this research did not. It can therefore be suggested that research should examine the influence of other phenomena on the relationship between AI usage and both flavors of innovation. Prior literature has examined the influences of the environment as well (Benner & Tushman, 2003; Chang, Hughes, & Hotho, 2011). For instance, Raisch & Birkinshaw (2008) have reviewed the environmental factors of environmental dynamism and competitive dynamism in the light of organizational ambidexterity.

5.3 Practical Implications

For an organization to survive in the long run, it must innovate to prevent being disrupted by environmental changes (Raisch & Birkinshaw, 2008) such as new disruptive technologies (Christensen, 1997). To do so, it must be ambidextrous – excelling in both explorative innovation and exploitative innovation. Managers and executives should therefore search for competencies that enable the organization to be ambidextrous. This research has shown that using AI in an organization’s supply chain activities is positively related to both flavors of innovation. Accordingly, two recommendations can be given for practitioners:

organizations currently using AI and organizations search for competencies that enhance ambidexterity.

For organizations already deploying AI in their supply chain activities, this research showed that neither centralization of decision-making, documentation of standards, nor connectedness between organizational functions influence AI's ability to increase explorative innovation or exploitative innovation. Managers should therefore search for alternative ways to leverage AI for innovation ambidexterity. For instance, Riahi, Saikouk, Gunasekaran, & Badraoui (2021) showed that an organization's capability to manage knowledge successfully mediates the relationships between big data capabilities and both types of innovation. Management should therefore implement information systems that enhance the acquisition, conversion, and application of knowledge to which AI can be a contributor. Similarly, Soto-Acosta, Popa, & Martinez-Conesa (2018) showed that, besides IT capability and environmental factors, an organization must possess adequate knowledge management capabilities to enhance innovation ambidexterity. Just as Wilson & Daugherty (2018) suggest that AI and humans must collaborate to unlock AI's full potential, this research recommends managers search for opportunities that enhance the management of knowledge so that AI complements human intelligence (and vice versa) for innovation purposes.

For organizations searching for opportunities that enhance both explorative innovation and exploitative innovation, this research has shown that AI (in the supply chain context) is an enabler of both types of innovation. While this research is limited to the use of AI in supply chain activities, it can be suggested that the use of AI in any function of the organization has the potential to increase both types of innovation – provided that it is implemented well. Therefore, I recommend managers look for the possibility to deploy a type of AI that is often referred to as 'weak AI' (Iansiti & Lakhani, 2020). Weak AI only relies on computer systems that can perform human-like tasks and is easier to implement compared to 'strong AI.' Iansiti & Lakhani (2020) argue that implementing weak AI requires a pipeline that safely gathers, cleans, and integrates data; algorithms that generate the required insights; experiments that test the efficacy of these algorithms; and an infrastructure that allows connection with internal and external actors. This research recommends starting to act on the opportunities of AI for innovation purposes by taking into consideration the requirements proposed by Iansiti & Lakhani (2020).

5.4 Limitations and Future Research

Not every hypothesis has found statistical support, which might have been caused by limitations associated with the design of this research. Zmud (1982) argues that the practice of innovation is a process with multiple stages. Therefore, it might occur that the influence of centralization, formalization, and connectedness changes during the innovation process. It is also imaginable that AI is not used in every stage of the supply chain with the same intensity. This implies that a longitudinal research design might have been more suitable for examining the constructs of both AI usage and organizational coordination mechanisms as the innovation process "takes place over multiple points in time" (Trochim, Donnelly, & Arora, 2016, p. 14). The cross-sectional design of this research only measured the constructs at one point in time, ignoring the possible changing influences of the moderators over time. Future research should therefore examine the effect of the coordination mechanisms over time during the innovation process. Besides, it should measure the extent to which AI is used during these stages so that it can be investigated when leveraging AI requires what coordination mechanisms to what extent.

Besides the cross-sectional nature of this research, it investigated the relationships between the phenomena rather than the causations which limit the ability to conclude the effects of AI usage on exploration and exploitation. It is therefore impossible to conclude such as "when an organization uses AI to a high degree within its supply chain activities, it fosters more in exploration than in exploitation." This would contribute to the literature by shedding light on how organizations should manage themselves to achieve one type of innovation or the other when using AI in supply chain activities. Or, in other words: what causes an organization to leverage its AI use in supply chain activities for different types of innovation outcomes? Therefore, future research could enrich the analysis by deploying causal study designs that investigate AI as a cause of the different types of innovation. This also allows the examination of what organizational structures cause AI to affect innovation types.

As this research examines the usage of AI in supply chain activities, it is limited by investigating the impact of this technology in this part of the organization. While it is suggested that the supply chain plays an important role in the innovation practices of an organization (Bellamy, Ghosh, & Hora, 2014; Modi & Mabert, 2010), it might be of greater impact within other functions of the value chain such as marketing, R&D, and operations. For instance, AI is suggested to be beneficial in spotting market trends (Muhlroth & Grottke, 2020) or selecting design techniques in R&D (Botega & da Silva, 2020). Considerably, the coordination mechanisms of centralization, formalization, and connectedness examined in this research might have different influences on the use of AI in organizational functions other than the supply chain. Accordingly, future researchers should aim to investigate the impact of AI in other organizational functions such as marketing, R&D, and operations. By doing so, practitioners know where in the organization innovation ambidexterity is to benefit most from the use of AI and how it should coordinate itself to leverage this.

Decisions made regarding the sampling procedure of this research potentially have caused some bias. Organizations operating in all kinds of industries were included in the sample and were allowed to participate in this research. This might have caused biased results. As the construct of AI usage was measured in the context of supply chain activities, it was assumed that organizations operating in any industry have the same intensity of supply chain activities. However, it might be considered that for instance organizations in the media industry are less reliant on supply chain activities than health care organizations. While the results showed no significant effect of the control variable industry, it can still be considered that it caused biased results. Therefore, future research should focus on one particular industry.

Finally, this research focuses on the impact of AI on the organization's innovativeness as a whole. However, as innovation starts with the generation of creative ideas at an individual level (Amabile, 1998), it is important to investigate the impact of AI on an individual's capability to generate novel ideas. Future research should examine how AI is deployed in organizations to complement human creativity. Preferably in a qualitative manner to explore how individuals interpret and experience the use of AI in the innovation process (Trochim, Donnelly, & Arora, 2016). Haefner, Wincent, Gassmann, & Parida (2021) argue that when AI is deployed in an organization it is still difficult to leverage it due to its complexity. This means that employees working with the developed AI solution lack the expertise to use it to its full potential. Qualitative research would contribute to the understanding of how individuals within an organization perceive AI solutions in the light of innovation.

5.5 Conclusion

Prior literature has suggested a positive impact of artificial intelligence on innovation. Yet, it was still to be discovered its relationship with both explorative innovation and exploitative innovation (i.e., innovation ambidexterity). Besides, it is unclear how an organization should coordinate itself to leverage AI for these two types of innovation. Therefore, this research aimed to investigate the relationship of AI usage between explorative innovation and exploitative innovation. Additionally, it examined the moderating roles of centralization, formalization, and connectedness on these aforementioned relationships. It can be concluded that a higher degree of AI usage is related to higher degrees of both explorative innovation and exploitative innovation. However, centralization, formalization, and connectedness show no influence on these two relationships. Future research should determine other factors that leverage AI usage in any function of the organization for innovation purposes.

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APPENDICES

Appendix A – Measurements

Table E. *Constructs of the Independent, Dependent, and Moderator Variables*

Construct	
Artificial Intelligence Usage, Chen, Preston, & Swink (2015)	To what extent has your organization implemented Artificial Intelligence in each area?
	(1 = none at all … 3 = a moderate amount … 5 = a great deal)
AIU1:	Sourcing analysis
AIU2:	Purchasing spend analytics
AIU3:	CRM /customer/patient analysis
AIU4:	Network design/optimization
AIU5:	Warehouse operations improvements
AIU6:	Process/equipment monitoring
AIU7:	Production run optimization
AIU8:	Logistics improvements
AIU9:	Forecasting/demand management – S&OP
AIU10:	Inventory optimization
Explorative Innovation, Jansen, Tempelaar, van den Bosch, & Volberda (2009)	Regarding innovation in your organization, to what extent do you agree with the following statements?
	(1 = strongly disagree … 4 = neither agree nor disagree … 7 = strongly agree)
ERI1:	Our organization accepts demands that go beyond existing products and services.
ERI2:	We commercialize products and services that are completely new to our organization.
ERI3:	We frequently utilize new opportunities in new markets.
ERI4:	Our organization regularly uses new distribution channels.
Exploitative Innovation, Jansen, Tempelaar, van den Bosch, & Volberda (2009)	Regarding innovation in your organization, to what extent do you agree with the following statements?
	(1 = strongly disagree … 4 = neither agree nor disagree … 7 = strongly agree)
ETI1:	We frequently make small adjustments to our existing products and services.
ETI2:	We improve our provision's efficiency of products and services.
ETI3:	We increase economies of scales in existing markets.
ETI4:	Our organization expands services for existing clients.
Centralization, Jansen, Van Den Bosch, & Volberda (2006)	Regarding decision-making within your organization, to what extent do you agree with the following statements?
	(1 = strongly disagree … 4 = neither agree nor disagree … 7 = strongly agree)
CEN1:	There can be little action taken here until a supervisor approves a decision.
CEN2:	A person who wants to make his own decisions would be quickly discouraged.
CEN3:	Even small matters have to be referred to someone higher up for a final decision.
CEN4:	Employees need to ask their supervisor before they do almost anything.
CEN5:	Most decisions people make here have to have their supervisor's approval.
Formalizatoin, Jansen, Van Den Bosch, & Volberda (2006)	Regarding procedures within your organization, to what extent do you agree with the following statements?
	(1 = strongly disagree … 4 = neither agree nor disagree … 7 = strongly agree)
FOR1:	Whatever situation arises, written procedures are available for dealing with it.
FOR2:	Rules and procedures occupy a central place in the organization.
FOR3:	Written records are kept of everyone's performance.
FOR4 (Reversed)	Employees in our organization are hardly checked for rule violations.
FOR5:	Written job descriptions are formulated for positions at all levels in the organization.
Connectedness, Jansen, Van Den Bosch, & Volberda (2006)	Regarding collaboration within your organization, to what extent do you agree with the following statements? (1 = strongly disagree … 4 = neither agree nor disagree … 7 = strongly agree)

CON1:	In our organization, there is enough opportunity for informal "hall talk" among employees.
CON2:	In this organization, employees from different departments feel comfortable calling each other when the need arises.
CON3 (Reversed):	Managers discourage employees from discussing work-related matters with those who are not immediate superiors.
CON4:	People around here are quite accessible to each other.
CON5:	In this organization, it is easy to talk with virtually anyone you need to, regardless of rank or position.

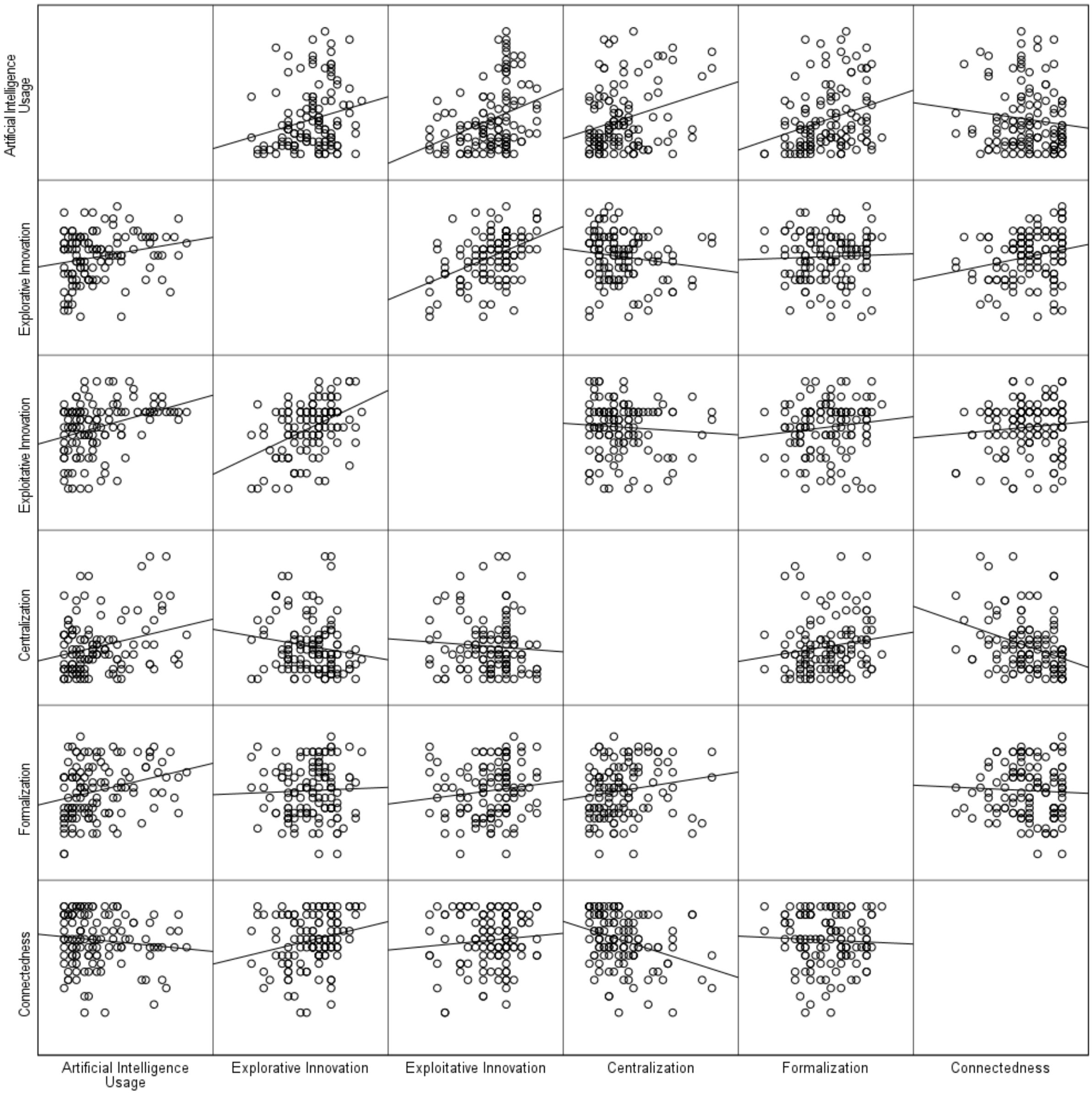
Table F. *Constructs of Control Variables*

Construct	
Industry	What industry does the firm operate in? Technology Bank & Financials ICT and Telecommunications Consulting Services Consumer Services Media Health Care Consumer Goods Other
Firm Size	How many employees does the firm count? 1-9 10-49 50-249 More than 250
Firm Age	When was the organization founded? 0-20 years ago. 21-40 years ago. 41-60 years ago. 61-80 years ago. More than 80 years ago.
Previous AI Experience	How many years has your firm been using Artificial Intelligence? Less than 1 year 1-3 years 3-6 years More than 6 years

Appendix B – Tests for Assumptions

Appendix B1 – Linearity

Figure 6. *Scatter Plot Matrix plotting AIU, ERI, ETI, CEN, FOR, and CON.*



Appendix B2 – Homoscedasticity

Table G. *ANOVA* [a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17.931	15	1.195	1.094	.370 [b]
	Residual	116.879	107	1.092		
	Total	134.810	122			

[a] Dependent Variable: Squared Residuals of Explorative Innovation.
[b] Predictors: (Constant), Connectedness, Industry: Cons. Services, Industry: Finance, Industry: Con Goods, Artificial Intelligence Usage, Industry: ICT, Industry: Media, Industry: Health, Industry: Consult, Firm Size, Centralization, Previous AI experience, Formalization, Industry: Tech, Firm Age

Table H. *ANOVA* [a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10.625	15	.708	1.153	.320 [b]
	Residual	65.735	107	.614		
	Total	76.360	122			

[a] Dependent Variable: Squared Residuals of Exploitative Innovation.
[b] Predictors: (Constant), Connectedness, Industry: Cons. Services, Industry: Finance, Industry: Con Goods, Artificial Intelligence Usage, Industry: ICT, Industry: Media, Industry: Health, Industry: Consult, Firm Size, Centralization, Previous AI experience, Formalization, Industry: Tech, Firm Age

Appendix B3 – Normally Distributed Errors

Table I. *Tests of Normality for Regression Predicting Explorative Innovation*

Model	Kolmogorov-Smirnov [a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	.064	123	.200 *	.982	123	.097
Standardized Residual	.064	123	.200 *	.982	123	.097

* This is a lower bound of the true significance.

a Lilliefors Significance Correction

Figure 7. *Normal P-P Plot of Regression Standardized Residuals (Dependent Variable: Explorative Innovation)*

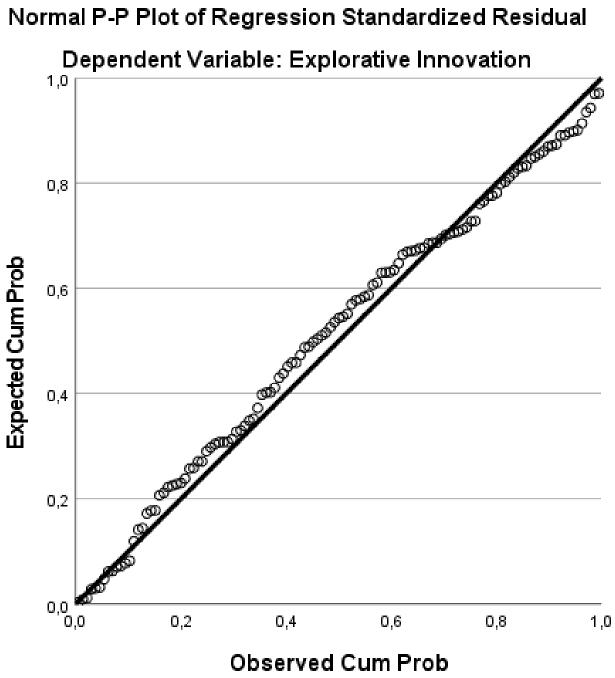
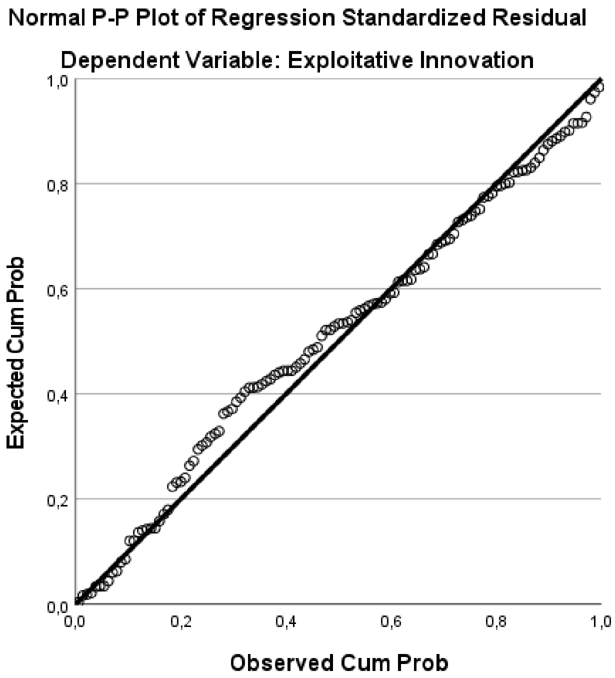


Table J. *Tests of Normality for Regression Predicting Exploitative Innovation*

Model	Kolmogorov-Smirnov [a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	.085	123	.031	.983	123	.121
Standardized Residual	.085	123	.031	.983	123	.121

a Lilliefors Significance Correction

Figure 8. *Normal P-P Plot of Regression Standardized Residuals (Dependent Variable: Exploitative Innovation)*



Appendix B4 – No Influential Outliers

Table K. *Residual Statistics* [a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3.8308	5.9969	4.9472	.44941	123
Std. Predicted Value	-2.484	2.336	.000	1.000	123
Standard Error of Predicted Value	.200	.669	.325	.077	123
Adjusted Predicted Value	3.9119	6.1408	4.9489	.47384	123
Residual	-2.49956	1.83072	.00000	.86669	123
Std. Residual	-2.701	1.978	.000	.937	123
Stud. Residual	-3.009	2.088	-.001	1.007	123
Deleted Residual	-3.10285	2.04053	-.00177	1.00497	123
Stud. Deleted Residual	-3.131	2.122	-.003	1.017	123
Mahal. Distance	4.700	62.763	14.878	8.613	123
Cook's Distance	.000	.137	.010	.017	123
Centered Leverage Value	.039	.514	.122	.071	123

a. Dependent Variable: Explorative Innovation

Table L. *Residual Statistics* [a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	4.5869	6.4466	5.5061	.38262	123
Std. Predicted Value	-2.402	2.458	.000	1.000	123
Standard Error of Predicted Value	.171	.573	.278	.066	123
Adjusted Predicted Value	3.7233	6.5095	5.5087	.42207	123
Residual	-2.18462	1.70396	.00000	.74285	123
Std. Residual	-2.754	2.148	.000	.937	123
Stud. Residual	-3.006	2.241	-.002	1.013	123
Deleted Residual	-2.60213	2.27667	-.00262	.88032	123
Stud. Deleted Residual	-3.127	2.285	-.004	1.024	123
Mahal. Distance	4.700	62.763	14.878	8.613	123
Cook's Distance	.000	.269	.013	.036	123
Centered Leverage Value	.039	.514	.122	.071	123

a. Dependent Variable: Exploitative Innovation

Appendix B5 – Common Method Bias

Table M. *Total Variance Explained*

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.539	2.435	2.435	5.863	18.323	18.323
2	4.461	13.939	34.374			
3	2.149	6.716	41.089			
4	2.075	6.485	47.574			
5	1.803	5.633	53.208			
6	1.477	4.616	57.824			
7	1.294	4.044	61.868			
8	1.145	3.579	65.447			
9	.999	3.123	68.570			
10	.914	2.856	71.426			
11	.852	2.661	74.087			
12	.747	2.335	76.422			
13	.718	2.244	78.667			
14	.675	2.110	8.776			
15	.649	2.029	82.805			
16	.592	1.851	84.657			
17	.564	1.762	86.419			
18	.489	1.529	87.948			
19	.453	1.414	89.362			
20	.440	1.374	9.736			
21	.372	1.163	91.899			
22	.359	1.123	93.021			
23	.346	1.082	94.103			
24	.307	.959	95.062			
25	.279	.871	95.933			
26	.259	.810	96.744			
27	.220	.689	97.432			
28	.205	.640	98.073			
29	.196	.614	98.686			
30	.186	.583	99.269			
31	.133	.417	99.686			
32	.101	.314	10.000			

Extraction Method: Principal Axis Factoring

Appendix C – Coefficients from Regression Analyses

Table N. *Coefficients* [a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1f	(Constant)	2.832	1.167		2.427	.017	.518	5.146		
	Industry: Tech	.318	.286	.128	1.111	.269	-.249	.886	.568	1.760
	Industry: Finance	.026	.412	.006	.064	.949	-.791	.844	.776	1.288
	Industry: ICT	.166	.400	.047	.415	.679	-.628	.960	.591	1.692
	Industry: Consult	.486	.280	.188	1.731	.086	-.071	1.042	.635	1.574
	Industry: Cons. Services	-.482	.705	-.063	-.684	.495	-1.880	.916	.890	1.123
	Industry: Media	.306	.467	.062	.655	.514	-.620	1.233	.831	1.204
	Industry: Health	-.073	.303	-.025	-.241	.810	-.673	.528	.721	1.388
	Industry: Con Goods	.777	.435	.172	1.785	.077	-.086	1.641	.805	1.243
	Firm Size	.034	.125	.034	.270	.788	-.214	.281	.481	2.080
	Firm Age	-.061	.074	-.101	-.823	.413	-.208	.086	.497	2.012
	Previous AI experience	.074	.118	.068	.625	.534	-.161	.309	.639	1.565
	Artificial Intelligence Usage	.277	.137	.220	2.024	.046	.006	.549	.634	1.578
	Centralization	-.180	.097	-.204	-1.853	.067	-.372	.013	.618	1.619
	Formalization	.053	.086	.070	.615	.540	-.117	.223	.580	1.726
	Connectedness	.244	.159	.160	1.533	.128	-.072	.560	.691	1.447
	AIUCEN_C	.005	.110	.006	.047	.963	-.213	.223	.524	1.909
	AIUFOR_C	-.004	.102	-.004	-.044	.965	-.206	.197	.774	1.293
	AIUCON_C	-.222	.233	-.107	-.953	.343	-.685	.240	.598	1.671

a. Dependent Variable: Explorative Innovation

Table O. *Coefficients* [a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95,0% Confidence Interval for B Lower Bound	95,0% Confidence Interval for B Upper Bound	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1f	(Constant)	4.309	1.004		4.289	.000	2.317	6.300		
	Industry: Tech	.188	.246	.088	.765	.446	-.300	.677	.568	1.760
	Industry: Finance	.439	.355	.122	1.238	.219	-.264	1.143	.776	1.288
	Industry: ICT	.120	.345	.039	.348	.729	-.564	.803	.591	1.692
	Industry: Consult	.079	.241	.036	.328	.744	-.400	.558	.635	1.574
	Industry: Cons. Services	-.768	.607	-.117	-1.266	.208	-1.972	.435	.890	1.123
	Industry: Media	-.110	.402	-.026	-.273	.785	-.908	.688	.831	1.204
	Industry: Health	.076	.261	.030	.293	.770	-.440	.593	.721	1.388
	Industry: Con Goods	.243	.375	.063	.648	.518	-.500	.986	.805	1.243
	Firm Size	-.015	.107	-.017	-.135	.893	-.228	.199	.481	2.080
	Firm Age	-.014	.064	-.026	-.213	.832	-.140	.113	.497	2.012
	Previous AI experience	-.103	.102	-.110	-1.008	.316	-.305	.099	.639	1.565
	Artificial Intelligence Usage	.448	.118	.415	3.799	.000	.214	.682	.634	1.578
	Centralization	-.116	.083	-.154	-1.392	.167	-.282	.049	.618	1.619
	Formalization	.045	.074	.070	.613	.541	-.101	.191	.580	1.726
	Connectedness	.105	.137	.080	.769	.444	-.167	.377	.691	1.447
	AIUCEN_C	.025	.095	.032	.262	.794	-.163	.212	.524	1.909
	AIUFOR_C	.028	.088	.032	.321	.749	-.146	.202	.774	1.293
	AIUCON_C	-.046	.201	-.026	-.230	.819	-.444	.352	.598	1.671

a. Dependent Variable: Exploitative Innovation