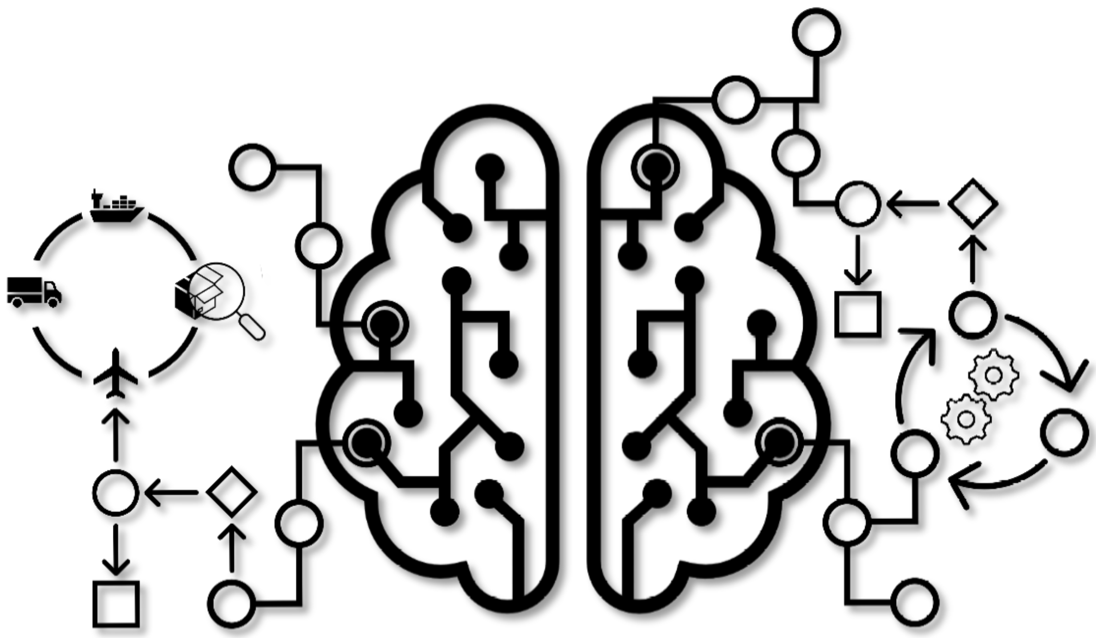
Thesis BSc. Business Administration

The Relationship between Artificial Intelligence Usage and Business Process Agility: Exploring the Mediating Role of Operational Supply Chain Transparency



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22nd of June 2020

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Statement of Originality

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Word count: 7906

Abstract

This study builds upon existing literature in the field of Information Technology (IT), agility, and supply chain visibility by examining the relationship between Artificial Intelligence usage (AIU), Business Process Agility (BPA), and Operational Supply Chain Transparency (OSCT). The research question investigated in this study is: *What is the relationship between Artificial Intelligence Usage and Business Process Agility, and is that relationship mediated by Operational Supply Chain Transparency?* Data has been collected through an online survey and testing the hypotheses has been done by using a sample of 95 managers specialized in the field of AI, business intelligence, supply chain management, and analytics. Support was found for all hypotheses, suggesting that a positive relationship between Artificial Intelligence Usage and Business Process Agility exists. Besides, that relationship is mediated by Operational Supply Chain Transparency, indicating that AIU has a positive impact on BPA through OSCT.

Contents

1. Introduction

Organizations are increasingly generating substantial amounts of data and in harmony with growing computational power and big data, new technologies as artificial intelligence (AI) and machine learning are widely deployed (Anthes, 2017; Duan, Edwards, & Dwivedi, 2019). In 2018, a survey among nearly sixty Fortune 1000, or sized-like, firms showed that 97.2% of executives are investing in AI and that the majority feel competitive pressure regarding these initiatives (Bean, 2018). Executives expect that AI has the potential to create a competitive advantage and has already been changing business models and value chains in many industries (Ransbotham, Gerbert, Reeves, Kiron, & Spira, 2018; Duan, Edwards, & Dwivedi, 2019). As today's global markets are changing with great momentum, organizations are forced to enhance their responsiveness to external and internal changes by establishing agile capabilities and processes. Organizational agility refers to a firm's ability to deal with unpredicted changes in the internal and external environment by changing resources (Helfat & Raubitschek, 2018; Van Oosterhout, Waarts, & Van Hillegersberg, 2006). According to Bazigos, De Smet, & Gagnon (2015), only 12 percent of 161 surveyed companies are considered to be agile and are outperforming less agile companies.

Information Technology (IT) enables a firm to be more agile by speeding up business processes, changing processes more quickly, and improving process innovation (Chen, et al., 2014). Preliminary research suggests that IT enables a process to be more agile (Chen, et al., 2014; Colson, 2019; Lou, Lou, & Hitt, 2019; Iansiti & Lakhani, 2020) and it can be improved by investing in new IT solutions (Lu & Ramamurthy, 2011). AI can be seen as such a new IT solution and it not only optimizes the speed of processes (Iansiti & Lakhani, 2020), but also improves innovation (Lou, Lou, & Hitt, 2019) and decision making (Colson, 2019). So, the agility of a process is expected to be enhanced by deploying AI. The agility of processes is referred to as Business Process Agility (BPA) – the capability of a process to easily and quickly alter its activities as a response to market changes (Chen, et al., 2014). However, not much research has been done yet on the relationship between AI usage, or AIU, (the extent to which an organization adopted and uses AI) and BPA. This research tries to add up to existing IT research by investigating the relationship between AIU and BPA.

Despite the broad interest in the field of AI research, little research addresses the use of big data and AI in supply chain risk management (SCRM) activities. Especially the use of AI to improve supply chain visibility lacks interest (Baryannis, Validi, Dani, & Antoniou, 2019). The majority of research in SCRM focusses on the exploitation of risk response and only deploys traditional analysis techniques in these practices. These techniques lack the capability of identifying the risk (Baryannis, Validi, Dani, & Antoniou, 2019). More sophisticated AI techniques such as big data analytics, machine learning, and network-based models are capable of both identifying the risk and responding to it. Some real-life cases exist where businesses deploy AI in their supply chain activities. For example, DHL uses a combination of blockchain technology and AI to track the distribution of pharmaceuticals to ensure secure medicine consumption (Daugherty, 2019).

Due to the high volatility of today's markets, firms are demanding solutions to mitigate risk (Chae, Olson, & Sheu, 2014) and gain transparency within the supply chain (Zhu, Song, Hazen, Lee, & Cegielski, 2018). This transparency can be referred to as Operational Supply Chain Transparency, or OSCT, (a firm's capability to coordinate with stakeholders to obtain visibility and traceability) and has a positive effect on agility (Dubey, et al., 2018b). This research tries to add upon existing literature by addressing the following research question: *What is the relationship between Artificial Intelligence Usage and Business Process Agility, and is that relationship mediated by Operational Supply Chain Transparency?*

The above-outlined research question will be investigated in the following sections. In the next section, prior literature will be reviewed to determine previously investigated relationships between AIU, BPA, and OSCT. Definitions, terminologies, and relationships will be covered which will serve as the foundation for the development of the hypotheses and the research model. The third section will cover the research methods used to test the hypotheses. The research design and the procedure of sampling and data collection will be discussed. Also, the measurements and corresponding reliabilities of the scales will be covered. Finally, the statistical procedure will be discussed. Section 4 presents the analysis, results, and hypothesis testing. A detailed presentation of the procedure and results to test the hypotheses will be provided. The fifth section will discuss the findings resulting from Section 4. Research limitations, practical recommendations, and future research suggestions will be discussed. Finally, Section 6 gives a brief conclusion about the research performed.

2. Literature Review and Hypothesis Development

2.1 Artificial Intelligence Usage

Designed by Alan Turing in 1950, and well-known in the field of AI, the Turing Test aimed to test whether a computer was able to talk like a human by letting a judge decide whether it was a human or a machine communicating (Turing, 1950). For a machine to pass the test, capabilities as natural language processing (NLP), knowledge representation and reasoning (KRR), machine learning (ML), computer vision, and robotics where needed (Russell & Norvig, 2010) – capabilities still present in current AI-practices (Anthes, 2017; Solomonoff, 1985). For example, chatbots, driven by NLP and KRR, have been deployed to automate customer service (Sheehan, Jin, & Gottlieb, 2020), General Electric uses machine learning in their predictive maintenance practices (Duan, Edwards, & Dwivedi, 2019), and car manufacturers are producing self-driving cars running on computer vision and robotics (Muthalagu, Bolimera, & Kalaichelvi, 2020).

The term artificial intelligence was firstly used at the Dartmouth Summer Research Project in 1956 (Solomonoff, 1985). Since then, the field of AI has known turbulent times in terms of interest and publications. So-called ‘AI winters’ resulted in times of silence, whereas ‘AI springs’ are known for uplifting periods (Baryannis, Validi, Dani, & Antoniou, 2019; Duan, Edwards, & Dwivedi, 2019).

No general definition of artificial intelligence exists yet. However, Russel and Norvig (2010) define four approaches to AI, which are constructed along two dimensions: ‘thinking versus acting’ and ‘rationality versus humanity.’ These two dimensions form four categories of AI definitions. Firstly, ‘thinking humanly’, where machines can think like humans and perform tasks as decision-making and problem-solving. Secondly, ‘acting humanly’, where machines can act like humans but do not exceed human intelligence. This is similar to a machine’s capability to learn from and be trained by new experiences and inputs to execute tasks humans can do as well (Duan, Edwards, & Dwivedi, 2019). Thirdly, ‘Thinking Rationally’, where machines can “think right” based on rationality. Rationality can be defined as the behavior of achieving the desired goal given the resources available and how well that behavior fits within the context it engages (Stanovich, 2016). And finally, ‘acting rationally’, where machines possess the capability to “act right” in a sense that it accomplishes its desired goals based on rationality. The definition of AI of ‘acting rationally’ will be used in the remainder of this study and builds upon the definition of Duan, Edwards, & Dwivedi (2019). It can be summarized as a machine's capability to learn from and be trained by new inputs and execute human tasks towards the achievement of the desired goal.

In recent years, AI research and applications have gained momentum as a result of advances in computational power and big data technologies (Anthes, 2017; Duan, Edwards, & Dwivedi, 2019). As earlier estimated by Moore's Law in 1965, component density on computer chips have been doubled every two years and other ingredients for the increase in computational power have shown similar growth (Denning & Lewis, 2017). These developments in technology enabled AI to evolve and have had an impact on many businesses already (Miller, 2018; Duan, Edwards, & Dwivedi, 2019). As earlier mentioned, this study refers to Artificial Intelligence Usage (AIU) as the extent to which organizations adopt and use AI.

2.2 Business Process Agility

According to Yang & Lui (2012), organizational agility positively affects a firm's performance by detecting unexpected changes, opportunities, and threats to reconfigure the deployment of resources and capabilities accordingly. It can be defined as the ability to deal with unpredicted changes by changing businesses and processes beyond pre-engineered flexibility (Van Oosterhout, Waarts, & Van Hillegersberg, 2006). Sambamurthy, Bharadwaj, & Grover (2003) suggest that agility consists of three interrelated capabilities that are all equally important for the achievement of agility. Firstly, a firm's ability to leverage customer insights to enable opportunity detection and market intelligence (known as customer agility). Secondly, a firm's ability to leverage resources and capabilities from partners (known as partnering agility). This can be achieved through corporate venturing, alliances, joint ventures, and acquisitions by generating pathways for learning beyond the firm's existing knowledge (Schildt, Maula, & Keil, 2005). Thirdly, a firm's ability to reconfigure business processes as a response to changing environmental conditions (known as operational agility).

The capability of operational agility (Sambamurthy, Bharadwaj, & Grover, 2003) is similar to BPA, which can be defined as the extent to which an organization is capable of altering its business processes to act upon internal and external changes (Chen, et al., 2014). Raschke (2010) identified four components that compose BPA: reconfigurability (the ability to deploy new capabilities to business processes), responsiveness (the ability to respond to changes promptly), employee adaptability (employees' ability to react upon changes), and process-centricity (management's ability to overview the process from end to end).

2.2.1 Artificial Intelligence Usage and Business Process Agility

IT enables a firm to detect and respond to market changes quickly (Chen, et al., 2014). However, Van Oosterhout, Waarts, & Van Hillegersberg (2006), identified several situations where agility is required but where firms find it difficult to be agile. They argue that IT can be both a disabler and an enabler of agility. IT can be a disabler because complex and rigid information systems are hard to reconfigure; it is both time and money consuming. On the other hand, agility can be enabled by easily reconfigurable IT systems.

IT capabilities can be divided into managerial and technical IT capabilities (Tallon, 2008). Managerial IT capabilities imply the management's establishment of a business and IT vision. Technical IT capabilities are concerned with the resources around the IT infrastructure and employee expertise. Both managerial and technical IT capabilities positively influence BPA. Besides, managerial IT capabilities indirectly influence BPA via technical IT capabilities, meaning managerial IT capabilities positively influence technical IT capabilities.

Facilitating BPA through IT can be done in three ways (Chen, et al., 2014). First, by speeding up business processes and decisions through an IT infrastructure that gives quick access to internal and external information. Secondly, IT capabilities facilitate flexible business processes by effectively replacing old with new processes, exchanging information with actors outside the firm's boundaries, and internal coordination between employees. Finally, IT enables business process innovation by automation and interchangeability of processes, creating opportunities for new processes to be deployed. AI, as a form of IT, allows firms to achieve this by improving the quality of routine decisions (Colson, 2019), enhancing a firm's innovation practices (Lou, Lou, & Hitt, 2019), optimizing processes (Ransbotham, Gerbert, Reeves, Kiron, & Spira, 2018), and increasing the speed of scalability of processes (Iansiti & Lakhani, 2020).

Sambamurthy, Bharadwaj, & Grover (2003) suggest that IT competence, consisting of the extent of IT investments and the quality of IT capabilities, will have a positive impact on agility and in turn firm performance. Investing in the enhancement of IT capabilities will improve business agility (Lu & Ramamurthy, 2011). These enhancements in IT capabilities, such as big data technologies, also showed a positive impact on market performance and operational performance (Gupta & George, 2016). As big data technologies enabled the evolvement of AI, this study predicts a positive relationship between AIU and BPA. Accordingly, the following hypothesis can be developed:

> **Hypothesis 1:** *Artificial Intelligence Usage (AIU) is positively related to Business Process Agility (BPA).*

2.3 Operational Supply Chain Transparency

Increased market volatility has gained interest in supply chain management (SCM) (Chae, Olson, & Sheu, 2014). Developments as rapid globalization and digitalization force firms to manage their supply chain activities in a way it mitigates risks associated with unpredictable threats (Baryannis, Validi, Dani, & Antoniou, 2019) and can be achieved by supply chain collaboration (Cao & Zhang, 2011). Collaboration within the supply chain can be viewed as the cooperation of two or more supply chain actors towards common goals. It consists of cooperating and sharing in terms of information, goals, decisions, incentives, resources, communication, and knowledge creation and has a positive effect on firm performance (Cao & Zhang, 2011). The sharing of information and collaboration between supply chain actors and stakeholders can also be referred to as supply chain transparency (Morgan, Richey Jr, & Ellinger, 2018).

Firms are demanding solutions for increasing the transparency within their supply chain to lower risks and improve coordination with supply chain partners (Zhu, Song, Hazen, Lee, & Cegielski, 2018). Supply chain transparency can be defined as the activity of reporting to and communicating with stakeholders to obtain traceability and visibility of historical and current activities for supply chain improvement (Morgan, Richey Jr, & Ellinger, 2018). Stakeholders are groups and individuals who influence or are influenced by a firm's activities, outcomes, mission, and vision (Volberda, et al., 2011, p. 23).

According to Morgan, Richey Jr, & Ellinger (2018), supply chain transparency can be achieved by obtaining visibility and traceability within the supply chain. Firstly, visibility is defined as a firm's access to information about the drivers of supply and demand. It can be seen as the outcome of sharing information about supply chain activities among supply chain actors. Visibility goes beyond the practices a firm is actively engaging in. Secondly, traceability is a system's ability to access the historical and current state of activities and it can be divided into three functions: status traceability (a systems ability to provide information about the current situation in terms of the environment and the process in a timely and accurate manner), performance traceability (a systems ability to provide information about progress), and goal traceability (the ability to indicate necessary actions to be taken regarding the achievement of a system's goals) (Cheng & Simmons, 1994). Operational Supply Chain Transparency (OSCT) is nearly similar and closely related to supply chain transparency, and can be defined as a firm's engagement in coordination with stakeholders to obtain both visibility and traceability of historical and current information within the whole supply chain (Zhu, Song, Hazen, Lee, & Cegielski, 2018).

2.3.1 Artificial Intelligence Usage and Operational Supply Chain Transparency

Analytics can affect supply chain performance (Trkman, Mccormack, de Oliveira, & Ladeira, 2010). More specifically, supply chain analytics (a firm's analytical capabilities to improve supply chain management (Zhu, Song, Hazen, Lee, & Cegielski, 2018)), enables a firm to leverage data to improve operational performance and have gained interest due to advantages in IT and big data. (Chae, Olson, & Sheu, 2014).

According to O'dwyer & Renner (2011), traditional analytics based on historical data of demand and supply are outpaced by the speed in which today's markets change. Only looking at what happened in the past does not provide a competitive advantage anymore. The new generation of analytics improves operational performance and better utilization of big data and IT capabilities increases the level of visibility in the supply chain (Chae, Olson, & Sheu, 2014). Traditional analytics are not adequate anymore to deal with the high market volatility firms are facing every day. Advanced supply chain analytics, such as big data and predictive analytics, provide firms with capabilities including, but not limited to, response to market changes, risk reduction, total cost visibility, supply chain flexibility, improved sales and operations planning, and goal alignment (O'dwyer & Renner, 2011).

Predictive analytics is the process of detecting patterns in data by using techniques as statistics, pattern recognition, machine learning, and AI, to gain meaningful insights. It has a positive impact on the environmental, social, and economic performance of a firm (Jeble, et al., 2018). According to Dubey, et al. (2018b), big data and predictive analytics have a positive impact on visibility and coordination within the supply chain. Besides, visibility mediates the relationship between big data and predictive analytics and coordination among supply chain actors, meaning that visibility has a positive impact on coordination.

Considering the above, AIU (as both an outcome and enabler of big data and predictive analytics) has a positive impact on OSCT. From which the following hypothesis can be developed:

Hypothesis 2: *Artificial Intelligence Usage (AIU) is positively related to Operational Supply Chain Transparency (OSCT).*

2.3.2 Business Process Agility and Operational Supply Chain Transparency

According to (Dubey, et al., 2018a), supply chain visibility (the ability to share information about units transiting the supply chain in a timely and efficient manner) has a positive effect on supply chain agility (the capability of the supply chain to quickly respond to changes). They argue that supply chain visibility is positively affected by supply chain connectivity and information sharing. Market-sensing, defined as the capability to continuously learn from and screen stakeholders, has a positive effect on supply chain agility (Aslam, Blome, Roscoe, & Azhar, 2018). Wei & Wang (2010) argue that supply chain visibility is positively related to supply chain reconfigurability, what they define as the ability to reconfigure resources in a timely and efficient manner to cope with changing environments.

The variables market-sensing and supply chain visibility are closely related to or similar to OSCT as it both state a firm’s capability to engage in coordination with stakeholders to obtain both visibility and traceability within the supply chain. Supply chain agility and reconfigurability are closely related to BPA as it is both concerned with the extent to which an organization is capable of altering its business resources (and thus processes) to act upon changes.

Sufficient research about the relationship between OSCT and BPA has not been done yet. However, considering the above, this study hypothesizes that OSCT has a positive impact on BPA. Therefore, the following hypothesis can be developed:

Hypothesis 3: *Operational Supply Chain Transparency (OSCT) is positively related to Business Process Agility (BPA).*

2.3.3 Operational Supply Chain Transparency as a Mediator

Brusset (2016) investigated the relationship between external collaborative capabilities, visibility, internal capabilities, and agility. External collaborative capabilities are defined as the tools supporting collaboration among supply chain actors, visibility capabilities are defined as the group of IT solutions that allows firms to coordinate through information systems, and internal capabilities refer to the processes that increase the responsiveness of a firm. They found that external collaborative capabilities and internal capabilities enhance agility and that visibility capabilities do not enhance agility.

This is in contradiction with the suggestion that visibility has a positive impact on agility (Dubey, et al., 2018a). The definition of visibility seems to be different in some of the studies mentioned earlier. While Brusset (2016) defines it as a set of IT tools to enhance coordination, others define it as a firm's ability to share information between stakeholders, whether it is through IT or more traditional pathways (Dubey, et al., 2018a; Morgan, Richey Jr, & Ellinger, 2018).

Now, as earlier mentioned, advanced analytics such as big data and predictive analytics, and thus so AI, have a positive impact on visibility (Dubey, et al., 2018b), and thus so OSCT. Also, visibility has proven to have a positive effect on agility (Dubey, et al., 2018a; Aslam, Blome, Roscoe, & Azhar, 2018; Wei & Wang, 2010), and thus so BPA. AIU is suggested to have a positive impact on OSCT and BPA by providing both visibility, traceability (Chae, Olson, & Sheu, 2014; O'dwyer & Renner, 2011). As a result, this study hypothesizes that OSCT mediates the relationship between AIU and BPA. Therefore, the following hypothesis can be developed:

Hypothesis 4: *OSCT mediates the relationship between AIU and BPA.*

Figure 1 shows the conceptual model as a result of the developed hypotheses. AIU is expected to be positively related to BPA. OSCT is expected to mediate the relationship between AIU and OSCT.

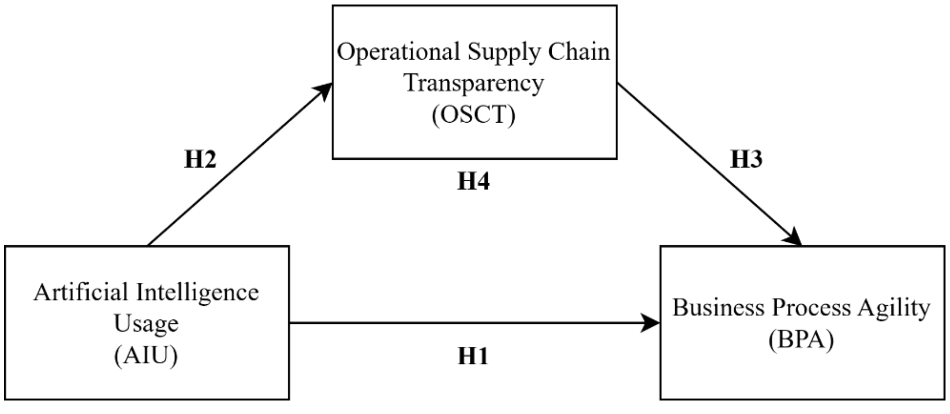

Figure 1. *Conceptual Model. Control variables: Industry, Firm Size, and Previous AI Experience*

3. Methodology

3.1 Research Design

Prior literature has been reviewed to develop hypotheses that have been tested, indicating a deductive approach of reasoning (Trochim, Donnelly, & Arora, 2016, p. 22). This study has been conducted using a cross-sectional design as the observations of the respondents are taken at a single point in time (Trochim, Donnelly, & Arora, 2016, p. 14). This design is considered best suitable for this study due to the time restrictions related to the completion of this thesis. The quantitative approach of this study is based upon the methods used by prior studies reviewed in Section 2, where the majority of studies used a quantitative approach. The data has been gathered using an online survey distributed among managers experienced in either artificial intelligence, business intelligence, supply chain intelligence, supply chain insights, supply chain analytics (or combination of these) working in organizations located in Europe (including the UK).

3.2 Sampling and Data Collection

The sample has been drawn from a population of managers experienced in artificial intelligence, business intelligence, supply chain intelligence, supply chain insights, and/or supply chain analytics working in organizations in Europe. Respondents were searched by using a combination of LinkedIn and RocketReach (a software providing access to email addresses of experts by mining contact information available on the Internet (RocketReach, n.d.)). Sampling has been done using expert sampling, which involves the assembly of a sample of persons with specific knowledge or expertise in the field of interest (Trochim, Donnelly, & Arora, 2016, p. 88).

Multiple queries were executed on LinkedIn. Each query has been done in all European countries and all results were using RocketReach to retrieve the corresponding email addresses. The following job-title queries have been executed in each European country (including the UK): ‘Artificial Intelligence Manager’, ‘Business Intelligence Manager’, ‘Supply Chain Analytics Manager’, ‘Supply Chain Insights’, ‘Supply Chain Intelligence Manager.’ This resulted in a total of 1510 verified email addresses. An invitation to all these email addresses has been sent. For the following four weeks, every week a reminder to participate has been sent. Once the respondents started the survey, two questions were asked to check whether they were eligible for completing the survey. This all resulted in 109 includible respondents, corresponding to a 7.22% response rate.

Among the respondents, the most common industries are ‘Other’ with 28 (25.7%) responses, ‘Computer / Software’ with 26 responses (23.9%), and ‘Services’ with 18 (16.5%) responses. 55% (60) of the organizations has more than 5000 employees and 14.7% (16) less than 100. Regarding previous AI experience, 62 (56.9%) organizations have been investing in AI for less than 3 years, 29 (26.6%) between the 2 and 6 years, and 18 (16.5%) for more than 6 years. After collection, data transformation and cleaning had to be done to establish the sample. This will be covered in Section 4.1.

3.3 Measurements

All main variables (AIU, OSCT, and BPA) were measured based on prior literature. The measures and constructs deployed can be found in Appendix A. The variables were measured and rated as follows:

Artificial Intelligence Usage. AIU is measured on a 5-point Likert scale, ranging from 1 = *no usage* to 5 = *extreme usage.* Chen, Preston, & Swink (2015) used an extension of the technological-environmental-organizational (TOE) framework to investigate the technological, organizational, and environmental driving factors of big data analytics usage. This study deploys the scale they used to measure big data analytics usage and translates it to Artificial Intelligence Usage. Respondents were asked to indicate the extent of AI implementation in areas such as, ‘Sourcing analysis’ and ‘Logistics improvements.’ Excellent reliability of the 10-item scale is indicated by a Cronbach’s Alpha of 0.917.

Operational Supply Chain Transparency. OSCT is measured on a 5-point Likert scale, ranging from 1 = *strongly disagree* to 5 = *strongly agree.* The 8 items measured were based on the scale proposed by Zhu, Song, Hazen, Lee, & Cegielski (2018). Excellent reliability of the scale is indicated by a Cronbach’s Alpha of 0.905.

Business Process Agility. BPA is measured on a 5-point Likert scale, ranging from 1 = *strongly disagree* to 5 = *strongly agree.* The 8 items measured were based on the scale proposed by Chen, et al. (2014) and Tallon (2008). Acceptable reliability of the scale is indicated by a Cronbach’s Alpha of 0.761.

The control variables in this study are Industry (the industry in which the organization operates), Firm Size (the size of the organization in terms of employees), and Previous AI Experience (how many years the organization has been investing in AI).

3.4 Statistical Procedure

All data analyses and transformations within this study are performed using IBM SPSS (Version 25). Before testing the hypotheses, data had to be cleaned and assumptions had to be tested. The research model shown in Figure 1 can be tested through three linear regression models (Field, 2018, p. 499). However, adding the control variables to the analysis results in a total of four linear models to be performed. The model containing only control variables (*Firm Size, Previous AI Experience,* and *Industry*) is referred to as model 1 and is added to the analysis to test for any spurious results. Model 2 predicts the outcome variable BPA from the predictor variable AIU (Hypothesis 1). Model 3 predicts the mediating variable OSCT from the predictor variable AIU (Hypothesis 2). Finally, model 4 predicts the outcome variable BPA from both AIU and OSCT. This corresponds to both Hypothesis 3 (the relationship between OSCT and BPA) and Hypothesis 4 (the mediating effect of OSCT on the relationship between AIU and BPA). After running the four linear models, the developed hypotheses can be tested. Model 2 will test for Hypothesis 1, model 3 for Hypothesis 2, and model 4 for Hypothesis 3. Hypothesis 4 will be tested by comparing the results from model 2 and 4. This will be done by using the PROCESS macro Model 4 of Hayes (2018). This tool is considered to be suitable to perform mediation analysis (Field, 2018, p. 483).

4. Results

4.1 Data Preparation and Descriptives

Data had to be cleaned to run the analysis. Responses from duplicate companies (5 in total) and respondents who replied after completing the survey about insufficient expertise in either SCM or AI (3 in total) were removed from the sample. Respondents with a short duration (less than 5 minutes) for completing the survey were excluded from the sample. After these corrections, a sample size of 95 has been established on which analysis will be performed. The sample attributes are shown in Table 1.

Table 1. *Sample Descriptives* [a]

Variable	Frequency	Percentage	Cumulative Percentage
Firm Size			
Less than 100	15	15.8	21.1
100 to 249	5	5.3	33.7
250 to 499	4	4.2	41.1
500 to 999	8	8.4	45.3
1000 to 2499	7	7.4	64.2
2500 to 4999	5	5.3	73.7
More than 5000	51	53.7	100
Industry			
Computer / Service	20	21.1	21.1
Manufacturing	12	12.6	33.7
Finance, Insurance, Real Estate	7	7.4	41.1
Services	18	18.9	45.3
Healthcare	9	9.5	73.7
Other	25	26.3	100
Previous AI experience			
Less than 3 years	54	56.8	56.8
2-6 years	27	28.4	85.3
More than 6 years	14	14.7	100

[a] $N = 95$

After the determination of the sample, new variables have been calculated. Table 2 provides an overview of the means, standard deviations, and correlations of all three main and control variables. Noteworthy are the correlations between the main variables, which all show significant ($p < 0.01$) positive correlations. Suggesting a positive relationship between them. However, these positive correlations are considered to be weak as they are all closer to

0 than to 1 (Keller, 2018, p. 112). Furthermore, a significant ($p < 0.01$) positive correlation between Firm Size and AIU is shown. Also, Previous AI Experience seems to be significantly ($p < 0.01$) positively correlated to both AIU and BPA. Again, the Cronbach's Alphas are computed to test the reliability of the scales (see Table 2).

Table 2. *Means, Standard Deviations, and Correlations*

Variables	*M*	*SD*	1.	2.	3.	4.	5.	6.
1. Firm Size [a]	5.1684	2.34136						
2. Industry [b]	4.2105	2.32880	.175					
3. Previous AI experience [c]	1.5789	.73772	.257*	-.177				
4. Artificial Intelligence Usage	2.1505	.87784	.328**	-.197	.404**	(.902)		
5. Business Process Agility	3.4474	.66734	.147	-.154	.319**	.358**	(.760)	
6. Operational Supply Chain Transparency	2.8987	.75382	.159	-.033	.131	.449**	.355**	(.906)

Notes. $N = 95$. Cronbach's Alphas presented in parentheses on the diagonal. [a] Firm Size is coded as 1 = Less than 100, 2 = 100 to 249, 3 = 250 to 499, 4 = 500 to 999, 5 = 1000 to 2499, 6 = 2500 to 4999, 7 = More than 5000. [b] Industry is coded as 1 = Computer / Service, 2 = Manufacturing, 3 = Finance, Insurance, Real Estate, 4 = Services, 5 = Healthcare, 6 = Other. [c] Previous AI experience is codes as 1 = Less than 3 years, 2 = 2-6 years, 3 = 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)

4.2 Assumptions Testing

To run the analysis for testing the hypothesis, some assumptions have to be made and tested. Assumptions are conditions that ensure the justification of the analysis and tests performed (Field, 2018, p. 229). To perform linear regression, linearity, normally distributed residuals, independence of residuals, homoscedasticity, no influential outliers, and no multicollinearity must be present. Appendix B provides all test results regarding the following assumptions:

Linearity. The relationship between AIU and BPA is considered to be linear, shown by the scatterplot in Appendix B1.

Normally Distributed Residuals. The residuals of the outcome variable are considered to be normally distributed as the Shapiro-Wilk and Kolmogorov-Smirnov tests are both not significant ($p > 0.05$). Besides, the P-P plot shows normality (See Appendix B2).

*Independence of Residuals***.** The independence of residuals has been tested by the Durbin-Watson test, which tests the correlations between residuals. The test showed a value of 1.633. It can be assumed that the residuals are independent when the value falls within the proposed interval of 1 to 3 (Field, 2018, p. 387). See Appendix B3.

*Homoscedasticity***.** The assumption of homoscedasticity is met, as the scatterplot in Appendix B4 shows a rectangular shape.

No Influential Outliers. Testing for influential outliers is done by calculating 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). Cases with a Cook's distance greater than 1 are considered to be an influential outlier. The highest value observed is 0.096 (See Appendix B5).

Multicollinearity. Multicollinearity has been tested using the variance inflation factor (VIF). The VIF between the predictor variables and the outcome variable is 1.252 and shows no multicollinearity (Field, 2018, pp. 401-402). See Appendix B6.

4.3 Hypothesis Testing

For the control variable 'Industry' to be included in the regression analysis, it must be dummy coded first. As the item 'Other' represents the majority (Table 1) of the cases it serves as the baseline group.

Linear regression analysis (model 2) will be performed to test Hypothesis 1 (recall, a positive relationship between AIU and BPA). Model 1 includes only control variables and in model 2 AIU is added. As shown in Table 3, model 1 indicates a significant ($p < 0.05$) impact of Previous AI Experience on BPA. The other control variables show no significant impact on BPA ($p > 0.05$). Model 2 shows an R^2 of 0.211, indicating 21.1% of the variance in BPA is explained by both control variables and AIU, meaning 78.9% is explained by predictors outside model 2 (Appendix C1, Table G). Moreover, including AIU into the model increases the explained variance (R^2) with 0.041, indicating a significantly ($p < 0.05$) more explained variance of 0.211 (or 21.1%) as the increase in the F-statistic of 4.454 is significant with a p-value of 0.038. Model 2 (Appendix C1, Table H) shows that the linear model significantly predicts BPA ($F(9, 85) = 2.527, p < 0.05$). The unstandardized coefficient b-value of AIU in model 2 is 0.180 and significant ($t = 2.111, p < 0.05$). The b-value of 0.180 indicates a positive relationship between AIU and BPA; when AIU increases with one unit, BPA increased with 0.180 units. Therefore, Hypothesis 1 found support.

Table 3. *Coefficients* [a]

Model		Unstandardized Coefficients *B*	*Std. Error*	Standardized Coefficients *Beta*	*t*	*Sig.*
1	(Constant)	2.879	.225		12.779	.000
	Firm Size	.032	.031	.111	1.033	.305
	Previous AI Experience	.213	.096	.235	2.209	.030
	Industry: Computer, Software	.289	.203	.177	1.423	.158
	Industry: Manufacturing	-.007	.224	-.004	-.032	.975
	Industry: Finance, Insurance, Real Estate	-.117	.276	-.046	-.426	.672
	Industry: Retail, Wholesale	.167	.343	.051	.488	.627
	Industry: Services	.198	.198	.117	1.002	.319
	Industry: Healthcare	-.283	.248	-.125	-1.141	.257
2	(Constant)	2.717	.234		11.621	.000
	Firm Size	.013	.031	.046	.421	.674
	Previous AI Experience	.151	.099	.167	1.527	.130
	Industry: Computer, Software	.207	.203	.127	1.020	.311
	Industry: Manufacturing	-.079	.222	-.039	-.354	.724
	Industry: Finance, Insurance, Real Estate	-.105	.271	-.041	-.389	.698
	Industry: Retail, Wholesale	.122	.337	.037	.362	.719
	Industry: Services	.165	.195	.097	.846	.400
	Industry: Healthcare	-.277	.243	-.122	-1.139	.258
	Artificial Intelligence Usage	.180	.085	.237	2.111	.038
4	(Constant)	2.108	.305		6.903	.000
	Firm Size	.013	.030	.046	.440	.661
	Previous AI Experience	.161	.095	.178	1.700	.093
	Industry: Computer, Software	.289	.196	.177	1.472	.145
	Industry: Manufacturing	-.043	.213	-.021	-.201	.841
	Industry: Finance, Insurance, Real Estate	-.202	.261	-.079	-.773	.442
	Industry: Retail, Wholesale	.105	.323	.032	.327	.745
	Industry: Services	.271	.190	.160	1.427	.157
	Industry: Healthcare	-.210	.234	-.093	-.897	.372
	Artificial Intelligence Usage	.058	.092	.076	.632	.529
	Operational Supply Chain Transparency	.281	.096	.318	2.934	.004

[a] Dependent Variable: Business Process Agility

To test Hypothesis 2 (recall, a positive relationship between AIU and OSCT) linear regression is performed. Model 3 (Appendix C2, Table I) shows a significant ($p < 0.001$) increase in R^2 of 0.188 with an F-statistic change of 22.043 resulting in an R^2 of 0.197, indicating that 19.7% of the variance in OSCT is explained by both control variables and AIU. Besides, model 3 (Appendix C2, Table J) shows that the linear model significantly predicts OSCT ($F(9, 85) = 3.563, p < 0.01$). The unstandardized coefficient of AIU shows a b-value of 0.435 (Appendix C2, Table K) and is significant ($t = 4.695, p < 0.001$). It indicates a positive relationship between AIU and OSCT; when AIU increases with one unit, OSCT increases with 0.435 units. Therefore, Hypothesis 2 is supported.

The model summary (Appendix C1, Table G) of model 4 to test Hypothesis 3 (OSCT is positively related to BPA) shows that the explained variance (R^2) increased with 0.073, indicating more explained variance when OSCT is included in the model. The increase in the

F-statistic of 8.609 is considered to be significant with a p-value of 0.004 (p < 0.01). Including all control variables, AIU, and OSCT in the model explains 28.4% ($R^2 = 0.284$) of the variance in BPA. In addition, linear model 4 (Appendix C1, Table H) significantly predicts BPA ($F(10, 84) = 3.338, p < 0.01$). Moreover, the b-value of OSCT (Table 3, model 4) is 0.281 and is significant ($t = 2.934, p < 0.01$). So, when OSCT increases with one unit, BPA increases with 0.281 units. Therefore, OSCT is positively related to BPA, supporting Hypothesis 3.

To test whether OSCT mediates the relationship between AIU and BPA (Hypothesis 4), the PROCESS macro Model 4 form Hayes (2018) is used. Mediation is considered to be present when the strength of the relationship between the predictor variable (AIU) and the outcome variable (BPA) is reduced when the mediator (OSCT) is included in the model (Field, 2018, p. 497). Without OSCT included in the model, the b-value between AIU and BPA is 0.180 ($p < 0.05$). Including OSCT into the model changes the b-value between AIU and BPA (model 4 in Table 3) to 0.058. Moreover, this b-value is not significant ($t = 0.632, p > 0.05$), which is a condition to hold – if the predictor variable (AIU) predicts the outcome variable (BPA) less strongly when the mediator is added to the model, mediation is present (Field, 2018, p. 499).

To test whether OSCT significantly mediates the relationship between AIU and BPA, the PROCESS (Appendix C3, Table N) tool has been deployed and found that there is a significant indirect effect of AIU on BPA through OSCT, $b = 0.122$ BCa CI $[0.039, 0.267]$. And because $b = 0$ would indicate no effect, a confidence interval without containing zero supports a significant indirect effect (Field, 2018, p. 505). Therefore, Hypothesis 4 is supported.

The research model with the corresponding tests is presented in Figure 2. Note that the direct effect is not supported (ns.) when OSCT is included in the model, indicating a mediating effect.

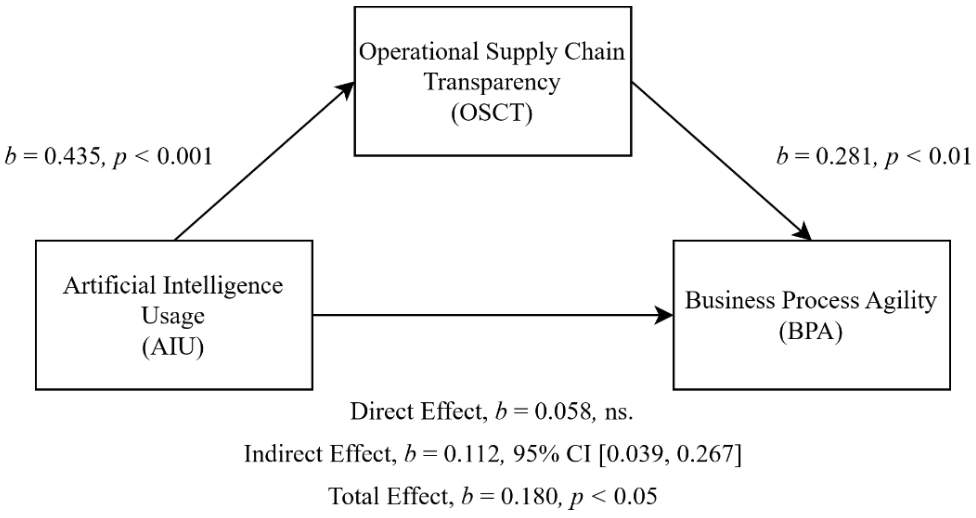

Figure 2. *Model of AIU as a predictor variable of BPA, mediated by OSCT. The confidence interval (CI) for the indirect effect is a BCa bootstrapped CI based on 5000 samples.*

5. Discussion

5.1 Findings

This study examined the relationship between Artificial Intelligence Usage and Business Process Agility. Besides, it tried to investigate whether Operational Supply Chain Transparency mediates that relationship. The corresponding research question investigated sounds as follows: *"What is the relationship between Artificial Intelligence Usage and Business Process Agility, and is that relationship mediated by Operational Supply Chain Transparency?"* The investigation was done by testing four hypotheses.

Firstly, Hypothesis 1 tested whether there is a positive relationship between AIU and BPA. The results in Section 4 have shown that there is a significant positive relationship between AIU and BPA, supporting Hypothesis 1. Due to the significance of the relationship, it can be concluded that a positive relationship between AIU and BPA exists.

Secondly, Hypothesis 2 tested whether a positive between AIU and OSCT exists. The results showed that there is a significant positive relationship between the predictor variable AIU and the mediating variable OSCT, supporting Hypothesis 2. It can be concluded that a positive relationship between AIU and OSCT exists.

Thirdly, Hypothesis 3 was tested by linear regression analysis as well. A significant relationship between the mediating variable OSCT and the outcome variable BPA is suggested to be significantly positive. Support for Hypothesis 3 was found and thus a positive relationship between OSCT and BPA exists.

Finally, Hypothesis 4 was tested to investigate whether the relationship between the predictor variable AIU and outcome variable BPA is mediated by the mediating variable OSCT. The results showed that the relationship between AIU and BPA was weakened when OSCT was included in the regression analysis, indicating an indirect effect of OSCT. Besides, the indirect effect is considered to be significant, and thus so it can be concluded that the relationship between AIU and BPA is mediated by OSCT.

5.2 Literature Contribution

In coherence with Chen, et al. (2014), who suggest than IT is an enabler of BPA, this study found support for a positive relationship between AIU (as a form of IT) and BPA. However, as Chen, et al. (2014) did not suggest nor investigated AI as an enabler of BPA.

Therefore, this study builds upon their suggestion. This is also in line with a study done by Lu & Ramamurthy (2011), who suggest that investing in IT capabilities improves a firm's agility. Because AIU can be seen as a possible outcome of investments in IT capabilities, this study supports that suggestion made. In contradiction with the suggestion of Van Oosterhout, Waarts, & Van Hillegersberg (2006) that IT is both an enabler and disabler of agility, this study only found that AI (as a form of IT) is an enabler of agility. IT systems can be rigid and complex which makes it difficult to reconfigure the system to be more agile. However, AI provides solutions in which it speeds up the scalability of processes (Iansiti & Lakhani, 2020) and allows manufacturing systems to be more agile (Cheng, Harrison, & Pan, 1998). This may result in the finding of a positive relationship between AIU and BPA.

Prior literature suggested that better utilization of big data and IT capabilities increase the level of visibility within the supply chain (Chae, Olson, & Sheu, 2014). In addition to IT capabilities, big data and predictive analytics have a positive impact on coordination within the supply chain as well (Dubey, et al., 2018b). In this study, AI is considered as either a successor, extension, or form of IT as it has gained momentum due to big data technologies (Anthes, 2017). And because visibility is considered to be a part of OSCT, it can be argued that it builds upon the reviewed literature in two ways: (1) just as IT capabilities, AI enhances visibility as well, and (2) OSCT, just as visibility, can be enhanced by IT capabilities or AIU.

The findings in this study conclude that OSCT has a positive relation with BPA. This is coherence with the findings of Dubey, et al. (2018a) who suggest that supply chain visibility has a positive impact on supply chain agility. Despite the difference in constructs, it still adds upon their findings as supply chain visibility is a part of OSCT, and supply chain agility is closely related to BPA.

Finally, this study concludes that the relationship between AIU and BPA is mediated by OSCT. This means that AIU enhances OSCT which in turn enhances BPA. It connects all three previously described contributions to preliminary literature: AIU (as a form of IT) enhances OSCT (as a construct of visibility) and in turn enhances BPA. BPA, as the outcome variable, was suggested to be enhanced by IT (2014) and visibility (Dubey, et al., 2018a; Wei & Wang, 2010). In this study, AIU does that as well.

5.3 Limitations

Unless support was found for all hypotheses, this research has some limitations.

First, due to time restrictions of this thesis-project, no extensive nor widespread data collection procedure could be deployed. The cross-sectional design has only given a snapshot of the respondents and might cause distortion. Besides, a cross-sectional design does not allow for cause and effect conclusions to be made. For example, it might have been useful to investigate AIU as a cause of BPA or OSCT: when a firm has a high extent of AIU, it excels in BPA.

Second, a sample size of 95 can be considered small regarding the population investigated. This study targeted 1510 respondents of which only 95 where included in the sample. Besides, LinkedIn does not ensure that the whole population could be targeted. It is likely to occur that a substantial share of the population does not use LinkedIn. Targeting more managers outside the boundaries of European countries could have resulted in a larger sample.

Finally, the construct of AIU has not yet been deployed. It was based upon the construct used by Chen, Preston, & Swink (2015) in which they investigate the construct of Big Data Analytics usage. This study directly translated all items in their construct where 'Big data analytics usage' was mentioned in 'Artificial Intelligence Usage.' No review of this method has been performed and therefore might cause unreliable results. Nevertheless, the reliability showed sufficiency with a Cronbach's Alpha of 0.902.

5.4 Practical Recommendations

Top management support is an important factor regarding the adoption of new IT solutions. When top management has positive beliefs about a new IT solution, it is more likely for that solution to be implemented (Liang, Saraf, Hu, & Xue, 2007). Therefore, as this study showed a positive relationship between the extent of AIU, BPA, and OSCT, this research may contribute to the positive beliefs of top management regarding AI. Because the minority of organizations is considered to be agile (Bazigos, De Smet, & Gagnon, 2015), they must try to implement solutions that enhance agility. IT has already proved to be an enhancer of agility, but today's technological innovation is moving fast, and traditional analytics are outpaced by AI and machine learning (O'dwyer & Renner, 2011).

Tabrizi, Lam, Girard, & Irvin (2019) suggest that digital transformation is not about the technical solution but it is rather a strategic dilemma. They suggest that it is important to figure out the business strategy for the solution before investing in it. As this study suggests that AI enables OSCT and BPA, it could be beneficial for managers to align their strategy with the possible outcomes of AI. For example, one could have a strategy to quickly fulfill customers' personal needs by offering customizable products in a timely and efficient manner. AI then enables a firm to predict certain threats within its processes or supply chain which makes it possible to respond and alter its processes so it can still deliver the customizable product on time. Here, AI is the solution, BPA or OSCT an outcome of that solution, and offering customizable products on time the strategy. Top management should focus on strategy and consider AI as a supportive tool for that strategy.

5.5 Future Research

This study recommends future research to deploy and investigate the reliability and validity of the construct of AIU used in this study. By deploying the construct including the predictor variable AIU, many outcome variables could be investigated concerning it. As by now, not much research has been done regarding the implementation of AI in supply chain management.

As AI has not yet been widely deployed, it might be difficult to measure the skills and knowledge regarding this topic. However, this research measured the extent to which an organization deploys AI, not the skills needed to successfully deploy it. Future research should, therefore, examine the drivers of AIU; it should identify the bottlenecks associated with implementing AI into a firm's supply chain activities. Again, this demands a more strategic lens, rather than a technical one. Examining the drivers of AIU is beyond the scope of this research and therefore serves as a direction for future research.

6. Conclusion

Previous research has found that IT has a positive impact on both agility and supply chain visibility. This study examined the relationship between Artificial Intelligence Usage (as a form of IT) and Business Process Agility (as a form of agility), and whether Operation Supply Chain Transparency (as a form of supply chain visibility) mediates that relationship. Support was found for all hypotheses. It can be concluded that Artificial Intelligence Usage is positively related to Business Process Agility and that Operational Supply Chain Transparency mediates the relationship. To summarize, AI can be an enabler of agility and supply chain transparency. Despite the yet untapped potential of AI, this study proposes a suggestion that AI enables business process agility through operational supply chain transparency.

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Appendices

Appendix A – Measures

Table D. *Constructs of Main Variables*

Construct	
Artificial Intelligence Usage, Chen, Preston, & Swink (2015)	To what extent has your organization implemented Artificial Intelligence in each area?
	(1 = no usage … 3 = medium usage … 5 = extreme usage)
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
Business Process Agility, (Chen, et al., 2014)	To what extent do you agree that your firm can easily and quickly perform the following business actions?
	(1 = strongly disagree … 3 = neither agree nor disagree … 5 = strongly agree)
BPA1:	Respond to changes in aggregate consumer demand
BPA2:	Customize a product or service to suit an individual customer
BPA3:	React to new product or service launches by competitors
BPA4:	Introduce new pricing schedules in response to changes in competitors' prices
BPA5:	Expand into new regional or international markets
BPA6:	Change (i.e., expand or reduce) the variety of products / services available for sale
BPA7:	Adopt new technologies to produce better, faster, and cheaper products and services
BPA8:	Switch suppliers to avail of lower costs, better quality, or improved delivery times
Operational Supply Chain Transparency, (Zhu, Song, Hazen, Lee, & Cegielski, 2018)	To what extent do you agree with the following statements?
	(1 = strongly disagree … 3 = neither agree nor disagree … 5 = strongly agree)
OSCT1:	OSCT1: Our suppliers provide us with operational plans (e.g. distribution plans, production plans) regarding the products they produce for us
OSCT2:	OSCT2: Our major suppliers provide us with detailed product design information
OSCT3:	OSCT3: Our major suppliers collect operations information (e.g.: batch size, run quality, transfer quality, buffer stock, available machines, machine breakdown time)
OSCT4:	OSCT4: Our major suppliers share their operations information with us
OSCT5:	OSCT5: Our major suppliers collect planning and design information (e.g.: current planning and design performance, operations performance, resource utilization, rework and scrap level, level of work progress)
OSCT6:	OSCT6: Our major suppliers share their planning and design information with us
OSCT7:	OSCT7: Our major suppliers collect strategic information (e.g.: new orders, product demand, internal and external expertise, teachability, culture, government regulations)
OSCT8:	OSCT8: Our major suppliers share their strategic information with us

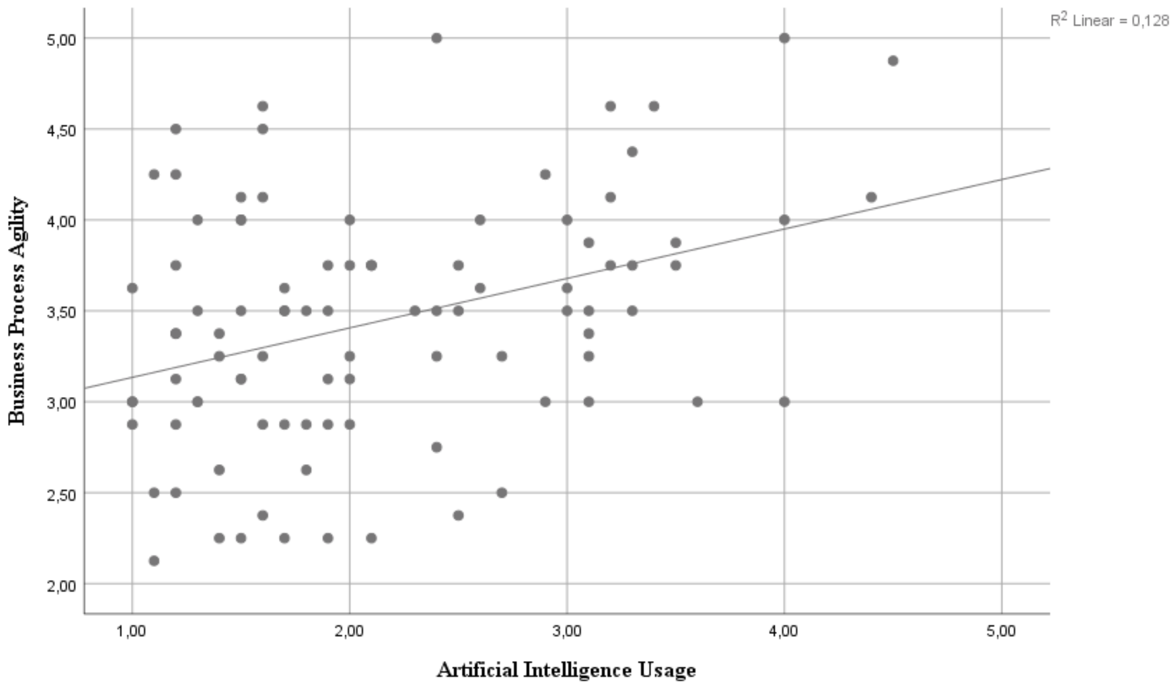
Table E. *Constructs of Control Variables*

Control variables	
Firm Size	How many employees does the firm count? Less than 100 100 to 249 250 to 499 500 to 999 1000 to 2499 2500 to 4999 More than 5000
Industry	What industry does the firm operate in? Less than 100 100 to 249 250 to 499 500 to 999 1000 to 2499 2500 to 4999 More than 5000
Previous AI Experience	For how many years has your firm been investing in Artificial Intelligence? Less than 3 years 3-6 years More than 6 years

Appendix B – Assumptions Testing

Appendix B1 – Linearity

Figure C. *Scatterplot with Line of Fit*



Appendix B2 – Normally Distributed Residuals

Figure D. *Normal P-P Plot of Regression Standardized Residual*

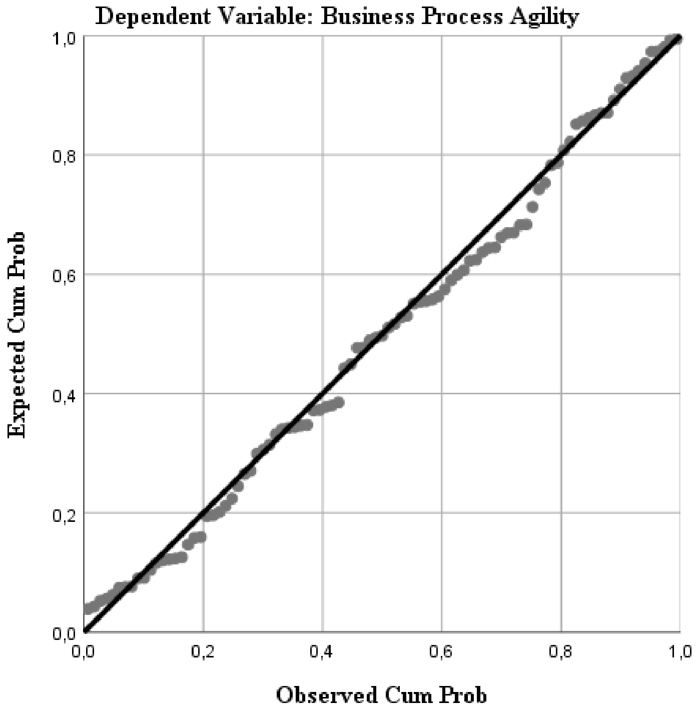


Table F. *Tests of Normality*

	Kolmogorov-Smirnov [a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig
Unstandardized Residual	.062	95	.200 *	.980	95	.149
Standardized Residual	.062	95	.200 *	.980	95	.149

* This is a lower bound of the true significance.
[a] Lilliefors Significance Correction

Appendix B3 – Independence of Residuals

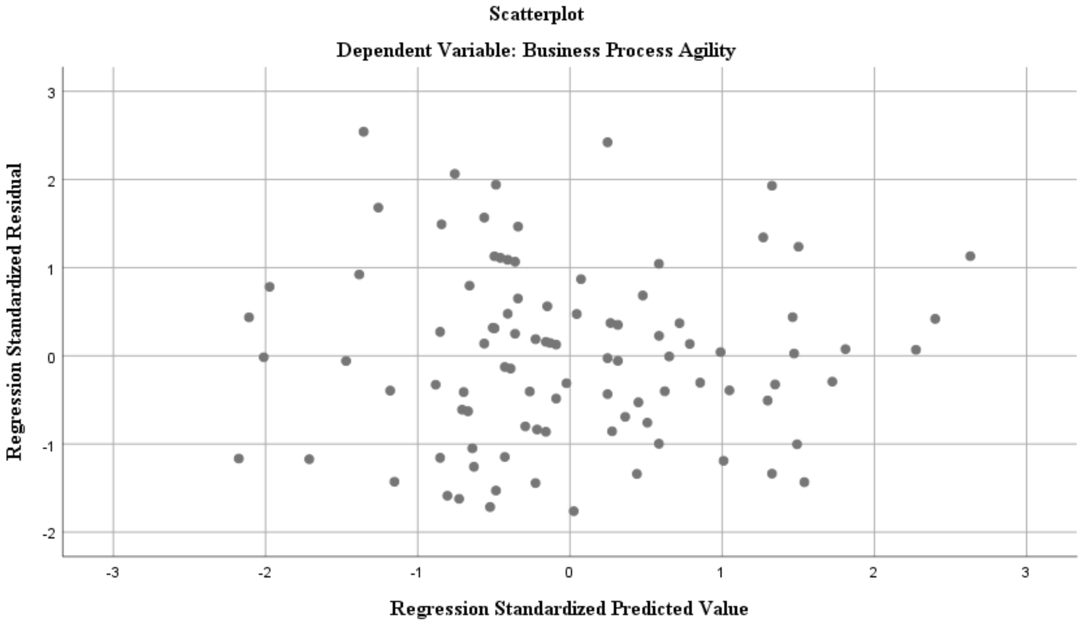
Table G. *Model Summary* [b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.419 [a]	.176	.158	.61248	1.633

[a]. Predictors: (Constant), Operational Supply Chain Transparency, Artificial Intelligence Usage
[b]. Dependent Variable: Business Process Agility

Appendix B4 – Homoscedasticity

Figure E. *Scatterplot of Standardized Residual and Standardized Predicted Variable*



Appendix B5 – No Influential Outliers

Table H. *Residuals Statistics* [a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.8389	4.1829	3.4474	.27963	95
Std. Predicted Value	-2.176	2.630	.000	1.000	95
Standard Error of Predicted Value	.064	.187	.104	.033	95
Adjusted Predicted Value	2.8351	4.1132	3.4466	.27888	95
Residual	-1.07923	1.55671	.00000	.60593	95
Std. Residual	-1.762	2.542	.000	.989	95
Stud. Residual	-1.776	2.596	.001	1.005	95
Deleted Residual	-1.09691	1.62347	.00078	.62579	95
Stud. Deleted Residual	-1.798	2.681	.003	1.015	95
Mahal. Distance	.035	7.775	.979	1.973	95
Cook's Distance	.000	.096	.011	.017	95
Centered Leverage Value	.000	.083	.021	.021	95

[a] Dependent Variable: Business Process Agility

Appendix B6 – Multicollinearity

Table I. *Coefficients* [a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.415	.256		9.431	.000		
	Artificial Intelligence Usage	.189	.081	.248	2.345	.021	.799	1.252
	Operational Supply Chain Transparency	.216	.094	.244	2.304	.023	.799	1.252

[a] Dependent Variable: Business Process Agility

Appendix C – Hypothesis Testing

Appendix C1 – Linear Regression Model 2 and 4

Table J. *Model Summary of Linear Regression* [d]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.412 [a]	.170	.092	.63573	.170	2.197	8	86	.035
2	.459 [b]	.211	.128	.62334	.041	4.454	1	85	.038
4	.533 [c]	.284	.199	.59718	.073	8.609	1	84	.004

[a] Predictors: (Constant), Industry: Computer, Software, Industry: Manufacturing, Industry: Finance, Insurance, Real Estate, Industry: Retail Wholesale, Industry: Services, Industry: Healthcare, Firm Size, Previous AI Experience
[b] Predictors: (Constant), Industry: Computer, Software, Industry: Manufacturing, Industry: Finance, Insurance, Real Estate, Industry: Retail Wholesale, Industry: Services, Industry: Healthcare, Firm Size, Previous AI Experience, Artificial Intelligence Usage
[c] Predictors: (Constant), Industry: Computer, Software, Industry: Manufacturing, Industry: Finance, Insurance, Real Estate, Industry: Retail Wholesale, Industry: Services, Industry: Healthcare, Firm Size, Previous AI Experience, Artificial Intelligence Usage, Operational Supply Chain Transparency
[d] Dependent Variable: Business Process Agility

Table K. *ANOVA* [a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.105	8	.888	2.197	.035 [b]
	Residual	34.757	86	.404		
	Total	41.862	94			
2	Regression	8.835	9	.982	2.527	.013 [c]
	Residual	33.026	85	.389		
	Total	41.862	94			
4	Regression	11.906	10	1.191	3.338	.001 [d]
	Residual	29.956	84	.357		
	Total	41.862	94			

[a] Dependent Variable: Business Process Agility
[b] Predictors: (Constant), Industry: Computer, Software, Industry: Manufacturing, Industry: Finance, Insurance, Real Estate, Industry: Retail Wholesale, Industry: Services, Industry: Healthcare, Firm Size, Previous AI Experience
[c] Predictors: (Constant), Industry: Computer, Software, Industry: Manufacturing, Industry: Finance, Insurance, Real Estate, Industry: Retail Wholesale, Industry: Services, Industry: Healthcare, Firm Size, Previous AI Experience, Artificial Intelligence Usage
[d] Predictors: (Constant), Industry: Computer, Software, Industry: Manufacturing, Industry: Finance, Insurance, Real Estate, Industry: Retail Wholesale, Industry: Services, Industry: Healthcare, Firm Size, Previous AI Experience, Artificial Intelligence Usage, Operational Supply Chain Transparency

Appendix C2 – Linear Regression Model 3

Table L. *Model Summary of Linear Regression* [c]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.293 [a]	.086	.001	.75361	.086	1.007	8	86	.437
3	.536 [b]	.274	.197	.67549	.188	22.043	1	85	.000

[a] Predictors: (Constant), Industry: Computer, Software, Industry: Manufacturing, Industry: Finance, Insurance, Real Estate, Industry: Retail Wholesale, Industry: Services, Industry: Healthcare, Firm Size, Previous AI Experience
[b] Predictors: (Constant), Industry: Computer, Software, Industry: Manufacturing, Industry: Finance, Insurance, Real Estate, Industry: Retail Wholesale, Industry: Services, Industry: Healthcare, Firm Size, Previous AI Experience, Artificial Intelligence Usage
[c] Dependent Variable: Operational Supply Chain Transparency

Table M. *ANOVA* [a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4.574	8	.572	1.007	.437 [b]
	Residual	48.842	86	.568		
	Total	53.415	94			
3	Regression	14.631	9	1.626	3.563	.001 [c]
	Residual	38.784	85	.456		
	Total	53.415	94			

[a] Dependent Variable: Operational Supply Chain Transparency
[b] Predictors: (Constant), Industry: Computer, Software, Industry: Manufacturing, Industry: Finance, Insurance, Real Estate, Industry: Retail Wholesale, Industry: Services, Industry: Healthcare, Firm Size, Previous AI Experience
[c] Predictors: (Constant), Industry: Computer, Software, Industry: Manufacturing, Industry: Finance, Insurance, Real Estate, Industry: Retail Wholesale, Industry: Services, Industry: Healthcare, Firm Size, Previous AI Experience, Artificial Intelligence Usage

Table N. *Coefficients* [a]

		Unstandardized Coefficients		Standardized Coefficients		
Model		*B*	*Std. Error*	*Beta*	*t*	*Sig.*
1	(Constant)	2.554	.267		9.565	.000
	Firm Size	.045	.036	.139	1.226	.224
	Previous AI Experience	.113	.114	.110	.988	.326
	Industry: Computer, Software	-.094	.240	-.051	-.391	.697
	Industry: Manufacturing	.045	.265	.020	.170	.866
	Industry: Finance, Insurance, Real Estate	.314	.327	.109	.961	.339
	Industry: Retail, Wholesale	.167	.406	.045	.412	.681
	Industry: Services	-.298	.235	-.155	-1.267	.209
	Industry: Healthcare	-.252	.294	-.098	-.858	.393
3	(Constant)	2.164	.253		8.542	.000
	Firm Size	.000	.034	.000	.001	.999
	Previous AI Experience	-.036	.107	-.035	-.337	.737
	Industry: Computer, Software	-.292	.220	-.159	-1.328	.188
	Industry: Manufacturing	-.127	.240	-.056	-.530	.598
	Industry: Finance, Insurance, Real Estate	.344	.293	.120	1.172	.245
	Industry: Retail, Wholesale	.058	.365	.016	.159	.874
	Industry: Services	-.378	.211	-.198	-1.791	.077
	Industry: Healthcare	-.238	.263	-.093	-.903	.369
	Artificial Intelligence Usage	.435	.093	.506	4.695	.000

[a] Dependent Variable: Operational Supply Chain Transparency

Appendix C3 – PROCESS Macro Model 4 Output

Table O. *Total Effect of X on Y* [a]

Effect	se	t	p	LLCI	ULCI	C_ps	C_cs
.1804	.0855	2.1105	.0378	.0104	.3503	.2703	.2373

[a] X = Artificial Intelligence Usage, Y = Business Process Agility

Table P. *Direct Effect of X on Y* [a]

Effect	se	t	p	LLCI	ULCI	C'_ps	C'_cs
.0580	.0919	.6316	.5294	-.1247	.2408	.0870	.0763

[a] X = Artificial Intelligence Usage, Y = Business Process Agility

Table Q. *Indirect effect(s) of X of Y* [a]

	Effect	BootSE	BootLLCI	BootULCI
OSCT	.1223	.0479	.0388	.2267

Notes. Level of confidence for confidence intervals: 95%. Number of bootstrap samples for percentile bootstrap confidence intervals: 5000.
[a] X = Artificial Intelligence Usage, Y = Business Process Agility, M = Operational Supply Chain Transparency