UNIVERSITÉ DU QUÉBEC EN OUTAOUAIS

IMPACT OF ARTIFICIAL INTELLIGENCE, ANALYTICS, AND PROCUREMENT STRATEGY ON COST REDUCTION

by

Sherif Barrad

A thesis submitted to the Département d'informatique et d'ingénierie, UQO

In conformity with the requirements for

the degree of Doctor of Philosophy in Information Science and Technology

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Abstract

Procurement is playing an increasingly important role in helping organizations achieve their savings and profitability objectives. Cost reduction or containment can be referred to as an organizations commitment to identify and capitalize on savings opportunities, ultimately improving shareholder value. While there is evidence that pure cost reduction efforts enable organizations in achieving savings, there have been conflicting research suggesting that cost reduction efforts can also have a reverse effect on long-term savings and goes as far as suggesting that the 'lowest bid' approach is not always an effective and sustainable procurement strategy. In this study, we identify the conditions under which emerging AI technologies and analytics (AIA), coupled with more evolutive and "intelligent" procurement strategies, can drive cost reduction. We propose to look specifically at the required organizational context conducive to enhancing the impact of AI and analytics, as opposed to implementing simplistic AI seeking only "lowest cost" rules. We also explored the notion of procurement strategy to highlight the degree of influence generated from strategic sourcing and supplier relationship management activities, as a lower-order dynamic capability, on cost reduction, a higher-order dynamic capability. Our primary hypothesis is that the application of procurement strategies, in an ideal organizational context, coupled with robust and effective AIA technologies, can have a significantly positive effect on cost reduction. This research is empirically validated by surveying procurement executives and guides as to how to prioritize and leverage AIA for cost reduction. A model is tested using the Partial Least Squares (PLS) regression technique and algorithm.

Keywords: Artificial Intelligence (AI), Analytics, Big Data Analytics (BDA), Cost Reduction, Machine Learning, Partial Least Squares (PLS), Procurement, Structural Equation Modeling (SEM), Strategic Sourcing, Supplier Relationship Management (SRM), System Dynamics.

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1 Introduction

Mixed perceptions around the concept of cost reduction and its long-term impact to the bottom line exist. In certain cases, scientists contend that the application of specific AIA technologies to the field of procurement have proven to generate benefit for the firm. For example, adopting AI models to solve supplier selection problems (Luan et al. 2019) or using big data as background intelligence to assess the demand for supplies (Zhai et al. 2018). On that same thought pattern, others will also argue that striking balance between supply and demand, in a multi-agent system with many individual self-interested rational agents, acting as suppliers, can also be leveraged using analytics (Chaturvedi et al. 2019). Finally, leveraging AI, in the context of supply chain risk management, can optimize the supply base portfolio (Hamdi et al. 2018).

In contrast, researchers who oppose such concepts suggest instead that cost reduction initiatives such as strategic sourcing can disadvantage the firm on the long run. Examples include overemphasizing pure cost reduction and consequently, witnessing cost overruns as a result of underestimating structural complexities associated with product design costs (Mandolini et al. 2018). As such, researchers recommend assessing the supply chain by adopting a holistic framework. In other similar cases, it is quite common in procurement operations to overlook inventory carrying costs (e.g., storage, tax, material handling, obsolescence, insurance, etc.) at the expense of placing large orders in exchange for quantity discounts (Munson and Rosenblatt 1998). These short-sighted procurement strategies typically take place during the sourcing process and unfortunately erode anticipated benefits through gross margin shrinkage (Gandhi and Sheorey 2017). Certain scientists argue that companies will not seek to achieve cost reductions or profit improvement at the expense of their supply chain partners, but rather seek to make the supply chain more competitive. In short, the contention that it is supply chains, and no single "rms," that compete is a central tenet in the "eld" of supply chain management (Christopher 1993).

In this thesis, we specifically explore the impact of AIA technologies on cost reduction. With the recent growth in analytics and artificial intelligence, combined with the mixed-messaging around the benefits resulting from cost reduction efforts, this paper has for objective to understand under which conditions the firm can maximize the use of AIA technologies for direct impact on cost reduction or the bottom line. To demonstrate this, we will discuss the notion of "Procurement Strategy" as a mediator variable and combine it with a moderating variable which we call "Organizational Context." The synergy associated with combining both approaches (i.e. strategy and executive leadership) will elucidate why certain firms have had enhanced success in leveraging AIA technologies for improved cost reduction performance.

Given its quantitative approach, the thesis consists primarily of traditional sections presenting hypotheses and reporting results. In section 2, we offer a brief overview of our research objectives and motivations for this study. Section 3 presents our literature review, while section 4 explains our hypotheses. In section 5, our Partial Least Square (PLS) methodology is presented, along with guidelines on ensuring validity of our tests. Section 6 offers details on our results and tests, and section 7 and 8 present our discussion and conclusion. Only one appendix is offered to share our questionnaire.

The contribution of this paper is to scientifically prove that AIA technologies, when applied in isolation of the human loop, will not and cannot fully replace humans in the field of procurement. We have seen the market being recently flooded with claims suggesting that AIA technologies can automate most procurement processes and in turn fully replace humans. This study proves that AIA technologies, coupled with human intervention in strategy, executive leadership and collaboration can all generate incremental cost reduction synergies compared to when leveraged separately. It is also proven that the human cannot fully be eliminated from the equation and this will be emphasized later when we discuss the work systems theory (Alter 2006) The application of this contribution allows firms to understand that a business case must include technology, strategy, and most importantly, organizational context such as executive leadership in order to generate the greatest yield.

2 Objectives

The study of AIA technologies and applications in Supply Chain Management (SCM) and procurement strategy is beginning to emerge in the literature. However, professional organizations have already launched several initiatives addressing the promise and challenges of AIA, and several managerial issues have been raised in the past few years. We define here a set of research questions we wish to address, given these trends and interest in the procurement profession.

2.1 Impact of AIA on Procurement

According to a 2018 survey administered by Forbes Magazine, Canada ranked last in the adoption of AI technologies such as machine learning and deep learning (Gordon 2019). The global survey interviewed 305 executives across 10 countries and two key reasons emerged as being contributing factors to this slow adoption. The first being access to talent such as data scientists (Osman and Anouze 2013).

Many Canadian firms do not have mature capabilities as it relates to data science. Data science involves digging deep into data to detect patterns that can be actioned for improved business results and savings (Provost and Fawcett 2013). Both data accessibility and quality are other factors as to why firms are not able to adopt AI technologies for efficiencies and cost reduction.

The success of any supply management program is largely dependent upon the ability to access, organize, and analyze data (Russo et al. 2015) . Big Data analytics, especially as it relates to procurement intelligence and spend cube architectures, must be understood and used as fundamental instruments in gathering the intelligence required to deliver on cost reduction (Barrad 2019b). Over the last few decades, emphasis has been put on setting up the infrastructure to gather data but now, with enormous amounts of data, firms are now overwhelmed and have fell behind in their ability to convert data into value for the firm (Kaisler et al. 2013). The future's biggest data challenge lies in effectively managing acquired data to give context to what is otherwise just a series of numbers across thousands of files (Wani and Jabin 2018). Data is power, assuming you know how to use it. The organizations that will be most successful over the next decade are those that recognize this simple fact (Snyder and Burress 2011).

Leadership within the procurement function has also come to play a significantly lacking capability in organizations wanting to adopt AI. Understanding procurement system dynamics as an analytics capability (Barrad et al. 2018) and modeling it in this study will help us understand the influence exerted by executives, and the reinforcing effect this has on the cost reduction process and results. Based on a 2017 C-Suite study published by IBM, CIOs are the only ones demonstrating the most urgency, among their peers, in transforming their enterprise from an IT perspective (Gunther McGrath 2019) . New technology is driving the need for new skills and talent and requires them to make significant investments in IT. The report also showed that reinventors, the ones investing heavily on emerging technologies, are reaping the greatest revenue growth, profitability and are also leading innovation.

2.2 Impact of AIA on Cost Reduction

From a cost reduction standpoint, firms are still struggling to adopt basic procurement technologies and standard sourcing strategies to drive savings, and this unfortunately dates back from the late 80's (DiTeresa 1988). Leveraging basic e-procurement systems will play an instrumental role in enforcing transaction compliance and will provide increased spend visibility (Barrad et al. 2018). Most firms, however, are still deploying efforts in both a scattered and ad-hoc fashion in an attempt to gather the data required to explain past business behaviour. For example, understanding what happened in terms of spend last year or, what we call descriptive analytics (Souza 2014).

Moreover, only a few have access to real-time data and can understand patterns, forecast the future and most importantly, action this data in return for cost reductions within the same year (i.e. predictive and prescriptive analytics). Supplier management will also play an instrumental role in mitigating supply chain risks and contribute to overall cost reductions (Barrad et al. 2018). Finally, optimizing the transactional side of procurement, including the deployment of new and innovative payment architectures (Barrad 2019c) for transactional cost savings when operating on a global footprint, will also be considered as a cost reduction lever in this study.

2.3 Organizational Factors Affecting AIA Impact

We believe there is an incredible opportunity for Canada to take a quantum leap in adopting AIA technologies, acknowledging that Montreal has been globally recognized as the hub for innovation and artificial intelligence by Brad Smith, President of Microsoft.

That said, our main research objective is to decompose and further analyze each of these barriers, and to assess, using a causality approach, based on the Partial Least Squares or PLS Regression methodology. That is, we want to accurately measure how each of these key drivers can be managed and regrouped in a systematic, prioritized and most importantly, a holistic fashion to accelerate cost reduction results.

We will highlight how each of the 4 key AIA technologies can support cost reduction efforts and describe how they can be applied to procurement, but not in isolation of other important factors such as strategy and leadership, as it has typically been done in the past, but in concert with procurement strategies (i.e. the strategic sourcing methodology and supplier relationship management process) all while navigating in a dynamic organizational context where strong executive leadership and teamwork are key success conditions.

The contribution of this study will objectively, and most importantly, confidently describe how to merge AIA technologies with both strategy and organizational context to deliver greater impact from a cost reduction standpoint. This paper will also emphasize best practice in terms of procurement strategy and leadership. Finally, it will quantify the importance of an ideal organizational context as an enabler to cost reduction, all in the context of AIA technology adoption. The output of this study will enable firms to understand how to prioritize efforts and to combine strategy, technology, and leadership in an integrated fashion to deliver incremental impact to the bottom line.

3 Literature

This section of the paper will focus on the literature review. Below is the approach we used to develop this section (Figure 1). We commence with a deep literature review on our dependent variable - cost reduction. We then move onto discussing the notion of procurement strategy and perform a deep dive on two mediating variables: Strategic Sourcing (SS) and Supplier Relationship Management (SRM). We then explore the four key AI technologies selected for the scope of this study. The fourth and final section of the literature review will then highlight the notion of organizational context, such as executive leadership and teamwork, as moderator variables. Finally, we combine AI technologies, Cost Reduction, Procurement Strategy, and Organizational context as the theoretical foundation for our research.

To perform the literature review, a systematic eight-step approach was utilized (Okoli 2015). The table below summarizes the activities performed under each of the steps.

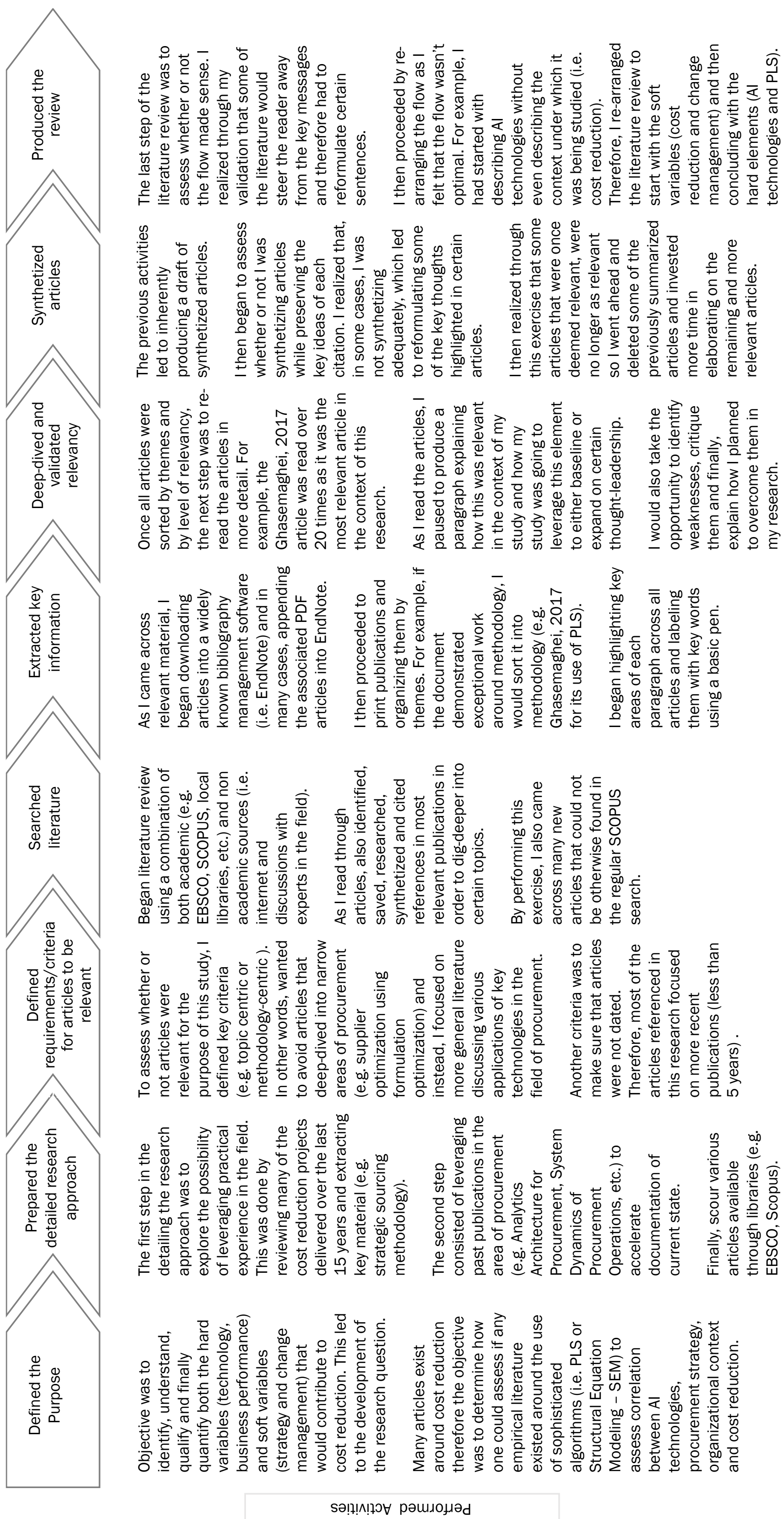

Figure 1 - Literature Review Approach

3.1 Cost Reduction

Cost reduction is often conceptualized as being a combination of two types of cutbacks: The first is around reducing the total cost of acquisition (TCA) of goods and services and the second, avoiding price increases (i.e. cost avoidance) typically resulting from inflation or suppliers progressively setting higher fees for after-sales and/or maintenance services (e.g. software maintenance agreements). Costs include many components such as supply chain and logistics costs, the cost of acquiring and managing products and services, after-sales support and so on. Both TCA and cost avoidance focus on cost reduction but it bears to mention that they are different in terms of impact from a Profit & Loss (P&L) standpoint where cost reduction has a direct impact on the bottom line of the P&L. For the sake of simplicity, only cost reduction is considered as our basis for research in this paper. In the public sector, cost reduction is not always the main mission and/or purpose. For example, with the recent outbreak of COVID-19, the entire healthcare industry has faced shortages in Personal Protective Equipment (PPE) such as N95 masks or respirators. What the public sector is now realizing is that it cannot solely depend on negotiating best prices with local medical distributors, but that they must also secure global suppliers outside the country to face future pandemics.

Leveraging business intelligence for cost reduction, a technology-driven process that provides executives with actionable information, can contribute to cost reduction in several ways and can also help an organization prioritize where best to invest its efforts for increased P&L impact. Said differently, it allows procurement to gather insight into the global supply market; hence, creating a better offering for internal users. Figure 2, highlights some of the most common procurement cost reduction levers typically fueled by business intelligence reports (e.g. spend analysis, contract analysis, procurement performance metrics, etc.). With information on spend and contracts, firms can identify opportunities to concentrate volumes, where fragmented spend exists, challenge internal demand, where different low-cost alternatives exist, and ultimately reduce Stock Keeping Unit (SKU) proliferation enterprise-wide, or what we call product simplification, in the goal of concentrating volumes in exchange for volume discounts (Altintas 2008). In addition to this, it must also be noted that, in setting up strategic partnerships, it is important to explore global sources of supply. This is otherwise referred to as Low Cost Sourcing (LCC). An example would be sourcing goods and services from Europe or Asia. Opportunities in terms of cost reduction exist however, tight control over quality must also be factored into the equation offsetting, to some extent the benefits of sourcing globally. Given the opportunity is still very relevant, many software companies have explored using artificial intelligence and machine learning algorithms and technologies to automatically suggest alternate sources of supply based on your existing supplier base.

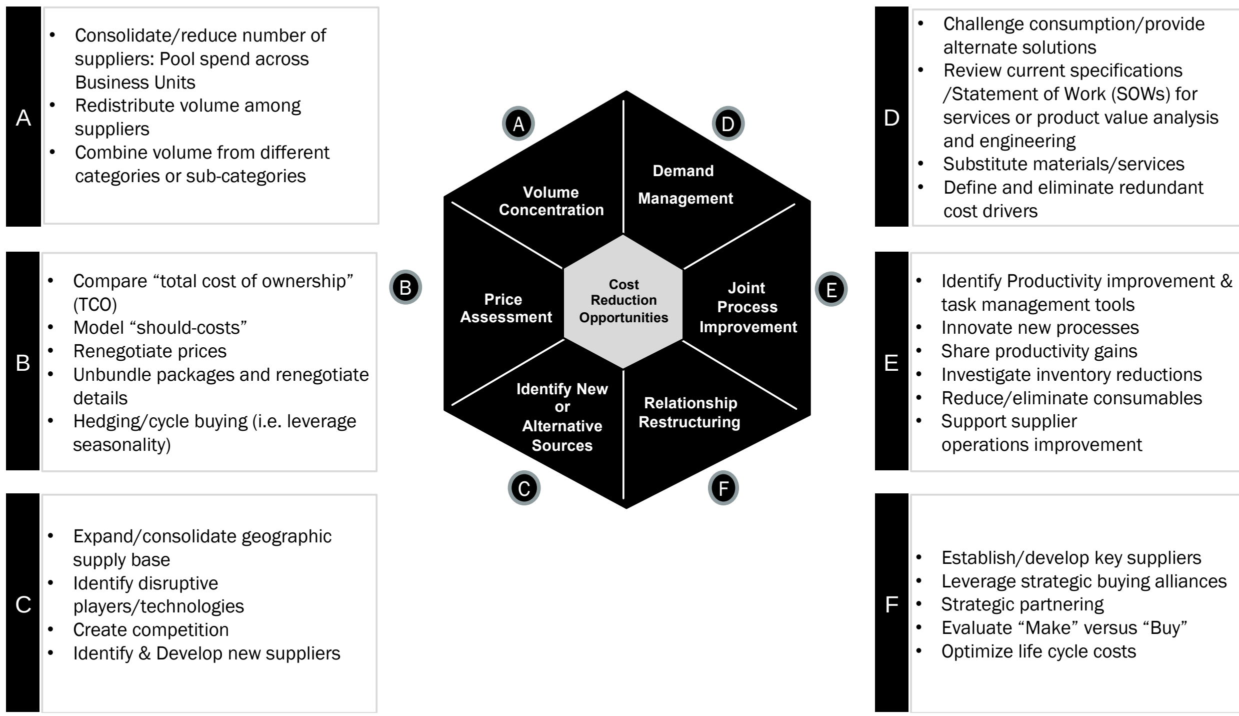

Figure 2 - Key Strategic Sourcing Levers

3.2 Procurement Strategy

Conventional wisdom tells us that optimal procurement strategies, under an “all-units” discounts approach (i.e. volume discounts) should be more complex and technically challenging to identify (Wang et al. 2019). Perhaps due to this reason, the available academic literature on procurement challenges related with all-units discounts and multiple periods is still in its infancy. In fact, most studies in the literature focus on studying single-period settings and only select studies consider the heuristic policy for the multi-period setting.

Procurement strategy is an overarching goal, supported by a comprehensive set of activities and processes, that enable organizations to maximize supplier value and minimize contract leakage (Barrad 2019b). A strategy can take many forms, but in essence, the focus is to shift away from tactical activities, such as purchase order (PO) processing, gathering and analyzing spend data, and instead, focusing on strategic activities that generate value for the firm. For example, negotiating internally with stakeholders to understand, and in some cases, challenge internal demand for specific products and services. In other cases, negotiating directly with suppliers to unlock potential value outside of the classical pure “cost-based approach”.

3.2.1 Strategic Sourcing

The strategic sourcing framework (Figure 3) consists of a systematic approach to support strategic objectives from both a top and bottom-line perspective. It focuses on identifying and securing value for the firm. The framework outlines a six-step systematic approach to identifying and securing value for the firm.

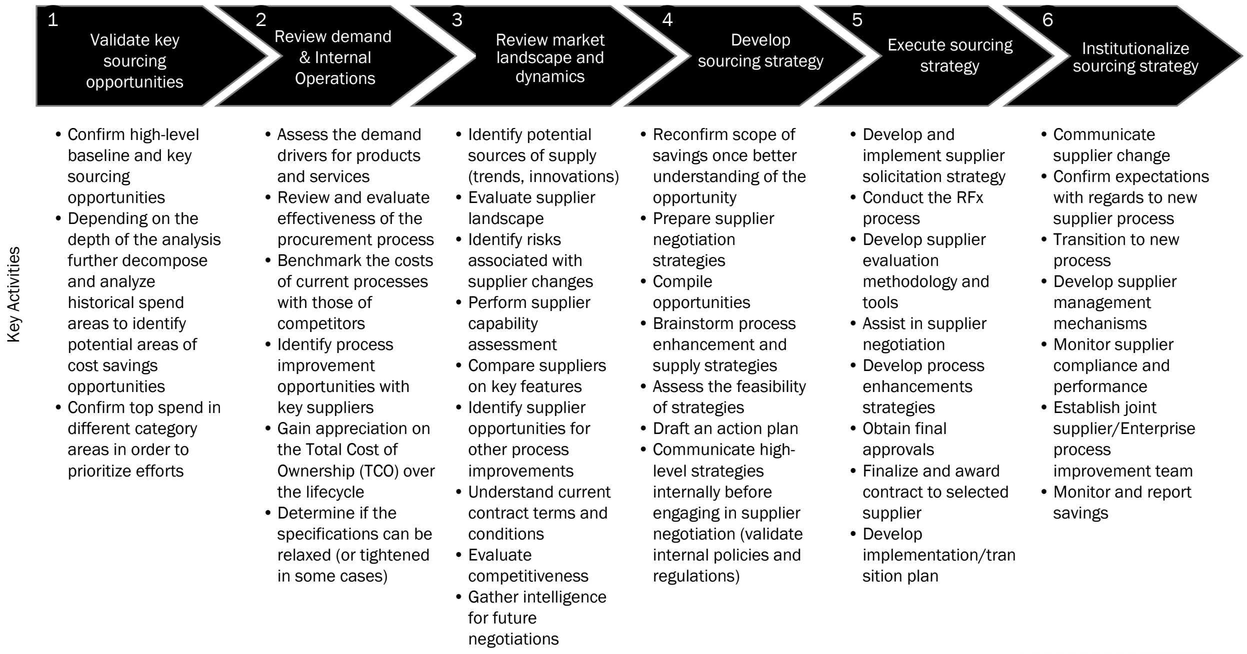

Figure 3 - Strategic Sourcing Methodology

The first step consists of validating key sourcing opportunities by assessing ongoing opportunities and areas where cost savings exist by decomposing the spend to get a better understanding of where the firm's resources are spent. The second step consists of understanding where the demand for goods and services are generated from (i.e. the source). With a better understanding of needs, the next step consists of challenging those needs as opposed to converting them into requisitions and consequently, reaching out directly to suppliers to negotiate pricing. The third step consists of taking an outside view and assessing the supply market for options such as alternate or substitute sources of supply. Once both internal and external assessments are fully understood, procurement is now ready to start formulating and executing on select sourcing strategies using key cost reduction levers (Figure 2). Once supplier negotiations completed, the most critical part of the process is socializing the new process and ensuring adoption so that value is secured downstream through supplier relationship management programs. Those programs exist to assess compliance through business activity monitoring (Figure 4).

3.2.2 Supplier Relationship Management

Supplier Relationship Management (SRM) focuses on managing vendors with the intent of delivering value to the firm through increased value or minimized leakage (Figure 4). This set of logically related activities (Figure 4) are typically led by a vendor management office (VMO) which has a sole focus on measuring efficiency, risk, performance, and relationship quality using measures appropriate to the value and risk associated with the products and services delivered. Some examples of metrics include Risk: Identified versus mitigated risks, increased regulatory compliance, business continuity management, relationship quality: improved customer satisfaction, vendor collaboration, and cooperation, improved relationship scores, responsiveness, flexibility, easy to work with and access to vendors. Performance: increased services levels, improved adherence to Service Level Agreements (SLA) and decreased dispute resolutions times.

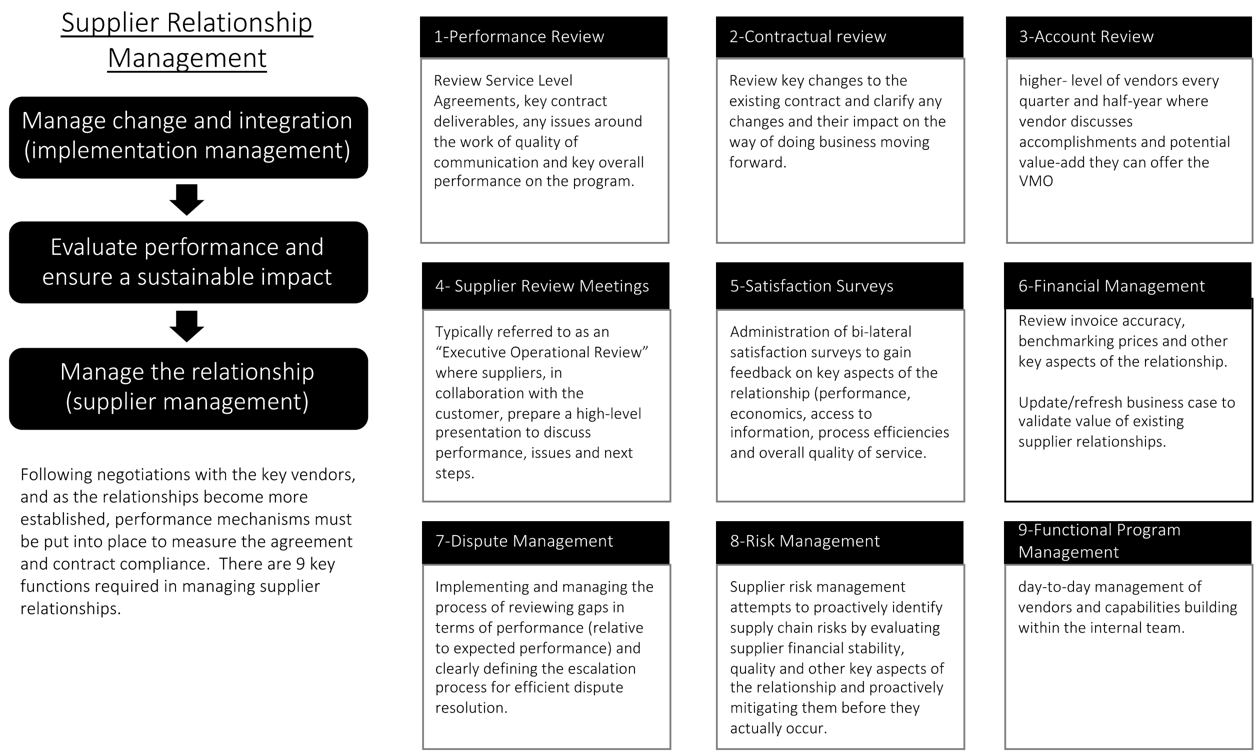

Figure 4 - Supplier Relationship Management Activities

In conclusion, SRM can be viewed as a comprehensive vendor management program that aims to maximize supplier value and minimize contract leakage (Barrad 2019a).

Studies show that a comprehensive supplier management program is key to realizing and sustaining value downstream from the strategic sourcing process. Without effective supplier performance management, up to 75% of the value identified and secured by sourcing teams upstream can erode within 6-18 months of signing a contract (Gartner). As organizations attempt to counter this, they usually come to the realization that managing the entire supply base is often impossible to do. That said, the best organizations provide lower tier suppliers with upfront guidance on performance and metrics that can drive self-improvement in most cases or trigger vendor managements involvement only when necessary. They then focus most of their efforts on partnerships with top tier strategic suppliers.

3.3 AIA technologies

This section starts by discussing the theory used to select the various AIA technologies applicable across all business domains. It then offers an overview of potential AIA technologies, along with Use Cases, and finally, confirming which AI technologies have been selected for the purpose of this study.

The work systems theory (Alter 2013) suggests that both humans and machines perform processes and activities using information, technology, and other resources to produce both products and services. Therefore, each work system has its own ecosystem. In this case, we are introducing the procurement ecosystem. In the context of this study, AI technologies, such as rules engines, can be characterized as a totally automated work system in which all the work is done by a machine. That machine (i.e. the rules engine) was created by humans, but in theory, operates autonomously once launched into production.

The work systems theory helps us understand why this study incorporated both AI and analytics technologies and organizational context as two key elements of the study. Let us discuss this in more detail. In order for a work system (figure 5) to operate effectively, nine components must be present (Alter 2006). The first consist of the infrastructure required to gather data. This data can be referred to as Big Data Analytics, one of the key variables in our study. The second key component is the environment, which in our case, would be declared as the organizational context. Strategy in this study, which is also the third factor, can be referred to cost reduction which is a metric that is directly tied to cost containment as a higher-level strategy. To drive the above, we require an ecosystem comprised of participants, in which refer to as the procurement staff and the executive leadership. The process and activities which we discuss in detail, in the work system architecture and theory, is the procurement strategy component of the study (i.e. strategic sourcing and supplier relationship management). The activities drive services that aim to maximize supplier value and minimize contract leakage and ultimately serve internal customers – in this case the various lines of business within a typical organization.

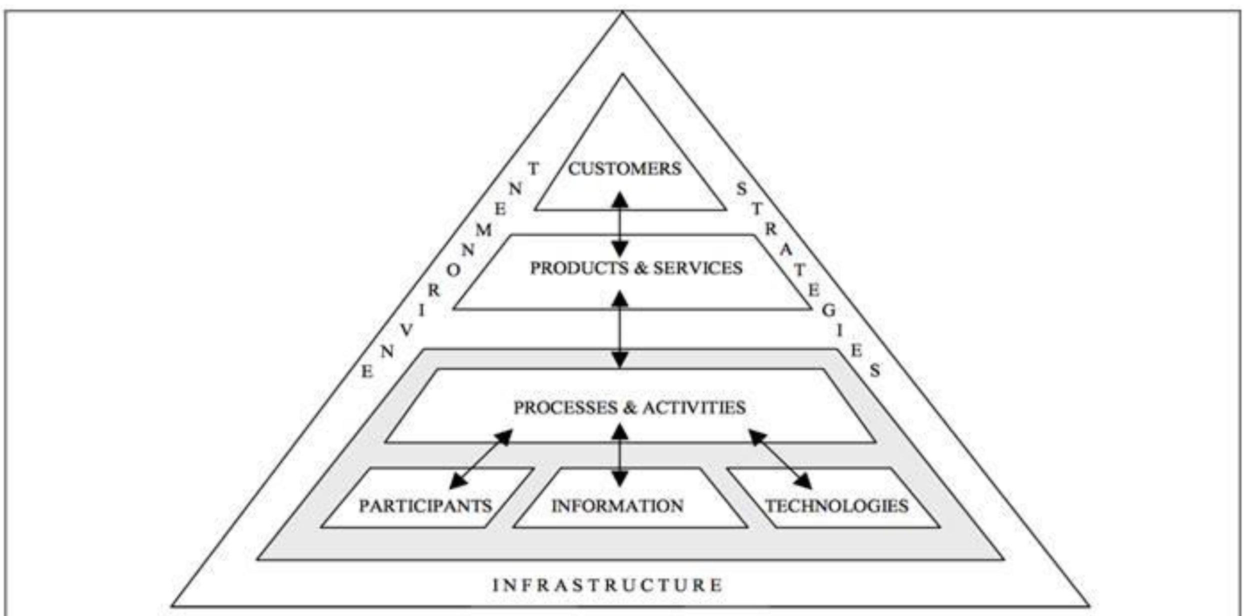

Figure 1. The Work System Framework (as updated in Alter (2008))

Figure 5 - Work System Framework, Alter (2008)

This framework has for purpose to allow business professionals to understand IT-reliant systems in organizations. It is important to note that some of the above elements are internal and within the work system (e.g. participants, activities, information, and technology). Other elements, however, are outside the work system, such as environment and strategies. As we begin covering the literature review, we plan to discuss each of the above elements in the work system framework in detail.

AIA technologies are typically brought to life through the development of AI assets. Each of these AIA assets are developed to address specific business challenges. Take for example, a data unification asset which leverages Machine Learning algorithms such as K-Nearest Neighbour to help organizations compress the time it takes to classify spend data before a spend analysis can be conducted. This is typically achieved by using product descriptions from transactional ERP data and to recommend category types and potential vendor type. Over time, this ML algorithm improves its ability to classify spend by becoming more accurate and by drastically minimizing human intervention. Other AI assets focus on digitizing documents via OCR to extract key information. For example, extracting key contract clauses (e.g. payment, terms, product prices, volume discount thresholds, etc.). These types of AI assets use unstructured text, structured data, and spreadsheets to extract, analyze and interrogate on a set of documents. By digitizing physical data into structured data tables, organizations can now mine the data for insight. Other AI assets include Natural Language Processing (NLP) to analyze sentiment, classify text and, summarize text, answer questions, and translate language using ML algorithms. Natural language processing can also be used to guide buyers in the procurement process by pointing them to the right resources, using digitally powered catalogues. Users type their need using natural language and the ML algorithms generates, with great accuracy, information on procurement key processes and/or products and services.

Other assets include optimization assets to dynamically price products, by leveraging ML algorithms, to predict prices to optimize margins in the context of shifting market conditions. Virtual agents that are brought alive through the implementation of conversational agents for customers, partners, and employees and that can answer questions, collect data, and perform transactions on behalf of the human. Finally, recommenders which leverage historical user and item interaction data to predict items users will be interested in. Each of these assets can help organizations across the various areas of the business.

Given the purpose of this study is cost reduction, four key AIA technologies have been carefully selected for further exploration. The first is Big Data Analytics. The concept of pure transactional ERP data as such is no longer sufficient to drive strategic impact in procurement. The concept of Big Data introduces additional paradigms such as the ability to analyze a wider set of data sourced from various instances of ERP systems, Source-to-Pay (S2P) systems, supplier data, market intelligence, etc. In addition, with Big Data, organizations now can run queries much faster than ever. Finally, and most importantly, Big Data unlocks the capability of performing predictive and prescriptive analytics which help predict and prescribe the best course of action. Descriptive analytics, which typically explains the past, now becomes a requirement for predictive and prescriptive data.

The second key technology explored in the context of this study is Machine Learning. There are two key reasons we selected machine learning. The first is to address one of the largest challenges faced in today's procurement organizations – the ability to extract and cleanse the data to begin analysis. With machine learning algorithms, we can train systems to classify incomplete procurement information with 1% of the data and have the ML algorithm process the remaining 99% of data with > 95% accuracy. This is achieved using widely accepted product taxonomies (i.e. UNSPC codes) and through the use of specific ML algorithms such the K-Nearest Neighbour algorithm. This compresses the time it takes to clean the data and exponentially increases spend data accuracy. Second, with machine learning algorithms, we can also improve our ability to forecast procurement spend. That is, as opposed to using traditional methods such as Naïve forecasting (i.e. forecasting based on historical performance) or time-series (e.g. linear-trend, exponential smoothing, trend-adjusted forecast, weighted-moving average, etc.) which consist of mathematical based models leveraging historical data leveraged to stabilize forecast data, with machine learning, we are now incorporating new and advanced techniques such as more complex mathematical models, and new layers of intelligence such as weather, POS transactional data, etc. With the recent advancements in AI, we believe machine learning will expand its applicability in the field of procurement and therefore we prioritized this technology.

The third, System Dynamics, focuses on addressing some of the key procurement challenges around sustainable procurement operations (Barrad et al. 2018). Procurement operations, especially in larger size organizations drive a high-level of operational complexity. For example, when measuring procurement performance, we typically focus on key performance drivers such as spend under management, percentage of compliant transactions, and most importantly, savings generated. What we noticed over time, is that as you improve certain drivers, they eventually generate positive impact on others but only up to a certain point, until which a negative effect is eventually witnessed. Take for example, spend under management where procurement will drive specific actions (e.g. roadshows or implementation of new policies) to increase the amount of spend funneled through however, with time, capacity will reach a peak at which, we will start witnessing reverse effects on benefits such as increased lead times to procure, shorter time windows to negotiate with suppliers and eventually shadow procurement operations (i.e. decentralization of procurement activities for improved response times) which eventually leak benefits.

With the advent of system dynamics as an analytics technology, powered by simulation software, organizations can now benefit from various angles. For example, with simulation, “What-If” Scenarios take less time to develop and can dynamically be reviewed to address shifting business conditions. There is also limited understanding/visibility of impacts associated with the shift of one strategic procurement lever on the entire ’ecosystem’. Finally, outcomes are typically hypotheses-driven (qualitative) with limited use of science, quantitative methods, and data analytics, making it more challenging to generate business predictions and support them.

With system dynamics, organizations can now explore the impacts of altering key business levers in a real-time and in a risk-free environment to significantly reduce uncertainty. Organizations can also accelerate the process of selecting strategic options that yield the greatest benefits. From a cost optimization standpoint, procurement can optimize operations and reduce costs by simulating various procurement strategies, while mathematically factoring in resource constraints, to select the most cost-effective execution plan and deliver a solid deployment plan at a fraction of the time. Finally, and most importantly, system dynamics can elevate the procurement departments’ strategic capabilities by allowing them to shift away from the classical business case approach, to a proven management science that enhances strategic decision-making.

Finally, Business Rules Engines (BRE) is the last selected technology in this study to help introduce the concept of intelligent automation such as artificial intelligence and robotic process automation (RPA) in procurement. Robotic software automates routine and repetitive task across disparate systems and software products. Aside from being accurate, efficient, and cheap, robots add value in other ways. For example, by updating and adding content to records, robots are a fast way to make your analytics better. The data harvested is usually more complete and deeper, thus the power of cognitive analysis has greater reach. In this study, we clearly show the power of embedding rules into a Business Rules Management System (BRMS) (Barrad 2019a) and managing those procurement rules using automation or rules engines.

3.3.1 Big Data Analytics (BDA)

Over the last decade, big data and supply chain management are key trends that have heavily influenced the procurement process (Andersen 2003). Procurement analytics is the key driving function for strategic sourcing (Barrad 2019a; Ellram and Carr 1994). Some of the most sophisticated organizations connect deeply to the data given its growing importance in supporting both strategic and operational decision-making. These firms go through the process of building spend cubes to increase the flow of information and enhance visibility across the entire supply chain. The purpose of business analytics, especially when it comes to procurement and sourcing, is to facilitate the firm's ability to analyze trends and to predict future purchasing patterns for increased leverage through negotiations. In fact, (Turban 2011), refer to it as a spectrum of technologies, analytical techniques, and methodologies combined to support decision-making. (Souza 2014) suggests that supply chain analytics is a field that exhibits how to use information and analytical tools to make better decisions regarding goods, information and finances across the entire supply chain. (Rafati and Poels 2015) suggest that the organization requires critical competencies to enable fact-based decision-making which ultimately rely on data. The first being data management, which includes data architecture and design, data extraction, data transformation, data storage and data integration. The second being data analytics as discussed previously (Barrad 2019a).

The ultimate objective is to find information and insight that one would otherwise not be able to find while running daily procurement reports and managing tactical procurement operations. Some examples of key metrics include, but are not limited to, the percentage (%) of spend purchased under pre-negotiated contracts, transaction compliance, number of suppliers for a spend category, etc. This information, along with policy enforcement, are beneficial as both can generate significant savings for the firm.

Analytics techniques are categorized into three categories: descriptive, predictive and prescriptive (Souza 2014). The first, descriptive analytics, gathers an enormous amount of data to describe the current state. For example, in sourcing, you can determine what does your current spend year-to-date and validate results against the forecast to make sure budget overruns do not occur.

Predictive, on the other hand, gathers past data and manipulates data sets, using methods such as exponential smoothing and regression analysis to predict the future. An example would be, the forecasting process where a firm would conclude, through a forecasting exercise, that demand for office supplies is seasonal with a peak around the back-to-school period.

Take for example the linear trend forecasting model where one is attempting to solve for:

$$y = a + bt$$

Where "*y*" stands for the current forecast, where *"a"* represents the "*y-intercept",* where *"b"* represents the "*slope*" and where "*n*" represents the number of periods. To calculate the "*y-intercept*", one must solve for *"a":*

$$a = \frac{\sum y - b\sum t}{n}$$

Where "*y"* represents the quantities sold, and where "*t"* represents the period in which "*y"* was sold. Finally, to solve for "*b*":

$$b = \frac{n\sum ty - \sum t\sum y}{n\sum t^2 - (\sum t)^2}$$

By solving for this, firms can eliminate variability in the forecasting process and hence, contribute towards bottom line savings.

Finally, prescriptive analytics emphasizes mathematical optimization, drawing from both descriptive and predictive analytics to model the future. According to (Souza 2014), the use of analytics is currently limited for strategic sourcing. Big Data is being leveraged to help firms manage their entire supply chain. Table 1 offers a snapshot on the application of data analytics for supply chain management over the last decade. The application of procurement analytics is commonly used in vendor evaluations to evaluate complete and timely deliveries. In demand forecasting, it is used to measure the average cycle volume and maximum demand peaks. In contract relationship management, it is used to optimize discount levels and to forecast financial liabilities. In Supplier Relationship Management (SRM), to score vendors and evaluate Purchase Order (PO) volumes. Finally, in strategic sourcing, to assess vendor consolidation opportunities, reducing duplicate orders and increase orders under pre-negotiated contracts.

Topic	Authors
Dynamic Pricing and Revenue Management	(Talluri 2004)
General Overview	(Snyder 2011)
Manufacturing Scheduling	(Kreipl and Dickersbach 2008; Kreipl et al. 2006)
Network Design	(Almaktoom et al. 2014)
Sales and Operations Planning	(F. Robert Jacobs 2011)
Transportation and Distribution Planning	(Ahuja et al. 1993)
Workforce Scheduling	(Campbell 2011; Campbell 2012)

Table 1 - Supply Chain Management Publications (2004-2014)

If we look at the literature review from a different perspective (i.e. journals published), we can see a clear takeoff in the field of Business Analytics and Supply Chain Operations Management (BA&SOM), (Chircu 2014). The number of both academic and practical papers in the field of BA&SOM (Table 2 and Figure 4) have surged since 2011.

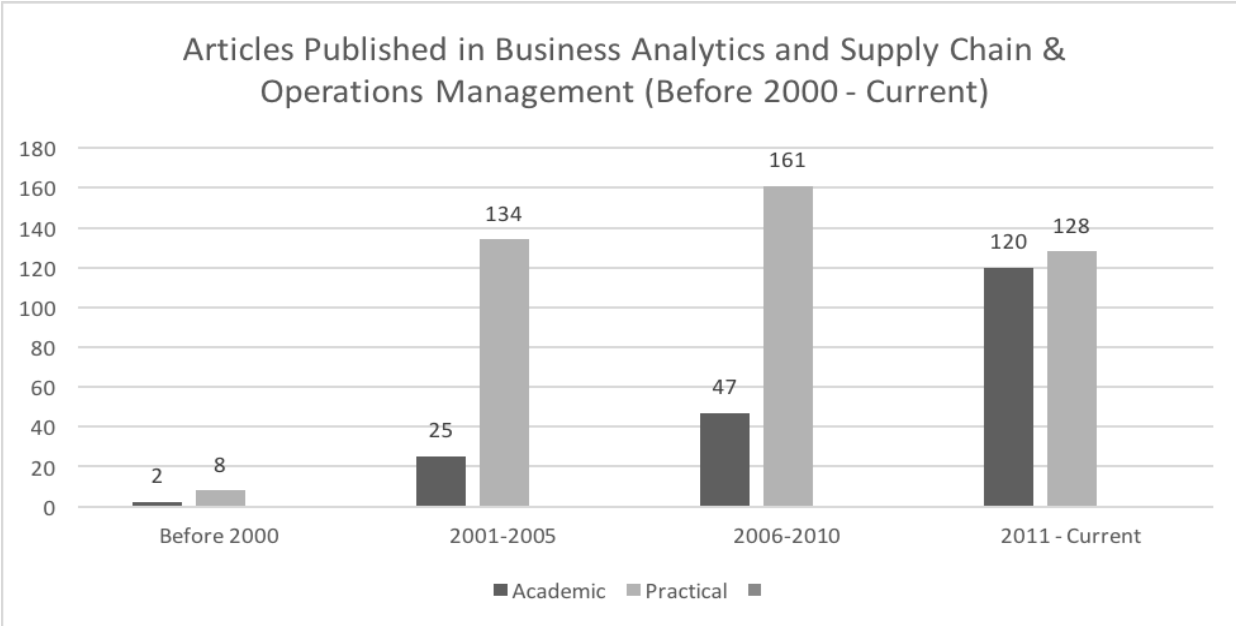

Figure 6 - Trend in Analytics & SCM Publications

Source: Chircu, A., Kononchuk, N., Gang, L., Yi, Q., & Stavrulaki, E. (2016). Business Analytics and Supply Chain and Operations Management---A Text Mining-Based Literature Review.

Name of Journals	No. of Publications
Computers in Industry	12
Expert Systems with Applications	20
Decision Support Systems	10
International Journal of Production Economics	10
International Journal of Production Research	7

Table 2 - Publications in Computer Science

As we can see from the tables above, the role of technology has been increasingly popular in procurement.

3.3.2 Machine Learning

Machine Learning (ML), classified as an AI technology, consists of a process that aims to automate the detection of patterns in the data analysis exercise (Murphy 2012b). It can also be defined as a machine's ability to generalize knowledge from data. In his work, (Mitchell 1999) suggests that it's a computer program said to learn from experience "E" with respect to some class of tasks "T" and performance measure "P" only if its performance at tasks in "T", as measured by "P", improves with experience "E". A simpler explanation would be to assume that if a computer can improve its judgement regarding the future based on experience, then we can say it has learned. ML is used in many different applications such as classification management. The effectiveness of Machine Learning depends not only on the quality of data, but also on the robustness of the algorithms and their ability to take good quality data and make sense of it.

There are three types of learning: Supervised learning, unsupervised learning, and reinforced learning. Supervised learning trains the machine using well-labeled data or in other words, data that is tagged with the correct outcome and answer. In supervised machine learning, the greater the data the better answer. Unsupervised learning consists of training the machine using a data set that does not have labels. In other words, the learning algorithms are given limited information. For example, the dataset can present the letter “A” without stating that it represents the letter “A” in the alphabet and/or dictionary. Another example would be to present the picture of an actor without specifying which actor it is. There are simply no dictionaries to refer to clearly identify and label the actual event. For the machine to learn, or for your brain to form a model, it must be exposed to many samples/observations and that is until the machine starts building a structure and begins to recognize patterns.

Reinforced learning is like unsupervised where data is also not labeled. When asked a specific question, the machine learning algorithm will be graded based on how it answers it. That is, if in the past, a certain series of activities led to a certain outcome, the machine will go back and record those patterns and re-use the same actions and logic to regenerate the same results.

Machine learning and Artificial Intelligence (AI) are two distinct concepts deemed to be complementary (Mitchell 1999). Artificial intelligence is a machine that focuses on mimicking the human mind and it involves knowledge representation, reasoning, and abstract thinking. Machine Learning (ML), on the other hand, consists of writing software that can learn from past experience and in turn predict the future (Mitchell 1999). It relies on data mining and statistics.

3.3.3. System Dynamics

System dynamics, classified as an analytics technology, is an approach to modeling complex systems using feedback loops to explain relationships between variables and to reflect their nonlinear interdependencies through time, along with their underlying driving forces (Sterman 2001). Causal loop diagrams are diagrams that depict relationships between variables. These relationships (causal loops) can be positive (reinforcing) or negative (balancing). The strength of these relationships can also vary over time. A positive relationship is typically annotated with a “+” sign and arises when an increase in one variable causes an increase in another variable. These positive causal relationships are also known as reinforcing loops as one behavior is reinforcing another. In contrast, a negative relationship (also referred to as a balancing loop) occurs when an increase in one variable creates a decrease on another variable. A negative relationship is typically annotated with a “-” sign and can also vary over time. Arrows are drawn in a circular manner indicating the causes and effect leading to a feedback loop which consists of a closed sequence of cause and effects (Tulinayo et al. 2012).

Applying this concept, from a qualitative aspect, within a Procurement operation (Figure 5), an increase in the amount of “spend under management”, otherwise known as the spend being managed by the “Procurement” function (i.e. purchasing/sourcing experts) typically leads to an increase in the likelihood that savings will be captured following expert involvement. This can be explained by the sourcing expert’s ability to analyze the category of spend in question and develop an intelligent and fact-based sourcing strategy ahead of supplier negotiations (Barrad et al. 2018). By better understanding the internal organization history of spend with a key supplier, assessing the supply market for competitive offers, decomposing and understanding the cost structure to clearly understand which cost elements can be negotiated, Procurement can enter supplier negotiations with a dominant position. This position can enable them to negotiate better pricing by committing to larger volumes, harmonizing product lists, concentrating/consolidating purchases for volume discounts, etc. Assessing the supply market for competitive offers can enable sourcing experts to be informed of their bargaining position and leverage this during supplier negotiations. For example, Procurement can uncover that the business offered to a certain supplier represents over 50% of the supplier's total sales volume and as such command lower costs or better value.

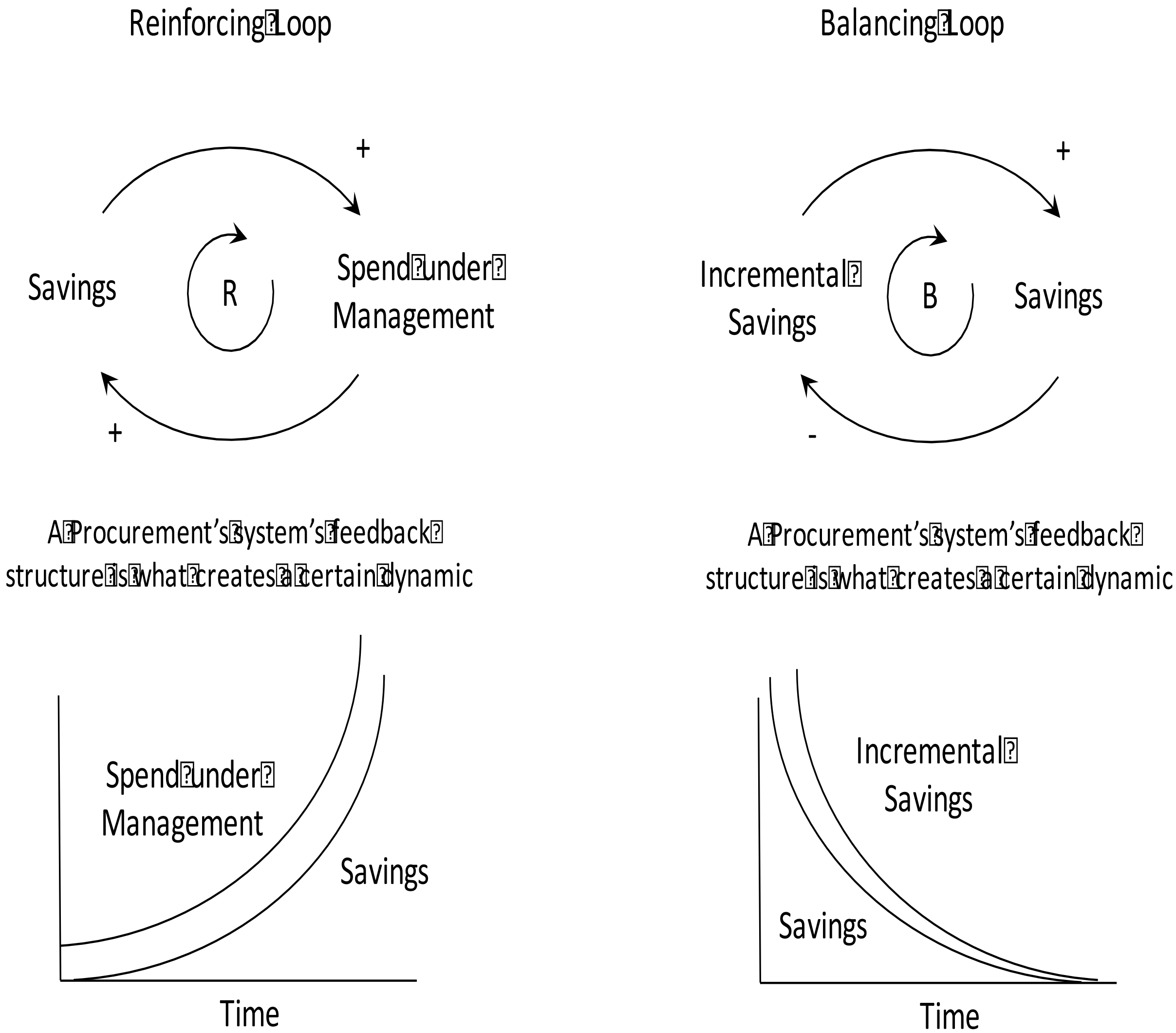

Figure 7 - Reinforcing & Balancing Loops in Procurement

Applying this concept, from a quantitative aspect, this can also be interpreted using mathematics in the following way. Considering all else is equal, if variable A increases (or decreases), then Y increases (or decreases) above (below) what it would have been (Sterman 2001).

$$\frac{\partial Y}{\partial X} > 0$$

and in the case of accumulations

$$\mathrm{Y} = \int_{\mathrm{t0}}^{\mathrm{t}} (\mathrm{X}+\ldots)\mathrm{ds} + \mathrm{Y}_{\mathrm{t0}}$$

If we take for example a loop gain in the dynamics of a sustainable procurement dynamics, we could assume that if the number of requisitions that are funneled through procurement increase, then savings would also increase given Procurement's intervention in the end-to-end sourcing event.

On the flipside, and when all else equal, if X increases (decreases) then Y decreases (increases) below (above) what it would have been

$$\frac{\partial \mathrm{Y}}{\partial \mathrm{X}} < 0$$

and in the case of accumulations

$$Y = \int_{t0}^{t} (-X+\ldots)ds + Y_{t0}$$

Another dynamic within the same procurement system emphasizes the positive relationship of increased spend under management because of increased savings. This can be explained by suggesting that the more value (i.e. savings, better purchasing options, etc.) procurement is able to deliver, the increased likeliness that the function will become more solicited from the various internal functions. To further illustrate this dynamic, perhaps a simple and straightforward example. When a business unit (i.e. marketing, operations, manufacturing, etc.) can gain more from suppliers with the same budget, this allows them to free up budget to purchase other necessities once constrained by their current budget. Improving supplier value (i.e. negotiating aggressive cost reductions, improved service levels, etc.) allows for more options. Therefore, the Procurement function can deliver value by expanding options for the function and this in turn is a rewarding process as it generates more dependence on the procurement function. This dynamic results in an increase in the amount of spend under management by Procurement and ultimately improved cost reduction results. Figure 7 attempts to demonstrate the positive relationship between savings and spend under management as well as the balancing relationship between savings and incremental savings.

It is important to note that, the positive system dynamic between "Spend Under Management" and "Savings" cannot go on infinitely. There will be constraints once the system has reached full capacity. This is where the concept of the "balancing loops" comes into play (see right-hand side of Figure 1). In a balancing loop, we have attempted to demonstrate that the increase in incremental savings will eventually taper off until negotiated savings erode, which will then trigger new cost reduction opportunities.

The savings a procurement function can generate cannot be considered as infinite. In other words, you can only negotiate suppliers for savings up until a certain point. After that point, incremental savings begin declining to a point where very little incremental savings can be achieved given suppliers have been fully "negotiated" and can no longer operate sustainably. Hence, incremental savings begin declining once the entire supplier based has been fully optimized/negotiated. We can then move onto maximizing supplier value through collaboration initiatives such as joint-investment initiatives or joint-process improvement initiatives.

3.3.3 Business Rules Engines

Business Rule Engines (BRE), as an artificial intelligence capability, in essence support the declarative specification of the business domain knowledge (Kluza and Nalepa 2017). Although there is a difference in abstraction levels between both modeling techniques, rules can be complementary to processes. Rules can also be efficiently used to specify processes at a low-level of logic, while processes can serve as a procedural specification of the workflow, including the inference control. Business rules are also statements that govern the decisions we make day in and day out. For example, procurement spend should be channeled through to preferred suppliers to accelerate the attainment of spend thresholds which would eventually trigger quantity discounts. More specifically, all requests for laptop purchases must point to the two most popular brands and models and to the top laptop suppliers. Rules engines combine different scenarios to lead to one particular outcome. Rules originate from a variety of internal and external sources such as policy, best practices, and external regulations, not to mention supplier contract information. They can be in the form of documents and/or in the form of coding in systems. Business rules management systems (BRMS) is the system used to capture decision logic and automate across enterprise applications.

Business rules and Business Process Management (BPM) work together. Business Process BPM is a holistic approach for improving an organization's workflow by aligning processes with client needs. It focuses on the reengineering of processes to obtain optimization of procedures, increase efficiency and effectiveness by the constant application of process improvement (Mendling 2019; Weske 2007).

In the context of our study, we believe that the application of business rules engines can automate key tactical procurement processes and increase compliance across the Source-to-Pay process in its entirety. That said, Business Rules Engines will be one of the key AI technologies studied in this research paper.

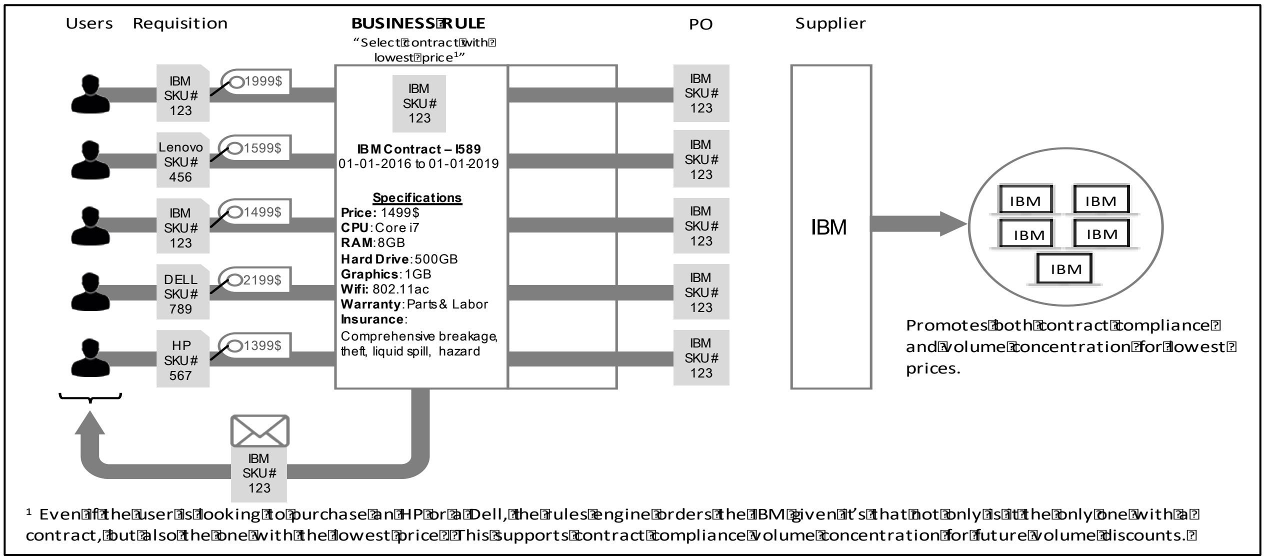

Figure 8 - Business Rules Engines for Hardware Procurement

In Figure 8, we conceptually demonstrate business rules engine applied in the context of hardware acquisition where users enter their desired specifications and even go as far as selecting a product however, an algorithm is put in place (in the form of Business Rules) which then automatically channels the request to a supplier where the best pre-negotiated contracts exist. This helps accelerates the speed at which the organization can concentrate volumes at one supplier to hit discount thresholds and benefit from volume discounts.

3.4 Organizational Context

The next section of this paper focuses on organizational context or on the soft skills required to deliver a moderating impact between AI technologies and procurement strategy as they relate to cost reduction. We selected both executive leadership and people teamwork as key moderating variables for three specific reasons. The first, according to a 2018 survey administered by Forbes Magazine, Canada ranked last in the adoption of AIA technologies such as machine learning and deep learning (Gordon 2019). One of the key reasons was the lack of executive leadership. The study concluded that, executive leadership was instrumental in driving the adoption of AI technologies in the workplace. In practice, procurement projects typically fail when there is an absence of executive leadership advocating procurement as a key strategic lever to maximize supplier value. The second is that procurement has always been seen as a support function solely existing to process requisitions at the lowest possible price however, and over the last decade, it's become more apparent that procurement is now being seen as a strategic competency within the overall organization (Barrad 2019a), because of its ability to re-engineer partnerships and financial models in a way that reduces risk and increases the ability of the firm to maximize benefits with key suppliers. Finally, people teamwork was selected given the need for cross-collaboration across business lines and procurement. What we typically witness in organizations is the frustration from the business line in dealing with procurement given lengthy cycle times that are wrapped with an abundant list of constraints and limitations in terms of what the business line can purchase and from whom. To overcome these challenges, and to adopt AIA in Procurement, it will be critical for organizations to have baseline collaboration as a starting point. Therefore, we believe that people-teamwork, especially cross business lines will be instrumental in unlocking the value that AIA can achieve in procurement to drive cost reduction.

As we reflect on the above, it is also important to note that (Teece et al. 1997) suggest that dynamic capabilities is the ability to integrate, build, and reconfigure both internal and external competencies to address rapidly changing environments'. The underlying theory around dynamic capabilities as also described by (Wernerfelt 1984), suggesting that it's the firm ability to dynamically adapt based on the changing business environment. Resources typically act as a buffer in such context. It becomes an opportunity for a firm to review, and potentially change its resources mix to maintain sustainability, and in most cases, develop a competitive advantage over competing firms. As opposed to the Resource Based View theory (Wernerfelt 1984), where the emphasis is put on selecting the appropriate resources, here, in dynamic capabilities, we are attempting to develop or renew existing staff skills.

In this model, it is our belief that executive leadership must not only review priorities as it relates to investing in AI, but must also emphasize the need to become a key ambassador to help drive the executive agenda from a leadership and direction perspective. From a people teamwork standpoint, it is typically known that most organizations work in siloes creating barriers to improvement, in this case what we call the functional silo syndrome (Ensor 1988). We are suggesting that department leaders and their staff must change their perception (or dynamic capabilities) to begin exploring the synergies associated with teamwork. We also believe that skills development will also play an instrumental role in achieving cost reduction, (Tassabehji and Moorhouse 2008).

In addition to this, if we for a moment also turn our attention exclusively on people, whether it be leaders or department members, we believe that motivation will be key in achieving cost reduction. We inspired ourselves from the Keller's ARCS Motivational theory (Keller 1983), which explores both strategies and tactics to effectively motivate learning. We believe that this is a fundamental requirement in the era of Artificial Intelligence which we consider a novelty in today's business world. In this theory, (Keller 1983), suggests that the motivational theory is grounded on the notion that perceived success, which he refers to as "expectancy" and perceived satisfaction of personal needs, in which he refers to as "value" both drive motivation for an individual to perform an activity. To achieve this, there are four fundamental requirements. The first is around attention which suggests the need for stimulation and curiosity to cure boredom. In our study, we are assuming that emerging technologies is one way to stimulate attention given they can be very powerful tools, and as some may suggest, may replace humans altogether (Makridakis 2017; Wilson and Daugherty 2018). This, in our opinion, is enough to solicit interest and to drive the need for the previous need around dynamic capabilities (Teece et al. 1997). The second area around the notion of motivation lies in the relevancy of the topic at hand and its ability to satisfy basic motives. For example, and from a career progression standpoint, some people may want to drive progressive careers where self-actualization (Maslow 1943; McLeod 2007) may take precedence and this, creates the need to motivate oneself through the learning of AI technologies and both its application and impact in the business environment. This then leads to the third motivational factor which is around confidence, or in other words, the need to feel competent and in control of their future and to gain satisfaction through both intrinsic and extrinsic motivation (Ryan and Deci 2000).

In conclusion, we operate in a dynamically evolving environment and we believe that for the firm to gain a competitive advantage, it must leverage both executive leadership and people teamwork as dynamic capabilities. They both, in our opinion, play a moderating role in cost reduction (Henseler and Fassott 2010).

3.4.1 Executive Leadership

Executive leadership, typically characterized as the upper echelon of the various managerial levels, comprise of individuals that make key strategic leadership decisions and that are most often regarded as the most powerful group of individuals within a firm. These leaders exert strong influence over the vision, mission, capacities and traits (Hambrick 1987). They are part of the management team and exert the highest levels of influence (Finkelstein 1996). There have been many studies around the impact of CEOs and executive leaders on the outcome of changes they bring about in organizational transformations (Dalton et al. 1998). Although there have also been some conflicting studies suggesting that there is almost no correlation between top leaders and organizational performance (Mak and Kusnadi 2005; Schmid 2009), in recent years many new studies suggest there is (Barsade et al. 2000; Carpenter 2002).

Leadership can be categorized into specific domains. For example (McCarthy 2014) presented leadership under five distinctive domains consisting of strategy, talent management, human capital development, execution and personal proficiency. (McCarthy 2014) suggests there are 14 effective and 13 ineffective managerial leadership categories. Effective categories include management support, openness, and appreciativeness towards employees. On the flipside, ineffective traits include observed behaviours such as unfair treatment towards specific employees, withholding information from staff and speaking with staff in a demeaning fashion.

In the context of leadership, one of the key elements we wish to highlight is the notion of empowerment. Empowerment has gained increased interest given the benefits it provides not only at the individual level, but also at the firm level thus, enhancing the performance of individual and teams (Carmeli 2011) and organizations (Stewart 2012). Empowerment has proven to have a positive effect on employees (Harris 2014). You can interchange the notion of empowerment with delegation of decision power or responsibility in allowing employees to perform their tasks (Leach 2010). Structural empowerment encompasses the concept of sharing power, decision-making and control over resources. All these elements have a positive impact on empowerment (Kanter 1977; Kirkman 1999; Spreitzer 2007).

By empowering subordinates to take on responsibility, you are motivating them through enhancing their personal efficacy (Conger 1988). This creates much more meaningfulness in their work (Chen et al. 2014; Chen et al. 2007; Maynard et al. 2012).

In the context of this research, we carefully analyze the role of executive leadership, as a moderator variable, in achieving cost reductions for the firm. Our hypotheses are formulated to highlight the importance in testing the degree of influence on procurement strategy and cost reduction by including organizational context (Executive Leadership and Teamwork).

3.4.2 Teamwork

A team refers to a group of two or more members interacting with one another interdependently towards a common and value goal (Salas et al. 2000). During this interaction it is normal for each of the team members to have individual tasks. There has been significant work in understanding team effectiveness as a function of both inputs (e.g. individual characteristics) and outputs (e.g. performance and team member satisfaction) to measure results (Campion et al. 1993; Goldstein 1993; Guzzo 1996). The moment-to-moment interaction or what is sometimes called the “black box” (Cannon-bowers 1998; Goldstein 1993; Tannenbaum et al. 1992) is also a clear indicator of measurement when assessing how well teams perform when interacting with each other.

There are also many conceptual models, taxonomies and even empirical studies that demonstrate how important teamwork is in reaching effective team performance (Cannon-bowers 1998; Hackman 1990; Sundstrom et al. 2000). It is important to note that teamwork is a multi-dimensional construct which makes it complex, elusive, and challenging to analyze. What’s also important to note is that, in the context of our study, not all teams are created equal (Sundstrom et al. 2000) and that teams are typically faced with a host of environmental factors that impact them throughout the process – in this case the procurement process.

There are certain emerging principles in teamwork design. First, teamwork is characterized by a set of flexible and adaptive behaviours, cognitions and attitudes (McIntyre 1995; Salas and Cannon-Bowers 2001). It is the mechanism by which members can adapt to meet other team member demand which ultimately leads to synchronization of tasks. By setting the above elements of the foundation, we can clearly suggest that teamwork will have a positive moderating impact between AI technologies and cost reduction.

Now that all the elements of our study have been discussed in detail, we are now ready to build our research model and linking the variables which will inform the key hypotheses of this study (Figure 9).

4 Hypotheses

In our research model (Figure 7), we have integrated several key hypotheses in a causal model. This section will outline in detail each hypothesis and their theoretical grounding.

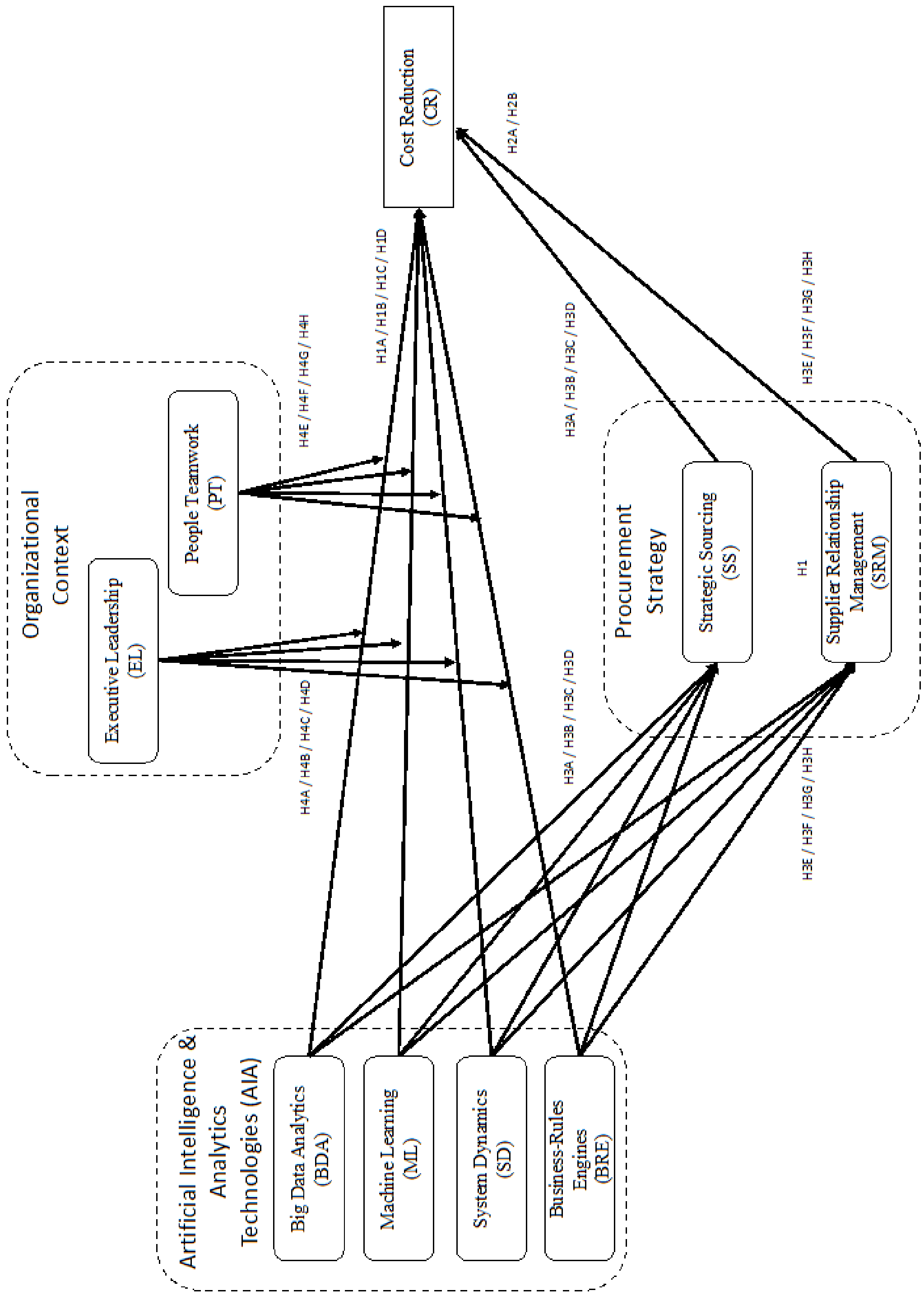

Figure 9 - Research Model

4.1 Direct Effect of AIA Technologies

The first subset of hypotheses focuses on the relationship between AIA technologies such as Business Rules Engines and Machine Learning. The second subset of hypotheses focus on the relationship between analytics such as Big Data Analytics and System Dynamics.

H1A: Positive Relationship between Big Data Analytics Technology and Cost Reduction
H1B: Positive Relationship between Machine Learning Technology and Cost Reduction
H1C: Positive Relationship between System Dynamics Technology and Cost Reduction
H1D: Positive Relationship between Business Rules Engines Technology and Cost Reduction

We believe that each of the four selected AIA Technologies all have a positive relationship on cost reduction (Ashrafi et al. 2019; Mahroof 2019). This stems from the fact that data plays an important role in understanding current spend patterns and in outlining opportunities for cost reduction (Singh et al. 2005). Machine learning algorithms support cost reduction, especially in the context of forecasting, if leveraged adequately. Take for example, the ability to continuously improve forecasting models to have a better understanding of future needs thus, allowing an extended window of time for procurement to optimize negotiations with suppliers.

Other AI technologies such as cognitive capabilities can leverage pattern detection to help predict equipment failure and to order critical replacement parts thus, enhancing maintenance optimization (Kuhnle et al. 2019). Business Rules Engines (BRE) allow for monitoring of procurement policies, where humans can’t, to constantly validate if procurement rules are being followed (Zhao 2010). For example, channeling spend to the appropriate channels before requisitions are sent out to active, or even non-active, suppliers. Compliant spend, when supported by BREs can improve cost reduction results. For all these reasons, we believe that the above AI technologies can have a positive impact on cost reduction.

4.2 Direct Effect of Procurement Strategy

We present procurement strategy as two distinct but complementary approaches. The first consists of applying the “*Strategic Sourcing Process*” to first gather intelligence that will drive negotiations and to, ultimately generate cost reductions. The second, “*Supplier Relationship Management (SRM)*”, typically results in maximizing supplier value for the firm while minimizing contract leakage by constantly monitoring supplier activities downstream from signing a contract (Amoako-Gyampah et al. 2019). When both approaches are combined, it is our belief that cost reduction results are typically improved.

H2A: Positive relationship between Strategic Sourcing and Cost Reduction
H2B: Positive relationship between Supplier Relationship Management and Cost Reduction

Procurement strategy is an approach used by many firms to manage both direct and indirect spend and leads to corporate improvement targets (Tchokogué et al. 2017). In Procurement strategy, there are several activities that are, in our opinion fundamental in achieving cost reduction. Within procurement strategy, we believe that the end-to-end process focuses on two distinct phases. What happens before you sign the supplier contract (sourcing) and how you manage the contract after it is signed (supplier relationship management or SRM). In the strategic sourcing process, efforts around spend analytics, supplier market assessment, strategy formulation and execution are all activities that drive cost reduction opportunities. SRM on the other hand, focuses on securing the value generated upstream in the sourcing process by maximizing supplier value and minimizing contract leakage (Amoako-Gyampah et al. 2019). This is achieved by administering supplier contract reviews, assessing performance on a periodical basis, managing risks and, most importantly, engaging in joint-process improvement initiatives. These SRM activities, coupled with procurement strategy activities, both lead to cost reduction.

4.3 Mediating Effects of Procurement Strategy

In general, and before we move into the next four hypotheses, it’s important to note that, AI technologies enable organizations in gathering intelligence to ensure compliance however, AI technologies cannot lead to cost reduction when leveraged on their own - they need to be supported by procurement strategies and activities such as monitoring contract leakage in the SRM process (Sujata et al. 2018). Procurement also needs to action the intelligence gathered in upstream activities (i.e. spend analytics) to drive cost reduction resulting from volume concentrations or from inducing competition. That said, we believe that procurement strategy, which encompasses both strategic sourcing and supplier relationship management plays a mediating effect on cost reduction. Said simply, you can generate a pipeline of cost reduction opportunities however, you need the leg that executes on those strategies – which we refer to as strategic sourcing and supplier relationship management.

4.3.1 Strategic Sourcing

Within the procurement strategy cluster, strategic sourcing (SS) focuses on systematically gathering intelligence to improve the outcome during supplier negotiations and improve value for the firm (Nguyen et al. 2018). In every organization, the importance of information is undeniable since it exerts prominent effects on all internal activities, ranging from strategy-devising to operational exercises. In the absence of high-quality information, an organization will not be able to adopt sound resolutions, which in turn squander opportunities and augment business risks (Hassan et al. 2018). That said, we believe that strategic sourcing, within procurement strategy, plays a mediating role to improve the outcome of the Big Data Analytics from a cost reduction standpoint. In other words, with good data, great opportunities emerge. Those opportunities are capitalized on during the strategic sourcing process and therefore we believe that procurement strategy activities will have a strong mediating effect on cost reduction. The next 8 hypotheses will discuss the impact of both strategic sourcing and supplier relationship management on each of the four AI technologies previously discussed (BDA, BRE, ML and SD).

H3A: SS plays a mediating effect on the impact of Big Data Analytics on Cost Reduction

Big Data Analytics is the complex process of analyzing enormous amounts of data (Hassan et al. 2018), providing the firm with the right information required to identify key sourcing opportunities. For example, by benchmarking prices across the various business lines internally, and even with competitors externally, the firm can capture very insightful data on IT consultant rates and in turn reduce rate gaps by opting for a price-leveling strategy. Negotiating rates without good baseline data will not yield the same type of results as if the firm would gather competitive intelligence and use that information as the basis for negotiation. That said, we believe that strategic sourcing activities such as the data gathering process (i.e. generating spend analytics) will play an instrumental and mediating effect on cost reduction.

H3B: SS plays a mediating effect on the impact of Machine Learning on Cost Reduction

We also believe that the same holds true for Machine Learning algorithms. Machine learning algorithms can play an instrumental role in improving a firm's ability to predict future needs and act strategically to source those needs from suppliers at an optimal price (Parmezan et al. 2019). This becomes an excellent support tool in the context of an ERP based environment as it may improve the quality of operations, improve a firm's agility in responding to market demand, and finally, increase the efficiency and the competitiveness in organizations as a whole (Jenab et al. 2019). That said, we believe that procurement staff can leverage Machine Learning algorithms through the strategic sourcing process to improve operations efficiency and cost reduction results. Time-series forecasting is an excellent entry point for ML algorithms as it helps reduce forecasting errors typically generated from the limitations associated with some simple linear regression models.

H3C: SS plays a mediating effect on the impact of System Dynamics on Cost Reduction

System Dynamics, as discussed in the literature review section of this paper, is the process by which a firm attempts to understand and master the non-linear relationships within the several variables within the procurement ecosystem as a whole (Barrad et al. 2018). For example, understanding the concept that the more spend is channelled through procurement, the greater the involvement of procurement staff to deliver on strategic sourcing activities and the greater the cost reduction results. Several papers suggest that the 'lowest bid' form of procurement is not necessarily the most efficient form of procurement. There are other more effective procurement strategies that lead to real cost reduction and service enhancements on a sustainable basis (Mackenzie and Tuckwood 2012). In the context of system dynamics, we are attempting to assess whether the ability of involving procurement staff ahead of negotiations, as opposed to the very end of negotiation process, helps improve cost reduction results. We are also attempting to uncover whether firms understand the capabilities trap where leadership is not able to free-up staff to work on strategic activities due to the fact that they are consumed in managing activities that are tactical in nature or also referred to as "firefighting".

H3D: SS plays a meditating effect on the impact of Business Rules Engines on Cost Reduction

Business Rules Engines plays a fundamental role in supporting procurement in compliance activities by applying business logic and rules to certain procurement scenarios. For example, activating payment discounting on supplier invoices and driving volume concentration to achieve spend thresholds and to benefit from volume discounts (Xiameter 2002). It is understood that quantity discount discussions must take place upstream in the sourcing process. The strategic sourcing process achieves this goal and as such plays a mediating effect between Business Rules Engines and cost reduction hence, our next hypothesis focuses on automating certain procurement processes by adopting business rules on select procurement activities, which would typically be overlooked by procurement staff and would ultimately lead to lower cost reduction performance.

4.3.2 Supplier Relationship Management (SRM)

Moving onto Supplier Relationship Management (SRM), we believe SRM acts as a mediating effect on the impact of AI technologies on cost reduction. In the context of managing suppliers, there are a series of logically related activities required. For example, administering quarterly business reviews (QBRs) to assess supplier performance, or diving into financial reviews to ensure both performance and price compliance, etc. As the firm delivers on key SRM activities, the use of AI technologies can support in achieving cost reductions. For example, the use of Business Rules Engines to automatically scan invoices and compare them to agreed upon prices and then channeling non-compliant transactions to procurement analysts for additional investigation. To enable cost reduction, the use of AI technologies must be mediated by SRM activities. In the next 4 hypotheses we discuss how we believe AI technologies can support SRM activities and how SRM activities can then have a mediating effect on cost reduction.

H3E: SRM plays mediating effect on the impact of Big Data Analytics on Cost Reduction

Big Data analytics is the core foundation of strategic procurement. Without good data, a firm can lack focus in terms of where to invest efforts to maximize value and minimize leakage. Many firms until today still struggle in building the appropriate spend cubes to assess opportunities. Instead, the rely on tactical activities to keep the lights on. For example, managing demand downstream and rushing through supplier negotiations to meet the last-minute demands of the organization. With a solid foundation around Big Data Analytics, the firm is now armed with the intelligence required to proceed in negotiations however, without a sound supplier management process in place, efforts can be diluted and lead to little or no effect on the bottom line. Another example consists of using Big Data Analytics to fuel Quarterly Business Review (QBR) reports and meetings, providing procurement with a 360-degree view across all contracts, for the same supplier, covering the various lines of business within the same firm. That said, we believe that SRM activities play an important and mediating role between the data the firm can capture and the cost reduction it can generate via SRM activities. Hence, the hypothesis that SRM plays a mediating role between BDA and CR.

H3F: SRM plays mediating effect on the impact of Machine Learning on Cost Reduction

Machine learning algorithms can support in supplier relationship management activities by evaluating supply partner’s capability for seasonal products using machine learning techniques (Hong and Ha 2008). With ML algorithms working in the background to assess which suppliers would default in upcoming procurement requirements, SRM would act as a mediating effect to dialogue with suppliers and assess how gaps between demand and supply can be addressed. In fact, the impact goes beyond sourcing and could support manufacturing by allowing them to dynamically optimize production schedules and sequences based on the arrival of raw materials and, consequently, avoid production interruptions. That said, we believe that machine learning will mediate the effect between SRM and cost reduction.

H3G: SRM plays mediating effect on the impact of System Dynamics on Cost Reduction

Supplier Relationship Management can positively influence the impact of System Dynamics on cost reduction by guiding procurement staff in systematically channeling most spend through procurement channels and in turn creating opportunities for volume concentration in exchange for improved pricing or cost reduction. In the context of system dynamics, we believe that, optimizing the portfolio of suppliers (and associated initiatives) is an important part of key procurement activities. We also believe that the more advanced procurement is in simulating "what-if" scenarios and developing risk-mitigation strategies, the better off they are in terms of cost reduction performance. The same holds true for cost avoidance resulting from supply interruption.

H3H: SRM plays a mediating effect on the impact of Business Rules Engines on Cost Reduction

Business Rules Engines can automate the process of dynamic discounting for cost reduction (Cheng 2013). If BREs are in place, in the process of managing suppliers, clear payment terms, documented in an BRE can enhance cost reductions. The application of business rules in decision making can result in improvements from a cost standpoint, when compared to current heuristics (Judd et al. 2014). As part of cost reduction efforts, some firms have leveraged the consolidation of business rules across supply chain processes for savings (Sevre et al. 2011).

4.4 Moderating Effects of Organizational Context

Moderating impacts are impacts that only strengthen or weaken the relationship between the independent variable (AI technologies) and the dependent variable (cost reduction). Regardless of the relationship between the independent variable and the dependent variable, moderating variables will always have an impact and instead of explaining the relationship like mediator variables do, they instead highlight the strength of the relationship or in other words, the level of influence.

Organizational context focuses on two key elements. The first, executive leadership and the second, teamwork. In an organization, both AI technologies as well as the application of procurement strategy principles, such as strategic sourcing and supplier relationship management, can both have a positive impact on cost reduction. Moreover, the application of procurement strategy would yield even greater results with a strong organizational context (Macke and Genari 2019). For artificial technology and procurement strategy to work well hand in hand, we believe firms require a solid organizational context (i.e. executive leadership and teamwork). Without ethical leadership, it is very difficult to generate cost reduction (Khan et al. 2018).

4.4.1 Executive Leadership

In the context of our study, we believe that executive leadership will always be present in organizations and under any circumstance. We are attempting to assess the strength of this moderating variable on cost reduction. We believe that AI technologies are at their embryonic stage and that adoption is currently very low (less than 30%). For a firm to leverage strategic sourcing and fully benefit from its ability to maximize value, it will require AI technologies for improved forecasts and for pattern detection when abnormal procurement behaviors are suspected.

Strategic sourcing sometimes leads to making unpopular decisions vis-à-vis the business line. For example, terminating a long-standing relationship between a business line and their preferred suppliers because of going through an objective supplier selection process in the context of contract renewals. What we typically see often in organizations is the business line resisting such change and instead continuing to nurture a relationship with that supplier.

For the strategic sourcing exercise to have a sustainable impact on cost reduction, we believe that executive leadership will play an instrumental moderating role in enforcing new rules, including supplier contract termination, in the context of cost reduction. In the next section, we discuss how both Executive Leadership and Teamwork, which we call organizational context, will play a mediating effect between each of the four AI technologies and cost reduction.

H4A: EL plays a moderating effect between the impact of BDA on CR

Big Data Analytics provides management with business intelligence required to make effective procurement decisions that generate impact to the bottom line. In the context of Supplier Relationship Management, AI technologies can support in identifying hidden patters of uncommon procurement behaviours. For example, different rates for the same service across the various business lines. Although a Master Services Agreement (MSA) may be in place, it is not uncommon to see this type of behaviour. Typically referred to as "backdoor selling", certain suppliers attempt to intentionally (or not) fragment sales across the various business lines in order to charge premium prices and avoid being subject to quantity discounts as a result of the aggregated volume they generate in terms of sales across their client as a whole.

Executive leadership plays a moderating role in supporting procurement in enforcing rules to ensure both procurement as a function, and the organization, maximizes supplier value and minimize contract leakage. It is therefore important to note that executive leadership is instrumental in enforcing such rules. We believe that, with the right level of executive leadership, procurement can impose specific regulations among suppliers, such as a one consolidated invoice for all the services rendered across the organization. Procurement can then explore the possibility of negotiating better clauses for the firm such as payment terms and volume discounts.

Executive leadership will have a moderating effect between strategic sourcing and cost reduction. As the procurement department executes on the strategic sourcing process to generate ideas around cost reduction and execute on them, it will require support from executives throughout the entire sourcing process. For example, once procurement has assessed historical spend, it may identify areas of opportunities. Take for example, concentrating volumes to preferred suppliers (Tang et al. 2019). Volume consolidation is a major consequence of supply base reduction (Cai et al. 2010). That would imply terminating contracts with existing suppliers to which, some internal users may have mature and preferred relationships with. The counter effects typically take place in this type of situation. The first, pushback from the business disallowing procurement to terminate contracts. The second, maverick buying where the business will continue to procure goods and services from non-registered suppliers leading to non-compliant transactions and spend proliferation.

When it comes to supplier relationship management, Big Data Analytics will play a big role in capturing data, but this data can only be actioned if executive leadership is fully onboard with procurements decisions. For example, if a compliance assessment leads to the conclusion that the supplier has had too many defaults in a specific period, the SRM team can automatically put the supplier in temporary “suspension” until the stations re-establishes. Suppliers may sometimes dispute that decision by having one of their executive members escalate to an internal executive member within the firm to suggest making an exception. In order for this not to take place, the executive leadership team within procurement must be ready to stand by its procurement staff and support the decision until further notice. That said, the executive leadership plays a moderating role between Big Data Analytics and Supplier Relationship Management by supporting fact-based decision on suppliers.

Executive leadership will play a moderating impact between SRM and CR as efforts are put forward to integrate the end-to-end supply chain (Birasnav and Bienstock 2019). As SRM focuses on managing activities downstream from sourcing a contract, for example managing supplier performance and data-to-day financial management, there will be significant need for support from the executive leadership. For example, the executive leadership must be involved in negotiations and supplier disputes to support procurement in improving buyer-seller exchanges (Janda et al. 2002). Our experience tells us that when disputes take place, supplier executives tend to bypass procurement by connecting with the executives from the Line of business (LoB) and leverage their relationships to circumvent procurement requests. To avoid this, executive leadership will have to play an active role in supporting procurement staff in enforcing actions on non-compliant suppliers.

H4B: EL plays a moderating effect between the impact of ML on CR

Machine learning can have a strong influence strategic sourcing if supported by teamwork. For example, the use of machine learning in procurement can support in managing suppliers by scanning various contracts across the supply base and generate a list of contracts coming to maturity. This would allow procurement to prioritize contract review priorities and assess where it can synchronize contracts to induce competition. The ability to empower procurement staff (i.e. teamwork) can play a moderator role between ML and CR if procurement is enabled. By the business line having the ability to negotiate directly with suppliers and make contract decisions autonomously, the firm can have better cost reduction results. To do this, client-unit leaders must also be heavily involved to share supplier historical context and support procurement in their proposed supplier strategies.

As machine learning algorithms are leveraged to enhance demand forecasting accuracy, specifically in the need assessment activity within the strategic sourcing process, the firm will be faced with new data and intelligence that it must action to reap benefits. For this to work, procurement must have a solid understanding of procurements objectives, and engage client-unit leaders in challenging demand and together agree on final demand requirements. That said, the following hypothesis suggests that teamwork will have a moderator effect on the impact of machine learning on strategic sourcing.

Machine learning can generate game changing insights when it comes to supplier forecasting. The output of ML algorithms can lead procurement to make decisions that can sometimes be risk averse for the business. For example, assessing that the forecast in terms of procurement needs will be double in the fourth quarter as it was the year before. This can represent millions for an organization and finance may resist in clearing up the funds to go ahead with such a large purchase.

For Machine Learning to have an impact on supplier relationship management activities, executive leadership will have to be very strong.

ML can generate insight that go against common logic, for example, predicting that stockouts may happened with certain suppliers creating a supply chain risk. In the context of strategic sourcing, procurement staff may opt for a new and different supplier which requires a large investment for their integration into the client firm. Bold moves like this can only take place if the executive leaders support procurement staff and allow them to make bold moves on the supplier base. Hence, to have a strong relationship between ML and SS, executive leadership must be very strong.

H4C: EL plays a moderating effect between the impact of SD on CR

Analyzing the portfolio and making decisions to shut down procurement initiatives, negotiating with internal stakeholders to involve procurement from the beginning of the sourcing process, and enabling the procurement team with analytics to compress the time it takes to generate insights are all activities that the executive leadership can push in order for system dynamics to have a positive effect on supplier relationship management and exert high levels of influence (Finkelstein 1996; Hambrick 1987).

H4D: EL plays a moderating effect between the impact of BRE on CR

Business Rules Engines (BRE) consist of procurement rules and logic embedded in software. For BRE to have an impact on strategic sourcing, the procurement rules established by procurement staff must be fully supported by the executive leadership. For example, if the business rules engine assesses that suppliers with which we have tail spend (less than $50,000 of spend per annum) should be eliminated from the active supplier profile, executive leadership must be able to support the decision. That said, BREs can have a longstanding effect on cost reduction if and only if, executive leadership is fully supportive of procurement decisions as it relates to the portfolio of suppliers and the terms that may be imposed on them by procurement. BRE can have a positive impact on SRM only if EL supports procurement in setting and enforcing procurement policies around the way they manage suppliers. Another example, if procurement enforces rules around purchasing at specific vendors and only through pre-negotiated catalogues, this would only be successfully enforced if procurement is supported by strong executive leadership.

4.4.2 People Teamwork

H4E: PT plays a moderating effect between the impact of BDA on CR

As discussed previously, Procurement Strategy can deliver greater results when supported with "state of the art" AI technologies such as Big Data Analytics, Business Rules Engines and Machine Learning algorithms. To build those technologies, put them to use, enterprise-wide collaboration is required. This collaboration, which we refer to as teamwork, is not only required to truly understand how the business can fuel procurement with intelligence but it is also required to make the right procurement decisions but and business objectives. Cross-enterprise teamwork will be required to put technology to work with the ultimate objective of benefiting the business.

H4F: PT plays a moderating effect between the impact of ML on CR

Machine learning algorithms have gained popularity over their effectiveness in predicting demand (Liu et al. 2018). For procurement to leverage machine learning algorithms when negotiating with suppliers, teamwork will be required. Procurement must collaborate with various lines of business to be able to gather both qualitative and quantitative data on demand in preparation for negotiations with suppliers. This requires cross-collaboration to improve forecast accuracy. Hence, the following hypothesis: teamwork will have a moderating impact between machine learning and supplier relationship management.

H4G: PT plays a moderating effect between the impact of SD on CR

System dynamics can show a positive impact on strategic sourcing if enabled by executive leadership (Barrad et al. 2018). Figure 10 outlines how procurement leadership can generate department growth and in turn lead to incremental cost savings. The three reinforcing loops (R1, R2 and R3) and the one balancing effect (B1) are further described below.

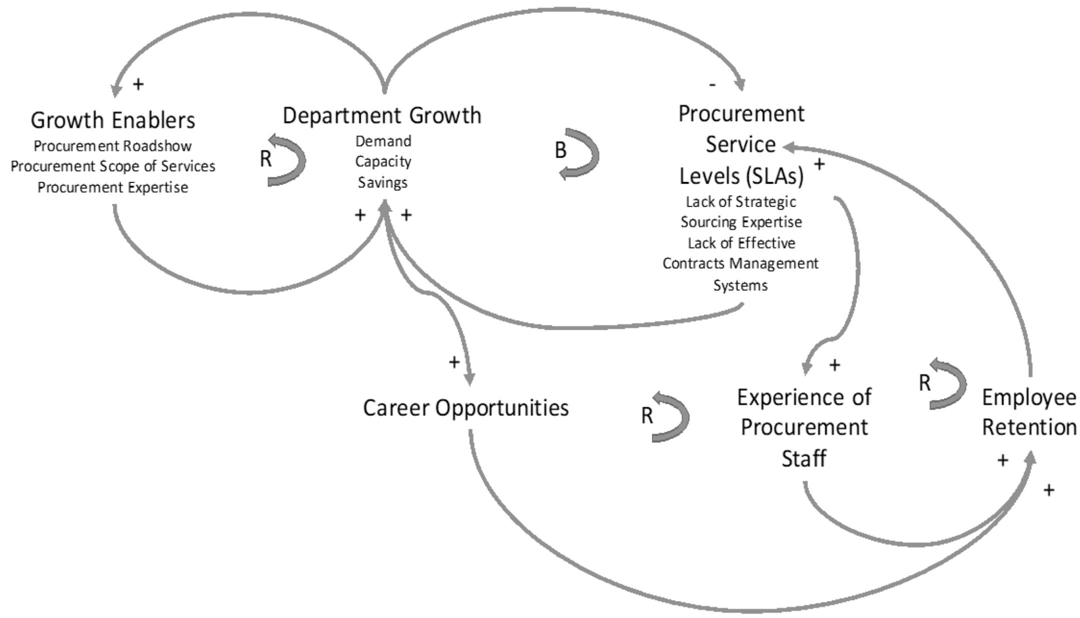

Figure 10 - Determinants of Procurement Attractiveness

1. **R1:** As Procurement executive leadership engages in doing a roadshow and creating awareness in terms of their potential contribution, the more solicited they will become. Also, the more Procurement expands its scope of services (by covering more categories of spend), the more they will become valued in the rest of the organization. This will create departmental growth. This growth will become Procurement's fuel to grow even larger and serve more internal clients.

2. **R2:** As the department grows, it will become more attractive given the strategic work they do (shifting away from pure tactical sourcing). This will create interest from employees operating in other business units who will now consider joining procurement. This will in turn promote employee retention. Employees that stick around will enjoy satisfaction from the work they do and, through their satisfaction, Procurement secure good service levels which will increase the participation in sourcing deals.

3. **R3:** Delivering great service levels to internal clients will in turn promote a great environment where procurement staff will be satisfied with the work, they perform not to mention the recognition they will receive for their work. This will induce employee retention and service levels will continue to rise.

4. **B1:** As Procurement grows and, as their scope of services expand, Service Level Agreements SLAs (between Procurement and internal business functions) will eventually take a hit. Once it does, some internal customers (especially the ones that have been impacted by negative experiences) may decide to go their own way and purchase

independently going forward (going back to a partially decentralized procurement operating model).

The most important predictor of success in the Procurement department lies its ability to shift their focus to strategic activities as opposed to tactical activities such as getting contracts signed and entered in a system. By becoming more strategic, the procurement department can generate millions in savings for the organization through strategic supplier negotiations. There is clearly a system dynamic that exists. This dynamic must be understood and managed in order maximize supplier value and minimize contract leakage. In this case, the role of executive leadership played a moderating role in improving the impact of SD on SS.

H4H: PT plays a moderating effect between the impact of BRE on CR

People and teamwork will have a moderating effect between business rules engines and strategic sourcing. In order for procurement to develop rules, based on both policies and best practices, to fuel procurement in negotiating those rules “sourcing strategy execution” within the strategic sourcing process, it will be extremely important for procurement to keep a “big picture” perspective and truly understand the role of procurement within the organization. For example, “squeezing” cost out of suppliers may result in higher costs over the course of the lifecycle of the contract. That said, negotiating long term-value and leveraging internal stakeholder engagement through teamwork will have a moderating impact on the applicability of business rules engines during strategic sourcing exercise.

Procurement organizations typically manage thousands of suppliers on a day-to-day basis (Barrad et al. 2018) and must prioritize supplier portfolios using tiering strategies. For top tier suppliers, teams are typically assigned to manage performance and mitigate risks on a day-to-basis. For bottom tier suppliers, the organization must depend on classic technologies such as automation, coupled with emerging technologies such as complex event processing or CEP (Barrad 2019c) that enable staff to be advised when exceptional circumstances arise such as non-compliant transactions or even opportunities where procurement can maximize supplier value and/or reduce supplier risk. This is where Business Rules Engines (BRE) are typically put in place to manage the lower tier of the supplier base. For business rules to be drafted and enforced, teamwork will be required to understand supplier historical context from a performance standpoint and to collaboratively set rules to be automated by BRE and CEP systems. That said, we believe that teamwork will have a moderating impact on the use of rules engines to manage Procurement Strategy activities both in strategic sourcing and supplier relationship management.

5 Methodology

In Figure 9 we highlight the research approach selected for this study. This section will present our survey methodology and how we used the Partial Least Squares Algorithm to test our hypotheses.

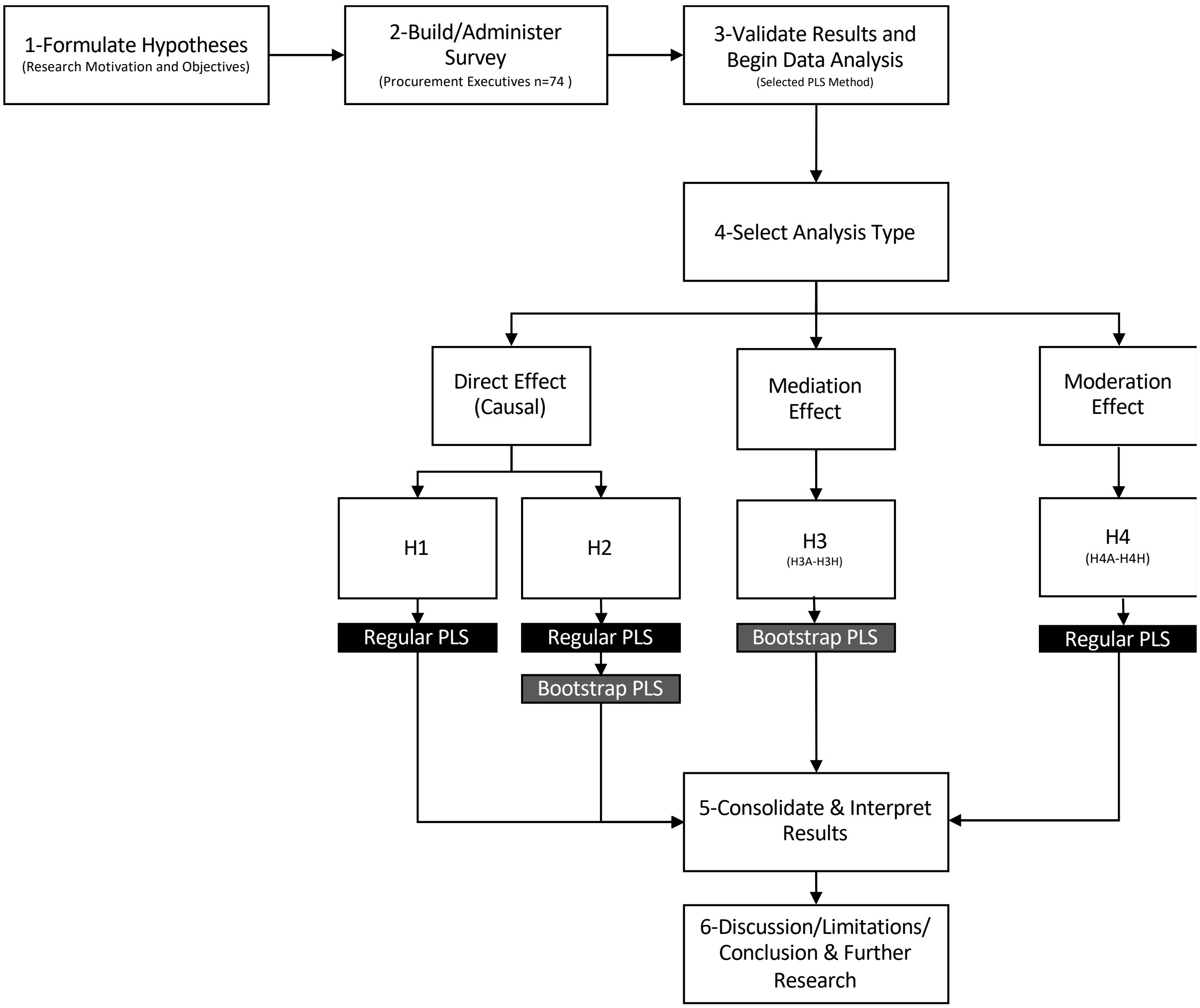

Figure 11 - Research Approach

We begin by formulating the hypotheses. There are in total 18 hypotheses that will be tested using various methods. The next step consists of building a survey which included 53 construct items (Table 73). We proceeded to administer the survey to generate results. Once results were in, we reviewed and discarded surveys (i.e. incomplete, non-qualified respondents) to leave us with a net sample size of 74 which satisfies conditions to pursue the study. We then proceeded to segregate hypotheses into direct causal effects, mediation effect and/or moderation effects. For all mediation effect, we strictly ran bootstrap analyses. Otherwise, for all other effects (direct and moderation) we ran the regular PLS algorithm which satisfies the standard for fully reflective models. We then proceeded in interpreting the results, highlighting certain limitation, and even providing recommendations for further research considerations.

5.1 Population and Sampling

To validate our hypotheses of this study, a survey was administered to senior procurement professionals across Canada. Survey respondents were either *Chief Procurement Officers, VP of Procurement, Senior Directors* or *Category Managers*. This sampling choice was the most relevant for this study as their experience in standing up procurement organizations, including the implementation of procurement analytics and systems governance would generate great insight for our research. Moreover, senior procurement professionals also have a strong mastery of the strategic sourcing process, from needs analysis to selecting and integrating suppliers within the supply chain, hence allowing us to capture their perspective as it relates to pure cost reduction. This was validated through a series of qualifying questions at the very beginning of the survey.

Only senior Procurement professionals operating mainly operating in Canada and who have access to and use business intelligence could take the survey. This is a reliable data collection approach for this type of paper. This paper used professional contacts in the field of procurement and leveraged an active network in this field. No incentives were offered to complete this survey.

By leveraging professional networks, we were able to gather and retain 74 surveys. The minimum sample size to detect an adequate effect size at a power of 0.80 and alpha of 0.05 would be 50 cases (Marcoulides 2006). Thus, the sample size used in this paper satisfies the requirements for the proposed research model. The sample size requirements will be further discussed in detail in section 6.2 of this paper.

5.2 Measurement Instrument

Cost reduction was measured as a first-order formative construct (Lu et al. 2011). The use of data-analytics was measured as a 10-point Likert scale (Venkatesh et al. 2003).

During this study, we also wanted to include several control variables to increase the relevance of the study. For example, age was used to cross-correlate between actual and target survey respondents. In other words, we assumed that executives typically have a certain number of years of experience relative to their peers. The size of the organization also mattered given that larger size enterprise typically has access to more resources for systems and to make investments in analytics (Chen et al. 2014). As discussed in the respondent’s profile, 70% of respondents worked in larger size organizations (1000+ employees).

We added industry as a discriminant as not all firms are subject to the same profit margins and this clearly affects the potential of achieving cost savings (e.g. capital-intensive industries compared to commodities industry typically have greater opportunities to compress costs). For example, reducing inventory levels by improving demand forecasting using Big Data Analytics or Machine Learning algorithms.

To ensure the quality of responses, we also proceeded with a series of qualifying questions to assess respondent’s familiarity with AI Technologies and classical procurement practices such as strategic sourcing and supplier relationship management (SRM).

5.3 Data Analysis

Structural Equation Modeling (SEM), which also known as Generalized Structured Component Analysis (GSCA), or a soft modeling approach, is a second-generation multivariate data analysis method to test theoretically supported linear and additive causal models (Chin 1998; Haenlin 2004; StatSoft 2013). PLS has become a foundational tool in both applied and theoretical research (Tenenhaus and Tenenhaus 2011). PLS has also become increasingly popular as a core research tool for academics in Computer Science.

PLS was selected as the method of choice for data analysis for several reasons but mainly because of the sample size and analytical focus (Table 3). Table offers a comparative analysis to suggest when is best to use SmartPLS over other general structured component analysis software such as Component-Based SEM or CBSEM (e.g. LISREL, AMOS, EQS and Mplus).

Elements of Consideration	CBSEM	PLS (SmartPLS, PLS, etc.)
Theory	Strong	Flexible
Distribution Assumptions	Multivariate normality	Non-parametric
Sample Size	Large (at least 200)	Small (30-100)
Analytical Focus	Confirms theoretically assumed relationships	Identification of relationships between constructs
Number of Indicators per construct	Depending on aggregation; ideally 4+	1 or more (depending on consistency)
Indicators to Construct	Mainly reflective	Both reflective and normative
Improper Solutions/Factor Indeterminacy (unique solution)	Depends on model	Always identified
Type of Measurement	Interval or ration	Categorical to ratio
Complexity of Model	Models with 100+ indicators	Can also deal with large models

Table 3 - Comparative Analysis of CBSEM vs PLS

Among many variance-based structural equation modeling techniques, Partial Least Squares (PLS) path modeling has been regarded as the "most fully developed and general system" (McDonald 1996). PLS modeling is one of the most used approaches in management information systems (Ringle et al. 2012). It is also quite often used in the area of marketing (Hair et al. 2012; Henseler et al. 2009) and also commonly used in strategy (Hulland 1999) and operations management (Peng and Lai 2012).

The goal of PLS-SEM is to maximize the explained variance through path significance testing. It is a superior approach model to testing predictive accuracy. The SmartPLS software, which has been used in the context of this study, offers academic the opportunity to deepen our capabilities (Ringle et al. 2012) in assessing the role of AI technologies and procurement strategies in the context of cost reduction.

In this paper, we use the PLS-SEM as an empirical approach to overcome some of the challenges that exist with first-generation techniques and regression-based approaches such as multiple regression analysis, discriminant analysis, logistic regression and analysis of variance (ANOVA) or factor cluster analysis. Existing limitations include, but are not limited to, the postulation of simple model structures, assumptions that all variables can be considered simultaneously and the conjecture that all variables are measured without error (Haenlin 2004). We strongly believe that, in a multivariate world there exists a limited set of variables. That is, we cannot consider certain variable in isolation of others or else the analysis could be qualified as "relatively artificial".

The PLS-SEM method used in this paper allows us to construct variables that may not be as easily observable and that are typically measured by indicators (i.e. manifest variables or observed measured). Structural Equation Modeling has become the tool of trade in survey-based research (Disjkstra and Henseler, 2015). Two families of SEM prevail (Chin 1998; Reinartz et al. 2009). Covariance-based SEM and variance-based SEM which is now the most popular (Bry et al. 2012; Hwang et al. 2010; Lu et al. 2011; Tenenhaus and Tenenhaus 2011) and frequent application, (Hair et al. 2013; Ringle et al. 2012).

In this paper, Partial Least Squares Regression (PLS) is used to support or reject theoretical assumptions in the research model (Figure 5). The path diagram we have developed in our PLS model graphically explains how the various elements relate to one another (Diamantopoulos 1994).

We adopted an Inner Model structural model where exogenous latent variables connect to indicators. PLS-SEM is ideal in applied research projects, when the sample size is small, the applications have little available theory, predictive accuracy is fundamental and, when correct model specification cannot be ensured beforehand. The indicators in our model are of formative nature as they're not highly correlated and interchangeable, therefore, reliability and validity should be investigated thoroughly (Haenlin 2004; Hair et al. 2013; Petter et al. 2007).

5.3.1 Composite, Common Factor and Mixed Models

In the context of our study, we have employed a fully reflective measurement model where relationships point outwards from all construct to the indicators (Hair et al. 2016). For example, each of the four AI technologies, or latent variables, have arrows pointing outwards to the specific survey items within the construct administered during our survey. More specifically, we have administered the standard PLS algorithm, or the recommended model for reflective measurement models, to assess correlations between constructs and indicators by looking at the outer weights. This is otherwise known as the common factor model where the PLSc algorithm computes the composites using Mode A. SmartPLS allows the ability to estimate proxies of latent variables that represent different model types (i.e. composite models, common factor models or even mixed composite models).

5.3.2 Bootstrapping

Bootstrapping focuses on two parameters (i.e. case and sample size) and is used to generate T-statistics to help gauge statistical significance (Hair et al. 2016). It is a simple and straightforward way to extrapolate estimates of standard errors and confidence intervals. It is also an approach used to verify the stability of results. Bootstrap is typically recommended in situations where the theoretical distribution of a statistic is complicated or unknown (Henseler et al. 2009). Bootstrap is completely disconnected from any distribution and be an indirect method to assess distribution properties of the sample as well as the parameters from the actual distribution.

There are other cases where the sample size is too small and creates challenges in making statistical inferences. In the specific case of our study, we are attempting to reach out to highly qualified procurement executives in approximately 70 firms located across North America who have experience in both procurement strategies and systems. In the context of our study, we must estimate relationships in the model over and overusing certain cases. In some cases, the sample size is too small (n=5) and this drives the standard error high. The solution is to increase the sample size of cases and the resampling size.

Another area where bootstrapping is a recommended procedure, is when there is a large amount of calculations to be performed on a small sample size. When you run a bootstrap if the path statistic is significant, but the T-statistic is not (i.e. <1.96), this may suggest that there may be an inconsistent relationship due to a smaller sample size. Bootstrapping is one of the algorithms available in SmartPLS and typically used to compute both T-Values and P-Values. In other words, it performs calculations for confidence intervals and outlays the P-Values required for model significance interpretation. This will reduce the standard error and the T-statistic will jump in value as opposed regressing and yielding minimal or no significance.

In our hypothesis testing, we used bootstrapping to assess the effect of mediation which represent the hypotheses laid out in H3 (i.e. H3A through to H3H). For direct and moderating effects, we used the standard PLS Algorithm.

5.3.3 Consistency

There are certain limitations associated with using Structural Equation Modeling (SEM). For example, the estimation of path correlations and their relative coefficients are typically only consistent with a very large sample size (Wold 1982). This causes estimates to be biased when assessing paths between observed variables and latent variables.

In PLS, the objective would be to run a consistent bootstrap only if the model is fully reflective (Table 3) or in other words, if it mirrors covariance based Structural Equation Modelling (SEM). In contrast, regular bootstrapping is best used when you have formative factors. In our study, this is the case – all latent variables point outwards to indicators therefore, we used the standard bootstrap algorithm.

Relationship between constructs (structural) and measures (measurement model). Two models between the relationship of constructs and measures (i.e. formative and reflective). The Reflective measurement model, or the one used in this study, the changes comes from the construct and go towards the measurement items. In the reflective measurement model, the correlation between the indicators is what is most important and should be high.

In the reflective model, our aim is to maximize the overlap between interchangeable indicators (i.e. high correlation between indicators). Theory suggests that, in a reflective measurement model, the aim is to develop theories around the relationship between constructs and to refine how data will be collected to prove or disprove those relationships (as opposed to a formative model where the aim is to detect patterns in the data and develop the basis for theories based on observations). Reflective model, indicators are interchangeable and can be removed without altering the model. The table below helps understand key differences between formative and reflective constructs:

Scale Type	Reflective
Indicators define characteristics of the model	X
Changes in indicators do not cause changes in construct	X
Changes in constructs cause changes in indicators	X
Indicators share a common theme (consistent)	X
Eliminating one indicator does not change conceptual domain of construct	X
A change in one indicator affects all other indicators	X
Indicators have same antecedents and consequences	X

Table 4 - Reflective Model Requirements

5.3.4 Mediation

Mediation is a test typically used to determine if an independent variable influences a dependent variable through some mediator. This is a very well-known approach used by many researchers (Zhao 2010) and has become more and more sophisticated over the past few years (Cepeda-Carrion 2018). The Baron and Kenny criteria for establishing mediation effects is widely used across scientific research (Baron 1986). The (Baron 1986) criteria, is also an article that has been cited in over 10,000 journal articles. It is important to note that although PLS-SEM testing has been around for years, there are some limitations associated with this approach. For example, not drawing on detailed enough statistical findings thus, keeping the model in its most basic and compromising accuracy. There are new models and techniques available to help researchers discuss their studies in a more accurate way such as the use of multiple mediators.

We can assess if a variable is a mediator when it meets the following conditions: The first is assessing whether the variance associated to an independent variable significantly accounts for variations in the mediator variable. The second is around the assessing if the variations in the mediator significantly account for variations in the dependent variable. Finally, the last condition, is assessing whether, when the path between the independent variable and the mediator is controlled and so is the path between the mediator and the dependent variable, there are no longer significant relationships between the dependent and independent variable, or in other words, the relationship disappears.

For this last condition to hold true, a significance test is required for all three paths using the following equations.

$$M = i_1 + aX + e_1. \qquad \textbf{(1)}$$

$$Y = i_2 + c'X + e_2. \qquad \textbf{(2)}$$

$$Y = i_3 + cX + bM + e_3. \qquad \textbf{(3)}$$

Equation 1 - Mediation Testing

The first equation focuses on regressing the mediator on the independent variable. The second focuses on regressing the dependent variable on the independent variable. Finally, the third equation focuses on regressing the dependent variable on both the independent variable and the mediator. The objective of running these three calculations is to assess if the first the independent variable affects the mediator, the independent variable must affect the dependent variable and, finally the mediator must affect the dependent variable. In conclusion, it's important to note that mediation has both a direct and indirect effect, as opposed to viewing it in a one-dimensional approach (full effect, partial effect, or no effect).

5.3.5 Moderation

A moderator variable is a variable that plays a role between the dependent and independent variable (Hair et al. 2016). Table 5 (Carte and Russell 2003) attempts to highlight the many different definitions of moderation from articles spanning across decades. As can be noticed, definitions vary from author to author and journal article to journal article.

Table 1. Definitions of Moderation

Citation	Definition of Moderation
Jaccard, Turrisi, and Wan (1990)	Moderation occurs when the relationship between X and Y depends on Z.
Cohen and Cohen (1983)	Moderation occurs when X and Z have a joint effect in accounting for incremental variance in Y beyond that explained by X and Z main effects.
Baron and Kenney (1986)	A moderator variable is a "variable that affects the *direction* and/or *strength* of the relationship between an independent or predictor variable and a dependent or criterion variable" (p. 1174, emphasis added).
James and Brett (1984)	Z is a moderator when "the *relationship* between two (or more) other variables, say X and Y, is a function of the level of" Z (p. 310, emphasis added).
Cortina (1993)	moderation occurs when "the *effect* of one variable, X, on another variable, Y, depends on the level of some third variable," Z (p. 916, emphasis added).
Schmitt and Klimoski (1991)	"a moderator variable affects the *nature of the relationship* between two other variables" (p. 18, emphasis added)
Arnold (1982, 1984, amplified by Baron and Kenney 1986)	Offer two definitions, distinguishing between circumstances where the strength of the X→Y relationship varies as a function of Z versus the nature of the X→Y relationship varies as a function of Z. The former is often referred to as differential validity while the latter is referred to as differential prediction.
Sharma, Durand, and Gur-Aire 1981	Offer a slightly different perspective on differential validity versus differential prediction. They refer to differential prediction as "pure moderators" and differential validity as "homologizer variables." Homologizer variables are those that affect the criterion through the error term.

Table 5 - Definitions of Moderation (Carte, T.A., Russell, C.J., 2003)

Moderating relationship, as opposed to simple linear or additive relationships, are the most interesting and perhaps the most difficult to establish empirically (Mcclelland 1993) and as such has become more interesting in theoretical and applied research in the field of computer science.

In the context of our study, a total of 18 hypotheses were developed to understand the effect of AI technologies (independent variable) on cost reduction (dependent variable). Those moderator variables consisted of organizational context or specifically, executive leadership and teamwork. We believe that those two variables have a moderating impact on cost reduction outcomes. For example, and from an organizational context, we felt that, as good as both the data and outcomes are, without a favorable organizational context, comprising of solid executive sponsorship and teamwork, it will be difficult to achieve impact from a cost reduction standpoint.

5.4 Complex Data Analysis Methods

While PLS has become a routine technique in information systems research, more complex data analysis methods are emerging to help overcome some of the misinterpretations that may come from causal models. We outline here 3 recent methods that we consider complementary to ours. While not used in this study, they could be used later to make our results useful in implementation.

5.4.1 Prediction (Blindfolding Q2, Cross-Validation)

Predictions are explanations about what is going to happen in the future. Predictive performance goes beyond building purely predictive models to evaluating and improving the predictive power or explanatory models to such as those built by PLS researchers (Shmueli et al. 2016). Evaluating predictive performance is very useful approach in theory building especially in validation purposes (Shmueli 2010). It is extremely useful in building theories, assessing their relevance and even comparing them to other theories.

One of the challenges is determining which values to include given that you are typically more in an exploratory mode. For example, to understand the difference between explanatory and predictive modeling, one should know that explanatory modeling focuses on building theories and then testing them through data. In contrast, predictive modeling focuses on predicting “new” (unseen) observations, basically working on data that it has not seen yet. In other words, the role of theory is de-emphasized, and focus is rather on the data. As opposed to explanatory modeling, statistical significance is irrelevant, and the focus is on building good predictions. In predictive modeling, looking at Mean Error and Mean Squared Error is where emphasis is put forward. In predictive modeling, a minimum of two samples are required - typically a 75:25 split. The first sample (Training sample) and the second sample (holdout).

What is important to note is that “out-of-sample” behaviour helps evaluate predictive performance on new data. The “in-sample” behaviour, when used as a comparative. There have been limitations in terms of techniques and tools to generate and evaluate predictions from PLS (Shmueli et al. 2016). Blindfolding is a sample re-use technique that focuses on systematically deleting data points and provides a prognosis of their original values.

5.4.2 Segmentation

Segmentation is a technique for finding latent heterogeneity within data sets, especially if you have a PLS model with many observations (e.g. 1000+). When generating regression results, through a path model calculation in PLS, you are typically presented with two types of variables: the predicted level of dependent variable and observed level of dependent variable. The purpose of PLS-POS is to find undiscovered groups in the data, based on errors in a way to maximize R values (Becker et al. 2013).

Unobserved heterogeneity occurs when there are significance differences in model relationships between groups of data and the roots of the differences cannot be traced back to ant observable characteristics such as gender, age or income (Hair et al. 2016). The issue with today's techniques in analyzing full data sets is that researchers are implicitly assuming that the data stems from a single homogenous population (Jedidi 1999) and this assumption does not always hold true.

In the context of our study, we plan to survey procurement executives that have different perceptions in terms of the application of certain AI technologies and their understanding of procurement strategies. They also operate in different size and types of organizations – some highly capital intensive and others in a fully service-oriented business. (Sarstedt and Ringle 2010). Omitting or overlooking these factors can result in incorrect conclusions (Becker et al. 2013; Rigdon et al. 2010; Sarstedt and Ringle 2010).

It is also important to note that heterogeneity in data can either be observed or unobserved. When researchers can tell the difference between data sets using observable characteristics such as gender, are or size of organization, then we can say that heterogeneity is observed. The objective of identifying heterogeneity is that it allows for further segmentation and re-analysis yielding to more accurate results. For example, had we observed heterogeneity in our survey and had also realized that most smaller size companies use little or no AI technology, we could have carved out that specific group and perform a different type of analysis in order not to bias the results and ultimately achieve higher quality. This can also be referred to as clustering.

Certain techniques exist today to treat unobserved heterogeneity and they are commonly referred to latent class techniques, which have been proven to be very useful (Hair et al. 2016) and also help partition the data based on results. What is interesting to note about these techniques is that they don't influence the results, and as such support the analysis of a single model as data is analyzed at the aggregate level. Once heterogeneity has been identified, it must be treated. One of the ways to treat this is by using the FIXMIX-PLS, a four-step approach to determine the number of segments and explain the latent segment structure and finally estimate the segment-specific models (Hair et al. 2016).

In the context of our study, we did not use the FIMIX-PLS module in SmartPLS 3 to treat unobserved heterogeneity (Matthews et al. 2016) which consists of reassigning observations from one group to another across models, as its runs residuals and finds the models with the highest residual values (i.e. R^2 maximized). Multi-Group analysis, 3-way MGA, takes output from PLS-POS to assess if differences in the 3 groups based on estimated parameters. Also assesses differences in loadings. PLS Prediction-oriented segmentation (Becker et al. 2013) is a distance-based segmentation that has no distributional assumptions. To address segmentation in SmartPLS, we have to set parameters for the number of pre-defined segments for which the segmentation will be performed. There is also the number of iterations to perform, which we will set at a default system value. Segmentation allows us to understand if results vary from small to larger firms as well as other discriminant factors that may affect results.

5.4.3 Selection

To understand the notion of selection, it is important to first understand the difference between in-sample and out-of-sample. The in-sample data set is a dataset that comes directly from real and existing observations. We take the data and compute the Mean Squared Error using the following mathematical model:

$$MSE = \frac{\sum^{n} e^{2}}{n}$$

Equation 2 - Mean Square Error (MSE)

Where "MSE" stands for the Mean Squared Error, "Σ^n" represents the sum of the sample size observed multiplied by "e^2" which represents the delta (difference) between the actual observed variable and the initial forecast and where "*n*" stands for the number of observations. In the out-of-sample approach, we use test data (as opposed to the data we used to train the model), and then run an error test on the new set of data to test how far the residuals lie from the regression line.

6 Analysis

This section discusses the parameters used to configure SmartPLS in the context of this study. Composite, Common Factor Mixed Models. The model constructed in SmartPLS is a fully reflective model with all latent variables pointing outwards to construct items. Several algorithms could have been used in SmartPLS however, it is recommended that for fully reflective measurement model the standard is the application of the basic PLS algorithm (best for fully reflective models). Objective is to observe outer weights (covariance). Bootstrapping was also used for mediation to generate T-Statistics (standard errors and confidence intervals). Bootstrapping is ideal when sample size is small and specific (n=60). Enormous amounts of calculations to be made on sample size (over 15 hypotheses across 8 latent variables and 40+ construct items). A subset sample of 1,000 was used to increase the confidence interval. Bootstrapping involves taking a sample set out the data and reinjecting it into the initial data set.

6.1 Sample Size and Respondents Profile

The sample size is typically where researchers tend to underestimate the minimum requirements. In fact, there are many controversial articles published in this regard. We reviewed (Ghasemaghaei et al. 2017; Hair et al. 2013; Roldán 2012) to assess that for 8 latent variables with more than three constructs each, we require a minimum sample size of 50. We also need to detect an adequate effect size at a power of 0.80 (to make sure null hypothesis has been correctly rejected) and an alpha of 0.05 (to reject null hypothesis). Other sources (Faul 2007) suggest that a sample size of 74 would have been adequate for this study[1]. Below are the parameters used to generate the

[1] http://www.psycho.uni-duesseldorf.de/abteilungen/aap/gpower3/download-and-register

[1] http://www.psychologie.hhu.de/arbeitsgruppen/allgemeine-psychologie-und-arbeitspsychologie/gpower.html

minimum total sample size required and Figure 8 represents the "Critical-T" region to be investigated:

t tests – Linear multiple regression: Fixed model, single regression coefficient
Analysis: A priori: Compute required sample size
Input: Tail(s) = One
Effect size f^2 = 0.15
α err prob = 0.05
Power (1−β err prob) = 0.95
Number of predictors = 6
Output: Noncentrality parameter δ = 3.3316662
Critical t = 1.6679161
Df = 67
Total sample size = 74
Actual power = 0.9508227

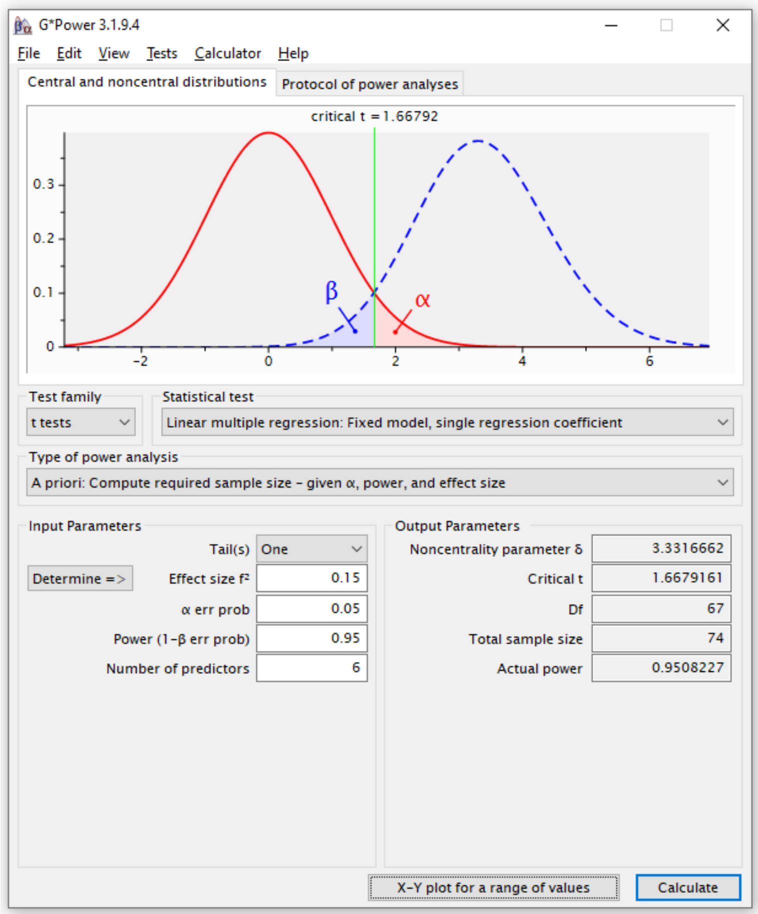

Figure 12 - G-Power Minimum Sample Size Requirements

Finally, and in another source (Marcoulides 2006), authors suggest that, in practice, a typical marketing research study would have a significance level of 5%, a statistical power of 80%, and *R2* values of at least 0.25. Using such parameters, the minimum sample size required can be looked up from the guidelines suggested by (Marcoulides 2006), depending on the maximum number of arrows pointing at a latent variable as specified in the structural equation model (see Table 5). In our case, the maximum number of arrows pointing at a latent variable is 5 therefore, a minimum sample size of 70 is sufficient for this study.

Minimum sample size required	Maximum # of arrows pointing at a latent variable in the model
52	2
59	3
65	4
70	5
75	6
80	7
84	8
88	9
91	10

Table 6 - Minimum Sample Size Requirements (Marcoulides & Saunders, 2006)

Our sample was collected via message posts on 7 of 10 top groups in procurement and supply chain professionals:

1. https://www.linkedin.com/groups/4993378/
2. https://www.linkedin.com/groups/3838703/
3. https://www.linkedin.com/groups/86093/
4. https://www.linkedin.com/groups/1984938/
5. https://www.linkedin.com/groups/62372/
6. https://www.linkedin.com/groups/1169757/
7. https://www.linkedin.com/groups/107172/

As for respondents' profile, we succeeded in gathering 98 surveys, of which 81 were complete, and 74 were valid and retained for analysis. In Table 6, we highlight respondent profiles.

Demographic Characteristics		%
Gender	Male	88
	Female	12
Age	18-29	6
	30-49	66
	50-65	27
	65+	1
Size of Organization	Small Business (0-100 empl.)	11
	Medium Enterprise (101-999)	19
	Large Enterprise (1000+)	70
Sector	Government/Public Sector	24
	Industrial Manufacturing	21
	Consulting (Professional Services)	10
	Finance and Assurance	10
	Information Technology	8
	Energy	6
	Transportation and Logistics	6
	Services	6
	Consumer Packaged Goods	3
	Healthcare	3
	Utilities	2

Table 7 - Respondents Profile

6.2 Hypothesis Testing

6.2.1 Results Summary

There are 18 hypotheses to test in the context of this study. Table 7 is the outline of tests to be performed in the upcoming section of this document. Direct effects as well as moderating effects will be tested using the standard PLS Algorithm however, mediating effects will be tested using the Standard PLS Bootstrap Algorithm. Below is the inventory of hypothesis testing, key objectives and most importantly, results.

Hypothesis		Test Type	Test Variables	Patch Coefficient		Bootstrap			Sobel T-Stats	Sobel P-Value	PLS Decision	Sobel Decision[1]
H1	H1A	Direct Effect	BDA->CR	0.675		1.1860			N/A		Accepted	N/A
	H1B		ML->CR	-0.441		0.708					Accepted	
	H1C		SD->CR	0.112		0.526					Rejected	
	H1D		BRE->CR	0.355		1.081					Rejected	
H2	H2A		SS->CR	0.258		1.681					Accepted	
	H2B		SRM->CR	0.282		1.680					Accepted	
				DV->M	M->IV	DV->M	M->IV	DV->IV				
H3	H3A	Mediation (using first PLS and then Sobel as a comparative test)	BDA->SS->CR	5.544	5.126	5.505	2.423	0.806	3.76	0.00016739	Accepted	Accepted
	H3B		ML->SS->CR	3.954	5.549	3.707	3.114	0.173	3.22	0.00128134	Accepted	Accepted
	H3C		SD->SS->CR	2.871	5.428	2.563	3.582	0.171	2.54	0.01115305	Accepted	Accepted
	H3D		BRE->SS->CR	6.066	5.241	5.773	2.390	0.381	3.96	0.00007315	Accepted	Accepted
	H3E		BDA->SRM->CR	4.294	5.187	4.336	3.377	1.624	3.31	0.00094078	Accepted	Accepted
	H3F		ML->SRM->CR	1.327	4.460	1.070	2.184	0.672	1.27	0.20341021	Accepted	Rejected
	H3G		SD->SRM->CR	1.748	5.974	1.759	3.925	0.500	1.68	0.08918046	Accepted	Rejected
	H3F		BRE->SRM->CR	8.963	4.819	8.866	2.502	0.359	4.24	0.00002192	Accepted	Accepted
						DV->M	M->IV	DV->IV				
H4	H4A	Moderation	BDA->EL->CR	N/A		0.306	0.251	0.203	N/A		Accepted	N/A
	H4B		ML->EL->CR			0.370	0.240	0.092			Accepted	
	H4C		SD->EL->CR			-0.239	0.344	-0.117			Accepted	
	H4D		BRE->EL->CR			0.529	0.166	0.191			Accepted	
	H4E		BDA->PT->CR			0.402	0.182	0.215			Accepted	
	H4F		ML->PT->CR			0.409	0.272	0.094			Accepted	
	H4G		SD->PT->CR			-0.343	0.137	-0.183			Accepted	
	H4H		BRE->PT->CR			0.479	0.229	0.197			Accepted	

Table 8 - Hypotheses Testing Results Summary

[1] Source: Sobel Test Website, http://quantpsy.org/sobel/sobel.htm, accessed September 22, 2019

6.2.2 Constructs Validity

In addition to hypothesis testing, we present in Table 8 below the details of our construct validity tests.

Constructs	Items	Loadings	AVE	CR
Big Data Analytics	We have access to a procurement "data warehouse" that stores structured/filtered data. This data is collected/used for internal reporting purposes.	0.556	0.530	0.847
	We have access to a "data lake" (vast pool of raw procurement data) such as contracts/invoices in PDF format to support our data mining activities.	0.626		
	We use "Distributed Processing" technologies (i.e. Hadoop, Spark, etc.) to accelerate data-processing and to gain access to business intelligence reports in real-time.	0.816		

Constructs	Items	Loadings	AVE	CR
	We use Cloud Computing services for enhanced cost savings, data security and flexible data storage options.	0.755		
	We have access to "real-time" procurement dashboards that provide information on spend, savings, compliance rates, etc.	0.846		
Machine Learning	We use forecasting techniques such as regression analysis and exponential smoothing and/or ML algorithms to predict procurement demand.	0.85	0.670	0.910
	We use "Association Rules" and/or "Rules-Based" models within our raw transactional procurement data to discover patterns and relationships (e.g. forensic transaction investigation)	0.916		
	We use "Text-Mining" and "Semantic Annotations" to store, process and retrieve key procurement data efficiently (i.e. contract details, purchase order cost breakdowns, etc.).	0.823		
	We leverage "Machine Learning" algorithms to help improve search results when employees search for products and services to buy.	0.775		
	We leverage "Machine Learning" to automate the "three-way" invoice matching process and to improve accuracy.	0.715		
System Dynamics	We continuously analyze the performance of our procurement initiatives (i.e. portfolio) and make key decisions on resource allocations (e.g. terminating initiatives, accelerating others, etc.)	0.709	0.262	0.602
	We simulate "what-if" scenarios, using simulation software, to assess potential outcomes of procurement strategies before we implement them.	0.708		
	We constantly find ourselves having to manage internal emergencies, of tactical nature, leaving our teams with little or no time to develop strategic skills (i.e. capabilities trap).	0.23		
	We are often involved too late in the sourcing process, leaving little or no time for productive negotiations with suppliers.	0.366		
	We are too consumed with tactical processes (e.g. data analysis, RFP/RFI/RFQ production) leaving little time for strategic activities (e.g. market study, strategy formulation, negotiation, etc.)	0.347		
Business Rules Engine	We use policy metadata (i.e. tagging keywords to your document to provide context) within our contracts management database to improve contract search effectiveness	0.766	0.648	0.902
	We use Business Rules Engines (BRE) that channel internal demand to pre-negotiated contracts and preferred suppliers	0.842		
	We use Complex Event Processing (CEP) to detect patterns of abnormal procurement behaviour (e.g. non-compliant spend, supplier preference biases, etc.)	0.877		
	We use Business Activity Monitoring (BAM) to gain visibility on transactions and trigger alarms when suspicious transactions occur. (e.g. overspending in a specific category, not going through the appropriate channels of spend, etc.)	0.788		
	We embed procurement rules in our Business Process Management (BPM) workflows to increase process compliance. (e.g. duplicate invoices are by default sent to a queue in accounts payable for pre-payment validation before suppliers are paid).	0.745		
Executive Leadership	My procurement department has a clear mission, vision, and purpose.	0.615	0.585	0.873
	Our leaders (Managers, Directors, VPs, CPO) are constantly engaged with internal stakeholders (e.g. IT, Operations, Program Office, etc.) to encourage the use of Procurement services.	0.981		
	Our leaders are actively involved in key procurement negotiations (internally and with key suppliers).	0.772		
	My procurement department can generate contract analytics to assess risks, opportunities, and to action them as needed.	0.69		
	Our leaders expose us and promote us in front of other senior members inside the organization (and outside of procurement) for visibility and to promote the use of our services.	0.717		
People Teamwork	We understand the role of procurement and its main objective as it relates to serving the business	0.468	0.389	0.755
	We can negotiate directly with suppliers and make decisions on behalf of the various business lines.	0.501		
	We are encouraged to share ideas and attend conferences to bring back fresh ideas in terms of innovation.	0.756		
	We have access to standard operating procedures that are documented and include tools and templates to support in the day-to-day role.	0.627		
	Our client-unit leaders and subordinates are engaged in procurement processes, and improvement ideas are identified, documented, and followed-up using a rigorous collaborative quality improvement program.	0.716		
Strategic Sourcing	We have real-time visibility on current spend (year-to-date).	0.835	0.561	0.863
	Most of our key contracts digitized and stored in a central repository for easy access.	0.659		
	Our staff are certified and experienced in procurement, purchasing and supply chain management.	0.602		

Constructs	Items	Loadings	AVE	CR
	Our staff understands and are fully engaged in the strategic sourcing process (i.e. spend analysis, market assessment, strategy formulation, negotiation, contracting, etc.).	0.845		
	Our staff have the authority to directly negotiate with suppliers and make decisions on behalf of the business.	0.774		
Supplier Relationship Management	We administer a quarterly business review (QBR) with strategic suppliers to manage performance and identify corrective measures.	0.79	0.568	0.865
	We review invoices (through manual sampling) on a periodical basis and compare them to contract clauses to ensure contract compliance (can be done in parallel with existing Procure-to-Pay (P2P) systems that may already exist).	0.711		
	We run periodical risk reviews on strategic suppliers and develop mitigation plans in the event of an incident.	0.888		
	We work closely and regularly with strategic suppliers to improve collaboration and efficiency.	0.797		
	We have a formally documented dispute and escalation management process that we follow to manage suppliers.	0.536		
Cost Reduction	All categories of spend confined, my organization can generate:	0.715	0.185	0.391
	My procurement department generates a Return on Investment (ROI) of:	0.391		
	My organization is transaction compliant on:	0.506		
	Our spend under management is:	0.042		
	The percentage (%) of suppliers that account for 80% of our spend is:	-0.035		

Table 9 - Consolidated Loadings, AVEs and CRs

6.2.3 Data Interpretation Guidelines

To provide clarity in terms of data interpretation, we have prepared Table 9 which guides our discussions around indicator reliability, construct composite reliability, convergent validity, discriminant validity, correlation, effect size and path coefficient significance testing. The following table will inform the next section of this document as it relates to the analysis of our PLS results.

Assessing Reliability and Validity Results

Analyses	**SmartPLS Report**	**Requirements**
Indicator Reliability	Outer Loadings Report	**0.70 or higher** however, 0.4 or higher is acceptable (Hulland 1999)
Internal Consistency Reliability	Construct Reliability	**0.70 or higher** however, 0.6 or higher is acceptable (Bagozzi and Yi 1988)
Convergent Validity	AVE	**0.5 or higher (Bagozzi and Yi 1988)**
Discriminant Validity	AVE and Latent Variable Correlations	(Fornell C 1981) suggest **Square Root of AVE** of each latent variable > **correlation amongst variables**
Correlation	R Square	Proportion of variance of the exogenous variables on the endogenous ones: **0.25 = Low** **0.50 = Medium** **0.75 = High**
Effect Size	F Square	**0.10 or higher** (Chin and Newsted 1999)

Analyses	SmartPLS Report	Requirements
Path Coefficient Significance	T-Statistics	**1.96 or higher** (Wong 2013)
Sobel Testing – Path Coefficient Significance	T-Statistics	**1.96 or higher (Sobel 1986)**

Table 10 - Guidelines for Assessing Reliability & Validity Results

6.3 Results

We initially ran the model with all survey items for all latent variables however, our initial observations focused on two latent variables which had lower scores in terms of construct reliabilities (CR). For cost reduction, when we initially ran the model the CR scores were lower relative to other latent variables. We then proceeded to removing items 4 and 5 which focused on spend under management (in percentage) and the numbers of suppliers accounting for most of the organizations spend or otherwise known as the Pareto analysis (in percentage). When removing those two items, we immediately noticed that items 2 and 3 went up in terms of CR but that item 1 went down (from 0.66 to 0.54) making it no longer valid.. Items 2 and 3 deal with return on investment or the amount of savings generated in return for the operating costs of a procurement department. Compliance deals with measuring the amount of spend that was purchased via traditional channels, on contract and where the invoice received was in check with the terms and conditions of the contract. Item 1, on the other hand, focused on the savings the procurement department was able to generate on its entire spend base with a subtle nuance on addressable spend which consists of the spend that is not already locked into a contract and that is up for negotiation. In conclusion, we decided to keep CR4 and CR5 to preserve a reliable construct. We proceeded with the same analysis for System Dynamics, where we noticed that two potential problems. The first being that the scores for the latent variables were inversed. That is the higher you scored, the lower it meant you applied system dynamics in your organization where in fact, it should have been the opposite. Therefore, we corrected the scale and reran the results and most of the numbers remained the same but this time with an inversed polarity. After reviewing the new scores, we still judged SD3-5 too low and therefore, they were removed for the rest of the study however, we did keep the scores in the cross-loading tables.

6.3.1 H1: Positive Impact between AI Technologies and CR

In the following hypothesis testing (Figure 10), we used the “PLS algorithm” to perform a path analysis and set the number of iterations to 1000. No weighting vectors were assigned. Results clearly demonstrate that AIA technologies contribute to Cost Reduction at (0.342). In other words, 34% of the variance in cost reduction can be explained by the 4 AIA technologies listed to the left of the diagram (i.e. BDA, BRE, ML and SD). The path coefficient’s highlights that Big Data Analytics (0.357) along with Business Rules Engines (0.224) had the greatest impact on Cost Reduction. All loadings (Figure 14), which typically highlight the relationships between the reflective construct and measured indicator variables show that values are above 0.700 which demonstrates indicator reliability.

The lines between each of the four AI Technologies and Cost Reduction are called “Standardized Regression Weights” or the “Effect”. The factors inside the blue circles represents the Average Variance Extracted (AVE) and the Construct Reliability is represented by CR in Figure 14.

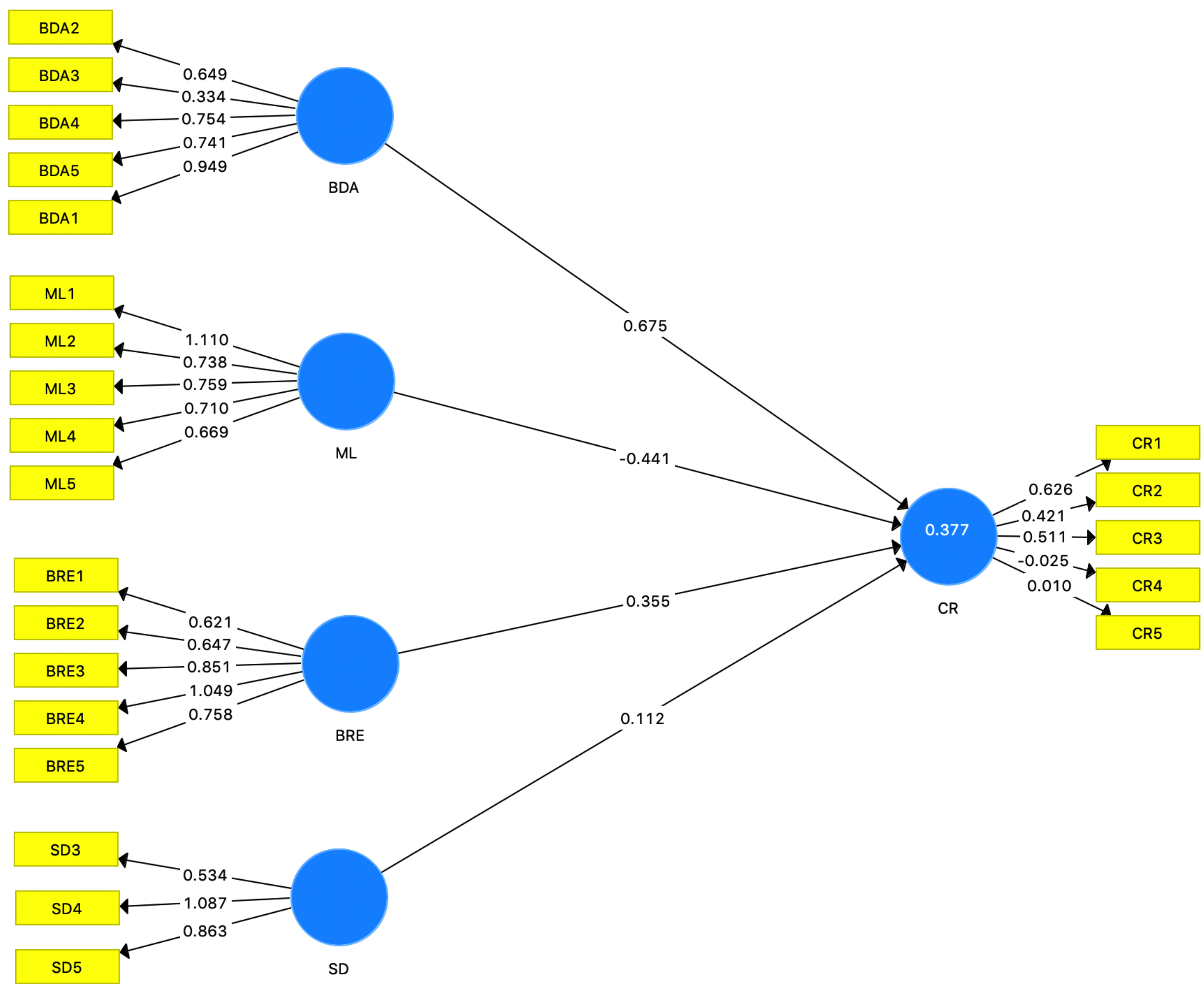

Figure 13 - H1 AVEs and Outer Weights

The next step, and to assess significance, we ran a PLS Bootstrap (Figure 15). This allowed us to generate T-Statistics and assess if paths were significant (i.e. > 1.96). We ran a 1000 iteration, basic bootstrapping, using the "Bias-Corrected and Accelerated (BCa) Bootstrap, using a "One-Tailed" test type at a significant level of 0.05. All AI technologies had a value of less than 1.96 and were considered non-significant.

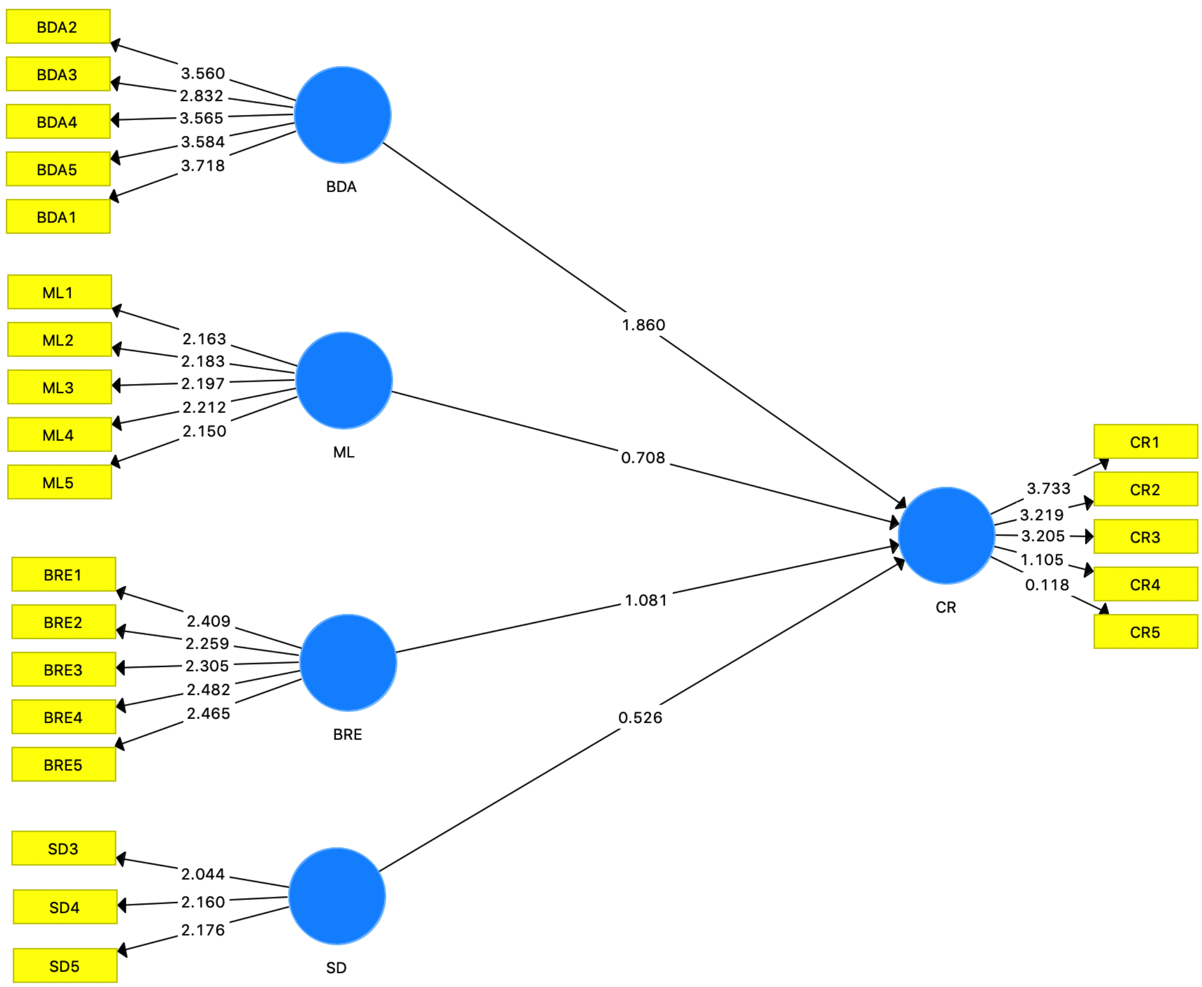

Figure 14 - H1 Bootstrap Test and T-Values

Basically, the only AI technology that has somewhat of an impact on cost reduction is Big Data Analytics (1.860). The convergent validity met the minimum requirement of 0.5 or higher in all cases meaning that the results are valid (Table 10). The discriminant validity also met the (Fornell C 1981) requirements where the square root of AVE of each latent variable was greater than the correlation amongst the latent variables.

	Loadings	AVE	CR
BDA1	0.825		
BDA2	0.752		
BDA3	0.715	0.784	0.889
BDA4	0.812		
BDA5	0.817		
BRE1	0.843		
BRE2	0.842		
BRE3	0.899	0.715	0.926
BRE4	0.869		
BRE5	0.769		
ML1	0.847		
ML2	0.886		
ML3	0.868	0.733	0.932
ML4	0.887		
ML5	0.788		
SD3	0.819		
SD4	0.939	0.799	0.923
SD5	0.92		
CR1	0.757		
CR2	0.739		
CR3	0.684	0.342	0.667
CR4	0.349		
CR5	0.036		

Table 11 - Loadings, AVEs and CRs for H1

When reviewing the loadings (Table 12), we can assess that, except for CR3, CR4 and CR5, all loadings were above 0.7. The AVE for all constructs was also above 0.5 which typically signify that there is convergent validity which means that two measures of the same construct are in fact (an in theory) related to one another. When reviewing construct reliability, we are assessing the reliability of numbers. In this case, we are aiming for a number that is also above 0.7. In this case, all construct items, except for CR, were above 0.7. To ascertain that the construct is reliable, and that subjectivity is removed, we aimed for a number above 0.7. In this case, all constructs are consistently reliable.

Discriminant Validity

Discriminant Validity					
	BDA	BRE	CR	ML	SD
BDA	**0.785**				
BRE	0.464	**0.845**			
CR	0.366	0.309	**0.585**		
ML	0.735	0.611	0.264	**0.856**	
SD	-0.247	-0.18	-0.176	-0.255	**0.894**

Table 12 - Discriminant Validity for H1

In discriminant validity (Table 13), we are assessing the values of AVE and our objective is to understand the correlations between latent variables. The objective is to make sure that the square root of AVE of each latent variable should be greater than the correlations amongst the variables. In other words, we want to make sure there is subjective independence of every indicator on its latent variable or also called "vertical collinearity". As we can see from the table above, in all cases, the square root of AVE for each latent variable was greater that the correlations of each latent variable meaning that there is discriminant validity.

HTMT

Heterotrait-Monotrait					
	BDA	BRE	CR	ML	SD
BDA					
BRE	0.561				
CR	0.423	0.383			
ML	0.866	0.688	0.293		
SD	0.265	0.199	0.266	0.246	

Table 13 - Heterotrait-Monotrait for H1

For HTMT (Table 14), the objective is to make sure we have values that are below 0.85, which is deemed to be the most conservative value. The objective it to identify the highest value in the table below and assess if any of the values are significantly above 0.85. Only ML to BDA scores higher at (0.866). Overall, we can see from the table below that discriminant validity has been established meaning that every single latent variable is significantly different from one.

R Square		
	R Square	R Square Adjusted
CR	0.174	0.126

Table 14 - R Square for H1

The objective of assessing R Square (Table 15) is to assess the proportion of variance of the exogenous variables on the endogenous ones. Although there is no consensus on the minimum level that this index should reach, (Falk 1992) recommend a minimum value of 0.1, which ensures that at least 10 percent of the construct variability is due to the model. The R Square results show that there is little correlation between AI Technologies and cost reduction which goes against the primary hypothesis of this study. For us to assess confidently that there is enough of correlation, we would have required a value of at least 0.25.

F Square

	BDA	BRE	CR	ML	SD
BDA			0.07		
BRE			0.038		
CR					
ML			0.011		
SD			0.009		

Table 15 - F Square for H1

The F Square results (Table 16) in this analysis are lower than the minimum requirement suggesting that the effect size is very small. Typically, effect sizes are above 0.1. This can be explained by the fact that there are so many other factors that could potentially account for cost reduction. For example, in our study, we discussed technology, strategy and organizational context however, many other factors such as volume concentration, SKU rationalization, process automation, contract negotiations and strategic alliances could have been considered potential factors to reduce costs.

6.3.2 H2: Positive Impact between Procurement Strategy and Cost Reduction

When testing for the direct effect of procurement strategy (i.e. strategic sourcing and supplier relationship management) on cost reduction, 36.8% of the variance in cost reduction was explained by Strategic Sourcing (64.4%) and Supplier Relationship Management (64.7%). They both had equal impact on cost reduction. When looking at the loadings, we also assessed that, except for CR4 (0.561) and CR5 (0.0114) most outer loadings met the minimum requirement of 0.7

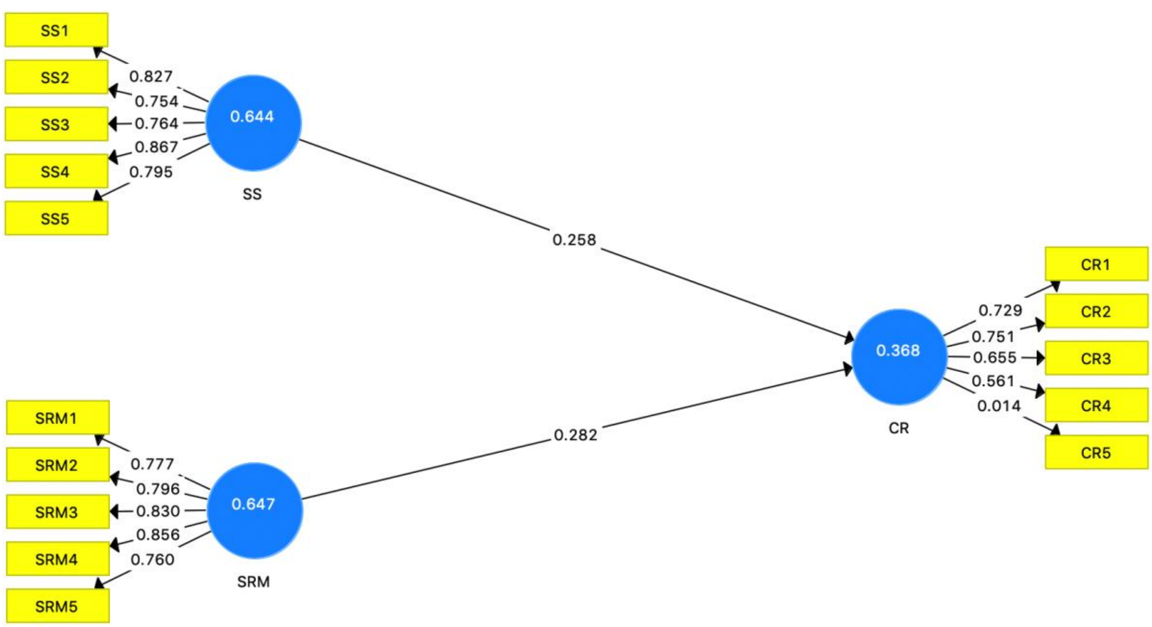

Figure 15 - H2 AVEs and Outer Weights

Loadings, AVE, and CR

	Loadings	AVE	CR
CR1	0.729		
CR2	0.751		
CR3	0.655	0.368	0.699
CR4	0.561		
CR5	0.014		
SRM1	0.777		
SRM2	0.796		
SRM3	0.83	0.647	0.901
SRM4	0.856		
SRM5	0.76		
SS1	0.827		
SS2	0.754		
SS3	0.764	0.644	0.900
SS4	0.867		
SS5	0.795		

Table 16 - Loadings, AVEs and CRs for H2

As we can see from the results (Table 17), most loadings, except for CR5 were above 0.5. As discussed previously and at the beginning of this chapter, in exploratory research, it is fine to have loadings of 0.4 (Hulland 1999).

The Average variance extracted was above 0.5 except for CR. This suggests that for CR, there was not enough variance between the constructs items to make them significantly different.

Discriminant Validity

	CR	SRM	SS
CR	**0.606**		
SRM	0.424	**0.804**	
SS	0.414	0.553	**0.802**

Table 17 - Discriminant Validity for H2

In discriminant validity (Table 18), we are assessing the values of AVE and our objective is to understand the correlations between latent variables. The objective is to make sure that the square root of AVE of each latent variable should be greater than the correlations amongst the variables. In other words, we want to make sure there is subjective independence of every indicator on its latent variable or also called “vertical collinearity”. As we can see from the table above, in all cases, the square root of AVE for each latent variable was greater that the correlations of each latent variable meaning that there is discriminant validity between Cost Reduction, Supplier Relationship Management and Strategic Sourcing.

Heterotrait-Monotrait

	CR	SRM	SS
CR			
SRM	0.561		
SS	0.423	0.383	

Table 18 - Heterotrait-Monotrait for H2

For HTMT (Table 19), the objective is to make sure we have values that are below 0.85, which is deemed to be the most critical conservative value. The objective it to identify the highest value in the table and assess if any of the values are significantly above 0.85. Both SRM and CR did not score higher than 0.85. This means that, overall, we can see from the table below that discriminant validity has been established between SRM and SS meaning that every single latent variable is significantly different from one another.

R Square

	R Square	R Square Adjusted
CR	0.226	0.204

Table 19 - R Square for H2

The objective of assessing R Square (Table 20) is to assess the proportion of variance of the exogenous variables on the endogenous ones. Although there is no consensus on the minimum level that this index should reach, (Falk 1992) recommend a minimum value of 0.1, which ensures that at least 10 percent of the construct variability is due to the model The R Square results show that there is correlation between Procurement Strategy. That is, Strategic Sourcing and Supplier Relationship Management activities both contribute to Cost Reduction.

F Square

	CR	SRM	SS
CR			
SRM	0.071		
SS	0.06		

Table 20 - F Square for H2

The effect size (Table 21) can be calculated directly in SmartPLS and typically, the value we are looking for is above 0.10. At a value of 0.10 or higher, we can assume that SRM had a strong enough effect on the impact of SS to CR. In this case SRM scored 0.071 which means it did not and SS scored 0.06 which means it had an even lesser effect on CR. This means that other factors could have been considered to increase the impact of cost reduction. This could have included, the automation of intelligent workflows to minimize tactical procurement processes or even Rules Engines to ensure a higher level of compliance leading to increased cost reduction performance. In other words, this study focused on assessing the effect of one key dependent variable on the independent variable and the outcome was that effect size was low. There are other factors to consider which will be discussed in the “further research” section of this document.

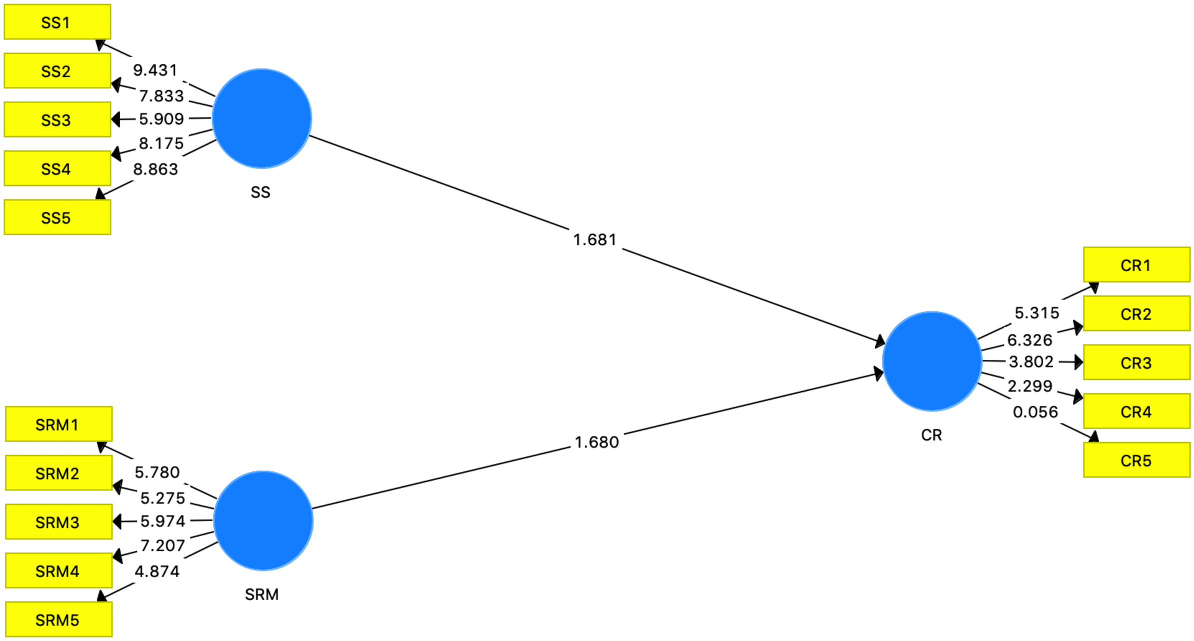

Figure 16 - H2 Bootstrap

For H2, a one-tailed bootstrap test (1000 iterations) was performed using 0.05 significance level (Figure 17). T-Values for outer-weights are all significant however, the significance level of both strategic sourcing (SS) and supplier relationship management (SRM) fell short of the required significance level (i.e. less than 1.96). That said, results suggest that both SS and SRM did not play a significant enough role in contributing to cost reduction.

6.3.3 H3: Mediating Effect of Procurement Strategy

6.3.3.1 H3A: SS has a Mediation Effect Between BDA and CR

Strategic sourcing is the act of capitalizing on analytics to make strategic decisions in terms of where to reduce costs. As we can see from the Bootstrap PLS algorithm (Figure 18), the T-Statistics were high (i.e. above 1.96) suggesting that all paths were significant.

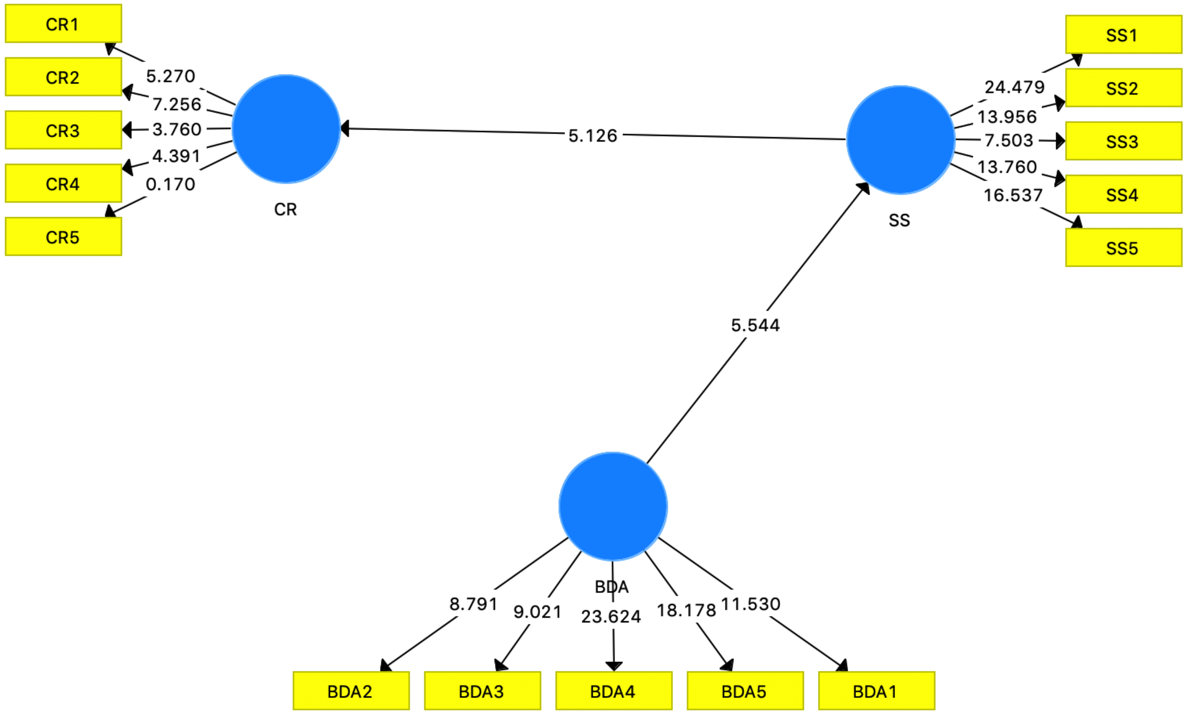

Figure 17 - H3A

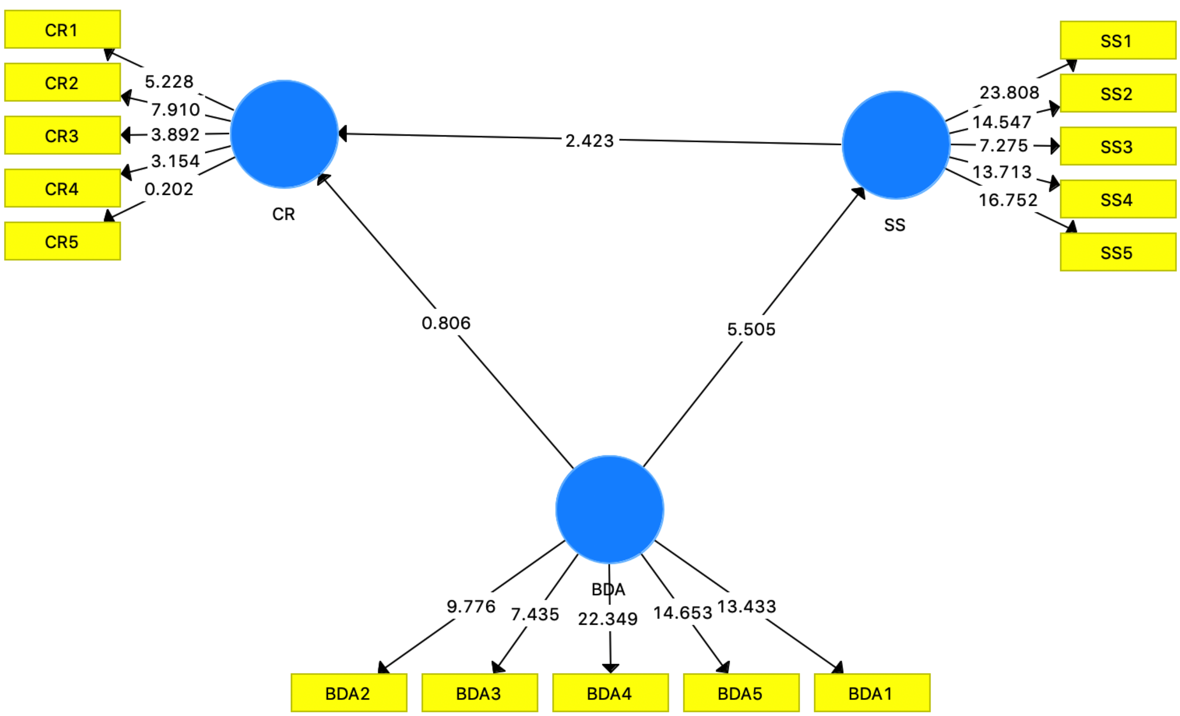

Figure 18 - H3A Bootstrap Test

A mediation analysis was performed using a one-tailed t-test bootstrap test using 1000 iterations. The results in Figure 19 and Table 22 highlight T-Test statistics and highlight the significance of each path. As we can see from the results, BDA did not have significant impact on CR (0.806) however, SS played a strong mediation role on the impact between BDA and CR (2.423).

Therefore, one can conclude that SS does indeed play a mediation role on the impact of BDA on CR.

Outer Loadings

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BDA1 <- BDA	0.793	0.785	0.059	13.433	0
BDA2 <- BDA	0.744	0.737	0.076	9.776	0
BDA3 <- BDA	0.726	0.712	0.098	7.435	0
BDA4 <- BDA	0.837	0.838	0.037	22.349	0
BDA5 <- BDA	0.828	0.821	0.056	14.653	0
CR1 <- CR	0.68	0.653	0.13	5.228	0
CR2 <- CR	0.774	0.739	0.098	7.91	0
CR3 <- CR	0.639	0.601	0.164	3.892	0
CR4 <- CR	0.626	0.599	0.199	3.154	0.001
CR5 <- CR	-0.046	-0.04	0.227	0.202	0.42
SS1 <- SS	0.86	0.857	0.036	23.808	0
SS2 <- SS	0.776	0.774	0.053	14.547	0
SS3 <- SS	0.723	0.716	0.099	7.275	0
SS4 <- SS	0.84	0.838	0.061	13.713	0
SS5 <- SS	0.793	0.789	0.047	16.752	0

Table 21 - Outer Loadings for H3A

R Square

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
CR	0.189	0.26	0.073	2.595	0.005
SS	0.241	0.269	0.09	2.69	0.004

Table 22 - R Square for H3A

The objective of assessing R Square (Table 23) is to assess the proportion of variance of the exogenous variables on the endogenous ones. Although there is no consensus on the minimum level that this index should reach, (Falk 1992) recommend a minimum value of 0.1, which ensures that at least 10 percent of the construct variability is due to the R Square results show that there is little correlation between AI Technologies and cost reduction which goes against the primary hypothesis of this study. For us to assess confidently that there is enough of correlation, we would have required a value of at least 0.25.

F Square

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BDA -> CR	0.02	0.055	0.063	0.31	0.378
BDA -> SS	0.318	0.39	0.183	1.738	0.041
SS -> CR	0.112	0.176	0.123	0.908	0.182

Table 23 -F Square for H3A

The effect size (Table 24) can be calculated directly in SmartPLS and typically, the value we are looking for is above 0.10. At a value of 0.10 or higher, we can assume that BDA had a strong enough effect on the impact of SS to CR. In this case BDA scored 0.378 which means it did indeed have a positive effect on CR. This means that most factors could were considered to increase the impact of cost reduction.

6.3.3.2 H3B: SS has a Mediation Effect Between ML and CR

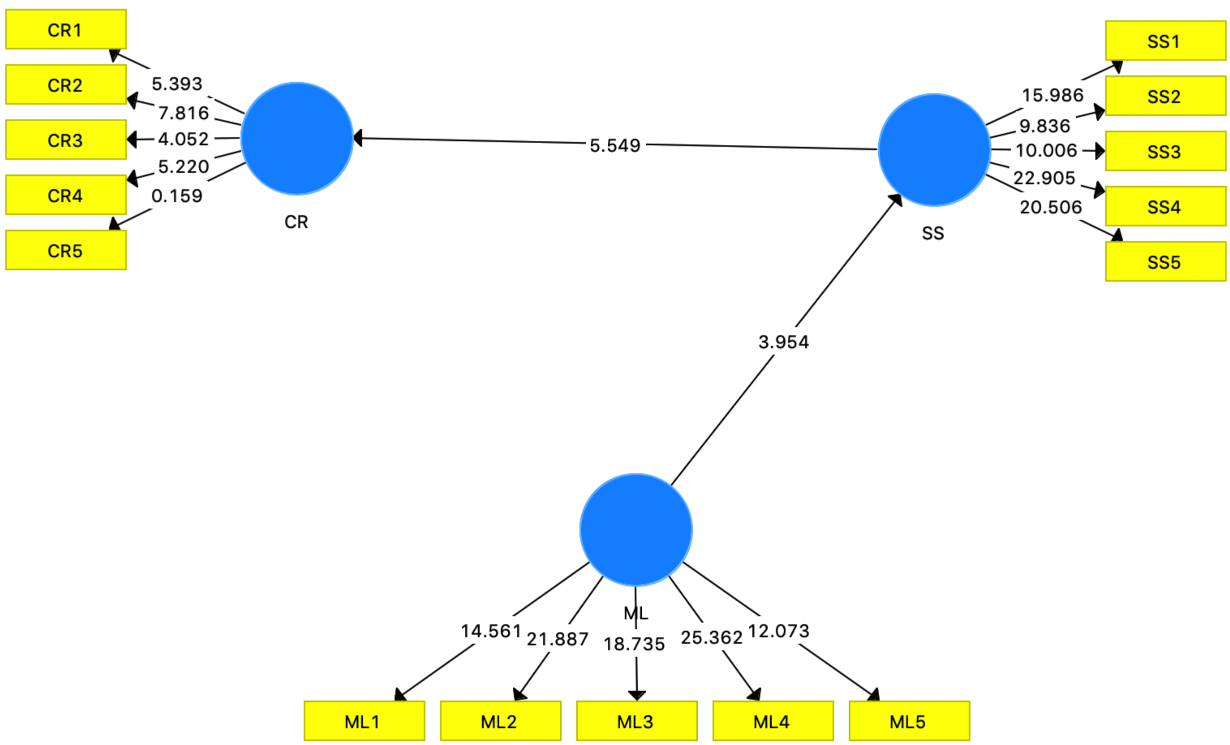

Figure 19 - H3B

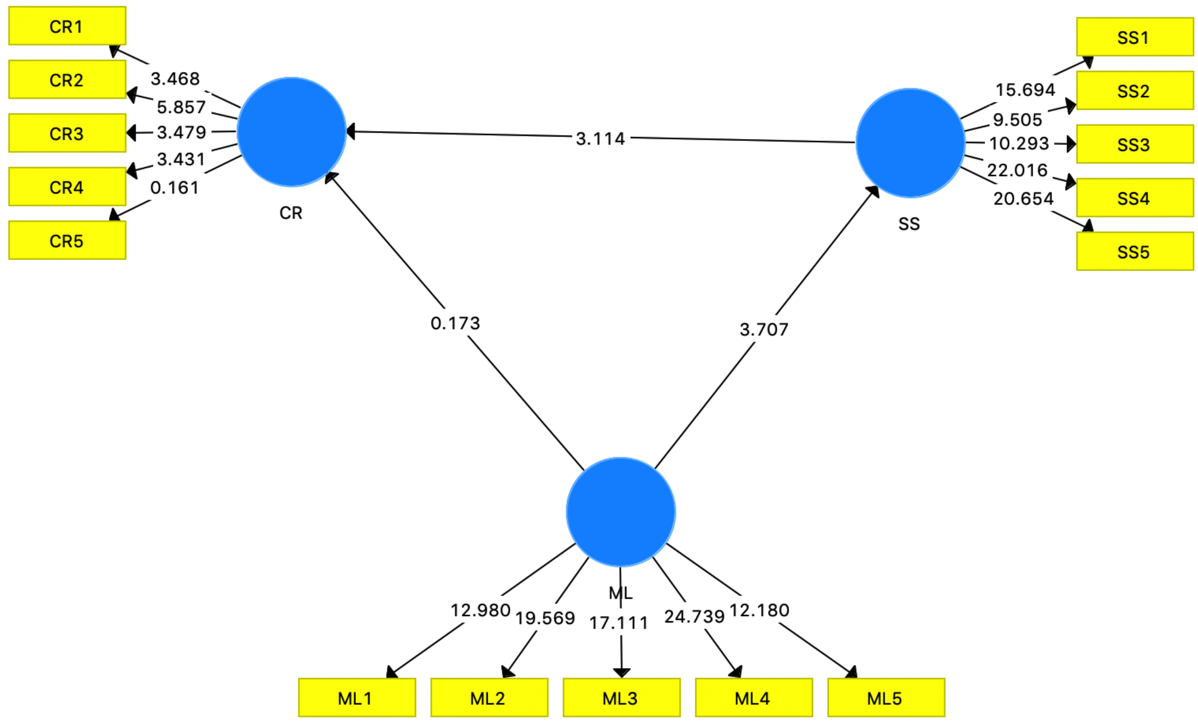

Figure 20 - H3B Bootstrap

A mediation analysis was performed using a one-tailed t-test bootstrap test using 1000 iterations (Figures 22 and 23). To assess whether the hypothesis can be accepted, we are aiming for a path value of 1.96 (at the 95% confidence level). The results in Figure 23 highlight T-Test statistics and highlight the significance of each path. As we can see from the results, ML did not have significant impact on CR (0.173) however, SS played a strong mediation role on the impact between BDA and CR (3.114). Therefore, one can conclude that SS does indeed play a mediation role on the impact of BRE on CR.

Outer Loadings

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
CR1 <- CR	0.658	0.633	0.19	3.468	0
CR2 <- CR	0.746	0.7	0.127	5.857	0
CR3 <- CR	0.635	0.58	0.183	3.479	0
CR4 <- CR	0.687	0.633	0.2	3.431	0
CR5 <- CR	-0.039	-0.042	0.245	0.161	0.436
ML1 <- ML	0.812	0.809	0.063	12.98	0
ML2 <- ML	0.891	0.888	0.046	19.569	0
ML3 <- ML	0.877	0.874	0.051	17.111	0
ML4 <- ML	0.902	0.899	0.036	24.739	0
ML5 <- ML	0.804	0.797	0.066	12.18	0
SS1 <- SS	0.82	0.818	0.052	15.694	0
SS2 <- SS	0.719	0.717	0.076	9.505	0

SS3 <- SS	0.773	0.766	0.075	10.293	0
SS4 <- SS	0.883	0.879	0.04	22.016	0
SS5 <- SS	0.815	0.814	0.039	20.654	0

Table 24 - Outer Loadings for H3B

Path coefficients for table 27 were low for Machine Learning suggesting that the confidence interval requirements were not met and that the results were not significant. However, when assessing the mediation effect of SS on ML and CR, it was clear that SS is indeed playing a mediating role between SD and CR.

Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
ML -> CR	0.033	0.041	0.189	0.173	0.431
ML -> SS	0.356	0.374	0.096	3.707	0
SS -> CR	0.408	0.434	0.131	3.114	0.001

Table 25 - Path Coefficients for H3B

6.3.3.3 <u>H3C: SS has a Mediation Effect Between SD and CR</u>

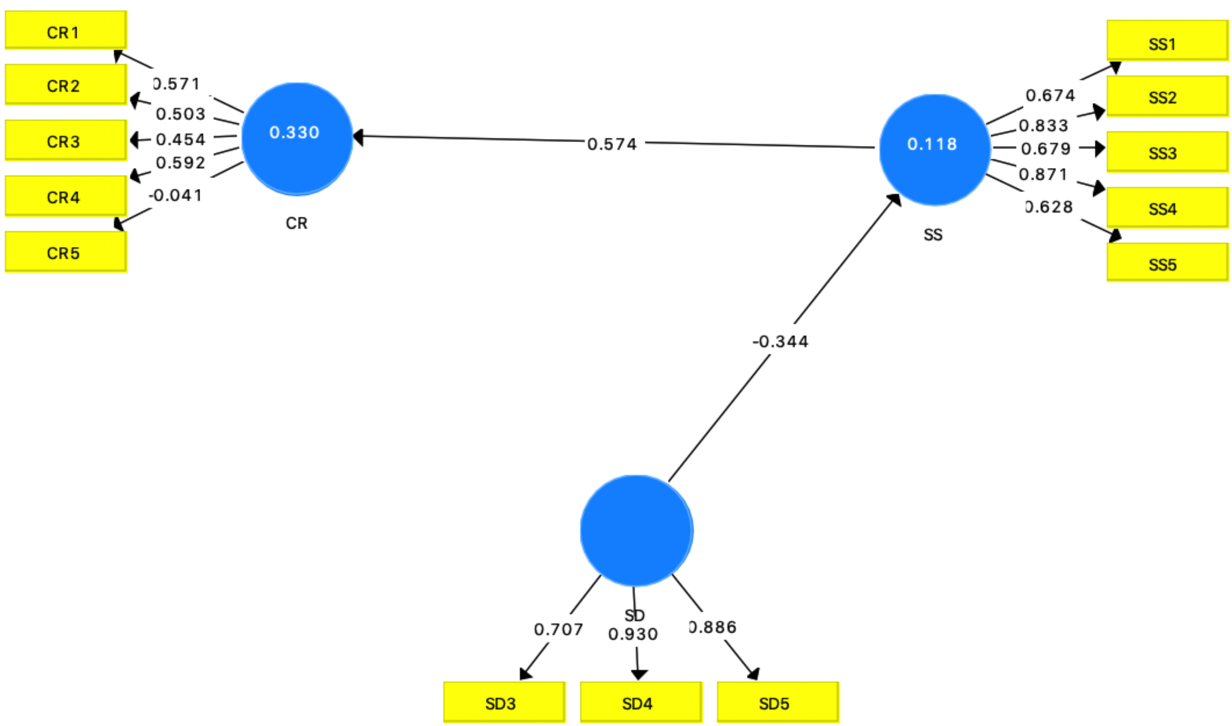

Figure 21 - H3C

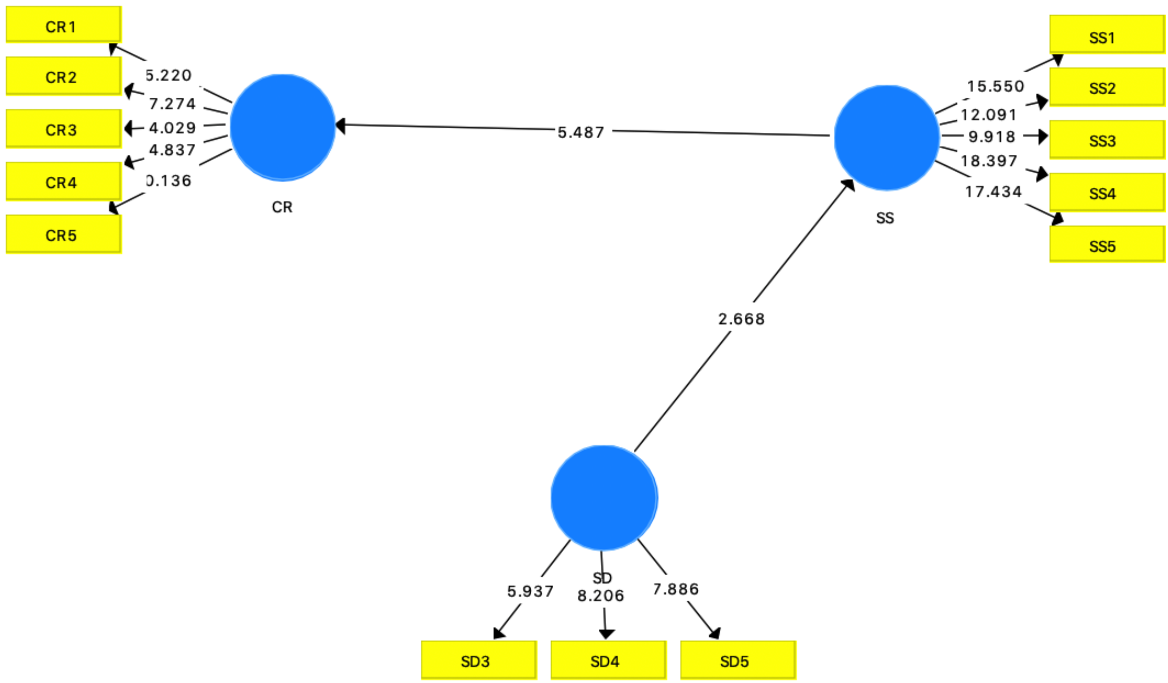

Figure 22 - H3C Bootstrap

A mediation analysis using a one-tailed t-test bootstrap test using 1000 iterations (Figures 24 and 25). To assess if the hypothesis can be accepted, we are aiming for a path value of 1.96 (at the 95% confidence level). The results in Figure 25 highlight T-Test statistics and highlight the significance of each path. As we can see from the results, SD did not have significant impact on CR (0.171) however, SS played a strong mediation role on the impact between BDA and CR (3.582). Therefore, one can conclude that SS does indeed play a mediation role on the impact of SD on CR.

Outer Loadings

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
CR1 <- CR	0.645	0.626	0.136	4.73	0
CR2 <- CR	0.744	0.711	0.111	6.696	0
CR3 <- CR	0.644	0.63	0.149	4.314	0
CR4 <- CR	0.695	0.656	0.145	4.792	0
CR5 <- CR	-0.025	-0.021	0.239	0.107	0.458
SD3 <- SD	0.834	0.821	0.124	6.748	0
SD4 <- SD	0.93	0.918	0.104	8.918	0
SD5 <- SD	0.92	0.904	0.099	9.287	0
SS1 <- SS	0.816	0.811	0.057	14.392	0
SS2 <- SS	0.742	0.737	0.07	10.597	0
SS3 <- SS	0.78	0.774	0.076	10.326	0
SS4 <- SS	0.875	0.872	0.045	19.595	0
SS5 <- SS	0.798	0.795	0.046	17.341	0

Table 26 - Outer Loadings for H3D

Except for SD->CR, the path from SD->SS and SS->CR were both above 1.96 signaling high confidence interval (at the 95% confidence level). Suggesting that SS played a mediating role between SD and CR.

Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
SD -> CR	-0.028	-0.049	0.161	0.171	0.432
SD -> SS	-0.306	-0.324	0.119	2.563	0.005
SS -> CR	0.413	0.448	0.115	3.582	0

Table 27 - Path Coefficients for H3C

6.3.3.4 H3D: SS has a Mediation Effect Between BRE and CR

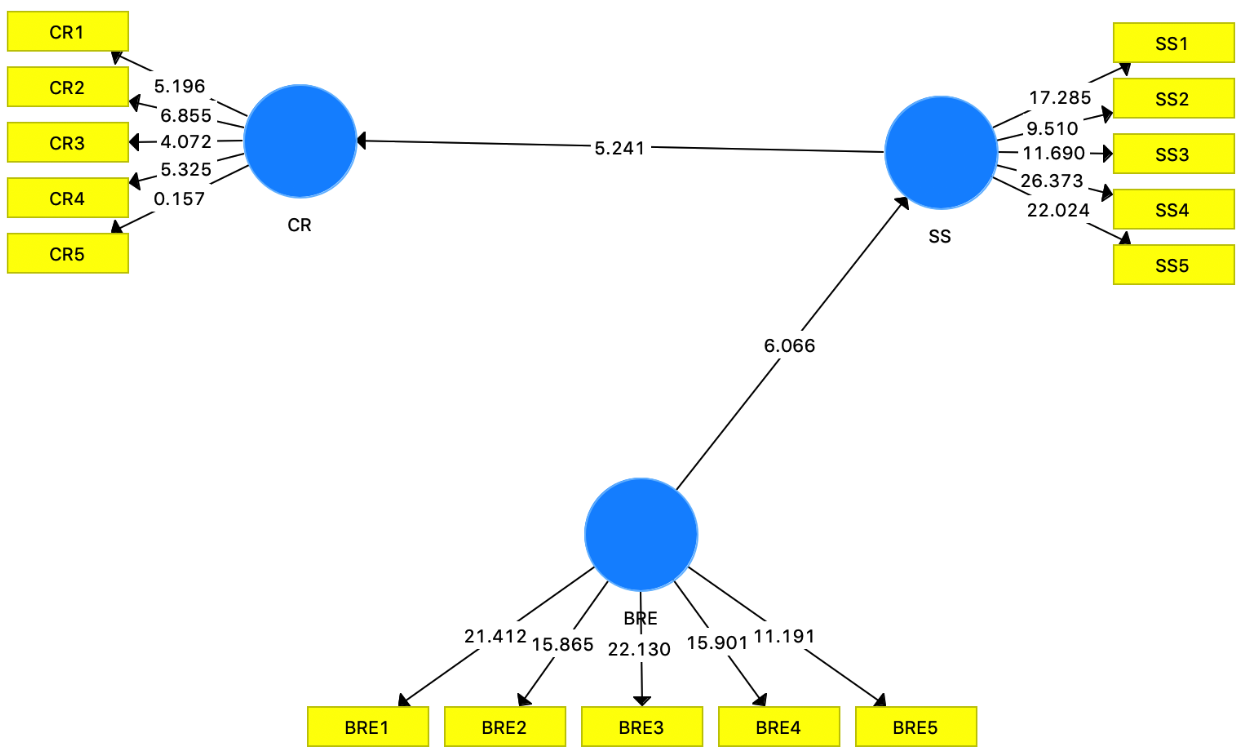

Figure 23 - H3D

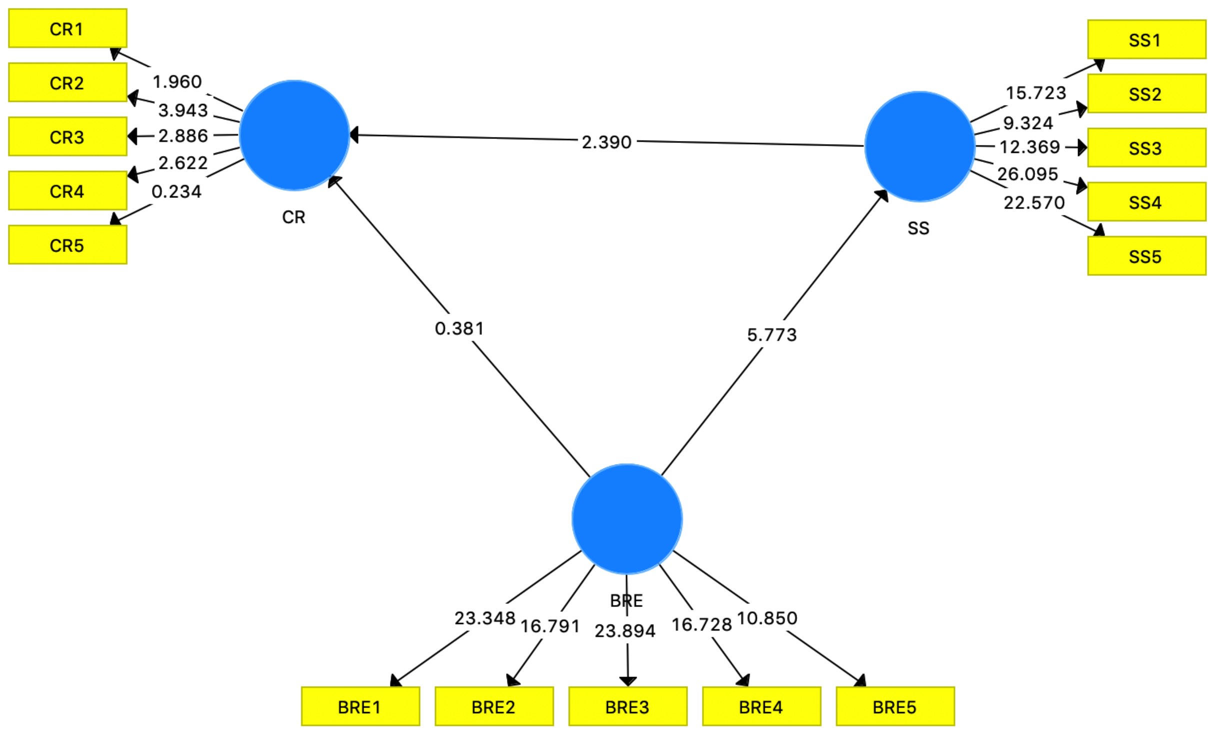

Figure 24 - H3D Bootstrap

A mediation analysis was performed using a one-tailed t-test bootstrap test using 1000 iterations (Figure 21). To assess whether the hypothesis can be accepted, we are aiming for a path value of 1.96 (at the 95% confidence level). The results highlight T-Test statistics and highlight the significance of each path. As we can see from the results, BRE did not have significant impact on CR however, SS played a strong mediation role on the impact between BDA and CR (2.390). Therefore, one can conclude that SS does indeed play a mediation role on the impact of BRE on CR.

Outer Loadings

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BRE1 <- BRE	0.866	0.864	0.037	23.348	0
BRE2 <- BRE	0.844	0.847	0.05	16.791	0
BRE3 <- BRE	0.89	0.894	0.037	23.894	0
BRE4 <- BRE	0.844	0.843	0.05	16.728	0
BRE5 <- BRE	0.786	0.777	0.072	10.85	0
CR1 <- CR	0.566	0.505	0.289	1.96	0.025
CR2 <- CR	0.74	0.654	0.188	3.943	0
CR3 <- CR	0.615	0.543	0.213	2.886	0.002
CR4 <- CR	0.774	0.669	0.295	2.622	0.004
CR5 <- CR	-0.058	-0.053	0.25	0.234	0.408
SS1 <- SS	0.814	0.812	0.052	15.723	0
SS2 <- SS	0.704	0.702	0.076	9.324	0

SS3 <- SS	0.786	0.783	0.064	12.369	0
SS4 <- SS	0.885	0.886	0.034	26.095	0
SS5 <- SS	0.82	0.822	0.036	22.57	0

Table 28 - Outer Loadings for H3D

When reviewing the T-Statistics (Figure 21), the significance of confidence level intervals across each of the items, pointing towards the latent variables (BREn –>BRE) all had significant T values and sample means were also high. This suggests that confidence intervals (at the 95% confidence level) are high. Cost reduction on the other hand, met the minimum requirements in terms of significance testing (except for CR5). Finally, Strategic Sourcing also had high path values for each of the construct items and the P-Values were also in check and higher than 0.5

Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BRE -> CR	-0.125	-0.107	0.329	0.381	0.352
BRE -> SS	0.481	0.494	0.083	5.773	0
SS -> CR	0.473	0.463	0.198	2.39	0.009

Table 29 - Path Coefficients for H3D

6.3.3.5 <u>H3E: SRM has a Mediation Effect Between BDA and CR</u>

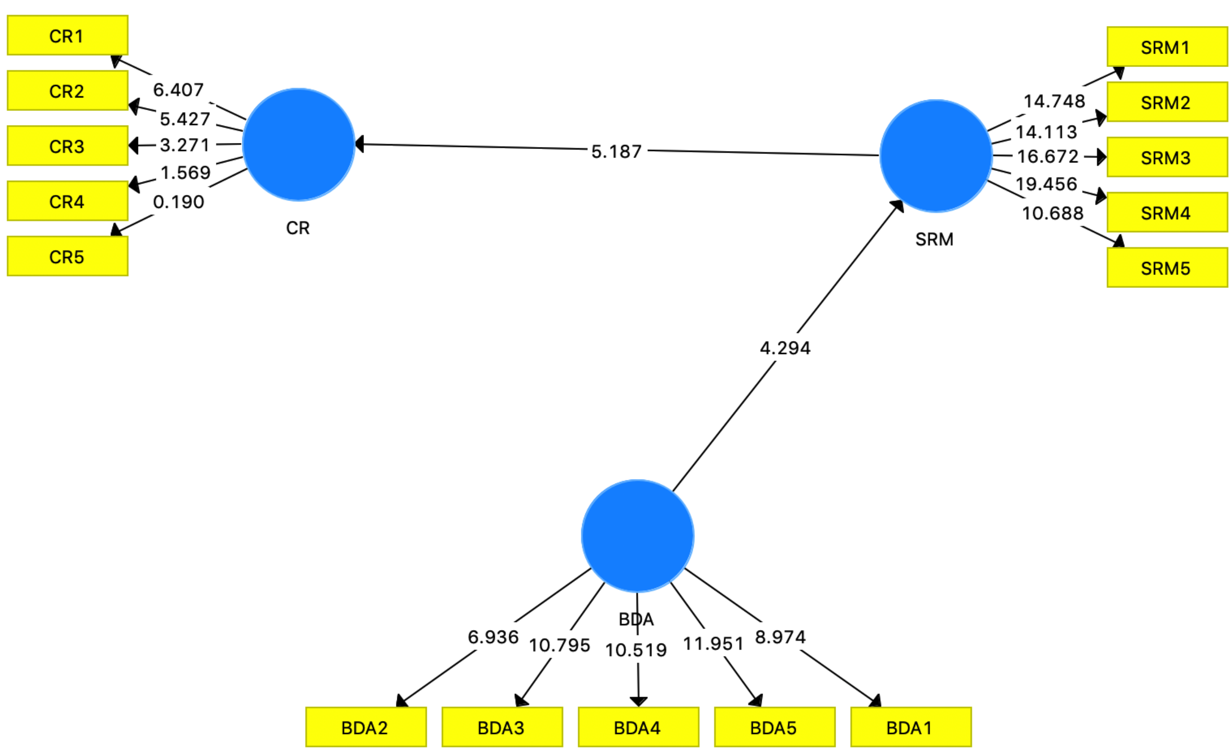

Figure 25 - H3E

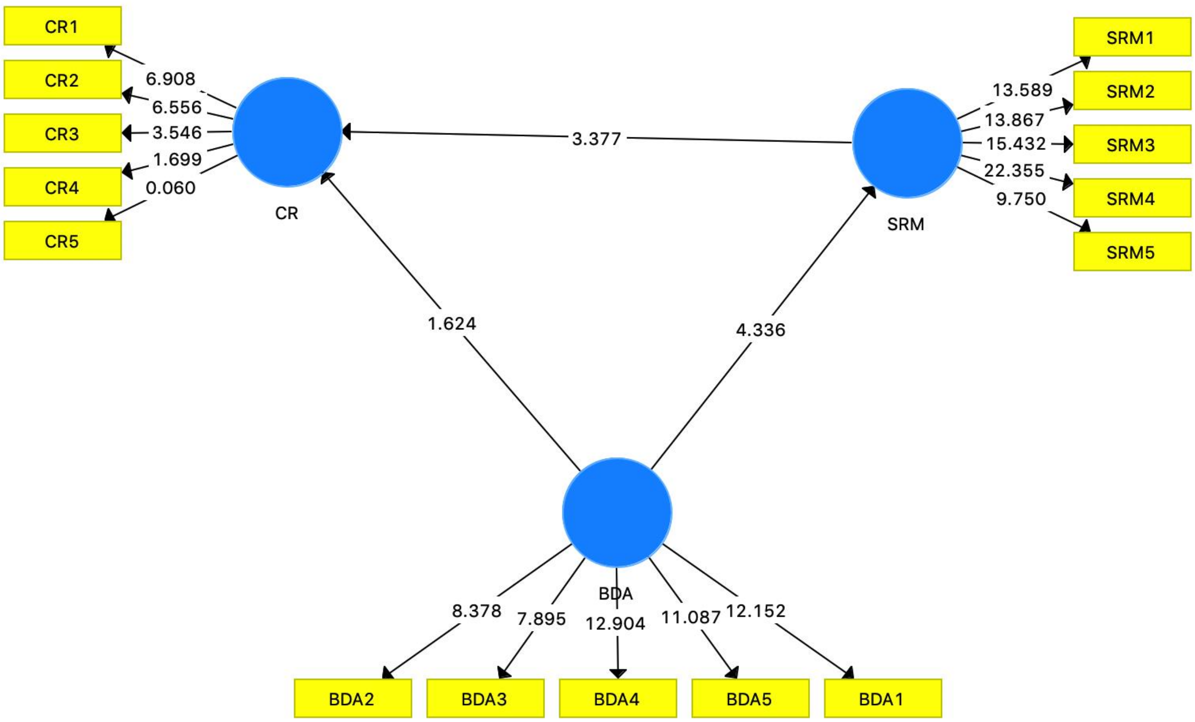

Figure 26 - H3E Bootstrap

A mediation analysis was performed using a one-tailed t-test bootstrap test using 1000 iterations (Figures 26 and 27). To assess whether the hypothesis can be accepted, we are aiming for a path value of 1.96 (at the 95% confidence level). The results in Figure 27 highlights T-Test statistics and highlight the significance of each path. As we can see from the results, BDA did not have significant enough impact on CR (1.624) however, SRM played a strong mediation role on the impact between BDA and CR (3.377). Therefore, one can conclude that SRM does indeed play a mediation role on the impact of BRE on CR.

Outer Loadings

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BDA2 <- BDA	0.751	0.745	0.09	8.378	0
BDA3 <- BDA	0.754	0.74	0.096	7.895	0
BDA4 <- BDA	0.818	0.816	0.063	12.904	0
BDA5 <- BDA	0.825	0.818	0.074	11.087	0
CR1 <- CR	0.771	0.743	0.112	6.908	0
CR2 <- CR	0.754	0.715	0.115	6.556	0
CR3 <- CR	0.65	0.613	0.183	3.546	0
CR4 <- CR	0.405	0.364	0.238	1.699	0.045
CR5 <- CR	0.014	0.02	0.236	0.06	0.476
SRM1 <- SRM	0.801	0.795	0.059	13.589	0
SRM2 <- SRM	0.816	0.814	0.059	13.867	0
SRM3 <- SRM	0.838	0.833	0.054	15.432	0

SRM4 <- SRM	0.832	0.832	0.037	22.355	0
SRM5 <- SRM	0.744	0.736	0.076	9.75	0
BDA1 <- BDA	0.793	0.791	0.065	12.152	0

Table 30 - Outer Loadings for H3E

All paths were significant at the 95% confidence interval in H3E and the P-Value of 0.052 between BDA->CR suggests that a mediation effect was present.

Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BDA -> CR	0.204	0.224	0.126	1.624	0.052
BDA -> SRM	0.381	0.403	0.088	4.336	0
SRM -> CR	0.37	0.393	0.11	3.377	0

Table 31 - Path Coefficients for H3E

6.3.3.6 H3F: SRM has a Mediation Effect Between ML and CR

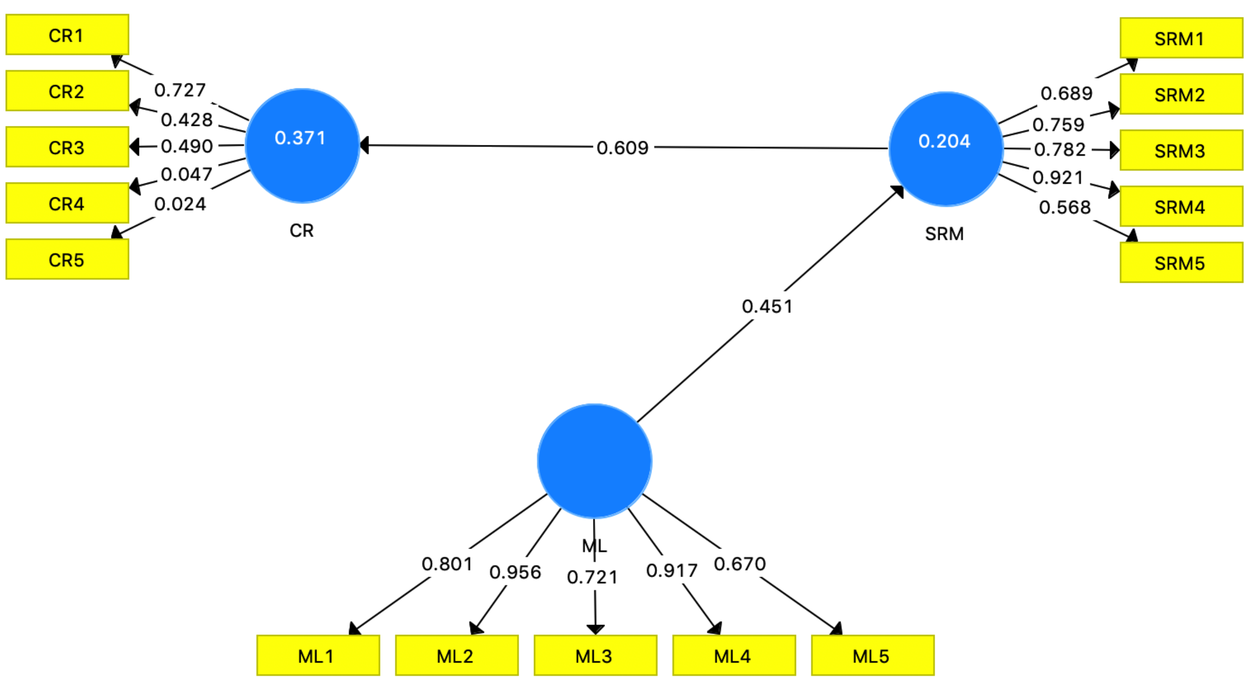

Figure 27 - H3F

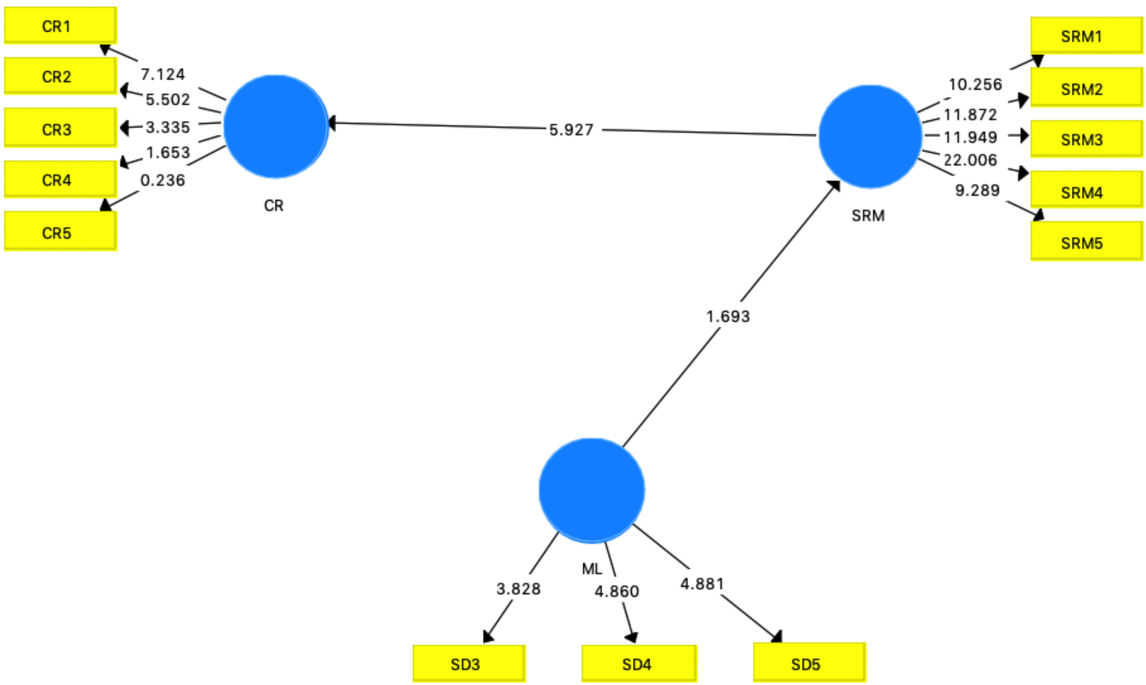

Figure 28 - H3F Bootstrap

A mediation analysis was performed using a one-tailed t-test bootstrap test using 1000 iterations (Figures 30 and 31). To assess whether the hypothesis can be accepted, we are aiming for a path value of 1.96 (at the 95% confidence level). The results in Figure 31 highlight T-Test statistics and highlight the significance of each path. As we can see from the results, ML did not have significant impact on CR (1.724) however, SRM played a strong mediation role on the impact between ML and CR (5.832). Therefore, one can conclude that SS does indeed play a mediation role on the impact of BRE on CR.

Outer Loadings

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BRE1 <- BRE	0.755	0.714	0.142	5.321	0
BRE2 <- BRE	0.745	0.699	0.135	5.534	0
BRE3 <- BRE	0.677	0.64	0.169	4.004	0
BRE4 <- BRE	0.413	0.394	0.231	1.792	0.037
BRE5 <- BRE	-0.008	-0.004	0.27	0.031	0.488
CR1 <- CR	0.707	0.379	0.6	1.177	0.12
CR2 <- CR	0.773	0.381	0.652	1.184	0.118
CR3 <- CR	-0.426	-0.003	0.478	0.891	0.187
CR4 <- CR	-0.606	-0.098	0.606	1	0.159
CR5 <- CR	-0.604	-0.092	0.605	0.998	0.159

SRM1 <- SRM	0.801	0.796	0.06	13.361	0
SRM2 <- SRM	0.82	0.815	0.055	14.861	0
SRM3 <- SRM	0.847	0.843	0.05	17.099	0
SRM4 <- SRM	0.818	0.82	0.035	23.251	0
SRM5 <- SRM	0.751	0.746	0.073	10.291	0

Table 32 - Outer Loadings H3G

Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
ML -> CR	0.156	0.062	0.232	0.672	0.251
ML -> SRM	0.552	0.257	0.516	1.07	0.143
SRM -> CR	0.354	0.371	0.162	2.184	0.015

Table 33 - Path Coefficients H3G

6.3.3.7 H3G: SRM has a Mediation Effect Between SD and CR

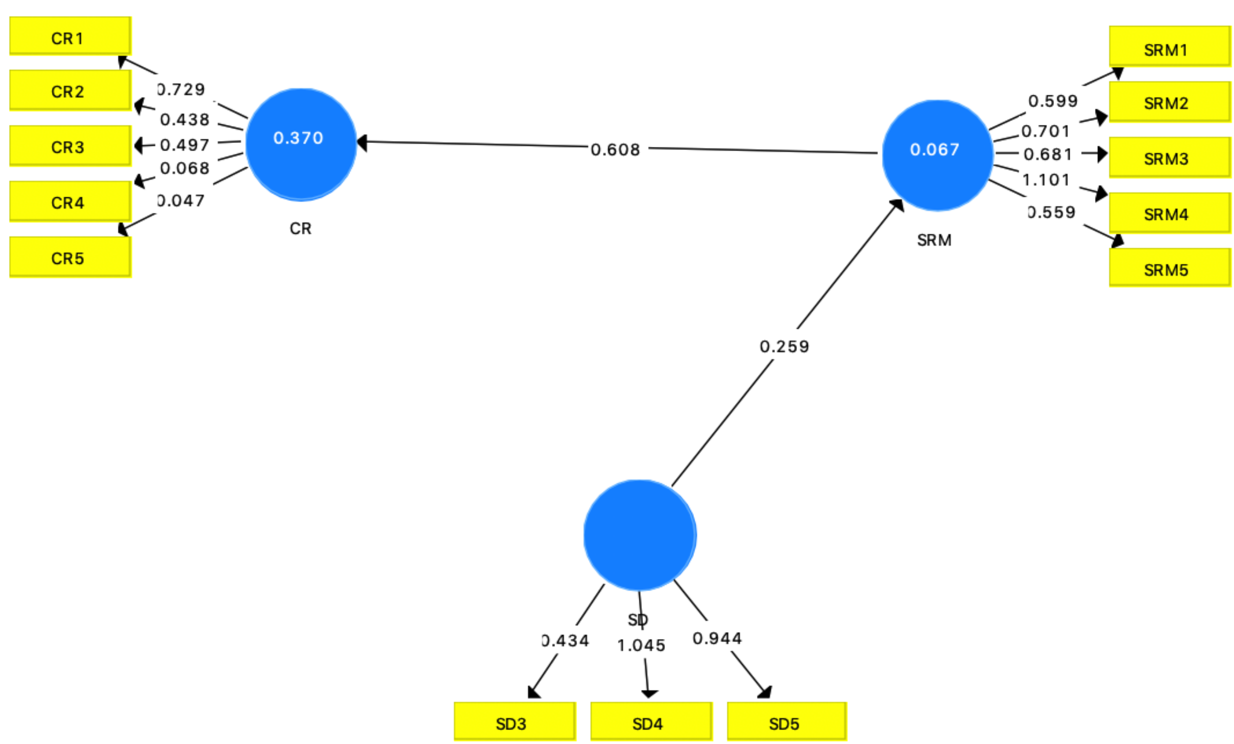

Figure 29 - H3G

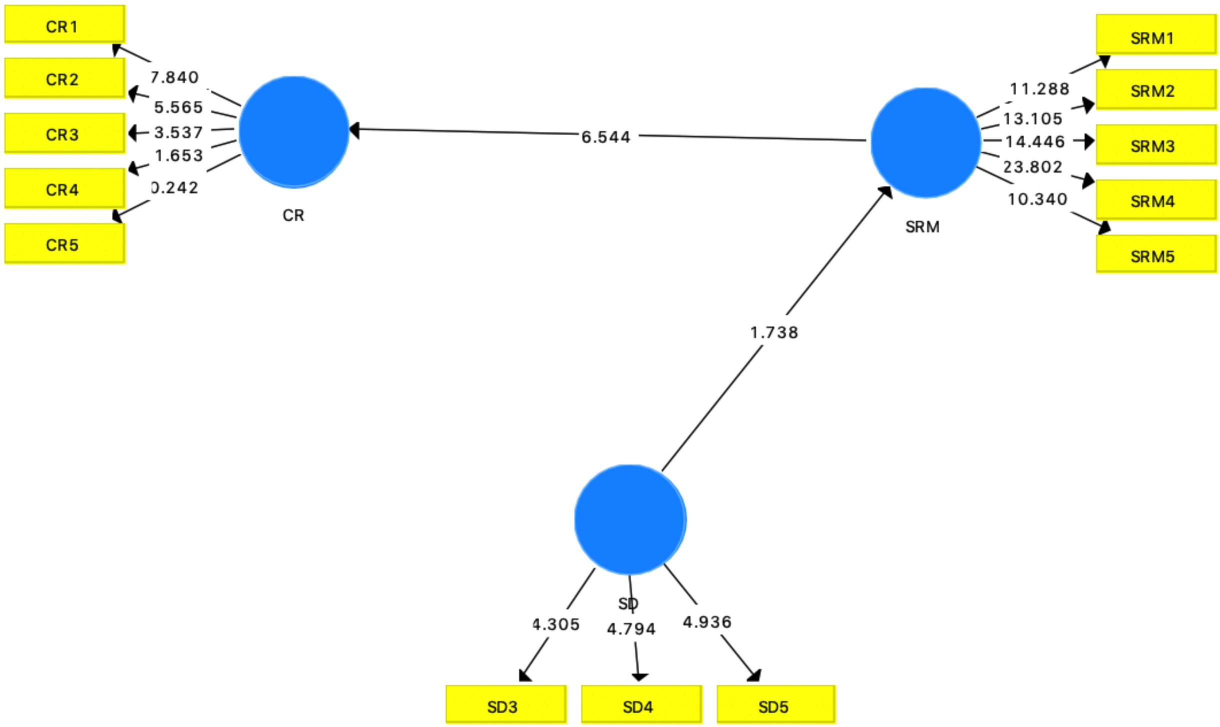

Figure 30 - H3G Bootstrap

A mediation analysis was performed using a one-tailed t-test bootstrap test using 1000 iterations (Figures 32 and 33). The results in Figure 33 highlight T-Test statistics and highlight the significance of each path. As we can see from the results, SD did not have significant impact on CR (1.759) however, SRM played a strong mediation role on the impact between SD and CR (3.925). Therefore, one can conclude that SS does indeed play a mediation role on the impact of BRE on CR.

Outer Loadings

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
CR1 <- CR	0.776	0.726	0.147	5.275	0
CR2 <- CR	0.721	0.67	0.15	4.798	0
CR3 <- CR	0.669	0.633	0.188	3.562	0
CR4 <- CR	0.418	0.379	0.245	1.71	0.044
CR5 <- CR	0.069	0.065	0.257	0.27	0.394
SD3 <- SD	0.808	0.775	0.182	4.446	0
SD4 <- SD	0.938	0.902	0.179	5.242	0
SD5 <- SD	0.927	0.887	0.185	5.008	0
SRM1 <- SRM	0.779	0.768	0.087	8.95	0
SRM2 <- SRM	0.814	0.806	0.079	10.27	0
SRM3 <- SRM	0.828	0.821	0.082	10.115	0
SRM4 <- SRM	0.847	0.844	0.057	14.963	0
SRM5 <- SRM	0.756	0.748	0.094	8.034	0

Table 34 - Outer Loadings H3H

Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
SD -> CR	-0.071	-0.091	0.142	0.5	0.308
SD -> SRM	-0.244	-0.262	0.139	1.759	0.039
SRM -> CR	0.439	0.462	0.112	3.925	0

Table 35 - Path Coefficients H3H

6.3.3.8 H3H: SRM has a Mediation Effect Between BRE and CR

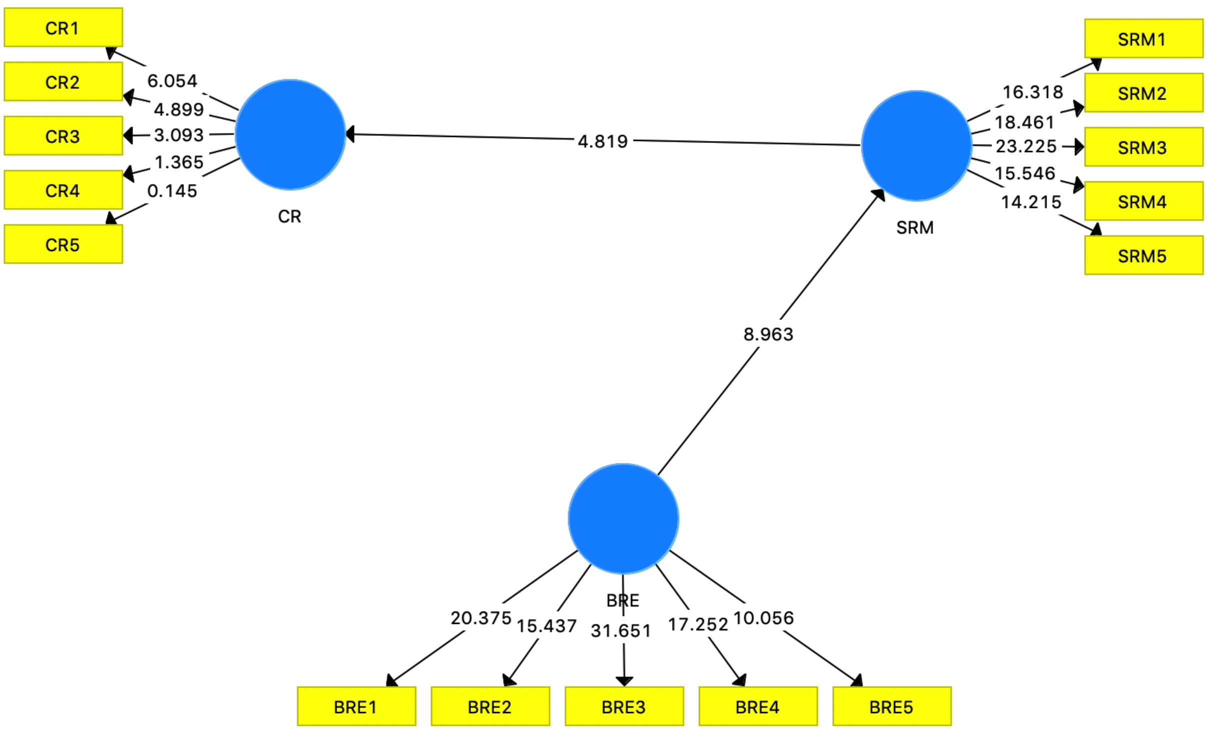

Figure 31 - H3H

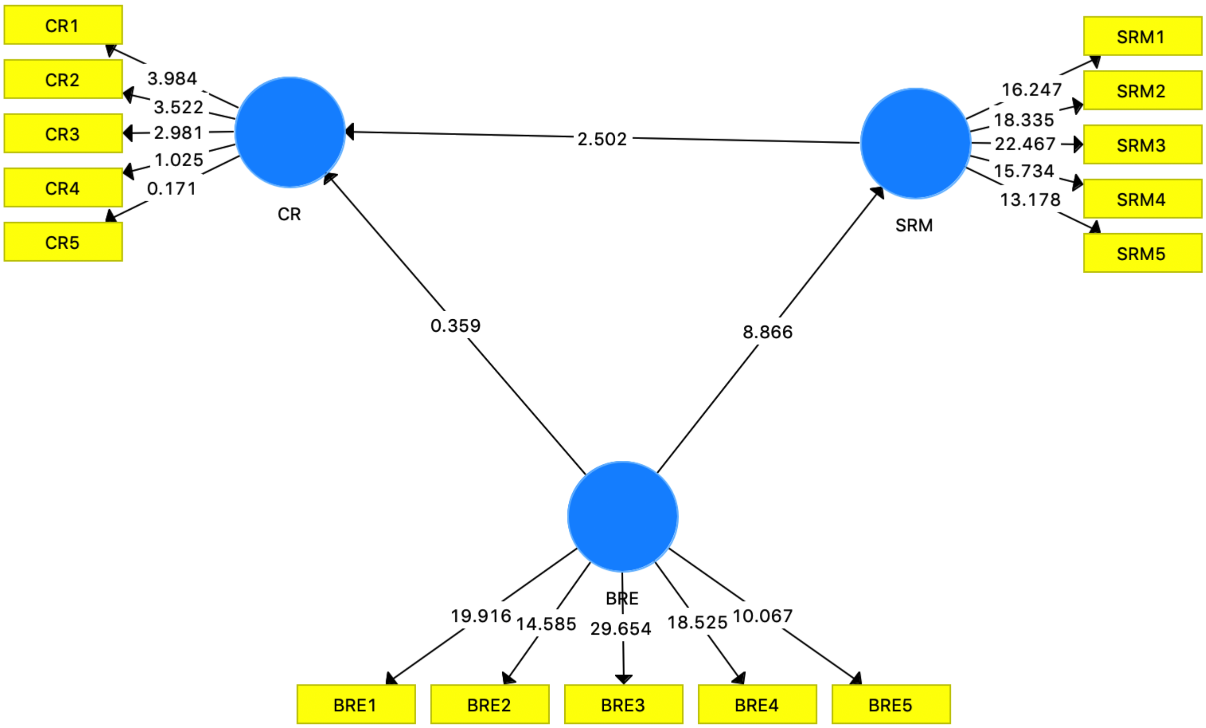

Figure 32 - H3H Bootstrap

A mediation analysis was performed using a one-tailed t-test bootstrap test using 1000 iterations (Figures 28 and 29). To assess whether the hypothesis can be accepted, we are aiming for a path value of 1.96 (at the 95% confidence level). The results in Figure 29 highlight T-Test statistics and highlight the significance of each path. As we can see from the results, BRE did not have significant impact on CR (0.359) however, SRM played a strong mediation role on the impact between BRE and CR (2.502). Therefore, one can conclude that SS does indeed play a mediation role on the impact of BRE on CR.

Outer Loadings

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BRE1 <- BRE	0.857	0.856	0.043	19.916	0
BRE2 <- BRE	0.848	0.844	0.058	14.585	0
BRE3 <- BRE	0.904	0.905	0.03	29.654	0
BRE4 <- BRE	0.858	0.86	0.046	18.525	0
BRE5 <- BRE	0.759	0.759	0.075	10.067	0
CR1 <- CR	0.81	0.727	0.203	3.984	0
CR2 <- CR	0.701	0.636	0.199	3.522	0
CR3 <- CR	0.642	0.573	0.215	2.981	0.001
CR4 <- CR	0.34	0.305	0.331	1.025	0.153
CR5 <- CR	0.045	0.034	0.265	0.171	0.432
SRM1 <- SRM	0.801	0.8	0.049	16.247	0

SRM2 <- SRM	0.828	0.827	0.045	18.335	0
SRM3 <- SRM	0.851	0.853	0.038	22.467	0
SRM4 <- SRM	0.797	0.796	0.051	15.734	0
SRM5 <- SRM	0.767	0.766	0.058	13.178	0

Table 36 - Outer Loadings for H3H

Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
BRE -> CR	0.08	0.064	0.223	0.359	0.36
BRE -> SRM	0.594	0.603	0.067	8.866	0
SRM -> CR	0.401	0.43	0.16	2.502	0.006

Table 37 - Path Coefficients H3H

In the Zhao classification framework (Figure 34), the objective is to first assess is the product of the path coefficient (a x b) is significant. If so, we assess if “c” is also significant. If so, the next steps are to multiply a x b x c and to assess if the effect is still positive, if so than we can suggest “Complementary mediation” if not, then we can suggest “Competitive Mediation”. If on the flipside, c was not significant, we can classify as “indirect-only” mediation. If a x b is non-significant, we can assume non-mediation as a foreground. The next step is to assess whether it was a “Direct-Only” (i.e. “c” was significant) or a “No-Effect” mediation (i.e. “c” was not significant).

In our case, during mediation testing, all hypotheses were classified, and indirect-only mediation given that each “c” value was non-significant (Table 39). There is evidence of a hypothesized mediator and there is a low probability that we may have omitted certain other mediators.

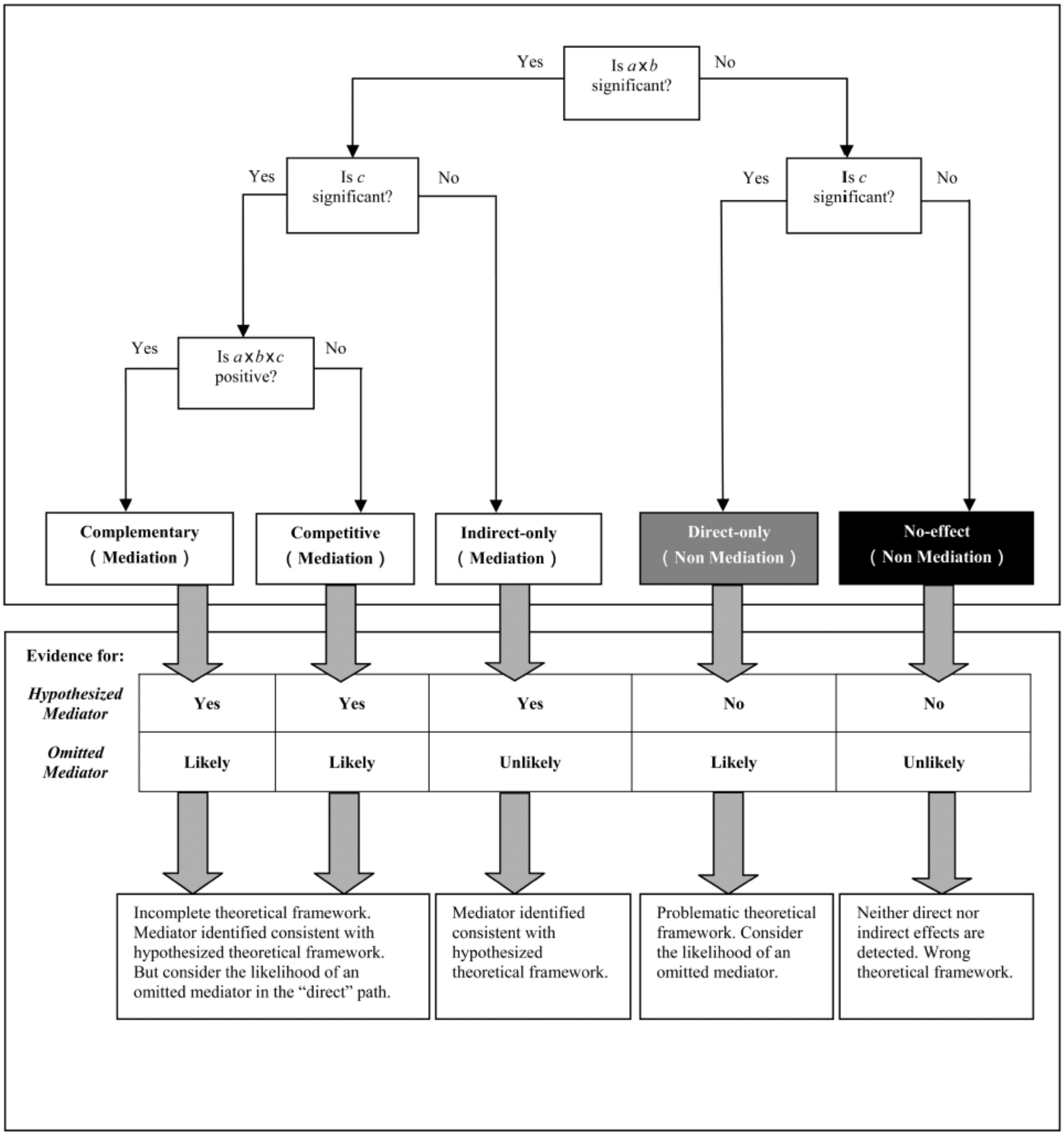

Figure 33 - Zhao Mediation Classification Table

Results Interpretation using the Zhao Classification Table

	"a x b"	"c"	"a x b x c"	Mediation Type	Hypothesized Mediator	Omitted Mediator
H3A	Significant	Non-Significant	Significant	Indirect-only	Yes	Unlikely
H3B	Significant	Non-Significant	Significant	Indirect-only	Yes	Unlikely
H3C	Significant	Non-Significant	Significant	Indirect-only	Yes	Unlikely
H3D	Significant	Non-Significant	Non-Significant	Indirect-only	Yes	Unlikely
H3E	Significant	Non-Significant	Significant	Indirect-only	Yes	Unlikely
H3F	Significant	Non-Significant	Significant	Indirect-only	Yes	Unlikely
H3G	Significant	Non-Significant	Non-Significant	Indirect-only	Yes	Unlikely
H3H	Significant	Non-Significant	Significant	Indirect-only	Yes	Unlikely

Table 38 - Zhao Classification Interpretation Table

6.3.4 H4: Moderating Effect of Organizational Context

<u>6.3.4.1 H4A: EL has a Moderation Effect Between BDA and CR</u>

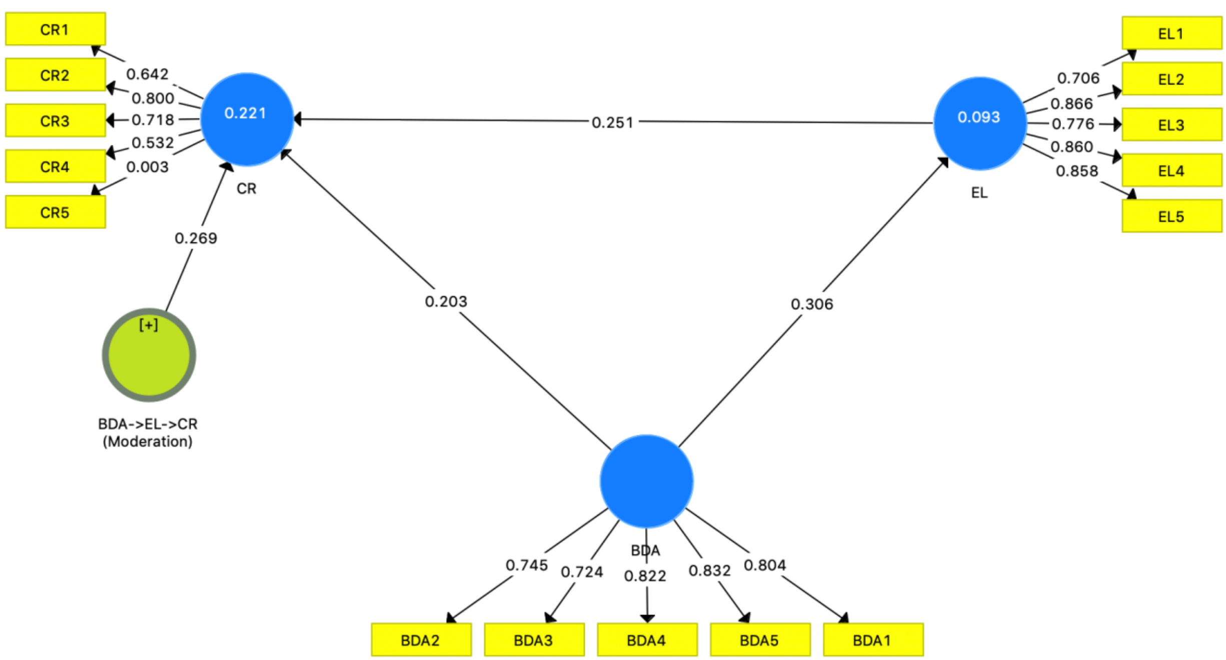

Figure 34 - H4A

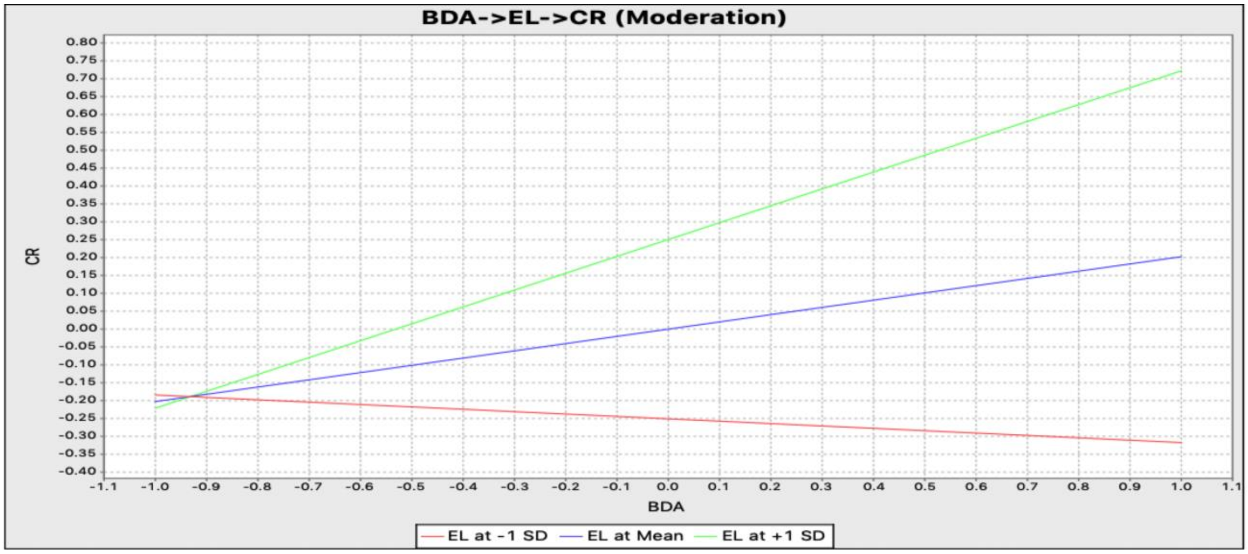

Figure 35 - H4A Simple-Slope Analysis

When looking at the simple slope analysis (Figure 36), the objective is to determine whether EL had a moderation effect between BDA and CR. The blue line represents EL at mean. The first observation is the correlation between BDA and CR and as we can see, there is a positive relationship between BDA and CR. This means, the more we apply BDA technologies to reduce costs, the greater (and more positive) the effect on CR. As we move onto looking into moderation, we can see that if we add EL as a moderator (EL at +1 SD), the effect on CR increases however, if we remove EL (EL at -1 SD), the results decrease. This proves that there is a moderation effect. Another way to assess whether moderation exists, is by looking at the lines and determining if there are parallel or not. When the lines are not parallel, we can clearly state that moderation exists.

R Square

	R Square	R Square Adjusted
CR	0.221	0.188
EL	0.093	0.081

Table 39 - R Square H4A

Although there is no consensus on the minimum level that this index should reach, (Falk 1992) recommend a minimum value of 0.1, which ensures that at least 10 percent of the construct variability is due to the model. As we can see from the model (Table 38) CR did have an explainable variance however EL fell short of the 0.1 value and cannot explain justifiably the correlation.

F Square

	BDA	BDA->EL->CR (Moderation)	CR	EL
BDA			0.045	0.103
BDA->EL->CR (Moderation)			0.095	
CR				
EL			0.071	

Table 40 - F Square H4A

Construct Reliability

	Cronbach's Alpha	rho_ A	Composite Reliability	Average Variance Extracted (AVE)
BDA	0.849	0.866	0.89	0.619
BDA->EL->CR (Moderation)	0.933	1	0.793	0.205
CR	0.513	0.638	0.697	0.37
EL	0.873	0.901	0.908	0.665

Table 41 - Construct Reliability H4A

When reviewing construct reliability (Table 42), we are assessing the reliability of numbers. In this case, we are aiming for a number that is also above 0.7. In this case, all construct items, except for CR, were above 0.7. In order to ascertain that the construct is reliable, and that subjectivity is removed, we aimed for a number above 0.7. In this case, all constructs are consistently reliable.

Discriminant Validity

	BDA	BDA->EL->CR (Moderation)	CR	EL
BDA	**0.787**			
BDA->EL->CR (Moderation)	0.184	**0.453**		
CR	0.331	0.294	**0.608**	
EL	0.306	-0.092	0.287	**0.815**

Table 42 - Discriminant Validity H4A

In discriminant validity (Table 43), we are assessing the values of AVE and our objective is to understand the correlations between latent variables. The objective is to make sure that the square root of AVE of each latent variable should be greater than the correlations amongst the variables. In other words, we want to make sure there is subjective independence of every indicator on its latent variable or also called “vertical collinearity”. As we can see from the table above, in all cases, the square root of AVE for each latent variable was greater that the correlations of each latent variable meaning that there is discriminant validity between Big Data Analytics, Executive Leadership and. Cost Reduction.

6.3.4.2 <u>H4B: EL has a Moderation Effect Between ML and CR</u>

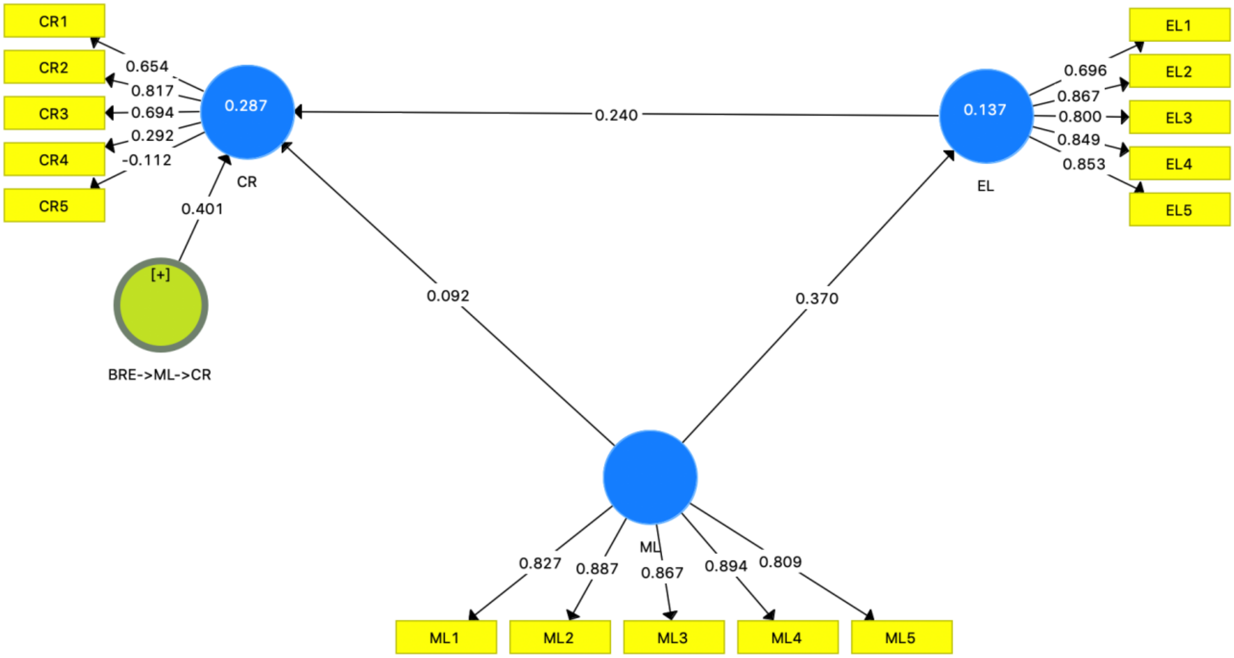

Figure 36 - H4B

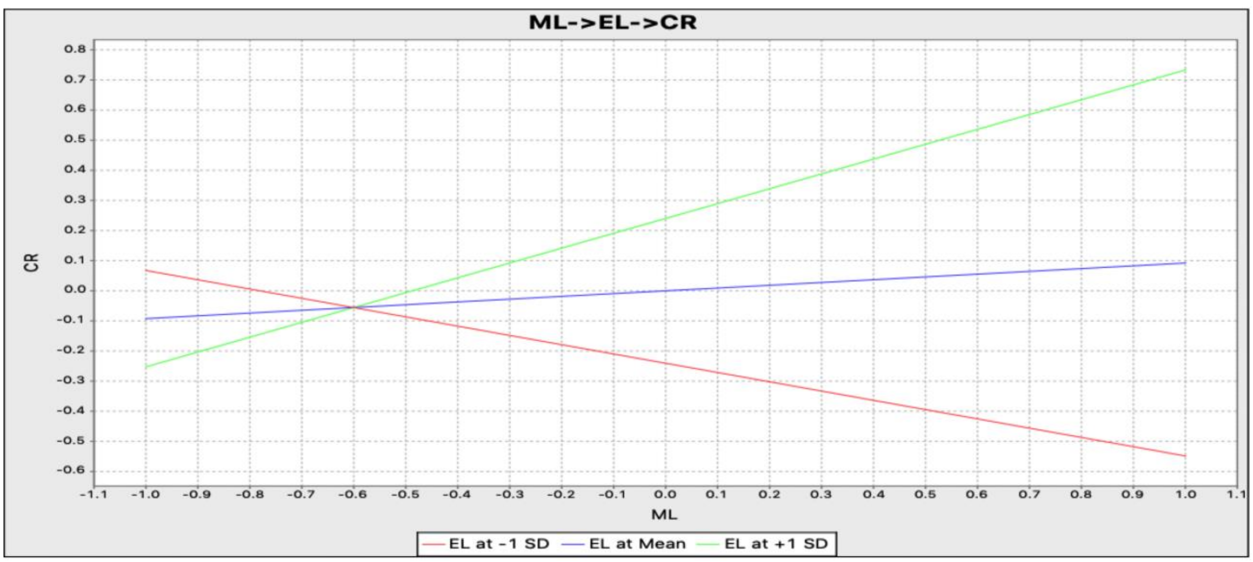

Figure 37 - H4B Simple-Slope Analysis

When looking at the simple slope analysis (Figure 40), the objective is to determine whether EL had a moderation effect between ML and CR. The blue line represents EL at mean. The first observation is the correlation between ML and CR and as we can see, there is a positive relationship between ML and CR. This means, the more we apply ML technologies to reduce costs, the greater (and more positive) the effect on CR. As we move onto looking into moderation, we can see that if we add EL as a moderator (EL at +1 SD), the effect on CR increases however, if we remove EL (EL at -1 SD), the results decrease. This proves that there is a moderation effect.

Another way to assess whether moderation exists, is by looking at the lines and determining if there are parallel or not. When the lines are not parallel, we can clearly state that moderation exists.

R Square

	R Square	R Square Adjusted
CR	0.287	0.257
EL	0.137	0.125

Table 43 - R Square H4B

Although there is no consensus on the minimum level that this index should reach, (Falk 1992) recommend a minimum value of 0.1, which ensures that at least 10 percent of the construct variability is due to the model. As we can see from Table 46, the model above CR did have an explainable variance (0.287) and EL (0.125) value and can both justifiably the correlation.

F Square

	BRE->ML->CR	CR	EL	ML
BRE->ML->CR		0.238		
CR				
EL		0.07		
ML		0.01	0.158	

Table 44 - F Square H4B

Construct Reliability

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
BRE->ML->CR	0.965	1	0.038	0.08
CR	0.513	0.461	0.623	0.335
EL	0.873	0.887	0.908	0.665
ML	0.91	0.913	0.933	0.735

Table 45 - Construct Reliability H4B

When reviewing construct reliability (Table 50), we are assessing the reliability of numbers. In this case, we are aiming for a number that is also above 0.7. In this case, all construct items, except for CR, were above 0.7. In order to ascertain that the construct is reliable, and that subjectivity is removed, we aimed for a number above 0.7. In this case, all constructs are consistently reliable.

Discriminant Validity

	BRE->ML->CR	CR	EL	ML
BRE->ML->CR	**0.284**			
CR	0.454	**0.579**		
EL	0.09	0.312	**0.816**	
ML	0.159	0.248	0.37	**0.857**

Table 46 - Discriminant Validity H4B

In discriminant validity (Table 51), we are assessing the values of AVE and our objective is to understand the correlations between latent variables. The objective is to make sure that the square root of AVE of each latent variable should be greater than the correlations amongst the variables. In other words, we want to make sure there is subjective independence of every indicator on its latent variable or also called “vertical collinearity”. As we can see from the table above, in most cases, except for the moderation effect between BRE->ML and ->CR, the square root of AVE for each latent variable was greater that the correlations of each latent variable meaning that there is discriminant validity between Cost Reduction, Executive Leadership and Machine Learning.

6.3.4.3 <u>H4C: EL has a Moderation Effect Between SD and CR</u>

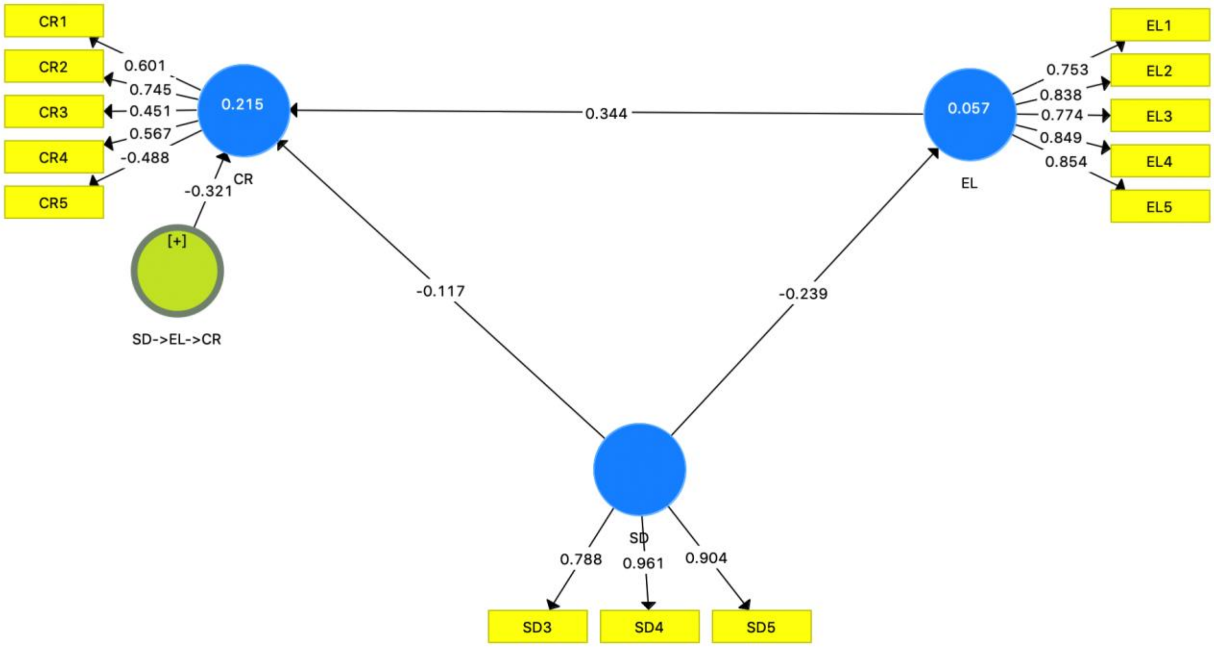

Figure 38 - H4C

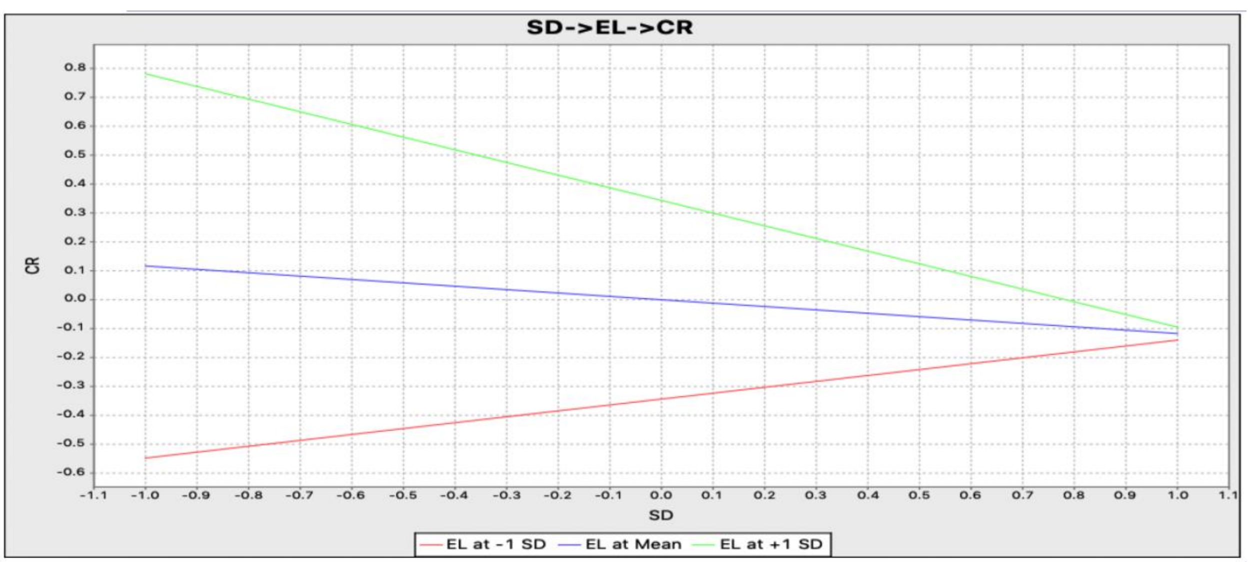

Figure 39 - H4C Simple-Slope Analysis

When looking at the simple slope analysis (Figure 42), the objective is to determine whether EL had a moderation effect between SD and CR. The blue line represents EL at mean. The first observation is the correlation between SD and CR and as we can see, there is a negative relationship between SD and CR. This means, the more we apply SD technologies to reduce costs, the greater (and more negative) the effect on CR. As we move onto looking into moderation, we can see that if we add EL as a moderator (EL at +1 SD), the effect on CR decreases however, if we remove EL (EL at -1 SD), the results increase. This proves that there is a moderation effect. Another way to assess whether moderation exists, is by looking at the lines and determining if there are parallel or not. When the lines are not parallel, we can clearly state that moderation exists.

R Square

	R Square	R Square Adjusted
CR	0.215	0.182
EL	0.057	0.044

Table 47 - R Square H4C

Although there is no consensus on the minimum level that this index should reach, (Falk 1992) recommend a minimum value of 0.1, which ensures that at least 10 percent of the construct variability is due to the model. As we can see from Table 50, the model above CR did have an explainable variance (0.182) and EL (0.044) unfortunately was not high enough to explain justifiably the correlation.

F Square

	CR	EL	SD	SD->EL->CR
CR				
EL	0.142			
SD	0.016	0.06		
SD->EL->CR	0.12			

Table 48 - F Square H4C

Construct Reliability

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
CR	0.513	0.467	0.515	0.336
EL	0.873	0.875	0.908	0.664
SD	0.879	1.198	0.917	0.787
SD->EL->CR	0.947	1	0.949	0.555

Table 49 - Construct Reliability H4C

When reviewing construct reliability (Table 53), we are assessing the reliability of numbers. In this case, we are aiming for a number that is also above 0.7. In this case, all construct items, except for CR, were above 0.7. In order to ascertain that the construct is reliable, and that subjectivity is removed, we aimed for a number above 0.7. In this case, all constructs are consistently reliable.

Discriminant Validity

	CR	EL	SD	SD->EL->CR
CR	**0.58**			
EL	0.343	**0.815**		
SD	-0.14	-0.239	**0.887**	
SD->EL->CR	-0.259	0.092	-0.188	**0.745**

Table 50 - Discriminant Validity H4C

In discriminant validity (Table 54), we are assessing the values of AVE and our objective is to understand the correlations between latent variables. The objective is to make sure that the square root of AVE of each latent variable should be greater than the correlations amongst the variables. In other words, we want to make sure there is subjective independence of every indicator on its latent variable or also called "vertical collinearity". As we can see from the table above, in all cases, the square root of AVE for each latent variable was greater that the correlations of each latent variable meaning that there is discriminant validity between Cost Reduction, Executive Leadership and System Dynamics.

6.3.4.4 H4D: EL has a Moderation Effect Between BRE and CR

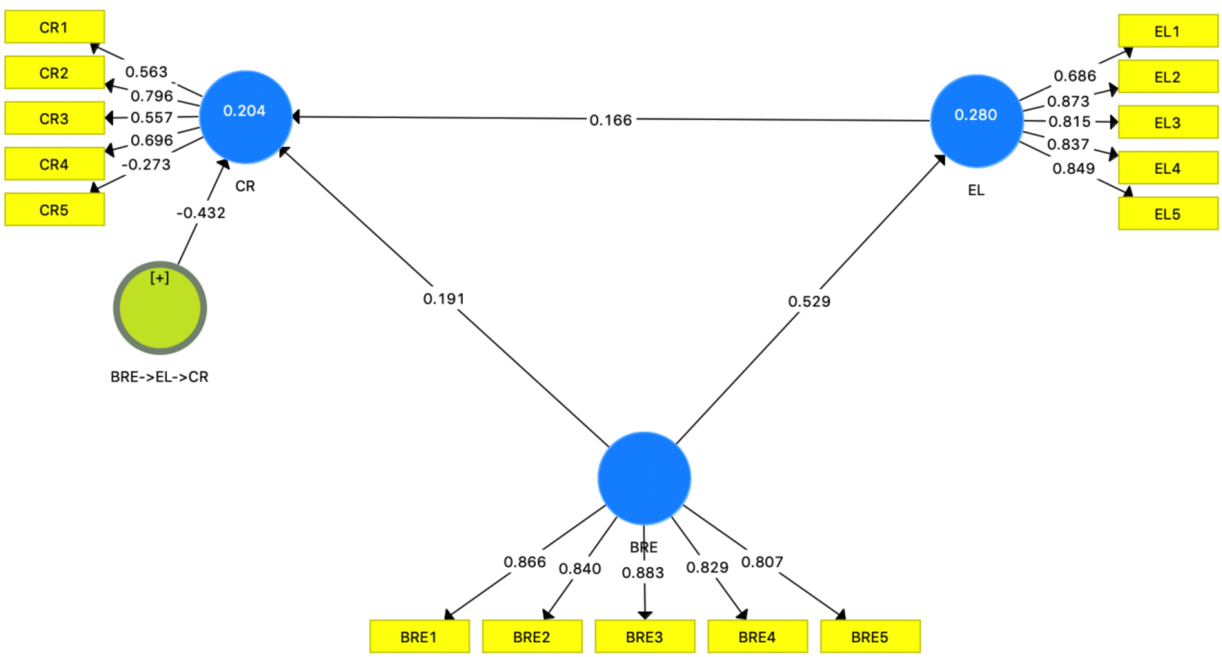

Figure 40 - H4D

Figure 41 - H4D Simple-Slope Analysis

When looking at the simple slope analysis (Figure 38), the objective is to determine whether EL had a moderation effect between BRE and CR. The blue line represents EL at mean. The first observation is the correlation between BRE and CR and as we can see, there is a positive relationship between BRE and CR. This means, the more we apply BRE technologies to reduce costs, the greater (and more positive) the effect on CR. As we move onto looking into moderation, we can see that if we add EL as a moderator (EL at +1 SD), the effect on CR decreases however, if we remove EL (EL at -1 SD), the results increase. This proves that there is a moderation effect. Another way to assess whether moderation exists, is by looking at the lines and determining if there are parallel or not. When the lines are not parallel, we can clearly state that moderation exists.

R Square

	R Square	R Square Adjusted
CR	0.204	0.17
EL	0.28	0.27

Table 51 - R Square H4D

Although there is no consensus on the minimum level that this index should reach, (Falk 1992) recommend a minimum value of 0.1, which ensures that at least 10 percent of the construct variability is due to the model. As we can see from Table 42 CR did have an explainable variance (0.17) and EL as well (0.27) and can explain justifiably the correlation.

F Square

	BDA	BDA->EL->CR (Moderation)	CR	EL
BRE			0.024	0.389
BRE->EL->CR			0.15	
CR				
EL			0.022	

Table 52 - F Square H4D

Construct Reliability

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
BRE	0.901	0.912	0.926	0.715
BRE->EL->CR	0.935	1	0.937	0.389
CR	0.513	0.576	0.633	0.364
EL	0.873	0.893	0.907	0.664

Table 53 - Construct Reliability H4D

When reviewing construct reliability (Table 46), we are assessing the reliability of numbers. In this case, we are aiming for a number that is also above 0.7. In this case, all construct items, except for CR, were above 0.7. In order to ascertain that the construct is reliable, and that subjectivity is removed, we aimed for a number above 0.7. In this case, all constructs are consistently reliable.

Discriminant Validity

	BRE	BRE->EL->CR (Moderation)	CR	EL
BRE	**0.845**			
BRE->EL->CR	0.402	**0.623**		
CR	0.117	-0.334	**0.603**	
EL	0.529	-0.051	0.288	**0.815**

Table 54 - Discriminant Validity H4D

In discriminant validity (Table 47), we are assessing the values of AVE and our objective is to understand the correlations between latent variables. The objective is to make sure that the square root of AVE of each latent variable should be greater than the correlations amongst the variables. In other words, we want to make sure there is subjective independence of every indicator on its latent variable or also called “vertical collinearity”. As we can see from the table above, in all cases, the square root of AVE for each latent variable was greater that the correlations of each latent variable meaning that there is discriminant validity between Business Rules Engine, Executive Leadership and Cost Reduction.

6.3.4.5 <u>H4E: PT has a Moderation Effect Between BDA and CR</u>

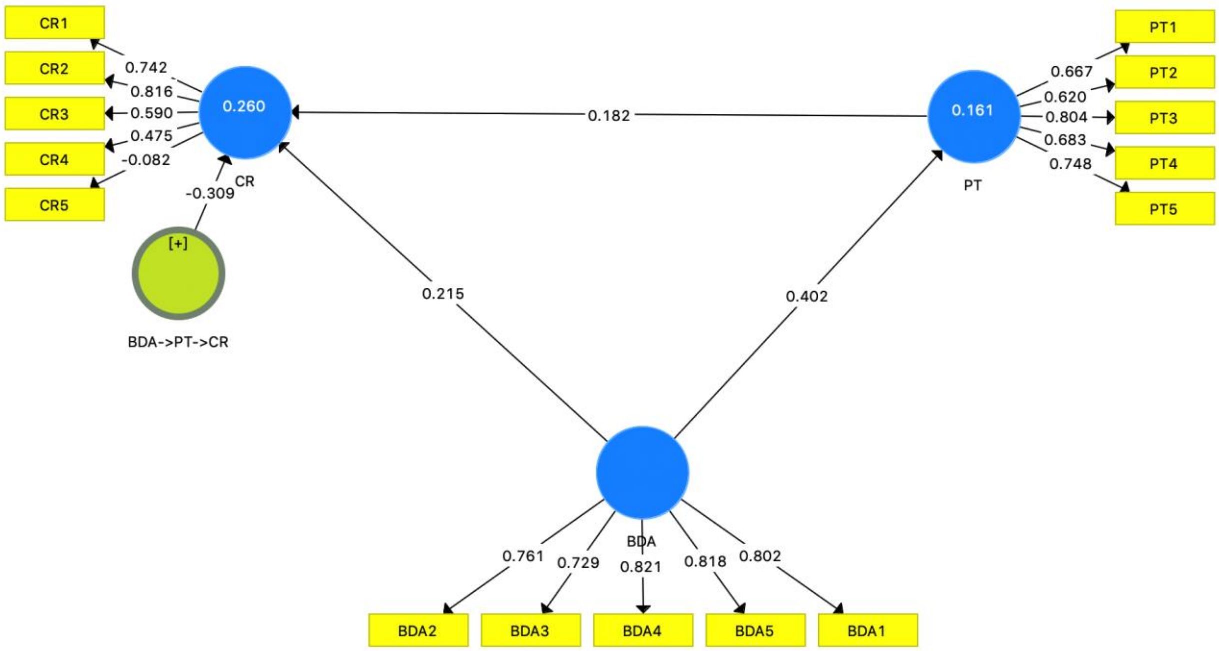

Figure 42 - H4E

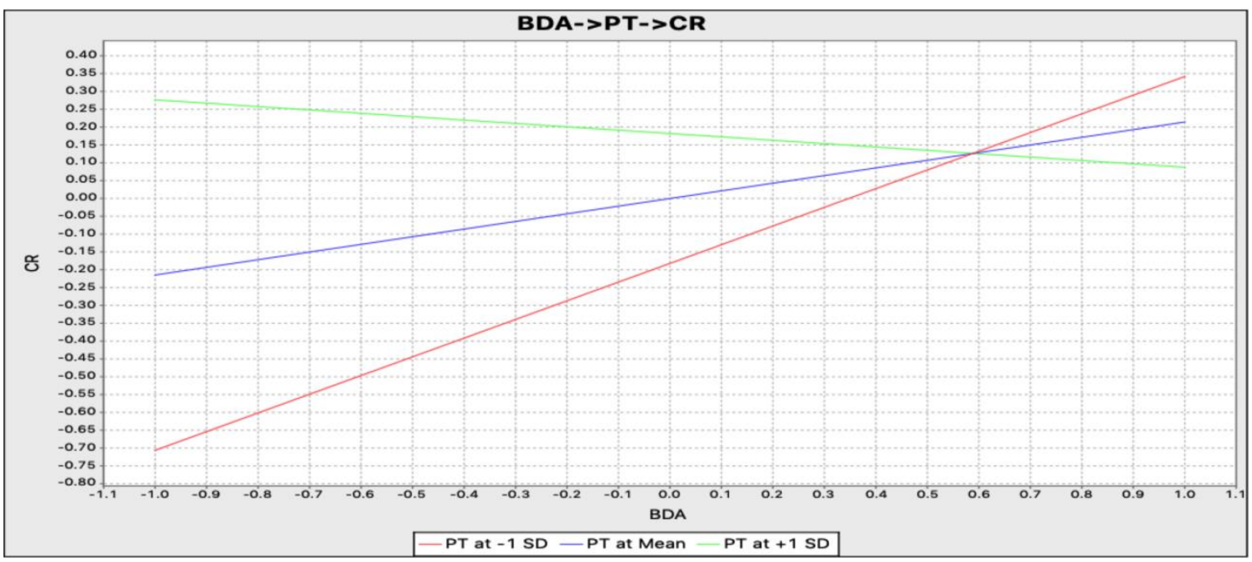

Figure 43 - H4E Simple-Slope Analysis

When looking at the simple slope analysis (Figure 44), the objective is to determine whether PT had a moderation effect between BDA and CR. The blue line represents PT at mean. The first observation is the correlation between BDA and CR and as we can see, there is a positive relationship between BDA and CR. This means, the more we apply BDA technologies to reduce costs, the greater (and more positive) the effect on CR. As we move onto looking into moderation, we can see that if we add PT as a moderator (PT at +1 SD), the effect on CR decreases however, if we remove PT (PT at -1 SD), the results increase. This proves that there is a moderation effect.

Another way to assess whether moderation exists, is by looking at the lines and determining if there are parallel or not. When the lines are not parallel, we can clearly state that moderation exists.

R Square

	R Square	R Square Adjusted
CR	0.26	0.228
PT	0.161	0.15

Table 55 - R Square H4E

Although there is no consensus on the minimum level that this index should reach, (Falk 1992) recommend a minimum value of 0.1, which ensures that at least 10 percent of the construct variability is due to the model. As we can see from Table 53, the model above CR did have an explainable variance (0.228) and PT (0.15) value and can both justifiably the correlation.

F Square

	BDA	BDA->PT->CR	CR	PT
BDA			0.051	0.192
BDA->PT->CR			0.146	
CR				
PT			0.037	

Table 56 - F Square H4E

Construct Reliability

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
BDA	0.849	0.861	0.89	0.619
BDA->PT->CR	0.92	1	0.78	0.166
CR	0.513	0.647	0.668	0.36
PT	0.755	0.8	0.832	0.5

Table 57 - Construct Reliability H4E

When reviewing construct reliability (Table 57), we are assessing the reliability of numbers. In this case, we are aiming for a number that is also above 0.7. In this case, all construct items, except for CR, were above 0.7. In order to ascertain that the construct is reliable, and that subjectivity is removed, we aimed for a number above 0.7. In this case, all constructs are consistently reliable.

Discriminant Validity

	BDA	BDA->PT->CR	CR	PT
BDA	**0.787**			
BDA->PT->CR	-0.164	**0.408**		
CR	0.343	-0.391	**0.6**	
PT	0.402	-0.117	0.308	**0.707**

Table 58 - Discriminant Validity H4E

In discriminant validity (Table 58), we are assessing the values of AVE and our objective is to understand the correlations between latent variables. The objective is to make sure that the square root of AVE of each latent variable should be greater than the correlations amongst the variables. In other words, we want to make sure there is subjective independence of every indicator on its latent variable or also called "vertical collinearity". As we can see from the table above, in all cases, the square root of AVE for each latent variable was greater that the correlations of each latent variable meaning that there is discriminant validity between Cost Reduction, Executive Leadership and System Dynamics.

6.3.4.6 <u>H4F: PT has a Moderation Effect Between ML and CR</u>

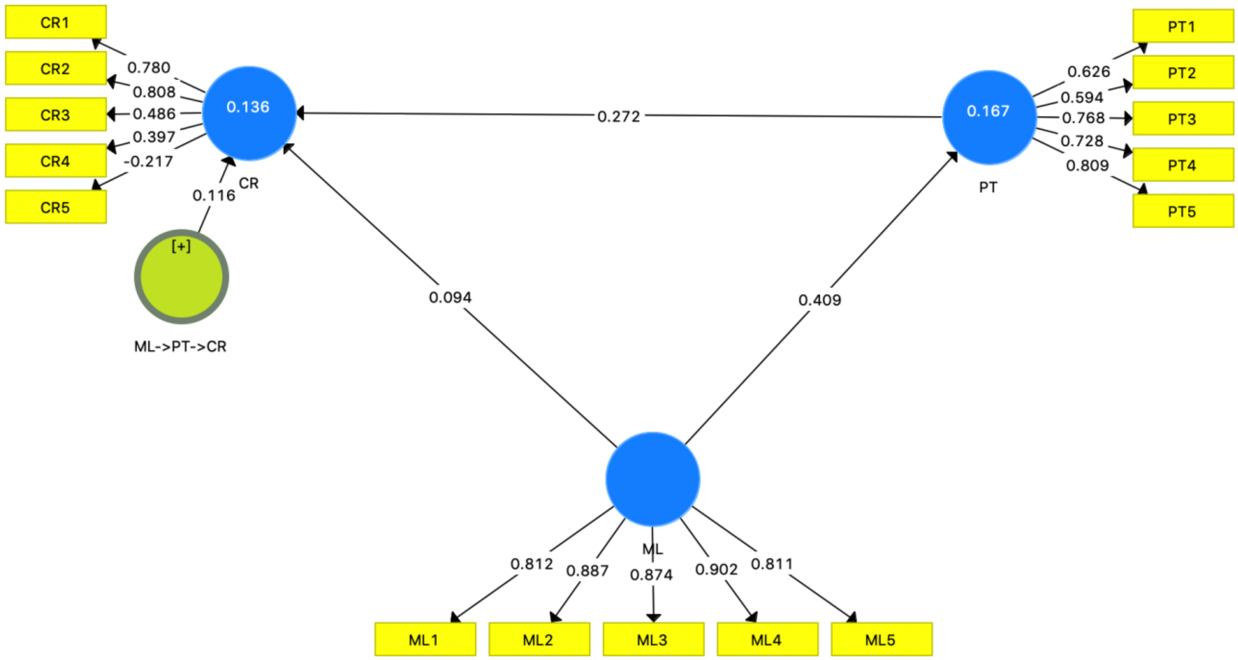

Figure 44 - H4F

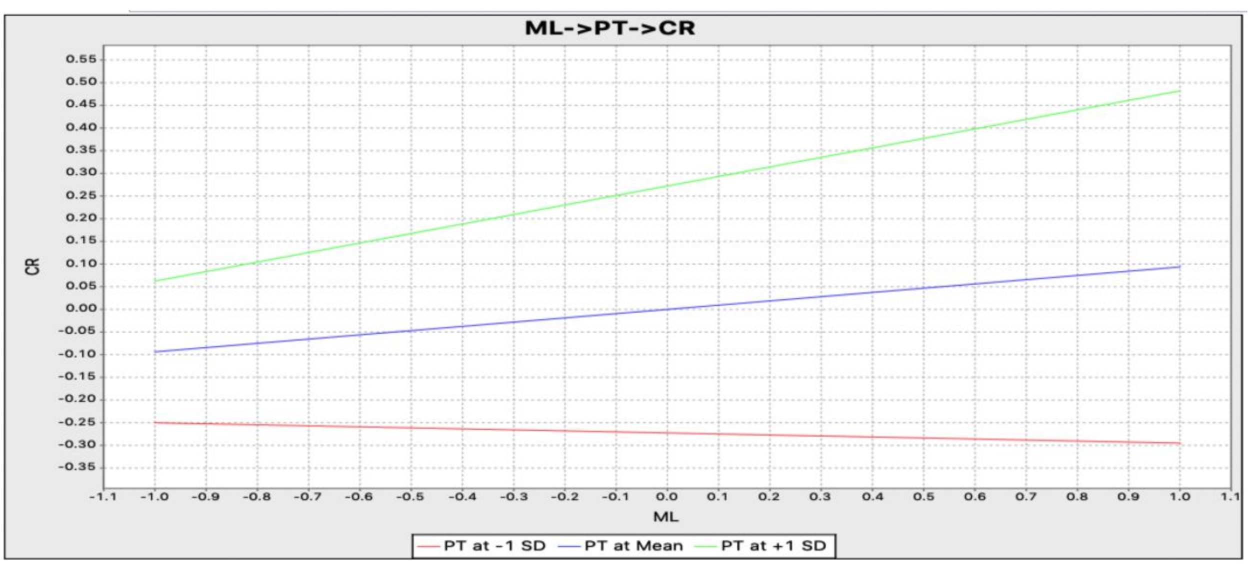

Figure 45 - H4F Simple-Slope Analysis

When looking at the simple slope analysis (Figure 48), the objective is to determine whether PT had a moderation effect between ML and CR. The blue line represents PT at mean. The first observation is the correlation between ML and CR and as we can see, there is a positive relationship between ML and CR. This means, the more we apply ML technologies to reduce costs, the greater (and more positive) the effect on CR. As we move onto looking into moderation, we can see that if we add PT as a moderator (EL at +1 SD), the effect on CR increases however, if we remove EL (EL at -1 SD), the results decrease. This proves that there is a moderation effect. Another way to assess whether moderation exists, is by looking at the lines and determining if there are parallel or not. When the lines are not parallel, we can clearly state that moderation exists.

R Square

	R Square	R Square Adjusted
CR	0.136	0.099
PT	0.167	0.156

Table 59 - R Square H4F

Although there is no consensus on the minimum level that this index should reach, (Falk 1992) recommend a minimum value of 0.1, which ensures that at least 10 percent of the construct variability is due to the model. As we can see from Table 61, the model above CR did not have an explainable variance (0.099) and PT (0.156) value did justifiably highlight the correlation.

F Square

	CR	ML	ML->PT->CR	PT
CR				
ML	0.008			0.201
ML->PT->CR	0.015			
PT	0.072			

Table 60 - F Square H4F

Construct Reliability

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
CR	0.513	0.596	0.606	0.341
ML	0.91	0.909	0.933	0.736
ML->PT->CR	0.955	1	0.944	0.425
PT	0.755	0.776	0.834	0.504

Table 61 - Construct Reliability H4F

When reviewing construct reliability (Table 65), we are assessing the reliability of numbers. In this case, we are aiming for a number that is also above 0.7. In this case, all construct items, except for CR, were above 0.7. In order to ascertain that the construct is reliable, and that subjectivity is removed, we aimed for a number above 0.7. In this case, all constructs are consistently reliable.

Discriminant Validity

	CR	ML	ML->PT->CR	PT
CR	**0.584**			
ML	0.247	**0.858**		
ML->PT->CR	0.195	0.342	**0.652**	
PT	0.329	0.409	0.146	**0.71**

Table 62 - Discriminant Validity H4F

In discriminant validity (Table 66), we are assessing the values of AVE and our objective is to understand the correlations between latent variables. The objective is to make sure that the square root of AVE of each latent variable should be greater than the correlations amongst the variables. In other words, we want to make sure there is subjective independence of every indicator on its latent variable or also called "vertical collinearity". As we can see from the table above, in all cases, the square root of AVE for each latent variable was greater that the correlations of each latent variable meaning that there is discriminant validity between Cost Reduction, Machine Learning and People Teamwork.

6.3.4.7 H4G: PT has a Moderation Effect Between SD and CR

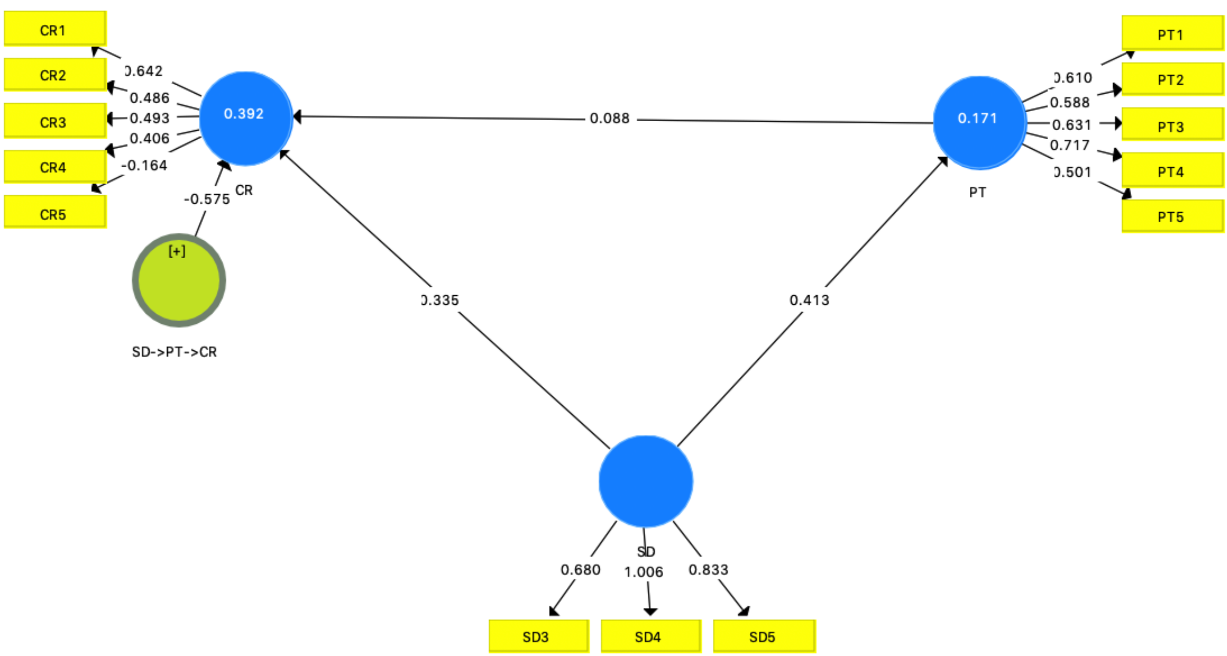

Figure 46 - H4G

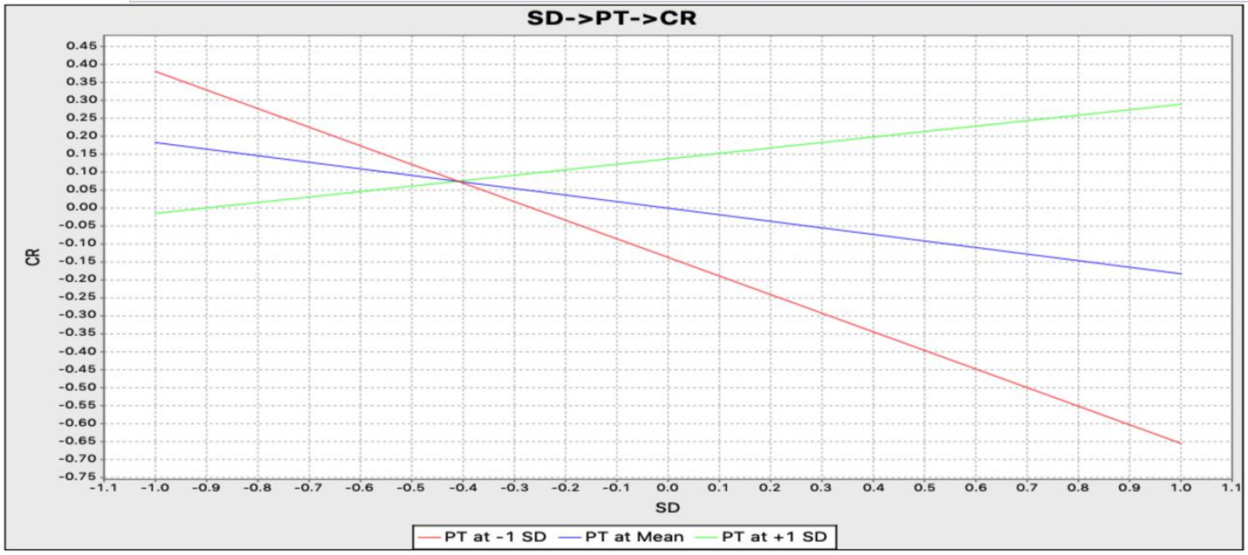

Figure 47 - H4G Simple-Slope Analysis

When looking at the simple slope analysis (Figure 50), the objective is to determine whether PT had a moderation effect between SD and CR. The blue line represents PT at mean. The first observation is the correlation between SD and CR and as we can see, there is a negative relationship between SD and CR. This means, the more we apply SD practices to reduce costs, the greater (and more negative) the effect on CR. As we move onto looking into moderation, we can see that if we add PT as a moderator (PT at +1 SD), the effect on CR increases however, if we remove PT (PT at -1 SD), the results decrease. This proves that there is a moderation effect. Another way to assess whether moderation exists, is by looking at the lines and determining if there are parallel or not. When the lines are not parallel, we can clearly state that moderation exists.

R Square

	R Square	R Square Adjusted
CR	0.174	0.139
PT	0.118	0.106

Table 63 - R Square H4G

Although there is no consensus on the minimum level that this index should reach, (Falk 1992) recommend a minimum value of 0.1, which ensures that at least 10 percent of the construct variability is due to the model. As we can see from Table 65, the model above CR did have an explainable variance (0.139) and PT (0.106) value and can both justifiably the correlation.

F Square

	CR	PT	SD	SD->PT->CR
CR				
PT	0.018			
SD	0.032	0.134		
SD->PT->CR	0.112			

Table 64 - F Square H4G

Construct Reliability

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
CR	0.513	0.604	0.68	0.37
PT	0.755	0.757	0.836	0.507
SD	0.879	0.913	0.925	0.804
SD->PT->CR	0.918	1	0.841	0.309

Table 65 - Construct Reliability H4G

When reviewing construct reliability (Table 69), we are assessing the reliability of numbers. In this case, we are aiming for a number that is also above 0.7. In this case, all construct items, except for CR, were above 0.7. To ascertain that the construct is reliable, and that subjectivity is removed, we aimed for a number above 0.7. In this case, all constructs are consistently reliable.

Discriminant Validity

	CR	PT	SD	SD->PT->CR
CR	**0.608**			
PT	0.278	**0.712**		
SD	-0.155	-0.343	**0.896**	
SD->PT->CR	0.323	0.234	0.227	**0.556**

Table 66 - Discriminant Validity H4G

In discriminant validity (Table 70), we are assessing the values of AVE and our objective is to understand the correlations between latent variables. The objective is to make sure that the square root of AVE of each latent variable should be greater than the correlations amongst the variables. In other words, we want to make sure there is subjective independence of every indicator on its latent variable or also called “vertical collinearity”. As we can see from the table above, in all cases, the square root of AVE for each latent variable was greater that the correlations of each latent variable meaning that there is discriminant validity between Cost Reduction, System Dynamics and People Teamwork.

6.3.4.8 ***H4H: PT has a Moderation Effect Between BRE and CR***

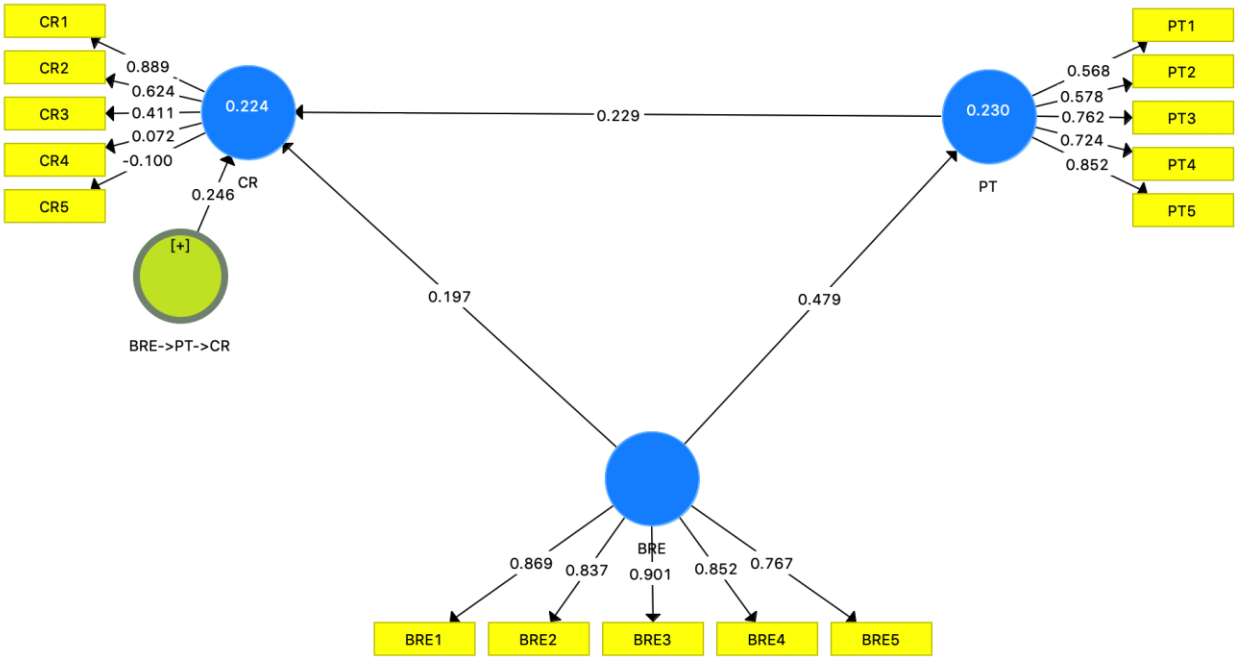

Figure 48 - H4H

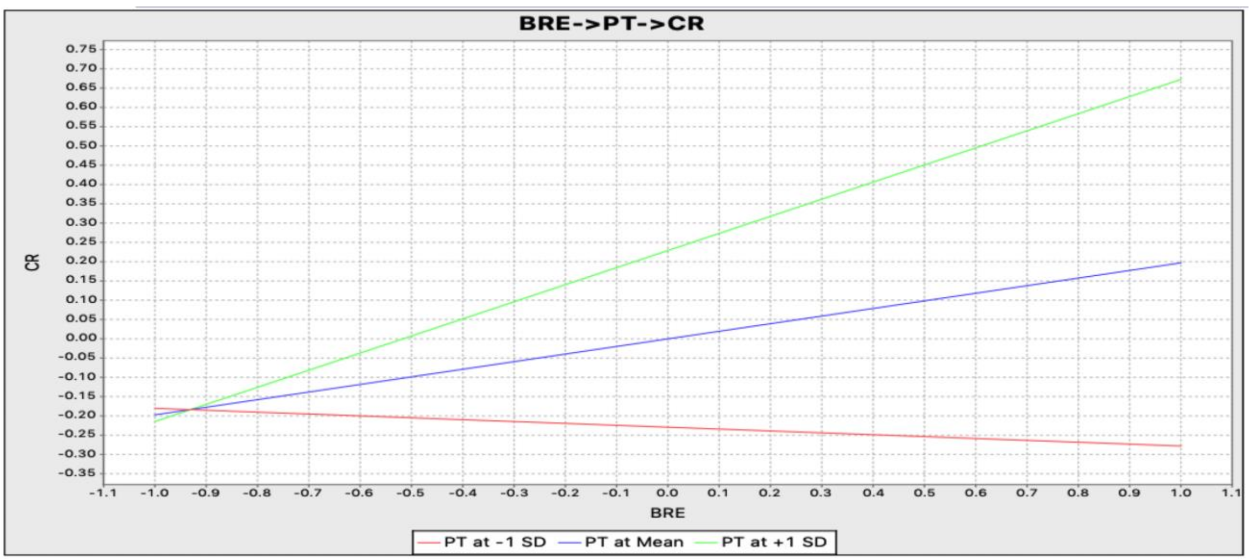

Figure 49 - H4H Simple-Slope Analysis

When looking at the simple slope analysis (Figure 46), the objective is to determine whether PT had a moderation effect between BRE and CR. The blue line represents PT at mean. The first observation is the correlation between BRE and CR and as we can see, there is a positive relationship between BRE and CR. This means, the more we apply BRE technologies to reduce costs, the greater (and more positive) the effect on CR. As we move onto looking into moderation, we can see that if we add PT as a moderator (PT at +1 SD), the effect on CR increases however, if we remove EL (EL at -1 SD), the results decrease. This proves that there is a moderation effect. Another way to assess whether moderation exists, is by looking at the lines and determining if there are parallel or not. When the lines are not parallel, we can clearly state that moderation exists.

R Square

	R Square	R Square Adjusted
CR	0.224	0.191
PT	0.23	0.219

Table 67 - R Square H4H

Although there is no consensus on the minimum level that this index should reach, (Falk 1992) recommend a minimum value of 0.1, which ensures that at least 10 percent of the construct variability is due to the model. As we can see from Table 57, the model above CR did have an explainable variance (0.191) and PT (0.219) value and can both justifiably the correlation.

F Square

	BRE	BRE->PT->CR	CR	PT
BRE			0.035	0.298
BRE->PT->CR			0.066	
CR				
PT			0.051	

Table 68 - F Square H4H

Construct Reliability

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
BRE	0.901	0.914	0.926	0.716
BRE->PT->CR	0.924	1	0.902	0.296
CR	0.513	0.256	0.498	0.273
PT	0.755	0.785	0.829	0.498

Table 69 - Construct Reliability H4H

When reviewing construct reliability (Table 61), we are assessing the reliability of numbers. In this case, we are aiming for a number that is also above 0.7. In this case, all construct items, except for CR, were above 0.7. In order to ascertain that the construct is reliable, and that subjectivity is removed, we aimed for a number above 0.7. In this case, all constructs are consistently reliable.

Discriminant Validity

	BRE	BRE->PT->CR	CR	PT
BRE	**0.846**			
BRE->PT->CR	0.299	**0.544**		
CR	0.379	0.307	**0.522**	
PT	0.479	0.037	0.333	**0.706**

Table 70 - Discriminant Validity H4H

In discriminant validity (Table 62), we are assessing the values of AVE and our objective is to understand the correlations between latent variables. The objective is to make sure that the square root of AVE of each latent variable should be greater than the correlations amongst the variables. In other words, we want to make sure there is subjective independence of every indicator on its latent variable or also called “vertical collinearity”. As we can see from the table above, in all cases, the square root of AVE for each latent variable was greater that the correlations of each latent variable meaning that there is discriminant validity between Cost Reduction, Business Rules Engines and People Teamwork.

6.3.5 Global model

The last PLS test focused on testing the entire model at once (Figure 12) and then moving onto decomposing the model into 18 different tests, starting with direct, mediating and finally, moderating variable to validate overall consistency. The full model was generated using the ConsistentPLS algorithm, selecting the path analysis and setting iterations at 5,000. No weighted vector analysis was performed.

The first set of observation is around the effect of AI technologies on Strategic Sourcing. What we are attempting to assess is whether each of the AIA technologies have an impact (or not) on the ability to execute strategic sourcing activities. System Dynamics had the highest impact on strategic sourcing (1.136) followed by Big Data Analytics (0.513). The other two technologies, Business Rules Engines (-0.612) and Machine Learning (-0.828) had negative correlations suggesting that they had no impact on strategic sourcing. What these results suggest is that respondents really felt that system dynamics, which we refer to in this study, as the ability of procurement staff to work on transformational change, being involved sooner in the procurement process and having executive leadership support, are the most important factors in being able to drive strategic sourcing activities. In other words, if you have all the elements above exist in the organization, there is a higher chance of success in succeeding in strategic sourcing activities.

Big Data Analytics was the second highest correlation suggesting that without data, it is very difficult to engage in strategic sourcing activities. This holds true in practice as without access to good quality data, it is very difficult to assess if your spend is fragmented across too many suppliers or if you have too much tail spend thus, increasing the cost of running procurement operations from an administrative standpoint. Also, without good contract data, that is completed and presented in structured data tables, procurement cannot proactively manage intake and get alerts on which contracts are coming to maturity to free up enough time to perform strategic thinking and sourcing before negotiating with suppliers.

Business Rules Engines had a negative correlation which also makes sense because rules engines are typically applied after the strategic sourcing exercise. In other words, strategic sourcing activities focus on securing upstream value but once contracts terms and conditions negotiated, it is recommended to implement control measures in the form of business rules in order to enforce them throughout the lifecycle of the contract.

Finally, machine learning had the highest negative correlation of all four AI technologies. My observation around this factor is mixed. I would tend to agree with this result is not much machine learning opportunities existed prior to the strategic sourcing process however, based on practical experience, it is not the case. Take for example the spend analysis exercise where one must classify spend data before they can begin analysis. The challenge in today’s organizations is that the spend is distributed across various departments and on various instances of ERPs. The first obstacle we typically face in practice, is how to consolidate, clean, harmonize, complete, and enrich the spend data. Today, most organizations do this work manually. Although, at its embryonic stage, there are some ML algorithms that are being use today to help compress the time it takes to classify spend. This was discussed in the literature review section of this thesis.

The second area were ML algorithms can bring great benefit in the strategic sourcing process is in demand forecasting. In other words, typical forecasting methods can be complemented with state-of-the-art ML algorithms to improve accuracy. An excellent example is demand sensing where algorithms connect to external as well as unstructured data sources to capture near real-time consumption on spend patters and in turn take that data to compute a more accurate forecast. The flipside to all of this, and the reason this variable may have been scored as negative is because many organizations are still not aware of all these technologies given most of them are at their embryonic stage with low adoption rates.

The next set of observation focused on assessing the Impact of AI Technologies on Supplier Relationship Management. The AI Technology with the most impact on Supplier Relationship Management was System Dynamics (0.578), followed by Big Data Analytics (0.085), Business Rules Engines (0.054) and Machine Learning (-0.338).

BRE are probably deemed to be the most useful tool in enforcing contract compliance. By extracting key contract clauses using OCR as well as other ML algorithms, and importing that data into a structured data table, organizations would then be able to use BRE to compare invoices and make sure that invoices are compliant to pre-agreed terms. The second AI Technology with influence on Supplier Relationship Management was Big Data Analytics. Arguably a solid hypothesis given that suppliers are measured using key metrics. Value leakage can exist in several areas of the business. For example, invoices errors/duplicate payment, unrealized credits, discounts, and investments, paying for unachieved service levels. In other cases, incorrect demand forecasting resulting in excess payouts, rate card variations, weak tracking of work orders or simply performance standards not being achieved. What we have also seen in practice is contract amendments and changes impacting the initial business case making it less attractive than its initial state. Finally, sometimes Service Level Agreements (SLA) are not aligned with the business. For all these reasons, it indeed makes sense that Big Data Analytics is instrumental in being able to capture the above-mentioned value leakage opportunities.

Moving onto system dynamics which has the third highest score is explainable by using the same reasons used in strategic sourcing which is the inability to free up time to work on transformational change or the lack of business line leadership. Finally, Machine learning scored a negative high correlation (-0.338). This is also explainable for the same reasons as in strategic sourcing which is little access or knowledge of AI solutions that are categorized to be at their embryonic stage.

The next set of observations is around the influence of organizational context (i.e. executive leadership and people teamwork) on procurement strategy (i.e. strategic sourcing and supplier relationship management). In this next observation, we witness a very high correlation between executive leadership and strategic sourcing (0.619). We also witness a moderately high correlation between people teamwork and supplier relationship management. The former can be explained by the fact that strategic sourcing can only be successful to the larger portion of spend managed by the enterprise at its aggregate level. That is, if more spend is under management, and if executive leadership is present to promote procurement, the team will be legitimized to challenge business needs, assess the supply market and make key decisions in terms of which suppliers to remove and add from the portfolio. The team will also be sponsored to execute the sourcing strategy of their choice and the one that makes the most sense for the organization whether it be around harmonizing product lists, consolidating supply bases, optimizing certain contracts with key suppliers and/or investing in building key strategic alliances with key suppliers.

The latter can be explained by the fact that, what we typically witness in practice is that the line of business sometimes owns the direct relationship with key technology suppliers (i.e. IBM, Microsoft, etc.) and procurement also wants to own that relationship from a compliance standpoint. In practice, we see a lot of that tension and the dialogues tend to have much friction. Therefore, people teamwork becomes a fundamental requirement for supplier relationship management activities. In practice, to promote collaboration and full cooperation and the lines of business to unlock value, we typically invest time and energy in developing a governance model. This governance model describes the 5 key steps of procurement activities (i.e. category strategy, needs/specs definition, supplier selection/negotiation/approvals, contract management and vendor management). For each of these activities, it is important to determine who will decide, who will execute who will be informed and who will collaborate.

For example, in the category strategy definition, where the goal is to develop the strategy to maximize value while minimizing total cost of ownership, procurement will decide, and the line of business will collaborate. In the needs and specification definition where the goal is to articulate the needs and detailed specifications of products and/or services n needed in each deal, procurement will collaborate however, the line of business will decide. In the selection/negotiation/approvals step of the process where the purpose is to select vendors, negotiate contracts, obtain requisite approvals and finalize contracts, procurement would decide, and the line of business would collaborate. Once the contract is signed, in the contract management phase where the purpose is to manage vendors on a day-to-day basis against key Service Level Agreements, procurement would decide on metrics and the line of business would be informed and collaborate at a minimal level. The reason is simple – create a standardized way of measuring vendors. Finally, in the last step of the process, vendor management (as opposed to contract management), where the purpose is to track overall relationships, risk, performance and strategic collaborations across contracts and identify opportunities to increase value, procurement would decide and the line of business would execute.

What was just described is the typical operating model which would be instrumental in achieving cost reduction and for this reason, we agree with the high correlation between people teamwork and supplier relationship management. Executive leadership scored low (-0.050) on supplier relationship management suggesting that there is little influence. In fact, this would not hold true in practice as executive leadership is instrumental in successfully deploying in a supplier relationship management program. Same holds true for people teamwork and strategic sourcing (-0.101) as we also believe that the two go hand in hand.

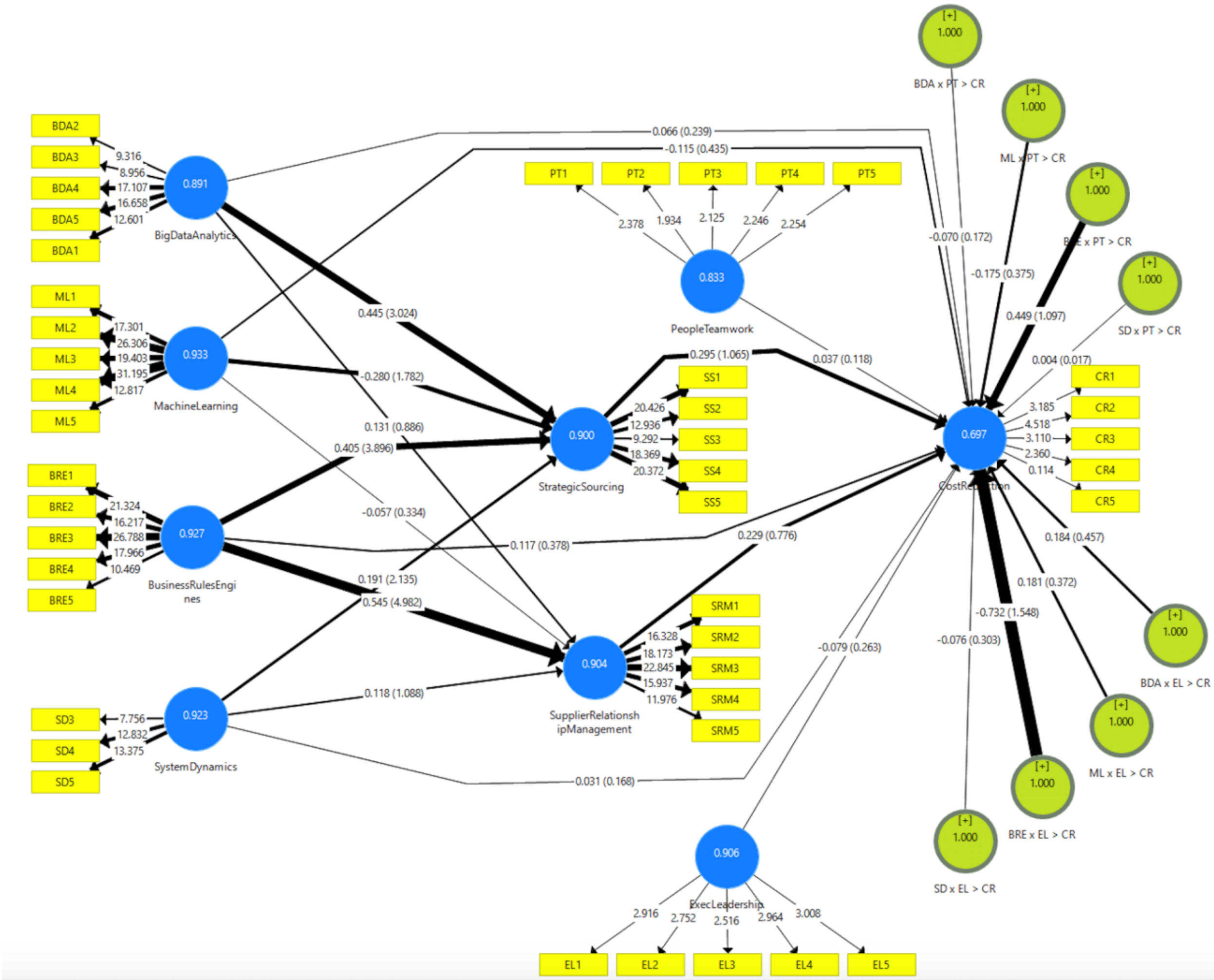

Figure 50 - ConsistentPLS Results for Full Model

In addition to the results noted above, we have also generated the cross-loadings across all variables. (Table 11). uOur objective was to ensure that every indicator loads the highest on the latent variable whether it is horizontal or vertical. As we reviewed each of the indicators, as it relates to latent variables, we assessed that those values were indeed highest. This suggests that there is little evidence of collinearity amongst the latent variables. In other words, and according to (Chin 1998) and to (Chin 2010), the Average Variance Extracted (AVE) of a latent variable should always be higher than the squared correlations between the latent variable and all other variables (Fornell C 1981).

	BigData Analytics	BusinessRulesEngines	CostReduction	ExecLeadership	MachineLearning	PeopleTeamwork	StrategicSourcing	SuppRel Mgmt	SystemDynamics
BDA1	**0.556**	0.401	0.471	0.249	0.46	0.31	0.363	0.272	0.543
BDA2	**0.626**	0.427	0.325	0.216	0.549	0.36	0.354	0.325	0.507
BDA3	**0.816**	0.534	0.164	0.205	0.792	0.23	0.255	0.336	0.528
BDA4	**0.755**	0.281	0.39	0.263	0.615	0.359	0.491	0.307	0.535
BDA5	**0.846**	0.397	0.367	0.315	0.749	0.346	0.431	0.35	0.569
ML1	0.771	0.497	0.379	0.348	**0.85**	0.364	0.3	0.36	0.717

ML2	0.813	0.664	0.267	0.334	**0.916**	0.38	0.345	0.435	0.725
ML3	0.803	0.539	0.268	0.311	**0.823**	0.397	0.331	0.331	0.591
ML4	0.647	0.579	0.266	0.327	**0.775**	0.399	0.332	0.416	0.588
ML5	0.557	0.539	0.246	0.358	**0.715**	0.398	0.316	0.309	0.563
SD1	0.544	0.542	0.408	0.366	0.509	0.525	0.55	0.516	**0.709**
SD2	0.504	0.79	0.329	0.348	0.639	0.309	0.398	0.494	**0.708**
SD3	0.119	0.179	0.122	0.125	0.113	0.303	0.234	0.113	**0.23**
SD4	0.238	0.152	0.259	0.273	0.259	0.375	0.313	0.262	**0.366**
SD5	0.286	0.172	0.193	0.198	0.258	0.324	0.298	0.239	**0.347**
BRE1	0.431	**0.766**	0.257	0.482	0.547	0.522	0.469	0.537	0.594
BRE2	0.484	**0.842**	0.256	0.369	0.605	0.314	0.375	0.464	0.746
BRE3	0.494	**0.877**	0.353	0.481	0.631	0.469	0.444	0.598	0.691
BRE4	0.407	**0.788**	0.425	0.404	0.485	0.433	0.446	0.611	0.747
BRE5	0.416	**0.745**	0.328	0.556	0.496	0.41	0.431	0.427	0.595
CR1	0.291	0.357	**0.715**	0.309	0.302	0.272	0.325	0.435	0.297
CR2	0.247	0.045	**0.391**	0.249	0.099	0.313	0.28	0.257	0.247
CR3	0.223	0.207	**0.506**	0.125	0.134	0.137	0.251	0.288	0.368
CR4	0	-0.155	**0.042**	0.083	-0.043	0.026	0.334	0.024	0.049
CR5	-0.046	0.014	**-0.035**	-0.184	-0.05	-0.16	-0.032	-0.001	-0.11
EL1	0.101	0.236	0.342	**0.615**	0.18	0.65	0.467	0.517	0.334
EL2	0.456	0.569	0.31	**0.981**	0.433	0.799	0.752	0.541	0.504
EL3	0.262	0.569	0.259	**0.772**	0.367	0.626	0.527	0.329	0.454
EL4	0.252	0.324	0.397	**0.69**	0.265	0.62	0.435	0.5	0.338
EL5	0.16	0.406	0.353	**0.717**	0.269	0.608	0.547	0.543	0.4
PT1	0.178	0.117	0.193	0.512	0.142	**0.468**	0.46	0.282	0.32
PT2	0.244	0.265	0.22	0.396	0.285	**0.501**	0.342	0.366	0.501
PT3	0.481	0.407	0.348	0.582	0.412	**0.756**	0.481	0.584	0.527
PT4	0.255	0.33	0.324	0.527	0.298	**0.627**	0.613	0.3	0.378
PT5	0.159	0.464	0.227	0.662	0.291	**0.716**	0.555	0.613	0.44
SRM1	0.396	0.477	0.374	0.429	0.357	0.653	0.582	**0.79**	0.527
SRM2	0.354	0.597	0.404	0.398	0.398	0.451	0.281	**0.711**	0.576
SRM3	0.342	0.586	0.439	0.585	0.4	0.683	0.597	**0.888**	0.605
SRM4	0.374	0.402	0.676	0.535	0.312	0.481	0.569	**0.797**	0.57
SRM5	0.137	0.412	0.388	0.403	0.222	0.36	0.312	**0.536**	0.331
SS1	0.528	0.444	0.399	0.535	0.332	0.664	**0.835**	0.579	0.589
SS2	0.452	0.276	0.502	0.387	0.209	0.589	**0.659**	0.366	0.452
SS3	0.162	0.361	0.285	0.565	0.189	0.471	**0.602**	0.37	0.424
SS4	0.405	0.476	0.446	0.647	0.407	0.594	**0.845**	0.514	0.625
SS5	0.345	0.429	0.336	0.579	0.308	0.622	**0.774**	0.526	0.58

Table 71 - Cross-Loading (Discriminant Validity) for Full Model

When analyzing cross-loadings, one of the first observations will be the negative values and the question we must as is if whether negative values are acceptable. The short answer is yes, and this means that they are negatively loaded or that there is a negative correlation between the survey items and the latent variables.

The cross-loadings should always be assessed to make sure that no indicator is incorrectly assigned to a wrong factor. In the table above All square roots of the AVE were larger than the correlation between that construct and any other construct (Chin 2010). This supports discriminant validity. In the table above, most Cronbach alpha (Peterson 1994) scores for most reflective constructs and construct loadings exceeded the 0.7 threshold (Fornell C 1981). The next analysis to be performed on the cross-loading table (Table 11) is to make sure that the loadings of the measurement items on their assigned latent variables should have higher values than any other loadings and that if there is a difference, that difference should be more than 0.10 (Gefen et al. 2000). When reviewing values in Table 11, we do notice that, in most cases, that differences, when present, do exceed 0.10. Therefore, after thoroughly reviewing the structural model, we deemed it to be appropriate. After reviewing the results of SD3-5 we assessed that the results were consistently negative all across and as such, we decided to continue the study without including them. Therefore, we kept SD1 and SD2 and removed the SD3-5. For CR5, we also felt the results were negative however, after reversing the scale, we realized the results made more sense. CR5, although had a negative value, was considered a critical question in the study and as such could not be removed. We validated if the scale was reversed and result was negative. The question was around Pareto analysis where the closer to 100% you were when assessing how much of your spend was spent with 20% of your total supplier base, the better off you were given benefits associated with volume concentration and potential volume discounts. The questions was clear and so were the results. It is not unusual for the score to be low. Many organizations struggle with supplier proliferation. Typically, almost no organization is able to concentrate over 80% of its spend at only 20% of their supply base. This can be due to many reasons such as rogue or maverick spending, purchases being done without a Purchase Order (PO), and some suppliers providing products and services that cannot be otherwise sourced from your largest suppliers (i.e. specialty products and services).

7 Interpretation

7.1 Significance of Results

The objective of our study was four-fold. The first was to assess whether AIA Technologies had a direct impact on cost reduction (H1). In other words, we attempted to uncover, through a survey, the firms that engaged in adopting AI technologies such as Big Data Analytics for spend analytics, Machine Learning for forecasting purposes, System Dynamics to optimize the portfolio of initiatives and to assess the level of focus on strategic priorities and, finally Business Rules Engines to see their level of maturity in terms of automating key procurement processes. Before we discuss results, it’s important to note that all hypotheses yielded positive values and therefore, the polarity on each of the arrows was assumed to be positive by drawing a full straight line (would have been dotted if values were negative).

We immediately concluded that BDA (T-Value = 1.816) was the only AIA technologies deemed significant in our study (i.e. closest to 1.96). From this study, we can conclude that certain AIA technologies can have a positive impact on cost reduction. Specifically, hypothesis H2A was accepted while H2B-H2D were rejected.

The next step in our study was to assess the impacts of procurement strategy on cost reduction (H3). More specifically we attempted to quantify the impact of engaging in strategic sourcing and supplier relationship management activities and its associated impact on cost reduction. The results clearly highlighted that Strategic Sourcing accounted for 64.4% of cost reduction improvement while Supplier Relationship Management accounted for 64.7% of cost reduction results.

We then dug deeper into each of the AIA Technologies and assess whether Procurement Strategy (i.e. Strategic Sourcing and Supplier Relationship Management) played a mediating effect between AIA Technologies and Cost Reduction. Those tests represented hypotheses H3A to H3H. We ran both a PLS test followed by a Sobel test to assess significance. The results highlighted that mediation was present in almost all cases except for H3G (T-Value = 1.27) and H3H (T-Value = 1.68) where, although PLS accepted the hypotheses, the Sobel Test did not hence, given acceptance was not unanimous, we decided to reject that SRM played a mediating effect between ML and CR and between SD and CR.

Finally, the last step of our study was to assess whether moderation existed (H4). More specifically, we attempted to uncover if Executive Leadership and Teamwork played a moderating effect between AIA Technologies and Cost Reduction. In other words, were the executives, both within the procurement line of business and outside, supportive of key procurement decisions driven by AIA. We also attempted to uncover whether teamwork, within and outside the business line, existed and if so whether it had a positive impact on cost reduction as driven by AIA. The results showed that moderation existed across each single hypothesis and hence, H4A to H4H were all accepted.

7.2 Implications and Discussion

The overall significance of our results, and consequent validation of most of our hypotheses, have important implications for the practice of Procurement Strategic and Cost Reduction by leveraging AI technologies. We identify at least 3 major consequences, all of which point to the need of further study considering the increasing pervasiveness of AIA. But before we discuss future areas of opportunity, we discuss the implications of this study.

Through this study, what we realized is that although new and emerging technologies exist and that their application to procurement is highly relevant, firms are still struggling to perform some of the most basic linear procurement activities. From gathering and classifying spend data, to understanding if pre-negotiated contracts exist seems like an unsurmountable task – at least this is generally witnessed in practice. What we also observed through this study is that firms typically attempt to benchmark themselves to identify incremental and non-transformational improvements as opposed to envisioning tomorrow and modernizing today to get to the tomorrow of the future. This suggests that tomorrow will seldomly be considered advanced and cutting edge. On another note, when digging deeper into system dynamics as a key latent variable, it became quite evident that staff is so consumed with tactical activities that there’s almost no time to invest in transformational change (Barrad et al. 2018). This study also explored Big Data Analytics to understand if organizations are still immersed in generating descriptive statistics to explain the past or if they were adopting predictive and prescriptive statistics to control the future. Our results concluded the latter. This also highlighted another problem area which is the need to compress the time it takes to aggregate data from multiple instances and cleansing the data in preparation for AI technologies. In practice, what we see is that data is typically the bottleneck to many AI projects. Although some advanced AI technologies exist to overcome this barrier such as spend classification tools (as discussed earlier) or even feature engineering models such as imputation (i.e. ML algorithm) to help complete records with missing data to facilitate data preparedness and migration for AI technologies.

That is, some of the strategic procurement engagements rapidly hit a wall at the early stages of the project due to data quality and completeness. Therefore, opportunities for cost reduction are significantly underrepresented. Table 72 shows the results of a spend analysis conducted at a Canadian bank where most of the analyses could not be conducted given limited data accessibility. We attempted to perform 15 different types of analyses on spend data but could only perform 3 of them. This represents 20% when the objective would typically be 80%+. On the flipside, what we also see in practice, which is usually rare but does indeed happen, is that organizations explore and deploy AI technologies in procurement but just don’t have the execution arm to action insight (i.e. absence of a strategic sourcing team). For example, what we’ve seen is organizations implementing a sophisticated Source-to-Pay system that generates 6-10 spend analytics dashboards but, unfortunately savings identified never go onto being validated or realized (Barrad et al. 2020).

#	Potential Analyses	Completed
1	Spend by supplier, category, sub-category and sub-sub-category – split out by capital expenses (CAPEX) versus operational expenses (OPEX)	✗
2	Number of invoices per year, by supplier, by category and by sub-category	✔
3	Spend by business unit (for each supplier, category and subcategory)	✗
4	Number of suppliers by category, sub-category, sub-sub-category	✔
5	Number of SKU’s (aggregated, by category, sub-category and sub-sub-category)	✗
6	Average invoice dollar amount (by supplier and category)	✔
7	Average Purchase Order (PO) dollar amount	✗
8	Min/Max in prices and fees for all line items (by SKU) - lowest and highest prices we pay for each product or service	✗
9	Number of checks/payments issued in a year (aggregated and by supplier)	✗
10	Number of Purchase Orders issued in a year (aggregated and by supplier)	✗
11	3-yr overview of supplier spend history (progressing or regressing relative to the market and to BNC’s internal needs)	✗

12	3-yr overview of spend history (by category and sub-category)	✗
13	For each Pareto (key) supplier in each key category, history of spend over last 3 yrs. cost-breakdown (e.g. IBM: software, licenses, servers and min/max of professional service fees)	✗
14	% of $$$ purchased under contract (catalogued items)	✗
15	Agreed upon payment terms (found in contract agreement, "Ariba Contract Management" Module or through interviews with contract owners from the business) Actual Days Payable Outstanding (DPO) – Supplier, Amount, Invoice Date, Approval Date, Payment Date (ideally transactions for the last 3 years)	✗

Table 72 - Spend Analysis Result - Client Engagement

What this study also demonstrated is that, coupling both technology and procurement strategies yield far greater results from a cost reduction standpoint (i.e. synergies) as opposed to when they are deployed independently. In practice, this is very true. An important point to note is that this revelation contradicts what is currently being advertised on the market. In other words, it disproves the statement made by many AIA firms flooding the market and suggesting that AI will replace humans.

What this study also allowed us to uncover is that most clients have not implemented a digitized process. They are still operating in linear and sequential processes where they have little visibility on data and transactions. What we also uncovered is that most organizations do not have access to digital catalogues that channel buyers through pre-negotiated contracts even though those contracts exist. This drives a compelling need for the organization to prioritize digital transformation and explore/adopt some key AI technologies described in this thesis.

This study allowed us to gauge clients' maturity from a data analytics perspective. In terms of insight, what this study highlights are that many clients have not developed advanced analytics that allow them to drive additional insights from the process they run. They may be looking at what was spend last month and last year however, they are not looking forward – what are my sales forecasts and my demand for operations and my HR plans – and what do they mean to my spend? How do I get ready for it? This study proves that this stems from the lack of digital process and the lack of enriched data. Looking at spending habits over time or understanding through spend analysis to see where they are missing savings is something clients generally are not doing. So, they are not able to leverage spend and not able to negotiate the right terms and the right pricing that drive benefits to the organization. The survey items clearly captured this insight.

The same holds true from both a contract management and supplier negotiation perspective. That is, having digitized the process and having enriched the data, the organization would be able to drive actionable insights from AI tools. What those allow them to do, is not just bring the data and the digitization from the process, but also to capture unstructured data from outside, across the web, or from other systems that allow to drive an even higher level of insight and correlated information back into the process that allows the client sourcing teams to negotiate differently because they now better understand the needs and can leverage that to drive value. That allows us to drive better results from a cost reduction standpoint. Procurement is all about supplier partnerships and driving deep, innovative, sustainable, long-term value from strategic supplier relationships.

Going deeper into the contribution of this study, we conclude by discussing one of the most important elements this study allowed us to uncover. The lack of digitized processes and the absence of insight means that procurement personnel in strategic sourcing and category management are not able to focus on stakeholder management, interaction with the user, and negotiations with the supplier because they are wasting time building up insights, building up data, focused on Purchase Orders (PO) and transactions where they should be spending very little or no time.

This study reveals that AI technologies such as Robotic Process Automation (RPA) can help free people up to work on strategic and value maximizing activities. Especially when we cycle back and forth from recessionary periods and back into growth periods. Those type of cycles are going to require an increased emphasis on cost reduction and will also set increased pressure for more talent and skills to get more value out of the supply base. The organizational context element of this study in this thesis suggest that executive leadership, teamwork, and the talent that you have in house will be instrumental in contributing to delivering cost reduction.

To conclude this section, we would like to discuss further areas to explore. First, we suggest that there is a need to dig deeper into key components within AI in procurement. More specifically the application of Robotic Process Automation (RPA) as an enabler to cost reduction. RPA is being promoted as a key cost reduction through automation of tactical processes and the reduction of full-time equivalents. Robotic software which automates routine and repetitive task across disparate systems and software products can help improve profitability and cost, productivity, and efficiency, as well accuracy, compliance, and security. RPA is also easily scalable and flexible as a solution.

Second, we believe that beyond negotiating for better prices, firms should first fully explore opportunities around compliance. Technology can be leveraged in this instance. For example, using analytics-based solutions for enterprise-wide fraud detection, prevention, and management using behavioral statistical analytics. Fraud and anomaly detection through continuous transaction monitoring and identification of potential control exceptions. Analytics based solutions can also identify potential bad actors through review of the vendor against Public Data Profiling.

Third, a detailed analysis on organizational context is also suggested where the focus would be on gathering data around past implementations relating to AIA technologies in procurement and assessing what worked well and key lessons learned for future implementation considerations.

7.3 Dynamic Capability Theory

When reviewing the results in relations to Dynamic Capability Theory (DCT) or the firm's ability to dynamically adapt based on the changing business environment and where resources typically act as a buffer in such context, we realized that it indeed became an opportunity for a firm to review, and potentially change its resources mix to maintain sustainability, and in most cases, develop a competitive advantage over competing firms.

More specifically, when reviewing the correlation between executive leadership and strategic sourcing (0.86) we clearly see that executive leadership is viewed to be unarguably the most important factor in enabling the firm to perform strategic sourcing activities. In other words, for the firm to adapt to changing market dynamics and to secure value for the firm, it will require strong executive influence and leadership. This is important to help shift the mindset from tactical activities such as data collection and analysis and technical drafting of contracts and to move over to a more strategic focus emphasizing strategic market analysis coupled with strategic supplier negotiations.

When reviewing the results of executive leadership, which also encompasses DCT, and when assessing correlation with supplier relationship management, we also witnessed a strong correlation (67%). This means that in order, for the firm to adapt to a changing business environment that attempts to shift the focus away from a transactional relationship management, where emphasis is on pure cost reduction and improved payment terms, executive leadership will be instrumental in mobilizing the firm to engage in more strategic discussions around strategic alliances, joint-process improvement and even supplier collaboration through joint investments. This research confirms that executive leadership is required to drive the firm’s dynamic capability to engage in more strategic discussions based on shifting market demand.

8 Conclusion & Research Limitations

We proposed a new model analyzing the impact of AIA technologies on Cost Reduction. Our hypotheses take in consideration a series of key interdependent variables that work together to support management in achieving costs reduction results. They consisted of the use of AIA technologies such as Big Data Analytics and Machine Learning, along with Procurement strategy activities, such as strategic sourcing upstream from signing a contract and supplier relationship management programs downstream from signing a contract. Finally, we looked at the organizational context under which the firm operates such executive leadership and teamwork to assess its fundamental role in supporting, and in some cases, accelerating cost reduction results.

We followed a PLS methodology, using SmartPLS to test our hypotheses, and validate our results using several techniques. First, we developed a fully reflective model consisting of eight latent variables pointing outwards to 5 indicators each. The survey we administered gathered the required data to assess the validity of key hypotheses. To test the model, we ran the most appropriate test for reflective models, which in this case was the standard PLS algorithm.

Our theoretical contribution focused on assessing whether AIA technologies, independent of procurement strategy and organizational context, would yield the same performance from a cost reduction standpoint. At first, the answer seems obvious that AI technologies, especially the use of automation such as Business Rules Engines (BRE), would drive bottom line impact, independent of procurement strategy and organizational context. This study proves that AIA technologies can have little or no impact without a solid understanding of procurement strategy and an ideal organizational context.

Our results provide some leads to improve the practice of AIA technology and procurement strategy to seek cost reduction. Some practices that may change are, for example, the classical strategic sourcing process (Figure 2) and the Supplier Relationship Management process (Figure 3), to infuse new AIA technologies across the entire process and renaming the entire process to Cognitive Procurement Management, where systems are leveraged to detect patterns and opportunities to help procurement in leading more effective negotiations with suppliers.

Our results should be qualified as per some limitations of this research, namely that AIA technologies discussed in this paper are mainly at their embryonic stage of commercialization and as such, assessing their clear impact on business performance comes with many limitations typically around proof of concepts with extremely narrow scopes, the lack of clean data to run a pilot and very challenging tasks around converting the proof of concept, generated by the pilot, to a proof of value allowing firms to start small and scale fast.

We envision developing a research program around the findings of this thesis. Future research may include extending the research to include the notion of neural networks or deep learning to help increase support in decision-making as opposed to providing data on which procurement staff can make decisions. Procurement is a mature function within a typical organization and opportunities only exist because of gap in terms of technology and skills. The most advanced procurement operations have digitized and automated their processes and have completely shifted their focus on activities that are of strategic nature. The objective of future research would be to take a best-in-class organization and embed their strategic decision-making in systems that not only mimic human behaviour but that are also able to leverage the concept of neural networks for pattern detection and automated decision-making.

Finally, and in practice, this study uncovers a new and different view into the maturity of the client's process and what that really means for AIA in procurement. Low levels of compliance and low levels of spend under management puts the client in the "Assessing" level (low level) of maturity. As we go up the spectrum, from Developing, Practicing, optimizing… to Leading, where we are looking at a very high level of automation, a high level of spend under management, and an extremely high level of compliance. Higher data and digital process maturity allows a customer to derive the best out of analytics and AI solutions.

It is our belief that every client comes into that maturity scale at different points, and the steps and timing can be tailored of course. But it is recommended that clients begin by exploring with process automation, transformation and strategic sourcing to drive early value within the first few months. This is underpinned by data enrichment and advanced spend analytics. That allows organizations to get a clear view of spend, to understand it, and to better predict what they should be doing and how they should be directing efforts. That in turn allows the organization to put the foundation in place to bring in the proposed AIA technologies.

From experience, that first step can drive about 10-15% of spend savings for organizations. The goal is to take a progressive approach to optimizing the level of maturity. At that point, or for those who already have that foundation, the next steps would be to introduce some of the most relevant AIA technologies enabling organizations to drive a higher level of value.

9 Appendix

9.1 A. Survey Respondent Qualifying Questions

To qualify respondents (Table 69), and their ability to adequately assess their internal practices as it relates to both procurement and technology, we used a series of qualifying questions:

General Qualifying Questions		
	Measurement items (10-point scale)	Resources
1. Process & Technology	10-point Likert scales ranging from "not familiar" to "very familiar": General Knowledge	
How comfortable are you with the following processes and technologies?	Big Data Analytics	
	Machine Learning	
	System Dynamics (simulation)	
	Business-Rules Engines	
	Executive Leadership	
	Teamwork	
	Strategic Sourcing	
	Supplier Relationship Management	
	Cost Reduction	

Table 73 - Qualifying Questions

9.2 A. Survey Construct and Item

Table A1 Measurement items of the variables.		
Construct names	Measurement items (7-point scale)	Resources
1. Big Data Analytics	*10-point Likert scales ranging from "strongly disagree" to "strongly agree": Cost reduction effectiveness*	
	We have access to a procurement "data warehouse" that stores structured/filtered data. This data is collected/used for internal reporting purposes.	(Andersen 2003) (Ellram and Carr 1994)
	We have access to a "data lake" (vast pool of raw procurement data) such as contracts/invoices in PDF format to support our data mining activities.	(Rafati and Poels 2015) (Souza 2014)
	We use "Distributed Processing" technologies (i.e. Hadoop, Spark, etc.) to accelerate data-processing and to gain access to business intelligence reports in real-time.	

	We use Cloud Computing services for enhanced cost savings, data security and flexible data storage options.	
	We have access to "real-time" procurement dashboards that provide information on spend, savings, compliance rates, etc.	
2. Machine Learning	*10-point Likert scales ranging from "strongly disagree" to "strongly agree": Cost reduction effectiveness*	(Murphy 2012a) (Mitchell 1999)
	We use forecasting techniques such as regression analysis and exponential smoothing and/or ML algorithms to predict procurement demand.	
	We use "Association Rules" and/or "Rules-Based" models within our raw transactional procurement data to discover patterns and relationships (e.g. forensic transaction investigation)	
	We use "Text-Mining" and "Semantic Annotations" to store, process and retrieve key procurement data efficiently (i.e. contract details, purchase order cost breakdowns, etc.).	
	We leverage "Machine Learning" algorithms to help improve search results when employees search for products and services to buy. We leverage "Machine Learning" to automate the "three-way" invoice matching process and to improve accuracy.	
3. System Dynamics	We continuously analyze the performance of our procurement initiatives (i.e. portfolio) and make key decisions on resource allocations (e.g. terminating initiatives, accelerating others, etc.)	(Sterman 2001) (Tulinayo et al. 2012) (Barrad et al. 2018)
	We simulate "what-if" scenarios, using simulation software, to assess potential outcomes of procurement strategies before we implement them.	
	We constantly find ourselves having to manage internal emergencies, of tactical nature, leaving our teams with little or no time to develop strategic skills (i.e. capabilities trap).	
	We are often involved too late in the sourcing process, leaving little or no time for productive negotiations with suppliers.	

	We are too consumed with tactical processes (e.g. data analysis, RFP/RFI/RFQ production) leaving little time for strategic activities (e.g. market study, strategy formulation, negotiation, etc.)	
4. Business Rules Engines	*7-point Likert scales ranging from "strongly disagree" to "strongly agree": Cost reduction effectiveness*	(Kluza and Nalepa 2017)
	We use policy metadata (i.e. tagging keywords to your document to provide context) within our contracts management database to improve contract search effectiveness	(Mendling 2019) (Weske 2007)
	We use Business Rules Engines (BRE) that channel internal demand to pre-negotiated contracts and preferred suppliers	
	We use Complex Event Processing (CEP) to detect patterns of abnormal procurement behaviour (e.g. non-compliant spend, supplier preference biases, etc.)	
	We use Business Activity Monitoring (BAM) to gain visibility on transactions and trigger alarms when suspicious transactions occur. (e.g. overspending in a specific category, not going through the appropriate channels of spend, etc.)	
	We embed procurement rules in our Business Process Management (BPM) workflows to increase process compliance. (e.g. duplicate invoices are by default sent to a queue in accounts payable for pre-payment validation before suppliers are paid).	
5. Executive Leadership	*10-point Likert scales ranging from "strongly disagree" to "strongly agree": Cost reduction effectiveness*	(Hambrick 1987)
	My procurement department has a clear mission, vision, and purpose.	
	Our leaders (Managers, Directors, VPs, CPO) are constantly engaged with internal stakeholders (e.g. IT, Operations, Program Office, etc.) to encourage the use of Procurement services.	
	Our leaders are actively involved in key procurement negotiations (internally and with key suppliers).	
	My procurement department can generate contract analytics to assess risks, opportunities, and to action them as needed.	
	Our leaders expose us and promote us in front of other senior members inside the organization (and outside of procurement) for visibility and to promote the use of our services.	

6. People Teamwork	*10-point Likert scales ranging from "strongly disagree" to "strongly agree": Cost reduction effectiveness*	(Salas et al. 2000) (Campion et al. 1993)
	We understand the role of procurement and its main objective as it relates to serving the business	
	We can negotiate directly with suppliers and make decisions on behalf of the various business lines.	
	We are encouraged to share ideas and attend conferences to bring back fresh ideas in terms of innovation.	
	We have access to standard operating procedures that are documented and include tools and templates to support in the day-to-day role.	
	Our client-unit leaders and subordinates are engaged in procurement processes, and improvement ideas are identified, documented, and followed-up using a rigorous collaborative quality improvement program.	
7. Strategic Sourcing	*7-point Likert scales ranging from "strongly disagree" to "strongly agree": Cost reduction effectiveness*	(Barrad 2019a)
	We have real-time visibility on current spend (year-to-date).	
	Most of our key contracts digitized and stored in a central repository for easy access.	
	Our staff are certified and experienced in procurement, purchasing and supply chain management.	
	Our staff understands and are fully engaged in the strategic sourcing process (i.e. spend analysis, market assessment, strategy formulation, negotiation, contracting, etc.).	
	Our staff have the authority to directly negotiate with suppliers and make decisions on behalf of the business.	
8. Supplier Relationship Management	*10-point Likert scales ranging from "strongly disagree" to "strongly agree": Cost reduction effectiveness*	((Barrad 2019a)
	We administer a quarterly business review (QBR) with strategic suppliers to manage performance and identify corrective measures.	
	We review invoices (through manual sampling) on a periodical basis and compare them to contract clauses to ensure contract compliance (can be done in parallel with existing Procure-to-Pay (P2P) systems that may already exist).	

	We run periodical risk reviews on strategic suppliers and develop mitigation plans in the event of an incident.	
	We work closely and regularly with strategic suppliers to improve collaboration and efficiency.	
	We have a formally documented dispute and escalation management process that we follow to manage suppliers.	
9. Cost Reduction	*We used ranges to address cost reduction results. The values selected were then converted into a numerical value that would fit into a 10-point Likert scale. For example, if organizations generated 0% savings, the Likert score would be 0 however, if they scored 10%+, the score would be converted to 10.*	
	All categories of spend confined, my organization can generate:	0% of savings per annum 1-2% 3-5% 6-9% 10%+
	My procurement department generates a Return on Investment (ROI) of:	Less than 1X (less than 100%) between 1X-2X (100-200%) More than 2X (more than 200%)
	My organization is transaction compliant on:	less than 70% of transactions between 71-80% of transactions between 81-90% of transactions 91%+ of transactions
	Our spend under management is:	0% 1-9% 10-25% 26-50% 51-75% 76-90% 91%+
	The percentage (%) of suppliers that account for 80% of our spend is:	less than 10% 11-20% 21-50% 51-75% 76%+

Table 74 - Survey Construct and Items

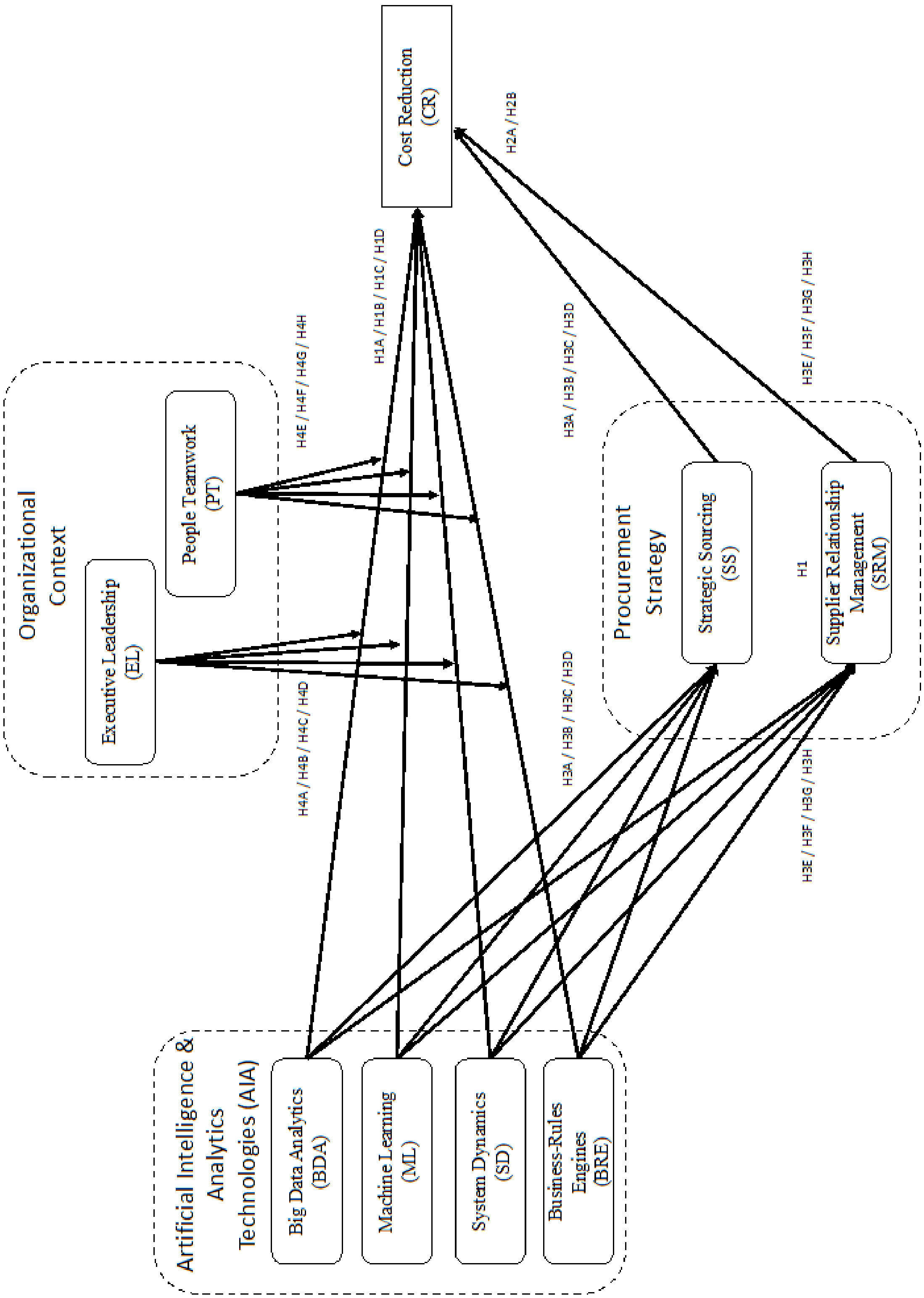

Figure 51 - Research Model

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