# ENHANCING SOURCING EFFICACY THROUGH FACT-BASED NEGOTIATION: THE ROLE OF SUPPORTIVE INTELLIGENCE

by

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NEGOTIATION: THE ROLE OF SUPPORTIVE INTELLIGENCE

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ABSTRACT

ENHANCING SOURCING EFFICACY THROUGH FACT-BASED NEGOTIATION: THE ROLE OF SUPPORTIVE INTELLIGENCE

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In the context of global procurement and sourcing strategies, the integration of Fact-Based Negotiation (FBN) with artificial intelligence (AI) and machine learning (ML) technologies marks a crucial transformative step. This research proposal, entitled "Enhancing Sourcing Efficacy through Fact-Based Negotiation: The Role of Supportive Intelligence," delves into the significant role AI and ML play in refining FBN—a data-driven approach that embraces objective, transparent and informed decision-making in contract negotiations. The study demonstrates how the adept incorporation of advanced analytics and automation can substantially streamline negotiation processes within organizations, leading to improved outcomes, higher efficiency, and reduced costs.

This research heralds the importance of systematic and data-centric approaches in today's digital era, where data equates to value. It advocates for novel sourcing negotiation strategies through a meticulous literature review and empirical analysis, specifically exploring AI and ML within the parameters of lean thinking. The literature reviewed highlights the urgent requirement to modernize conventional negotiation practices to excel in the evolving data-centric business environment.

Moreover, the research illuminates the pivot essential to adapt sourcing methodologies, proposing that the synergistic application of FBN, AI, and ML can induce a paradigm shift in procurement processes. This alignment is anticipated to set a new standard for management and operations, applicable across various industry sectors.

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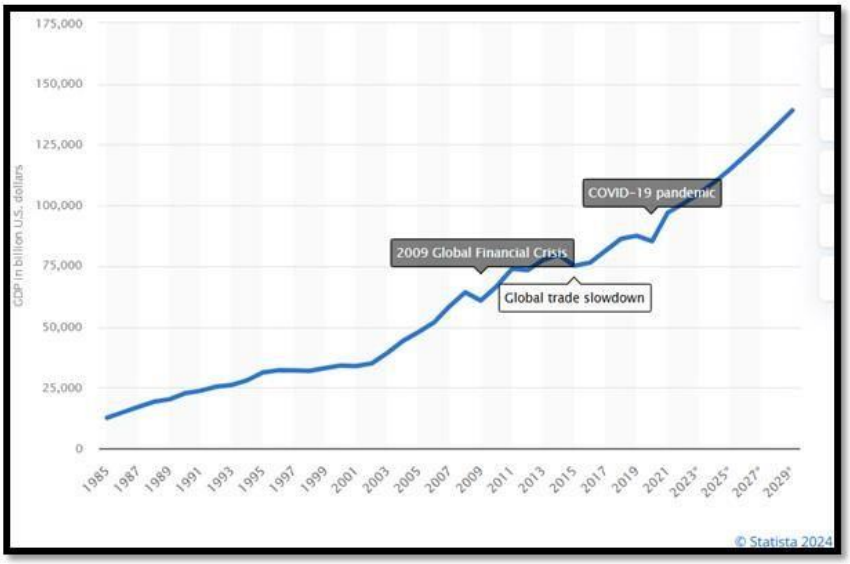
# CHAPTER I: INTRODUCTION

## 1.1 Introduction

Procurement and sourcing have long been recognized as essential pillars for organizations striving to maintain a competitive edge in the complex global market (Rognes, 1995; Spekman et al., 1999; Vitasek, 2016). As illustrated in Figure 1, the continuous growth of global GDP, with further increases projected, emphasizes the need for strategic agility in navigating ever-evolving supply chains.

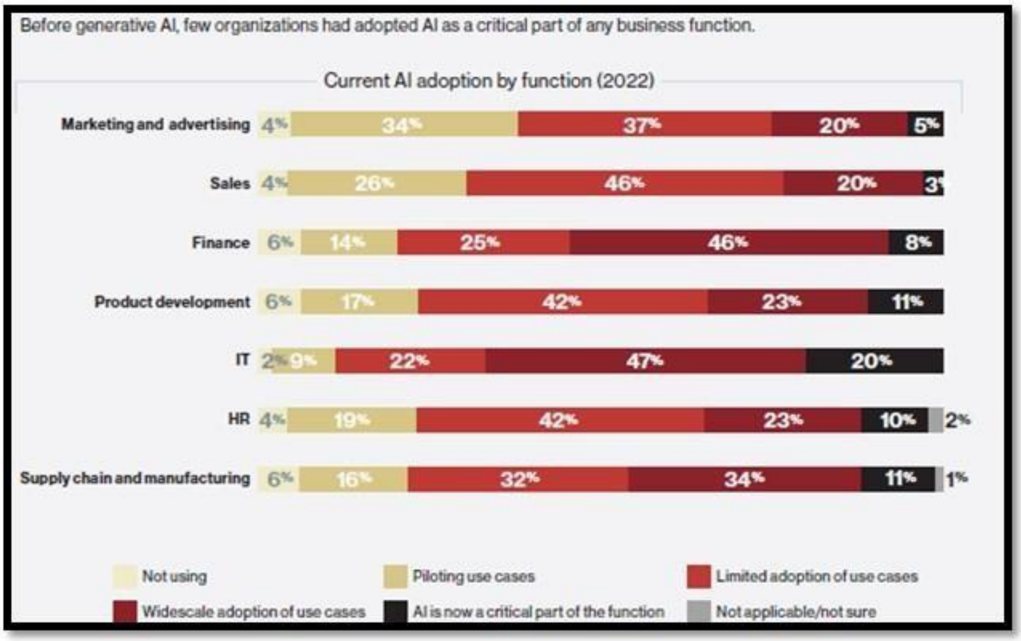
**Figure 1**: Global gross domestic product (GDP) at current prices from 1985 to 2029 in billion U.S. dollars




Source: Statista Global GDP 1985-2029

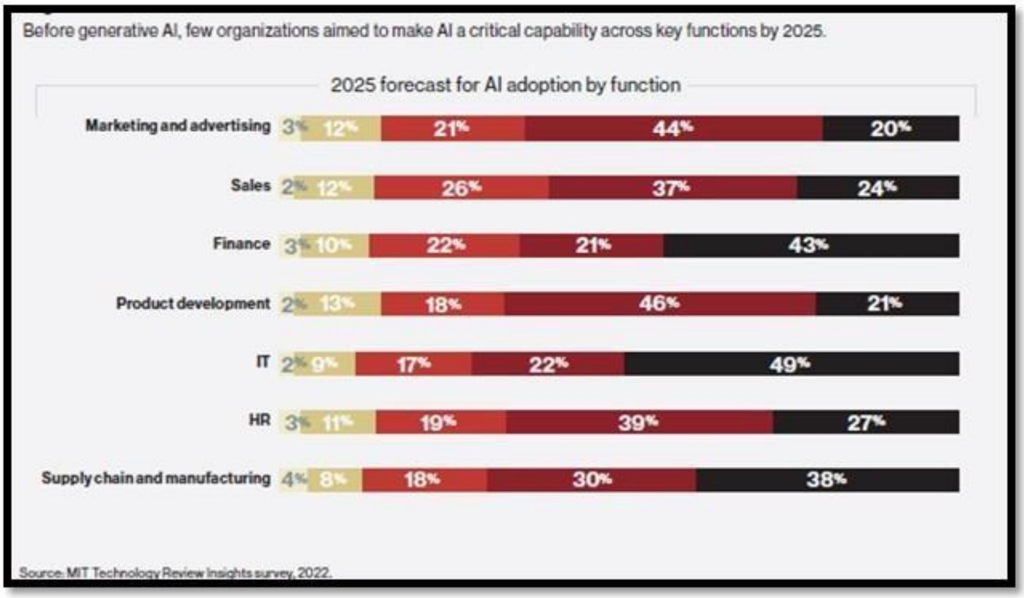
In this context, the research area of "Enhancing Sourcing Efficacy through Fact-Based Negotiation: The Role of Supportive Intelligence" becomes critically important. Integrating Artificial Intelligence (AI) and Machine Learning (ML) into Fact-Based Negotiation (FBN) provides organizations with a strategic advantage (Spekman et al., 1999). As noted in Figures 2 and 3 from the MIT Technology Review, AI adoption is set to play a pivotal role in critical functions (Shahzadi et al., 2024), including supply chain and manufacturing, by 2025. AI is now a Critical part of the function in Supply Chain and Manufacturing increased from 11% in 2022 to 38% as per the MIT Technology Review 2025 Forecast.

**Figure 2:** MIT Technology Review on AI adoption by function 2022 - The great reconsideration




Source: MIT Technology Review Insights survey, 2022.

**Figure 3:** MIT Technology Review on Limited AI ambitions




Source: MIT Technology Review Insights survey, 2022.

Fact-based negotiation (FBN) methods, adopted in procurement, human resources, sales, and legal departments, estimation and historical data, are used to achieve enhanced negotiation efficacy. Unlike conventional negotiation strategies that rely on intuitive judgment and anecdotal experiences. The main challenge of effective FBN utilization due compiling accurate data from internal and external sources, which can be time-consuming and complex. Here, supportive intelligence technologies like AI and ML provide a solution by simplifying the process and enabling a more effective, data-driven approach to decision-making (Guida et al., 2023; Allal-Chérif et al., 2020; Sandholm, 1999).

The integration of AI and ML into FBN marks a transformative shift. These technologies allow negotiators to rapidly analyze extensive data, uncover patterns, and make informed decisions, introducing new efficiencies in sourcing activities and supporting procurement digitalization (Lorentz et al., 2021).

By comprehensively understanding the negotiation landscape, considering resource availability and market dynamics—negotiators can seize opportunities and mitigate risks, achieving favorable outcomes. AI-powered predictive analytics can forecast counterpart behaviors, while soft computing methods like fuzzy logic enhance supply chain coordination. By leveraging supportive intelligence, procurement professionals can move from traditional bargaining to an interest-based negotiation framework (Shapiro, 2000), enhancing precision, agility, and strategic acumen. This shift improves negotiation outcomes and propels organizational success in a rapidly changing global marketplace (Murray & Raynolds, 2007).

This chapter lays the groundwork for addressing challenges explored in this research, outlining the aims, significance, and critical inquiries that guide the study of supportive intelligence's role in enhancing FBN efficacy. By delving into these aspects, this chapter establishes a foundation for examining how AI and ML technologies can revolutionize FBN practices, offering organizations unprecedented strategic benefits.

## 1.2 Research Problem

The research problem in the effective Fact-Based Negotiation to finalize contracts within the dynamic domain of procurement and sourcing is nuanced and multifaceted. Organizations worldwide grapple with balancing efficiency, long-term sustainability, and value, as highlighted by (Sönnichsen & Clement, 2020). Although Fact-Based Negotiation (FBN) has emerged as an innovative strategy employing data to inform decision-making (Parniangtong & Parniangtong, 2016), there remains a critical gap in its integration with cutting-edge technologies such as AI and ML. This disconnect is further compounded within the framework of lean thinking in sourcing (Rashad & Nedelko, 2020; Oliveira-Dias et al., 2022), as lean principles aimed at waste reduction and maximizing value have yet to be fully harmonized with AI and ML to enhance the effectiveness and robustness of FBN in modern procurement scenarios.

Despite the potential of these technologies to revolutionize procurement practices (Richey Jr et al., 2023), organizations continue to rely on conventional negotiation methods, often grounded in intuition and historical data, which poses several challenges to the effective implementation of FBN. There is a noticeable unfamiliarity with leveraging AI and ML, as these promising technologies can present a steep learning curve. This knowledge gap also extends to the procedural aspect of using these advancements efficiently, causing resistance to change (Pitari et al., 2020; Khaw et al., 2023) among professionals apprehensive about adopting new methodologies.

Moreover, the widespread skepticism and distrust (Quinn et al., 2021) associated with new-age technologies create a significant barrier. The opacity of AI algorithms, often referred to as the "black-box" issue, leads to doubts about their reliability (Omrani et al., 2022), creating a trust deficit (Quinn et al., 2021). Consequently, this hesitancy complicates integrating supportive intelligence technologies into existing Fact-Based Negotiation frameworks.

Additionally, the current market needs holistic and integrated AI/ML solutions from ERP providers. Most systems must seamlessly incorporate supportive intelligence into existing workflows, fragmenting adoption processes and increasing complexity. Organizations need a structured framework or benchmark that successfully melds FBN and supportive intelligence technologies, facilitating a cohesive interaction that boosts the efficacy of sourcing negotiations (Schulze-Horn et al., 2020). This lack of a holistic solution further extends to the complexities of AI and ML systems that require specialized skills for effective deployment (Tjondronegoro et al., 2022).

Compounding these challenges is the volatility of global supply chains, which requires sourcing strategies that are resilient to fluctuations and capable of leveraging data in real-time to predict market trends (Brunner et al., 2024) and adjust negotiations accordingly. However, a notable shortage of methodologies to guide firms through this integration leaves a substantial gap in structured approaches.

This research aims to bridge these critical gaps by exploring the hurdles of merging FBN with AI and ML to enhance sourcing efficacy. It seeks to identify and elucidate barriers to entry, such as the reliance on conventional negotiation methods, unfamiliarity with cutting-edge technologies, resistance to change (Pitari et al., 2020; Khaw et al., 2023), lack of trust in new-age technologies, and the absence of integrated solutions.

By crafting a comprehensive framework, this study intends to enhance negotiation outcomes, ensure cost efficiency, streamline procurement processes, and create substantial value through optimized sourcing efficacy. The industry's quest for methods that interpret complex data equalize negotiating landscapes, and fundamentally transform procurement practices (Cadden et al., 2021) stands at the heart of this investigation.

### 1.3 Purpose of Research

The overarching purpose of this research is to develop a comprehensive understanding of how Fact-Based Negotiation (FBN) can be enhanced through the support of advanced AI) and ML) technologies. Multifaceted objectives this research aims to achieve will be delineated.

**To Explore and Integrate AI and ML with FBN for Strategic Negotiation:**

The primary goal is to examine the role of AI and ML in refining Fact-Based Negotiation (FBN) processes, which are traditionally based on data-driven insights. A core aspect of this research involves exploring how supportive intelligence can augment the granular analysis of information that FBN relies upon, thereby offering a more robust strategic positioning in negotiations (Al-Sakran, 2014; Malchanau et al., 2014).

**To Provide a Systematic Approach for Technology Integration in Sourcing:**

The research aims to explore methodologies for integrating AI and ML technologies into existing sourcing strategies. Includes investigating potential frameworks that could guide organizations in adopting supportive intelligence technologies that complement current sourcing and procurement practices (Schulze-Horn et al., 2020).

**To Explore Resilient Sourcing Strategies Amid Global Market Fluctuations:**

The global supply chain is volatile so this research investigates sourcing strategies that could be flexible and adaptive to market changes. The focus is exploring how firms leverage real-time data and predictive analytics through FBN to potentially enhance their negotiation leverage and respond more effectively to market shifts (Richey Jr et al., 2023).

**To address the Knowledge and Skills Gap in Technology Deployment:**

Another objective of this research is to identify the challenges related to the knowledge and skills required to deploy AI and ML technologies within procurement processes. It aims to propose educational and training pathways for procurement professionals to acquire the necessary competencies for managing supportive intelligence tools (Khaw et al., 2023; Machireddy et al., 2021).

**To Explore Comparative Insights Across Industries:**

Recognizing that different industries face unique challenges and requirements, this study explores how FBN, when augmented by AI and ML, may be tailored to suit diverse industry sectors. It intends to investigate potential benchmarks that could be adapted and extended across various business domains (Cadden et al., 2021; Kejriwal, 2023).

**To Explore a Lean, Cost-Optimized Negotiation Framework:**

With cost efficiency as a guiding principle, this study aims to investigate the potential for developing a lean negotiation framework that leverages AI and ML to optimize expenditure during the negotiation process. The focus is on examining how organizations might reduce costs while enhancing the quality of their procurement outcomes (Rashad & Nedelko, 2020; Mishra et al., 2024).

**To Enhance Sourcing Efficacy and Organizational Profitability:**

Finally, the research signifies a step towards enhancing overall source efficacy, ensuring that organizations can negotiate more favorable terms, resulting in improved profitability and sustained growth. It entails evaluating how predictive insights and automated decision-making, powered by supportive intelligence, can become instrumental in achieving these goals (Parniangtong & Parniangtong, 2016; O'Brien, 2016; Schütz et al., 2016).

In essence, this research aims not just to expound on the theoretical implications of Fact-Based Negotiation (FBN) in the age of AI but to craft actionable, empirical strategies that industry leaders can utilize to revolutionize their sourcing and negotiation approaches. Through a data-driven lens, the research anticipates establishing a new gold standard for procurement excellence in the modern global marketplace.

## 1.4 Significance of the Study

This study stands at the confluence of technological advancement and strategic negotiation, addressing pivotal challenges in procurement and sourcing. The research's significance is underscored by its potential to redefine sourcing strategies and negotiation frameworks through the integration of FBN with AI and ML.

### Bridging the Technological Gap:

The study addresses a fundamental gap in the application of AI and ML in procurement, aiming to bridge current practices with supportive intelligence technologies. By enhancing FBN through advanced data analytics, the research could lead to a visible shift in negotiation strategies, offering organizations improved leverage and precision in their sourcing decisions. Align with the growing digital transformation trend in procurement (Richey Jr et al., 2023).

### Exploring Comprehensive Frameworks:

This study explores methodologies for integrating AI and ML into existing sourcing frameworks. It seeks to guide how organizations might navigate the complexities of technological assimilation (Schulze-Horn et al., 2020). Exploring structured frameworks could facilitate smoother adoption and help ensure that AI capabilities are harnessed effectively to support strategic sourcing initiatives.

### Enhancing Organizational Agility:

In light of global supply chain volatility, the study's exploration of resilient sourcing strategies offers critical insights into how organizations can remain agile and adaptive. By leveraging real-time data and predictive analytics, firms can confidently navigate market fluctuations, safeguarding their strategic interests and ensuring sustained growth (Rashad & Nedelko, 2020; Richey Jr et al., 2023).

### Addressing Skills and Knowledge Deficits:

The research acknowledges the skills gap in deploying AI and ML technologies within procurement processes. By identifying educational pathways and training needs, the study could significantly contribute to building workforce competencies and empowering professionals to effectively manage and utilize supportive intelligence tools (Khaw et al., 2023).

**Industry-Specific Insights:**

Through a comparative analysis across different industries, the study provides valuable insights into the tailored application of FBN augmented by AI and ML. By addressing unique industry challenges, the research can serve as a benchmark for diverse sectors seeking to optimize their sourcing and negotiation strategies (Cadden et al., 2021; Monczka et al., 2021).

**Cost-Optimization and Profitability:**

Exploring lean, cost-optimized negotiation frameworks highlight organizations' potential to reduce expenditures while enhancing procurement quality. By focusing on cost efficiency, the research emphasizes the importance of achieving balanced outcomes that contribute to overall organizational profitability (Rashad & Nedelko, 2020; Mishra et al., 2024).

This study represents a step in leveraging technology to enhance procurement practices. By addressing key challenges and providing innovative solutions, it aims to equip organizations with the tools and insights necessary to navigate the complexities of modern global supply chains successfully.

## 1.5 Research Purpose and Questions

### Research Purpose

The purpose of this research is to explore how to enhance sourcing efficacy through Fact-Based Negotiation (FBN) with the effective integration of Artificial Intelligence (AI) and Machine Learning (ML) technologies. This study aims to uncover methodologies that enhance negotiation strategies by leveraging data-driven insights, bridging existing technological gaps, and exploring comprehensive frameworks. It further seeks to address the skills and knowledge deficits in technology deployment, provide industry-specific insights, and highlight the pathways to cost-optimization and profitability (Richey Jr et al., 2023; Rashad & Nedelko, 2020; Khaw et al., 2023).

## Research Questions

1. How can AI and ML be effectively integrated with FBN to enhance strategic negotiation outcomes in procurement and sourcing? The above question explores right methodologies to integrate the supportive intelligence technologies into Fact Based Negotiation, guiding organizations through technological migration and facilitating a smoother adoption process (Schulze-Horn et al., 2020).
2. What strategies can be developed to ensure organizational agility in the face of global supply chain volatility, which will be suitable for organizations? Here, the focus is exploring sourcing strategies adaptable to market changes, leveraging real-time data and predictive analytics to enhance negotiation leverage (Rashad & Nedelko, 2020; Richey Jr et al., 2023).
3. What will be the right pathways to educate or train to empower the procurement professionals to effectively adopt AI and ML technologies? This question seeks to identify the necessary competencies and skills to bridge the knowledge gap in deploying and effectively using supportive intelligence tools (Khaw et al., 2023).
4. How can industry-specific insights be gained by comparing the application of AI-augmented FBN across diverse sectors? The research investigates benchmarks that can be adapted and extended across various business domains, addressing unique industry challenges (Cadden et al., 2021; Monczka et al., 2021).
5. What frameworks can be established to achieve lean, cost-optimized negotiation processes that improve procurement quality and organizational profitability? This question explores cost-efficient negotiation frameworks that leverage AI and ML to optimize expenditure and enhance procurement outcomes (Rashad & Nedelko, 2020; Mishra et al., 2024).

This research aims to explore these questions and provide comprehensive, in-depth insights that can guide strategic decision-making in procurement. The research output is envisioned as a valuable resource for stakeholders to adapt to industry evolution, ensuring that organizations can leverage the latest technology to secure a competitive advantage in the marketplace.

# CHAPTER II: REVIEW OF LITERATURE

## 2.1 Introduction and Background

Organizations face complex challenges in today's ever-evolving global market, highlighting the importance of effective procurement and sourcing strategies to stay competitive. Various experts have explored this idea (Rognes, 1995; Spekman et al., 1999; Vitasek, 2016).

Consistent growth in the global Gross Domestic Product (GDP) highlights the need for strategic agility in managing complex and ever-changing supply chains to address business expectations. This reality sets the stage for exploring the research topic "Enhancing Sourcing Efficacy through Fact-Based Negotiation: The Role of Supportive Intelligence." By integrating AI and ML into FBN, organizations can gain significant strategic benefits as they transition towards data-driven decision-making (Spekman et al., 1999).

Literature highlights the fundamental shift toward data-centric negotiation approaches, recognizing that data is the new currency in delivering competitive sourcing outcomes (Gates & Matthews, 2014; Ebner, 2017).

The traditional negotiation methods are increasingly being enhanced, and many organizations are adopting technology-driven strategies that focus on accuracy, efficiency, and strategic planning (Fasihullah et al., 2023). AI and ML technologies are critical to this shift because they can analyze large datasets, quickly spot patterns, and provide actionable insights. This technological advancement will enhance how negotiations take place in a new era of digital procurement. This transition has been discussed in the works of Guida et al. (2023), Allal-Chérif et al. (2020) and Lorentz et al. (2021).

This necessary shift in the landscape enables procurement professionals to negotiate more effectively by analyzing internal purchase history, estimation, and external insights. This leads to well-informed decisions that align with organizational goals.

Supportive intelligence enables procurement professionals to do real-time data analysis for data-driven decision-making, unlike traditional bargaining methods (Kelleher, 2000), which aims to equip procurement professionals to use available resources strategically and capitalize on market opportunities.

Therefore, this literature review aims to achieve two main objectives: To investigate how organizations can transform Fact-Based Negotiation (FBN) by using AI and ML as copilots with professionals. Moreover, it offers detailed insights into how emerging technologies affect procurement and sourcing strategies.

By doing so, this chapter lays a critical foundation for academic and practical deliberations on revolutionizing future sourcing practices with cutting-edge technologies to achieve organizational success and sustainability in the global market.

**2.2 The Technology Acceptance Model (TAM)**

The Technology Acceptance Model is a robust framework that has been widely used to predict and explain user behavior regarding the acceptance of new technology in the organization (Szajna, 1996; Sargolzaei, 2017). In the context of sourcing procurement and operation, this model highlights the importance of perceived practicality and perceived ease of use (Rahmi et al., 2018) as the primary drivers of technology adoption.

The TAM suggests that when procurement professionals view data-driven negotiation tools as easy to use and beneficial to their sourcing operations, they are more likely to embrace and utilize such systems effectively (Luo et al., 2023). In the dominion of Revolutionary Buying Networks, the integration of supportive intelligence like AI and ML plays a critical role. For these technology-powered analytic tools to be practical aligned with the company's strategic objectives and perceived as user-friendly and valuable by the procurement team members (Shi et al., 2024). Adopting such technologies can significantly enhance sourcing efficacy as decision-makers leverage data-driven insights to validate during Negotiation (Davis, 1993; Frank et al., 2023).

Expanding on the benefits of adopting data-driven negotiation tools, the integration of supportive intelligence like AI and ML can significantly enhance sourcing efficacy. When procurement professionals perceive these technology-powered analytic tools as user-friendly and beneficial in sourcing operations, they are more likely to adopt and effectively utilize them (Althabatah et al., 2023).

Empower decision-makers to leverage data-driven insights to validate their negotiation position, leading to more informed and strategic sourcing strategies. Additionally, aligning these technologies with the company's strategic objectives ensures their practical application and perceived value by the procurement team members, further driving their adoption and utilization (Singh et al., 2023).

Moreover, the TAM can be integrated with findings on organizational culture and readiness for change to offer a comprehensive outlook on the technology adoption process (Gangwar & Ramaswamy, 2015) in sourcing strategies. According to, diffusion of innovations theory (Rogers, 2003), factors such as organizational culture and change readiness can significantly impact the adoption of new technologies in sourcing and procurement (Calantone & Yalcinkaya, 2006; Sotelo & Livingood, 2015).

The TAM can be integrated with findings on organizational culture and readiness for change to offer a comprehensive outlook on the technology adoption process in sourcing strategies (Ramkumar et al., 2019). According to Rogers' diffusion of innovations theory (2003), factors such as organizational culture and change readiness can significantly impact the rate and extent of adoption of new technology in sourcing and procurement. For example, a company with a culture that embraces innovation and encourages experimentation may be more receptive to adopting data-driven (Visvizi et al., 2022) negotiation tools compared to an organization with a more traditional and risk-averse mindset (Vihonski, 2024).

## 2.2 Culture as an Important Factor in Technology Adoption

Adopting new technologies within an organization is one of the most complex processes heavily influenced by the organization's unique culture (Adinew, 2024). Companies that foster a culture open to innovation (Farayola, 2023) and change are better positioned to successfully implement AI and ML in their sourcing strategies (Steers et al., 2008).

An organizational culture that aligns with values such as evidence-based decision-making, transparency, and continuous improvement can facilitate the integration of supportive intelligence and increase its benefits. The literature suggests that organizational factors, including organizational design, culture, and values, play a critical role in shaping the business model innovation process around emerging technologies like AI (Zheng et al., 2010).

Organizations must recognize the cultural importance of users when assessing technology acceptability and utilization (Kripanont, 2006). Previous findings indicate that cultural values at the national level can significantly affect technology usage behaviors (Srite & Karahanna, 2006). Businesses must understand when, why, and whether customers would accept an innovation (Dunphy & Herbig, 1995), and various theoretical perspectives can help professionals and researchers understand how any invention is adopted (Rabina & Walczyk, 2007).

The attitude towards AI differs significantly among industries (Vasiljeva et al., 2021), and the three main factors that impact AI adoption are top management's attitude, competition, and regulations. Successful adoption of innovative technologies requires aligning the organization's culture and values with the requirements of the new technology (Lee et al., 2019).

Successful adoption of innovative technologies requires carefully aligning the organization's culture and values with the requirements of the new technology. This alignment is crucial for creating an environment that is receptive and supportive of technology's implementation and utilization (Crespell & Hansen, 2008; Rogers, 2003).

Organizations must foster a culture that aligns with key values such as evidence-based decision-making, transparency, and continuous improvement to fully leverage the benefits of supportive intelligence like AI and ML. This cultural alignment can smooth the integration of these emerging technologies and maximize their positive impact (Allal-Chérif et al., 2021).

### 2.3 The Emergence and Evolution of Fact-Based Negotiation

Fact-based Negotiation has emerged as a progressively beneficial model for contract negotiation, distinguishing itself from traditional methods that often rely on subjective instincts and circumstantial experiences. This approach leverages data-driven strategies that inform decision-making with measurable and objective criteria (Rolf et al., 2010; Parniangtong, 2016), enabling more effective and informed contract negotiations. (Nyhart & Samarasan, 1989; Tomlinson & Lewicki, 2015).

Negotiation of contractual agreements is a multifaceted process that demands meticulous consideration of various factors (Latilo et al., 2024). Successful negotiations not only attempt to maximize the possibility of reaching an agreement but also ensure that the agreement effectively fulfills its intended purpose, remains durable over time (Brett, 2007; Susskind & Ali, 2014), and lays the groundwork for future collaborative efforts (Tomlinson & Lewicki, 2015). This requires a nuanced understanding of the underlying dynamics and objectives driving each party's participation in the negotiation process.

Emerging research and practical applications have highlighted the significant advantages of adopting a fact-based approach to Negotiation (Labbo & Reinking, 1999). This innovative method departs from traditional negotiation tactics that often rely on subjective assessments and individual experiences, instead leveraging data-driven insights to objectively for the informed decision-making process (Schulze-Horn et al., 2020). By grounding the negotiation process in measurable and verifiable criteria, fact-based Negotiation enhances the possibility of reaching mutually beneficial agreements that are more likely to withstand the test of time and establish a stronger foundation for future collaborative efforts (Nyden et al., 2013). This data-centric approach allows negotiating parties to move beyond intuition and anecdotal evidence and make informed decisions supported by quantifiable data and analytical insights (Fiske et al., 2019). Ultimately, the fact-based negotiation model represents a progressive shift towards a more informed, equitable, and sustainable approach to contract negotiations (Hămuraru & Buzdugan, 2024).

## 2.4 The Impact of Artificial Intelligence and Machine Learning

Technological advancements, particularly in the domain of artificial intelligence and machine learning, have significantly transformed various aspects of procurement processes. As noted in Chapter 1 Figures 2 and 3 from the MIT Technology Review, AI adoption is set to play a pivotal role in critical functions, including supply chain and Manufacturing, by 2025. AI is now a critical part of the function of the supply chain, and Manufacturing increased from 11% in 2022 to 38% as per the MIT Technology Review 2025 Forecast. These innovations have enabled procurement professionals to leverage data-driven insights, leading to more efficient and agile decision-making (Segun-Ajao, 2024; Prud'homme et al., 2020; Riahi et al., 2021).

Intelligent automation and predictive analytics have been crucial in enhancing the procurement process. Emerging technologies such as robotic process automation and machine learning, have the potential to streamline procurement activities (Nzeako et al., 2024), improve accuracy, and reduce costs (Althabatah et al., 2023; Riahi et al., 2021). Integrating these technologies can also help procurement organizations respond more effectively to global events, such as the COVID-19 pandemic, by providing real-time visibility and enabling swift adaptations to supply chain disruptions (Yu, 2024).

Implementing artificial intelligence and machine learning in procurement has delivered substantial benefits across various dimensions. Blockchain-based solutions, for instance, can enhance supply chain traceability and transparency (Tsolakis et al., 2023), ultimately contributing to more sustainable and ethical procurement practices (Segun-Ajao, 2024). These distributed ledger technologies provide an immutable record of transactions, enabling greater accountability and visibility throughout the supply chain (Asante et al., 2021).

Furthermore, integrating natural language processing and ML algorithms has revolutionized the automation of procurement-related tasks (Dhaliwal et al., 2024). These advanced techniques can streamline contract management, supplier evaluation, and spend analysis, leading to increased efficiency, productivity, and data-driven decision-making (Riahi et al., 2021). NLP, in particular, can parse and interpret unstructured data, such as supplier contracts and invoices, to extract critical insights and automate time-consuming administrative duties (Baviskar et al., 2021).

Beyond these operational improvements, AI and ML also hold the potential to enhance the agility and responsiveness of procurement organizations. By leveraging predictive analytics and intelligent automation, procurement teams can better anticipate and adapt to global disruptions, such as the COVID-19 pandemic, ensuring the continuity of supply chains and the timely delivery of critical goods and services (Prud'homme et al., 2020).

## 2.5 The Integration of Lean Thinking in FBN

Existing research primarily explores the application of Artificial Intelligence and Machine Learning within a broad managerial context. However, more attention is required to align these technologies with lean principles within the sourcing domain to enable more positive outcomes (Lepri et al., 2018; Cui et al., 2021; Karlsson, 2020).

The potential integration of lean thinking principles, which focus on waste elimination and value maximization, with Fact-Based Negotiation could pave the way for more efficient and effective sourcing practices (Rashad & Nedelko, 2020; Oliveira-Dias et al., 2022).

Lean Manufacturing has been successfully integrated into supply chain management, enabling considerable performance improvements (Sah et al., 2024); similarly, incorporating lean principles into the negotiation process could streamline sourcing activities, reduce waste, and maximize value for all stakeholders (Nicoletti, 2013).

Lean Manufacturing is a proven approach that should be a core component of any organization's long-term strategy (Begum & Sumi, 2024). This methodology seeks to enhance production efficiency by systematically reducing waste in various forms (Sharma et al., 2023). The application of lean principles across the supply chain, referred to as a lean supply chain, can offer significant performance enhancements (Asmae et al., 2020).

The potential integration of lean thinking principles, which focus on waste elimination and value maximization, with Fact-Based Negotiation could pave the way for more efficient and effective sourcing practices (Adlin, 2022). The application of lean principles across the supply chain, referred to as a lean supply chain, can offer significant performance enhancements(Tortorella et al., 2017) To further explore the integration of lean thinking principles in Fact-Based Negotiation, the following areas should be investigated (Ashcraft, 2011; Cui et al., 2021; Helmold, 2022):

- Identifying and eliminating waste within the negotiation process, such as unnecessary steps, information redundancy, or inefficient communication
- Aligning negotiation objectives with lean principles of value maximization for all stakeholders involved

- Developing a comprehensive framework for seamlessly integrating lean practices and methodologies into Fact-Based Negotiation
- Conducting empirical evaluations to assess the impact of lean-infused Fact-Based Negotiation on overall sourcing performance, including factors such as cost savings, process efficiency, and stakeholder satisfaction

## 2.6 Theoretical and Empirical Underpinnings

The growing interest in the relationship between intelligent technologies and negotiation strategies has been a subject of notable discussion in literature. Scholars (Stoshikj & Gregu, 2014; Lee & Kwon, 2006) have examined the transformative impact of artificial intelligence on procurement processes and the influence of machine learning on predictive negotiations. This paper reflects on the intersection of these themes, highlighting the need for further scholarly discourse regarding their comprehensive integration within a lean framework for flexible buyer-supplier networks (Abdollahi et al., 2015).

Negotiation is a complex social interaction that involves exchanging information and decision-making between independent parties with interdependent goals (Wilson & Putnam, 2012; Lee & Kwon, 2006). While the literature has addressed common issues in business-to-business (B2B) negotiations, there still needs to be a gap in harmonizing primary and secondary negotiation terms (Lee & Kwon, 2006). Negotiation support systems have been proposed as a solution to the challenges faced in enterprise-level negotiations, offering the potential to facilitate integrative negotiations through software support (Stoshikj & Gregu, 2014).

To complement the existing analytical approaches to Negotiation, scholars have proposed examining negotiations as linked systems (Sebenius, 2006), where the connections between different negotiations can significantly influence negotiators' alternatives, preferences, and attitudes (Crump, 2011). This more holistic perspective on negotiations can provide valuable insights for organizations seeking to integrate intelligent technologies within their flexible buyer-supplier network strategies. By considering the interdependencies between negotiations, organizations can develop more sophisticated approaches to leveraging AI and machine learning to optimize their procurement and negotiation processes (Guida et al., 2023; Jahani et al., 2021; Althabatah et al., 2023).

### 2.7 Streamlining Trade-Offs with Intelligent Support in Fact-Based Negotiation

Negotiations often involve complex trade-offs, where decision-makers must weigh various aspects such as price, delivery times, service quality, and after-sales support (Van et al., 2009). While trade-offs are a common occurrence in negotiations (Walton & McKersie, 1991; Kersten, 2001; Faratin et al., 2002), the role of artificial intelligence and machine learning in enhancing these strategies has not been extensively explored (Lin et al., 2023; Lopes et al., 2008).

Artificial intelligence can provide valuable assistance to negotiators by offering insights to handle trade-offs more effectively (Schulze-Horn et al., 2020). AI systems can analyze data to identify the optimal balance between cost and quality, helping negotiators make informed decisions (Jarrahi, 2018). For example, AI can predict the impact of delayed deliveries, enabling negotiators to make better-informed choices about costs and customer satisfaction (Shrestha et al., 2019; Tafakkori et al., 2022).

Machine learning can also be crucial in streamlining logistics and scheduling (Khedr, 2024), reducing the compromise between delivery speed and costs. Advanced algorithms can learn from data and guide negotiation strategies that balance procurement objectives (Kalasani, 2023); algorithms can advise negotiators to accept minor losses that could result in more substantial benefits, such as strengthening supplier relationships or ensuring supply chain reliability (Niranjan et al., 2021; Riahi et al., 2021; Mohammadi et al., 2020).

By incorporating AI and ML into fact-based negotiation methods, negotiators can identify key trade-offs (Singh & Mazumdar, 2017) and develop innovative solutions. Instead of relying on guesswork, professionals can use solid data to make smarter, strategic choices when facing complex compromises. This allows them to streamline the negotiation process and make more informed decisions that balance various factors, such as cost, quality, and customer satisfaction (Riahi et al., 2021).

By seamlessly integrating AI and ML into their fact-based negotiation practices, professionals can navigate trade-offs with greater confidence and sophistication. Rather than relying on intuition or guesswork, they can leverage robust data-driven insights to make strategic choices that optimize multiple objectives simultaneously (Pathak, 2023). This holistic approach enables negotiators to streamline the negotiation process and achieve more favorable outcomes that balance all stakeholders' diverse needs and priorities (Chukwu et al., 2023).

## 2.8 Key Elements of Fact-Based Negotiation in Procurement Contracts

To enhance sourcing efficacy through fact-based Negotiation (FBN):

**1. Cost Breakdown Analysis:**

Cost breakdown analysis is a powerful tool that enables organizations to dissect the cost of goods or services into their fundamental components (Adedipe & Shafiee, 2021), facilitating transparent and well-informed negotiations. By providing a granular understanding of cost drivers, this analysis lays the groundwork for informed decision-making, revealing opportunities for cost reduction (Castellani et al., 2005).

The existing literature on cost breakdown analysis emphasizes its importance in various contexts. Study examined the concept of total cost of ownership, highlighting the need to move beyond conventional, abstract cost categories and instead focus on how costs arise and are understood in the everyday work of organizational members (Castellani et al., 2005). Another study presented a discounted cost model to calculate the costs associated with the active life cycle of automated systems, underscoring the complexity involved in estimating such costs (Vasconcellos & Yoshimura, 1999).

The simultaneous use of break-even analysis and demand analysis has also been explored as a teaching method to aid managers in making pricing decisions (Hawes et al., 1995). This approach demonstrates the practical utility of these two concepts, often perceived as more theoretical than practical (Castellani et al., 2005).

Combining AI, ML, and Robotic process automation (RPA) will enable effective automation of cost breakdown analysis and cost-benefit analysis (Jha et al., 2021), which procurement professionals can use as supporting documents to do fact-based negation.

**2. Internal Estimation /Zero-based Costing:**

In today's competitive business landscape effectively negotiating and setting defensible price targets is critical to organizational success. Internal Estimation or Zero-based Costing has emerged as a crucial preparatory step in this Process (Al-attara et al., 2020), enabling organizations to leverage both internal and external data to estimate fair prices for goods or services (Cunha et al., 2020; Anil et al., 2008).

The use of or as a negotiation benchmark is supported by extensive research (Kohli & Suri, 2011). Accurate cost estimation is essential for determining the economic advantage of a business and its ability to remain competitive (Anil et al., 2008). Market-oriented systems of control, measurement, and management of costs, such as target costing, are seen as appropriate strategic cost management practices that enable companies to engage in competitive pricing and deliver desirable profit at a maximum cost as determined by the selling price (Cunha et al., 2020). Pricing is a creative exercise in math and behavioral economics, and companies should stay focused on profits (Kohli & Suri, 2011).

Organizations must take a holistic approach to leverage Internal Estimation or Zero-based Costing effectively. Pricing should be viewed as a strategic tool, with a focus on precision to enhance profitability. Companies should stay focused on profits, create effective base prices, and modify them to enhance profitability. Additionally, monitoring prices at the transaction level can reduce leakage in profits and further add to the bottom line (Anil et al., 2008; Cunha et al., 2020; Kohli & Suri, 2011; Piercy et al., 2010).

Internal Estimation (IE) or Zero-based costing (ZBC) organizations use internal and external data to estimate fair prices for goods or services, creating a negotiation benchmark (Ghuzdewan & Narindri, 2018; Porter, 1990). This preparatory step of IE or ZBC is crucial for effective Negotiation and defensible price targets for vendors or service providers. Using artificial intelligence to handle Zero-based budgeting or Zero-based costing will improve productivity (Timmermans et al., 2019).

**3. Total Cost of Ownership (TCO):**

Total cost of ownership is a crucial metric that organizations consider when evaluating the actual cost of a product or service (King, 2007). This comprehensive approach to cost analysis encompasses all expenses associated with a purchase, including the initial purchase cost, logistics cost, finance cost, and support cost over the asset's lifespan (Machuca, 2006). The TCO framework provides a holistic view of the financial implications of a product or service, enabling informed decision-making (Roda et al., 2020; Degraeve et al., 2005).

The growing prominence of the total cost of ownership framework is evident across various industries. In the domain of network operations, TCO analysis has been applied to gain a comprehensive understanding of the costs associated with infrastructure, maintenance, and service provisioning (Machuca, 2006). Similarly, in the context of electric vehicle adoption, TCO analysis has been utilized as a crucial tool to assess the long-term financial implications of this emerging transportation technology, enabling informed decision-making for both individuals and organizations (Dumortier et al., 2015).

The importance of TCO analysis is further underscored by its application in many products and services procurements, including the spare parts management decisions that have a significant impact on the overall TCO and a robust conceptual framework that links these decisions to a total cost of ownership perspective is crucial for optimizing asset management strategies, Robotic Automation with artificial intelligence help organization to prepare TCO and compelling fact-based NegotiationNegotiation (Hosseini & Andersson, 2024; Wouters et al., 2005; Bataev, Dedyukhina & Nasrutdinov, 2020).

**4. Value Analysis:**

Value analysis and value engineering are powerful tools that can significantly benefit the negotiation process (Utomo, 2010), particularly in the context of fact-based Negotiation. Value analysis is a systematic approach to increasing functionality and reducing costs, while value engineering focuses on optimizing the balance between cost and performance (Green, 1994; Miles, 2015).

The integration of value analysis and value engineering can enhance the effectiveness of fact-based negotiation in several ways (Wao, 2017; Kelly et al., 2014). First, by systematically evaluating the functions and costs of a product or service, value analysis can provide a solid foundation for fact-based discussions, ensuring that both parties have a clear understanding of the true value proposition. Second, value engineering can help identify opportunities for cost optimization without compromising the necessary features, allowing for more favorable terms in the Negotiation (Shelote et al., 2018).

Furthermore, value analysis and value engineering can contribute to sustainable construction practices (Wao, 2017), which are increasingly important in modern negotiation contexts. These methodologies help identify renewable energy alternatives and other cost-effective and environmentally friendly solutions, demonstrating the negotiator's commitment to sustainability and enabling more mutually beneficial agreements (Shelote et al., 2018; Rachwan et al., 2016; Martin, 2012).

The implementation of value analysis and value engineering in fact-based Negotiation has been the subject of extensive research (Shelote et al., 2018). Studies have shown that these approaches can significantly improve the quality of construction projects, enhance consumer satisfaction, and reduce negative environmental impact (Shelote et al., 2018; Ishak et al., 2020). By integrating these principles into the negotiation process, negotiators can achieve better outcomes, protect their interests, and contribute to the long-term sustainability of the project or agreement.

**5. The Best Alternative to a Negotiated Agreement (BATNA) and Worst Alternative to a Negotiated Agreement (WATNA):**

The best alternative to a negotiated agreement and the worst alternative to a negotiated agreement are crucial concepts in negotiations (Lax & Sebenius, 1985; Jung & Krebs, 2019). A BATNA represents the minimum acceptable outcome for a negotiator, below which they would be better off walking away from the Negotiation (White & Neale, 1991). This gives negotiators a strong advantage, allowing them to make confident decisions and not settle for less than their desired outcome (Weiss, 2016). On the other hand, the WATNA is the least desirable outcome a negotiator is willing to accept, which helps them determine how far they are willing to go before abandoning the Negotiation altogether (Downie, 1991; Weiss, 2016).

Before any negotiation, one must thoroughly consider one's BATNA and WATNA. This preparation can facilitate the negotiation process and increase the likelihood of reaching an optimal agreement where both parties feel they have achieved a satisfactory outcome (Weiss, 2016). Accurate assessment of interests and possible agreements is often the decisive factor in successful negotiation, particularly in complex scenarios. Furthermore, adequate preparation and data gathering is essential for negotiators to be effective and achieve a better deal than the other party most of the time (Weiss, 2016; Sebenius, 2017; Andrade et al., 2010).

**6. Sustainability:**

Sustainability is a crucial consideration in the modern business landscape, as companies strive to balance economic, environmental, and social factors for long-term viability (Rahman & Islam, 2017; Ponte et al., 2020). Incorporating sustainability into Fact-Based Negotiation can lead to more nuanced and comprehensive procurement strategies, ultimately resulting in more effective and ethical outcomes (Ponte et al., 2020; Raj et al., 2020).

Fact-based Negotiation is a strategic approach that emphasizes using objective data and evidence to inform decision-making (Rahman & Islam, 2017; Ponte et al., 2020). By integrating sustainability considerations into this framework, companies can achieve a deeper understanding of the full impact of their procurement practices. This includes examining not only the economic implications but also the environmental and social consequences of their sourcing decisions (Hoejmose & Adrien, 2012).

Sustainable procurement has numerous benefits, as illustrated in the literature (Ruparathna & Hewage, 2015). It can help control costs by considering the whole lifecycle of products and services, improving internal and external standards through performance assessments, managing risk and reputation, building a sustainable supply chain, and engaging the local business community (Ponte et al., 2020).

However, integrating sustainability into procurement processes has challenges. A study found that while economic factors are often prioritized, adding sustainability criteria to the procurement process could limit competition (Rahman & Islam, 2017). To address this, organizations must carefully balance the need for sustainability with the requirements of fair and open competition.

To overcome these obstacles, a more comprehensive and nuanced approach is required. By leveraging supportive intelligence and tools such as e-procurement, companies can better assess the sustainability factors within their supply chains and make more informed decisions (Ramkumar & Jenamani, 2014).

Incorporating sustainability into FBN considers environmental and social factors alongside economic ones (Carter & Rogers, 2008). It is pivotal for companies focused on long-term viability, accountability, and ethical sourcing practices.

The convergence of these elements with supportive intelligence underpins a more nuanced, comprehensive approach to FBN, leading to more effective procurement outcomes.

**7. Preparation:**

Preparation is a vital component of successful fact-based NegotiationNegotiation, as it provides negotiators with the necessary insight and understanding to engage productively and steer discussions toward favorable outcomes (Helmold, 2022; Parniangtong & Parniangtong, 2016; Roloff et al., 2003). Thorough research, setting clear objectives, and understanding the market dynamics are crucial steps in the preparation process.

Adequate preparation equips negotiators with a clear vision of what they aim to achieve through the Negotiation and why they desire those outcomes. According to Thompson (1975), approximately 80% of negotiators' efforts should be devoted to the preparation stage (Liu & Chai, 2015; Jung & Krebs, 2019; Odell, 2000), highlighting its significance in the negotiation process. (Byrnes, 1987) Furthermore, preparation involves establishing target and reservation prices and considering the signaling effect of the opening offers, as these can impact the information asymmetry and potentially lead to impasses or high negotiation costs (Ma et al., 2006).

Accurate assessment of interests and possible agreements is a critical factor in successful Negotiation, particularly in complex settings. Negotiators who thoroughly prepare and assess the situation are more likely to be aware of opportunities and design superior agreements. Inadequate preparation and assessment, on the other hand, often result in failed negotiations or inferior outcomes, as negotiators may lack the necessary awareness of their own or their opponent's interests, as well as the possible means of meeting those interests (Liu & Chai, 2014; Chen & Underwood, 1988; Ma et al., 2006; Byrnes, 1987).

**8. Concessions and Compromise:**

Negotiation is a delicate dance in which parties must carefully balance their interests, identify potential trade-offs (Druckman, 2007), and ultimately reach an agreement that satisfies all involved. Concessions and compromise are essential elements in this process, as they enable negotiators to find common ground and move closer to a mutually beneficial outcome (Prakash, 1986; Falcão, 2012).

Successful negotiators must be adept at identifying what they are willing to offer or forsake to progress toward an agreement (Weiss, 2016). This requires a deep understanding of their own goals and priorities, as well as a keen awareness of the other party's interests and constraints. By making strategic concessions that do not undermine critical objectives, negotiators can demonstrate flexibility and a willingness to collaborate, ultimately increasing the chances of reaching a satisfactory conclusion (Falcão, 2012; Condlin, 1985).

Concessions and compromise are instrumental in reaching a mutually acceptable agreement in which both parties feel their interests have been addressed (Mwagike & Changalima, 2022). Negotiators must identify what they are willing to offer or forsake to move closer to an agreement (Mnookin et al., 2004), ensuring any concessions are strategic and do not undermine critical objectives.

**9. Problem-Solving:**

Problem-solving is a critical component of successful collaborative negotiations, as it enables parties to move beyond positional bargaining and work towards innovative and mutually beneficial solutions. This integrative approach to Negotiation (Ruth & Thompson, 2014) allows negotiators to diverge from competitive strategies and focus on jointly overcoming obstacles (Muir et al., 2008; Mehrabi & Hosseini, 2021).

Jonassen's research (2000) on problem-solving has shown that it is a highly relevant and authentic learning activity, where knowledge gained in the context of problem-solving is better understood and more transferable (Dabbagh, 2019). Further, the ability to solve problems has been identified as one of the most essential twenty-first-century skills sought by employers (Dabbagh, 2019). This highlights the practical importance of developing strong problem-solving skills, which are essential for effective collaboration and negotiation.

In line with these findings, O'Leary and Amsler (2007) emphasize that problem-solving in a negotiation context is about "collaboratively overcoming obstacles and creating solutions that benefit all negotiating parties." (Ranieri, 2008) This focus on collaborative problem-solving, rather than adversarial positioning, is critical to achieving constructive resolutions.

**10. Decision-Making:**

Within Fact-Based Negotiation, decision-making is a critical component driven by a robust analytical process. This process involves considering multiple scenarios and their potential outcomes, ensuring that decisions are grounded in data, rigorously evaluating options, and aligning with organizational goals (Ireland & Miller, 2004; Riggio & Saggi, 2015). Influential decision-makers must understand the dynamics of politics and group processes, as collaborative decision-making is inherently a political endeavor (Riggio & Saggi, 2015).

The integration of negotiation knowledge within organizations has been a subject of scholarly silence, leaving a gap in understanding how this knowledge is created, stored, and shared. By recognizing Negotiation as an organizational capability, researchers can provide new insights into how firms can better navigate the turbulent business landscape (Caputo et al., 2018).

Emotions play a significant role in the negotiation process, as they can influence the results in various ways. Positive emotions, like happiness, have led to more integrative and less competitive negotiation behaviors, resulting in higher joint gains (Salminen & Ravaja, 2017). Conversely, negative emotions, like anger, can induce more dominating behavior and decrease the likelihood of reaching an agreement (Choi et al., 2015). The management of emotions, mainly through the lens of emotional intelligence, has become a critical factor in improving the effectiveness of Negotiation (Schlegel et al., 2018; Sahoo & Goswami, 2023; Van et al., 2015).

**11. Persuasion:**

Persuasion is a fundamental aspect of Negotiation, where individuals or parties engage in a strategic exchange to achieve their desired outcomes (Behrmann, 2016). Aristotle's timeless work on the "art of rhetoric" emphasizes three key elements of persuasion: logical argumentation, emotional appeal, and credibility (Bülow-Møller, 2005; Kruglanski & Thompson, 1999). Effective persuasion in Negotiation involves presenting a compelling case that resonates with the other party's interests, anchoring the discussion on well-substantiated narratives (Lin, 2019).

Logical argumentation, or logos, is the appeal to reason. Negotiators must carefully construct their arguments, presenting a logical flow of ideas and supporting their claims with relevant facts and data (Bruns & Ganapati, 2020). Emotional appeal, or pathos, taps into the emotional sensibilities of the other party, evoking feelings that can sway their decision-making. (Lin, 2019). Credibility, or ethos, is established through the negotiator's reputation, expertise, and trustworthiness, which lend to weight their position (Richards, 2003).

Persuasion involves using logical argumentation, emotional appeal, and credibility to influence the other party (Conger,2017). It is about compellingly articulating the value and rationale behind one's position, anchoring the Negotiation on strong, substantiated narratives (Ivey, 2023).

**12. Agreement:**

Reaching an agreement is the culmination of the negotiation process, as it articulates common ground and a shared path forward for all parties involved (Zucker, 2012). A well-crafted agreement should be clear, comprehensive, and reflective of the negotiated terms, ensuring all parties fully commit to their responsibilities.

Effective Negotiation often depends on an accurate assessment of interests and possible agreements. Proper planning and preparation are crucial, as they allow negotiators to increase their awareness of opportunities and design superior agreements. Without a clear understanding of their own or their opponent's interests and the possible means of meeting interests, negotiators are unlikely to maximize the outcomes of their efforts (Chen & Underwood, 1988).

Furthermore, the agreement must be not only doable but also durable, as it needs to satisfy the interests of all parties involved to ensure long-term sustainability. Reaching an agreement is not merely about finding a resolution but also about considering the detailed steps necessary for its successful implementation. By anticipating potential contingencies and factors that may interfere with goal pursuit, negotiators can better navigate the dynamic communication process and increase the likelihood of achieving an optimal agreement (Liu & Chai, 2014; Berlin & Lexa, 2007).

Finally, reaching an agreement signifies the culmination of the negotiation process (Kumar, 2017); it articulates common ground and a shared path forward (Hayward, 2008). The agreement should be clear, comprehensive, and reflect the negotiated terms (Gross, 2007), ensuring all parties are committed to their responsibilities (Goo & Huang, 2008)

**2.10. Overview**

The literature review demonstrates a robust linkage between successful negotiation strategies and the incorporation of data alongside supportive intelligence, such as AI and ML tools (Schulze et al., 2020; Karlsson, 2020). The empirical research, expert insights, and relevant case studies reveal that FBN, though offering a solid, objective basis for strategic decisions, truly flourishes when it embraces supportive intelligence. By weaving in AI and ML applications (Heilig & Scheer, 2023), negotiators can analyze complex datasets, anticipate outcomes (George et al., 2023), and develop more robust, more innovative strategies that cater to the nuances of modern procurement.

To further bolster this data-driven approach, 'principled negotiation,' as outlined by (Fisher & Ury, 2012), provides a framework that resonates with these modern techniques. The four cornerstones of this approach—separating people from the problem, focusing on interests rather than positions (Moomaw & Papa, 2012). Creating a mutual gains climate regime through universal clean energy services. *Climate Policy*, *12*(4), pp.505-520.), generating options for mutual gain, and advocating for objective criteria—complement the analytic capabilities of AI and ML. Such an alliance facilitates informed decision-making (George et al., 2023) and ensures that negotiations are grounded in mutual benefit and objective standards.

The lean principles enrich this layer by inculcating process efficiency and reducing redundancies (Fliedner, 2011), echoing the necessity for agile sourcing strategies in an evolving procurement landscape (Khan et al., 2024).

The approach combines tradition and technology, mixing time-honored negotiation wisdom with data-driven preciseness. It creates a robust and adaptable framework that negotiators can leverage (Brett, 2007), to navigate the complexities of modern procurement and achieve superior outcomes.

In conclusion, fact-based negotiation, empowered by AI and ML, and the disciplined approach of principled negotiation offer a comprehensive strategy for contemporary procurement challenges. They facilitate an environment where decision-makers can judiciously balance efficiency with effectiveness, paving the way for contracts that deliver value and sustainability in the long term.

# CHAPTER III: METHODOLOGY

## 3.1 Overview of the Research Problem

The research problem addresses the indispensable to recalibrate and enhance sourcing strategies in an increasingly data-centric and volatile global business environment (Bechtsis et al., 2022). Traditional negotiation practices are challenged by the need for more sophisticated, precise, and flexible tactics that respond effectively to volatile supply chains (Chukwu et al., 2023).

The crux of the issue lies in how organizations can integrate Fact-Based Negotiation (FBN) with the burgeoning realms of Artificial Intelligence (AI) and Machine Learning (ML) technologies. While FBN provides a structured, data-driven approach to negotiations, there is a pressing need to harness AI and ML capabilities to refine strategy, increase efficiency, maximize cost savings, and facilitate better informed, transparent decision-making processes.

Moreover, organizations need help in effectively adopting these advanced technologies. These include the technical complexities of AI and ML systems, resistance to change within corporate culture, a gap in requisite skills among procurement professionals, and an absence of systematic methodologies for technology integration.

The research problem also extends to developing a comprehensive framework that can guide organizations in merging FBN with AI and ML. This framework must encompass best practices for driving acceptance and utilization of supportive intelligence technologies, ensuring scalability and applicability across various industries.

Overall, the research seeks to provide a novel examination of the potential paradigm shift that can be achieved in procurement and sourcing through the strategic incorporation of AI and ML into FBN methods, all while considering the broader organizational and human factors at play. It aims to set a new standard for procurement negotiations in the digital era, driving organizations to lead in the global marketplace with more analytically robust and pragmatic negotiation strategies.

### 3.2 Operationalization of Theoretical Constructs

Operationalization refers to the process by which we translate theoretical constructs into measurable variables that can be used in research (Rao and Reddy, 2013; Lim, 2024). By dissecting the theoretical concepts presented in the literature review, we can pinpoint specific, measurable elements that correspond to the application and impact of AI and ML in Fact-Based Negotiation (FBN).

**1. Technology Acceptance Model (TAM):**

To operationalize the Technology Acceptance Model, we need to measure perceived usefulness (PU) and perceived ease of use (PEOU) (Yusuf et al., 2024; Nie et al., 2023) in the context of AI and ML technologies for FBN. These can be operationalized as follows:

- **Perceived Usefulness (PU):** Survey and Interview on a Likert scale asking procurement professionals about their agreement with statements regarding AI and ML's ability to improve sourcing efficacy, negotiation outcomes, and overall business performance.
- **Perceived Ease of Use (PEOU):** Survey and Interview on a Likert scale that assesses the professionals' perceived complexity or ease of integrating AI and ML into existing negotiation processes.

**2. Organizational Culture and Innovation Adoption:**

The cultural and social norms affecting innovation adoption (Zhang et al., 2023) can be operationalized through:

- **Innovation-Friendly Culture:** Qualitative assessments through interviews and organizational culture assessments focus on values around change readiness, continuous improvement, and data-driven decision-making (Zhang et al., 2023).
- **Diffusion of Innovations:** Metrics that evaluate the adoption of AI and ML in Fact-Based negotiation within the organization and the integration of AI and ML in FBN processes relative to industry benchmarks, according to (Xu et al., 2024).

**3. Fact-Based Negotiation Principles:**

The constructs from FBN can be operationalized into measurable variables such as:

- **Cost Breakdown Analysis:** Frequency and depth of cost breakdown analyses conducted (Kampker et al., 2023) as part of sourcing negotiations before and after the implementation of supportive intelligence like (AI and ML).
- **Total Cost of Ownership (TCO):** A comparative study of Total Cost Of Ownership estimates the all-direct cost of purchasing products or services for practical use as suggested by (Scorrano & Giansoldati, 2020) with and without the support of AI and ML, measured through case studies and historical contract analyses.
- **Best Alternative to a Negotiated Agreement (BATNA):**
- The quantification of BATNA (Bolkan & Goodboy, 2021) in terms of money saved or additional value created in contracts due to the enhanced strategic position available. and effective use of AI and ML insights to find the BATNA.

**4. Lean Thinking in Procurement:**

To operationalize lean thinking principles within the FBN framework, we can measure:

- **Process Efficiency:** Through time-motion studies and process mapping to identify waste before and after the implementation of supportive intelligence technologies.
- **Value Creation:** By evaluating sourcing outcomes in terms of value added to the organization through efficiency gains, cost reductions, and improved supplier relationships.

**5. Impact and Application of AI and ML:**

To measure the impact of AI and ML, we will utilize:

1. **Negotiation Trade-Offs:** Analysis of negotiation outcomes where AI-informed strategies were used, measured by the quality of trade-offs.
2. **Predictive Analytics:**

3. Quantitative measurement forecasts the accuracy of decision-making quality improvements achieved with ML algorithms.

**6. Principled Negotiation Framework:**

Principled negotiation can be operationalized by examining the following:

- **Mutual Interest Focus:** Qualitative Analysis of negotiation tactics focusing on collaborative goals instead of positional bargaining, measured through interview narratives and negotiation transcripts.
- **Objective Criteria:** Evaluating the consistency and justification of decisions made during FBN that align with established standards and quantifiable data.

By transforming these theoretical constructs into measurable variables, we overlay the way toward empirical research that can analytically assess the benefits and challenges of integrating AI and ML into FBN. This operationalization serves as a crucial step for collecting and analyzing data systematically and drawing meaningful conclusions that will inform best practices and recommendations for practitioners in the field.

### 3.3 Research Purpose and Questions

The purpose of "Enhancing Sourcing Efficacy through Fact-Based Negotiation: The Role of Supportive Intelligence" is to provide an in-depth analysis of how Artificial Intelligence (AI) and Machine Learning (ML) can support procurement professionals to enhance the effectiveness of Fact-Based Negotiation (FBN). This project aims to create a nuanced understanding of the transformative potential of these integrations and the benefits they can bring to organizations regarding improved negotiation strategies and outcomes. It focuses on developing and evaluating a comprehensive framework that synergizes the principles of FBN with the advanced analytical capabilities of AI and ML within a lean thinking context. The ultimate goal is to propose actionable guidelines that drive sourcing efficiency, optimize cost, improve decision-making precision, and increase business performance by harnessing the strategic advantages of supportive intelligence in FBN.

**Research Questions**

Based on the previously outlined research purpose, the study is guided by research questions designed to delve into specific aspects of integrating AI and ML with FBN. These queries aim to dissect the intricacies of the topic comprehensively and comprehensively:

**Survey** Questions are captured in **Annexure A** and Interview Questions in **Annexure B**.

The answers to questions captured in Annexure A & will elucidate the role of supportive intelligence in revolutionizing FBN and sourcing methodologies. By addressing each query through comprehensive research methods, the study will contribute significant insights and recommendations for refining procurement operations in today's data-driven (Mandl & Minner, 2023) dynamic global market environment.

## 3.4 Research Design

The research design for "Enhancing Sourcing Efficacy through Fact-Based Negotiation: The Role of Supportive Intelligence" is a multi-method approach incorporating qualitative and quantitative elements. This mixed-method design was selected to explore the intricate nature of AI and ML integration into Fact-Based Negotiation (FBN) and to comprehensively capture the impacts across various industry sectors. The design includes literature review synthesis, data collection through primary and secondary sources, thematic and statistical Analysis, and developing and testing a comprehensive FBN framework.

**Literature Review Synthesis:** The research started with an extensive synthesis of existing literature on Fact-Based Negotiation (FBN), AI, and ML in sourcing and applying lean thinking principles. This step grounded the study in current academic thought and industry practices and identifies gaps in knowledge to which the research can contribute.

**Data Collection:** Data will be collected utilizing both qualitative and quantitative methods:

- **Qualitative Data:** In-depth interviews and surveys with procurement, sales, HR, and legal professionals from various industries were planned to understand their experiences and perceptions of AI and ML's role in FBN. The survey sample size was targeted at 200-215 participants. Interview with ~ 15 % of the survey participants count different sets of professionals from procurement, sales, HR, and legal professionals to ensure a breadth of perspectives. The survey included Likert-scale questions and open-ended responses to capture nuanced views (Allison et al., 2002) on Fact-Based Negotiation (FBN), AI/ML utility, challenges, and current adoption. The interview protocol consisted of structured and semi-structured questions.
- **Quantitative Data:** Data extraction from corporate databases, published reports, and case studies were planned to obtain metrics relating to sourcing outcomes, such as cost savings, time-to-negotiate, and success rates post AI/ML integration.

**Analysis:** The data collected was analyzed using appropriate methodologies:

**Thematic Analysis** was used to interpret qualitative data from interviews and surveys, identifying patterns and themes that emerge concerning the adoption and impact of AI and ML in FBN.

**Statistical Analysis:** Quantitative data was analyzed to assess outcomes associated with Fact-Based Negotiation (FBN), AI, and ML integration using Data visualization, Exploratory data analysis (EDA), Regression analysis, t-tests, ANOVA, Correlation Matrix, Various model evaluations Like KNN, Naive Bayes, Random Forest, Logistic Regression, LDA and other relevant statistical methods to draw meaningful inferences about effectiveness and efficiency gains.

**Lean Integration:** The research examined how lean principles can be incorporated into the Fact-Based Negotiation (FBN) process to identify non-value-adding activities and eliminate waste. Lean Integration will be achieved by mapping negotiation processes before and after AI/ML implementation.

**Framework Development:** As an outcome of this study, a comprehensive framework was created to guide organizations in effectively integrating AI, ML, and lean principles with Fact-Based Negotiation (FBN) methodologies.

**Pilot Testing:** The framework will be subjected to pilot testing within organizations willing to adopt this integrated approach to sourcing. The results of the pilot tests will support further refinement of the framework.

**Project Schedule:** The research follows a detailed timeline with specific milestones for conducting the literature review, data collection, data analysis, development and pilot testing of the FBN framework, and dissemination of the findings.

By employing this mixed-method research design, the study aspires to yield a rich, empirical understanding of how AI and ML can transform Fact-Based Negotiation (FBN) and deliver a pragmatic guide for industry professionals looking to innovate within their sourcing and procurement operations.

### 3.5 Population and Sample

For the research study "Enhancing Sourcing Efficacy through Fact-Based Negotiation: The Role of Supportive Intelligence," it was crucial to define both the population and the sample that would be examined to gain insightful results related to the integration of AI and ML into Fact-Based Negotiation (FBN) processes.

**Population:**

The population in this research refers to the entire group of individuals or entities relevant to the topic under investigation. For this study, the population included:

1. **Procurement Professionals:** These individuals are actively involved in procurement and sourcing within organizations; they possess varying degrees of experience and expertise in negotiation, supply chain management, and the use of technology in these processes.

2. **Legal, Sales, and HR Professionals:** These individuals are actively involved in their respective domains within organizations, possessing varying degrees of experience and expertise in negotiation and the use of technology in these processes.
3. **Organizations Engaged in FBN:** Entities that employ FBN strategies in their procurement operations and those interested in or currently integrating AI and ML technologies into such strategies.
4. **AI and ML Technology Providers:** Companies and developers that provide AI and ML tools, technologies, and platforms specifically designed for procurement and negotiations.
5. **Industry Experts and Academics:** Individuals who have substantial knowledge or have conducted research in the fields of procurement, AI, ML, and FBN.

The research targeted a broad spectrum of industries to ensure a comprehensive understanding of FBN implementation across diverse market sectors, including manufacturing, service industries, healthcare, technology, etc.

**Sample:**

The sample represents a subset of the population selected for actual participation in the study. In this case, the sample consists of:

**200-215 Professionals from Procurement, Sales, Legal, and HR for Survey and an Additional 15% of a new set of professionals for Interview:** A purposive sampling strategy was employed to select professionals who represent a cross-section of the population in terms of industry, experience, role, and engagement with Fact-Based Negotiation (FBN), AI and ML technologies. The goal was to gather a broad range of insights into the practical applications, challenges, and benefits of AI and ML in FBN.

**Experts and Academics:** A select group of industry experts and academics was consulted to provide a deeper theoretical and contextual understanding of the subject matter. They contributed through interviews, panel discussions, or consultations as part of qualitative data collection.

The sample selection process aimed for diversity to allow for the generalization of the findings and ensure that a specific type of industry or size of organization does not bias the results. Inclusion criteria were clear and transparent to maintain the study's integrity and the validity of its conclusions. The samples for interviews, surveys, and case studies were strategically chosen to gather rich, detailed, and varied data that reflect the current landscape of Fact-Based Negotiation (FBN) and the role of supportive intelligence in procurement and sourcing.

### 3.6 Participant Selection

The study's participant selection followed a systematic and purposeful approach designed to ensure that the individuals selected represent a broad and relevant range of experiences related to Fact-Based Negotiation (FBN) and the integration of AI/ML within the procurement, sales, legal, and HR processes.

The selection was made by engaging professionals, including CPOs, Heads of Sourcing, CEOs, CIOs, Directors of Legal, Sales Heads, VPs, and Managers in the respective domains.

The interviews were scheduled based on the convenience of the participants in a conducive setting to encourage open dialogue (Guo et al., 2024). Such an environment provides not only respect for the participants' time and commitments but also contributes to a more relaxed to give their best view on the research topic.

**Criteria for Selection:**

- **Experience in Procurement:** Participants should have good experience in procurement to ensure they possess a foundational understanding of procurement processes and negotiation strategies.
- **Experience in HR, Legal, and Sales:** Participants should have good experience in relevant domains like HR, Legal, and Sales and possess a required understanding of fact-based negotiation processes and strategies.

- **Engagement with AI and ML:** Preference will be given to those with direct experience with or exposure to AI and ML applications in sourcing and procurement.
- **Diversity in Industry Representation:** The participant group should span various industries to ensure the study captures various perspectives and practices concerning FBN and supportive intelligence technologies.
- **Organizational Role:** To glean insights from different levels of the procurement hierarchy, a diverse array of procurement roles—from front-line negotiators to senior procurement strategists and decision-makers—will be included.
- **Geographic Location:** Participants from different regions and markets will be considered to incorporate a global perspective on sourcing strategies and adopting AI and ML technologies.
- **Size and Type of Organization:** The study will aim to include participants from large, medium, and small organizations, as well as from different types such as private, public, non-profit, and multinational corporations and different industries, to understand the impact of organizational variability.

**Sampling Methods:**

- **Purposive Sampling:** This strategy will be employed to select individuals who meet the specific criteria set for the study, ensuring the sample represents the necessary expertise and backgrounds (Campbell et al., 2020).
- **Snowball Sampling:** Participants interviewed or surveyed might recommend other potential participants who fit the study criteria (Leighton et al., 2021), expanding the pool of knowledgeable candidates through their professional networks.

**Recruitment of Participants:**

- **Professional Networks and Associations:** Procurement and other professionals will be recruited via professional networks, online forums, and associations related to procurement, sourcing, and supply chain management.

- **Outreach to Organizations:** Companies known to use Fact-Based Negotiation (FBN) and those recognized for their innovative use of AI and ML in procurement will be contacted to identify suitable participants within their staff.
- **Academic and Industry Conferences:** Events where experts convene to discuss procurement strategies and technological advancements will be opportune places for recruiting participants.
- **Social media and Professional Platforms:** LinkedIn and other professional social media platforms will be utilized to identify and approach potential participants who have experience with FBN and AI/ML in procurement.

**Inclusion and Exclusion Criteria:**

- **Inclusion:** Most Participants must be currently or recently (within the last five years) active in procurement, HR, legal, or sales. They must be willing to provide informed consent and communicate in the language used for the study.
- **Exclusion:** Individuals who do not interact with FBN or are unfamiliar with AI and ML in a professional sourcing context may be excluded, as their insights may not align with the study's objectives.

The research aimed to compose a participant pool rich in experience and perspectives by adhering to these selection principles. This diversity contributed to the depth and validity of the findings, allowing the study to provide comprehensive insights into the impact of AI and ML on FBN practices across different organizational and industry contexts.

### 3.7 Instrumentation

This study adopted a comprehensive instrumentation strategy to ensure the collection of rich, multi-faceted data (Lewis et al., 2016). The study used semi-structured interviews and surveys as the primary tools for gathering participants' data based on the findings from various types of qualitative research literature. The interviews were conducted following the advice of Hunt et al. (2011); the surveys were designed and conducted by referring to the comprehensive guide of Rea and Parker (2014) to probe deeply into the domain experiences of the participants in Fact-based negotiation, Adoption of AI/ML to improved sourcing efficacy.

Primary data was collected through surveys and interviews; the study also engaged in document analysis, reviewing a range of materials, including organizational documents, industry reports, and academic journal articles (Tracy, 2024; Bowen, 2009). Based on Cooksey et al. (2019), this way of gathering data enabled a triangulation method that improved the trustworthiness and accuracy of the study's results (Gibson., 2017). The study gained additional context and corroborative evidence (Varpio et al., 2017) that enriched the Analysis by examining relevant documents related to Fact-based negotiation, AI/ML, and Sourcing efficacy.

Throughout the data collection process, careful attention was paid to establishing a comfortable and open environment for participants (Hunt et al., 2011). This is to ensure the participants felt at ease sharing their experiences candidly, contributing to the richness and authenticity of the data collected (Heath et al., 2018).

The study followed the principles of professional responsibility (Kang et al., 2021) to ensure strictly followed ethical conduct. All participants received the utmost respect, and all data was managed privately and honestly.

To verify the data's reliability, practicality, and accuracy, a methodological triangulation approach, combining data from different sources, such as surveys, interviews, document analysis, and observations, was used (Natow, 2020).

An Analytical framework for this study was guided by the framework method, which is suited for applied research and allows for both deductive and inductive theme development (Gale et al., 2013). This methodical way of analyzing the data ensures that the results are based on the factual evidence gathered (Tracy & Sarah, 2024), improving the study’s accuracy and dependability. The following instruments will provide the means for data collection and Analysis:

**Qualitative Instruments:** In-depth Interview Guides: Semi-structured interview guides will be developed, containing open-ended questions that probe into participants' experiences with AI and ML in FBN. These guides will facilitate detailed discussions on technology use, challenges, and benefits in negotiations and will be flexible enough to explore unexpected topics that arise during interviews.

**Quantitative Instruments:** Surveys and Questionnaires: Standardized questionnaires will collect quantitative data on perceived usefulness, ease of use, attitudes, subjective norms, and intentions to use AI and ML in FBN practices. These questionnaires will include Likert scale items and multiple-choice questions to assess critical theoretical constructs quantitatively.

**Analytical Tools:**

1. **Thematic Analysis Software**: Software such as Maxqda or Word Cloud in Python may facilitate the organization and thematic coding of qualitative data gathered from interviews and textual responses in questionnaires.
2. **Statistical Analysis Software:** Statistical packages such as Python and KNIME will be employed to perform Regression analysis, t-tests, ANOVA, Correlation Matrix, Various model evaluations like KNN, Naive Bayes, Random Forest, Logistic Regression, LDA, and other relevant statistical methods on quantitative data, and Data visualization using Tableau Software. This software will aid in modeling relationships between variables and determining the significance and magnitude of observed effects.

### 3.8 Data Collection Procedures

The interview and survey method were carefully chosen for this study because it can generate deep participants' understanding. Semi-structured interviews provided a conversational and focused platform, allowing for an exploration of the nuances of fact-based negotiation, AI/ML, and sourcing efficacy within participant's organizations. This format (LeBlanc, 2010) encouraged a structured conversation that prompted participants to reveal in-depth perspectives on their experiences, ensuring that all relevant topics were discussed while enabling the discovery of new themes.

A detailed survey and interview protocol were developed and included in the research documentation's appendix. This protocol helped as a comprehensive guide outlining the interview structure, instrumental in ensuring consistency across the surveys and interviews.

**Instrument Validation:** Instruments like surveys and interview guides will be pre-tested with a small subset of the target population to ensure clarity, relevance, and reliability, as recommended by (Taherdoost, 2016). Based on the feedback received, required adjustments will be made.

**Ethical research practices:** Ethical research practices were followed strictly, including informing the participants of the study's goals, the privacy of their answers, and their rights as research subjects before the start of the interviews. This transparency is essential for ethical research (Kang et al., 2021).

**Participant Recruitment:** Potential participants will be identified and contacted based on the selection criteria. Outreach activities involve professional networks, industry events, and direct contacts within organizations.

**Informed Consent:** Clear and detailed consent will be obtained during the interview, including a detailed explanation of the study's purpose, what participation entails, confidentiality measures, and the participant's rights will be distributed, and consent will be obtained before data collection begins (Singer, 1993).

**Data Management:** To ensure the correctness and accuracy of the gathered data, the interviews and surveys were recorded using digital devices. This approach captured the richness of participants' responses but also facilitated detailed transcription and Analysis, as highlighted by (Saldana, 2015). Securely store all collected qualitative and quantitative data using encrypted digital repositories by adhering to the standard cyber security guidelines to ensure confidentiality and comply with data protection regulations.

### 3.9 Data Analysis

The data analysis for "Enhancing Sourcing Efficacy through Fact-Based Negotiation: The Role of Supportive Intelligence" seeks to synthesize qualitative and quantitative data to extract meaningful insights. A detailed and systematic approach ensures that the findings are rigorous and can inform the development of an integrated Fact-based negotiation framework. Here is a step-by-step breakdown of the data analysis procedures.

**Preparation for Data Analysis:**

1. **Data Cleaning:** The initial step involves thoroughly checking the collected data for any errors, inconsistencies, or missing responses, especially in quantitative datasets, and cleaning it accordingly.
2. **Data Transcription:** All recorded qualitative data from interviews and focus group discussions will be transcribed verbatim. Observational notes will also be compiled and prepared for Analysis.
3. **Data Organization:** Data will be organized systematically, with quantitative data entered into spreadsheets or statistical software databases and qualitative data imported into text analysis software.

**Qualitative Data Analysis:**

**Coding Process:**

1. Implement an initial open coding process on a sample of the qualitative data to generate a list of codes reflecting the recurring themes and concepts.
2. Develop a coding scheme that categorizes these codes into broader themes relevant to the research questions. This process could be iterative, refining the scheme as more data is coded using Python.
3. Thematic Analysis:
4. Software such as Maxqda or a Word cloud in Python may facilitate the organization and thematic coding of qualitative data gathered from interviews and textual responses in questionnaires.

**Quantitative Data Analysis:**

- Descriptive Statistics: Calculate descriptive statistics, such as measures of central tendency and variability, to summarize the characteristics of the data.

- Inferential Statistics: Utilize inferential statistical methods, including regression analysis, to examine relationships between variables and hypothesis testing (e.g., t-tests, ANOVA) to compare groups or conditions within the data.
- Modeling and Prediction: If applicable, statistical models can be used to predict the impact of AI and ML on FBN efficacy or to identify key predictors of successful technology adoption in procurement processes.

**Integration of Qualitative and Quantitative Findings:**

- Comparative Analysis: Compare and contrast results from qualitative and quantitative analyses to identify convergence and divergence in the findings.
- Triangulation: Perform triangulation by cross-verifying the data from different sources or methods, enhancing the credibility and validity of the research findings.
- Synthesis and Interpretation: Synthesize the results into a coherent interpretation that addresses the research purpose and questions, linking to the theoretical framework and literature review.

**Reporting and Visualization:**

- Data Visualization: Employ graphical representations such as charts, graphs, and tables to present quantitative findings in an accessible manner.
- Narrative Reporting: Develop a narrative structure to communicate qualitative findings, often incorporating direct quotes from participants to illustrate critical points.
- Framework Development: Use insights from the data analysis to inform the creation of the proposed FBN framework, detailing how AI and ML can be integrated into procurement negotiation processes.

By meticulously conducting the data analysis following these outlined procedures, the study provides an empirically grounded understanding of the role of supportive intelligence in enhancing Fact-based negotiation. The analytical rigor significantly contributea to establishing evidence-based recommendations for business practices and theoretical contributions to procurement and negotiation literature.

### 3.9 Research Design Limitations

The comprehensive research design outlined for "Enhancing Sourcing Efficacy through Fact-Based Negotiation: The Role of Supportive Intelligence" incorporates a mixed-methods approach to explore the integration of AI and ML in FBN strategies. Despite the robustness of this design, it is essential to acknowledge and understand potential limitations that may influence the research outcomes. Aware of these limitations can lead to a more critical interpretation of the results and can guide future research. The following are several limitations intrinsic to the research design:

**1. Sample Diversity and Size:**

- While efforts will be made to ensure a diverse sample from various industries and geographic locations, reaching a fully representative cross-section of the procurement professional population may be constrained.
- The targeted sample size for the survey (200-215 participants and in-person interview with 15 % of the Survey participants count from different sets of participants) may not be sufficient to generalize findings across all sectors and sizes of organizations, especially considering the vast differences that exist in organizational cultures and practices.

**2. Self-Reporting Bias:**

- Reliance on self-reported data, particularly from surveys and interviews, introduces the possibility of biases, including social desirability bias, recall bias, or the tendency of participants to give responses they believe are expected of them (Krohn et al., 2013).

**3. Cross-Sectional Design:**

- The design is predominantly cross-sectional, which may not capture the longitudinal impacts of AI and ML integration in procurement negotiations. The long-term effects and adoption rates may thus be underrepresented in the study findings.

**4. Subjectivity in Qualitative Analysis:**

- Despite rigorous coding and thematic analysis procedures, interpreting qualitative data involves a certain degree of subjectivity, which could affect the consistency of findings. Researcher bias can inadvertently influence the categorization and Analysis of qualitative data.

**5. Limitations of Quantitative Measures:**

- The complexity and ever-evolving nature of AI and ML technologies may not need to be fully captured by the formulated survey questions or metrics, which could lead to an incomplete understanding of their use and impacts.

**6. Technological Rapid Evolution:**

- Given the rapid pace of technological advances in AI and ML, the research might quickly become outdated, and further enhanced studies may be required based on the evolution of technology.

**7. Impact of External Variables:**

- External factors such as changes in market conditions, regulatory environment (Demirel & Kesidou, 2019), and technological disruptions could influence the readiness and ability of organizations to adopt AI and ML in FBN, and these may not be controllable within the scope of the study design.

**8. Implementation Challenges:**

- Implementing AI and ML within FBN processes may face challenges beyond the theoretical framework proposed in this study, such as integration with existing legacy systems or resistance to change among personnel, which will not be fully explored.

Being transparent and mindful of these limitations is critical to providing a balanced and honest evaluation of the research findings. Addressing them proactively when possible or noting them for future research considerations adds to the integrity and robustness of the study.

### 3.10 Conclusion

The research study titled "Enhancing Sourcing Efficacy through Fact-Based Negotiation: The Role of Supportive Intelligence" aims to shed light on the integration of Artificial Intelligence (AI) and Machine Learning (ML) technologies within Fact-Based Negotiation (FBN) for optimizing procurement strategies. The conclusion of this study must encapsulate the findings, discuss the implications of these findings for both theory and practice, acknowledge the limitations, and suggest directions for future research.

**Findings:** The study is anticipated to yield several key findings:

- AI and ML can significantly enhance the FBN process, providing data-driven insights that empower procurement professionals to make more informed decisions.
- Integrating AI and ML with FBN aligns with the principles of lean thinking, streamlining the negotiation process by eliminating non-value-adding activities.
- Organizational culture, perceived usefulness, and ease of use are critical determinants of AI and ML adoption in FBN.
- The developed framework, born from rigorous data analysis and case studies, is expected to provide actionable guidelines that enhance the sourcing efficacy of organizations.

**Implications for Theory and Practice:**

- This study adds to the existing body of knowledge by providing empirical evidence on the role of supportive intelligence in enhancing FBN, confirming theoretical models such as TAM in a procurement context.
- It bridges academic research with practical implications, suggesting organizations can gain a competitive edge by adopting AI and ML in negotiations.
- The study offers a precedent for a systematic method to incorporate technology into traditional sourcing strategies, potentially influencing organizational best practices.

**Limitations:**

- The research recognizes the intrinsic constraints imposed by sample diversity and size, self-reporting biases, and the potential obsolescence of findings due to the rapid evolution of technology.
- These limitations, alongside external variables and pilot testing constraints, provide context for the findings, underscoring the need for circumspect interpretation and application.

In conclusion, "Enhancing Sourcing Efficacy through Fact-Based Negotiation: The Role of Supportive Intelligence" is primed to significantly contribute to procurement practice and the strategic deployment of FBN within the modern landscape of business negotiations. It demonstrates a clear path forward for the application of AI and ML, encourages continuous innovation in procurement strategies, and lays the groundwork for future research in this dynamic and critical field.

# CHAPTER IV: RESULTS

## 4.1 Introduction

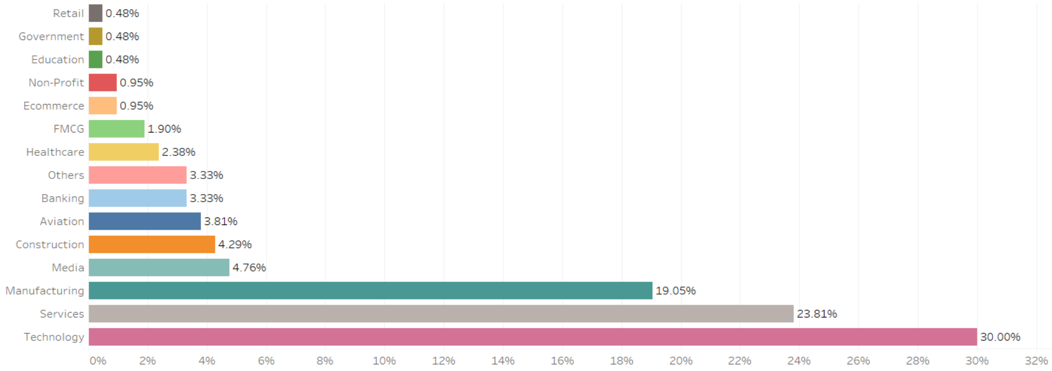
This chapter systematically unfolds the outcomes derived from the qualitative research conducted with key personnel engaged in Negotiations from various functional domains like SCM-Procurement, Sales, Technology, HR and Legal professionals across industries Retail, Government, Education, Non-profit, ecommerce, FMCG, Healthcare, Banking, Aviation, Construction, Media, Manufacturing, Services, Technology and Others not captured in the above industries.

This comprehensive study explored the enhancement of sourcing efficacy through fact-based negotiation, with a particular focus on the role of supportive intelligence. The results elucidated in this chapter are grounded in extensive data collection, including a survey conducted with 210 participants and 33 in-depth person-to-person interviews, which collectively offer a robust understanding of current trends, perceptions, and practices in the field of procurement. The survey participants, spanning various industries and functional domains, provided a profound snapshot into the current landscape of procurement practices. The participant pool was meticulously curated to incorporate a diverse range of organizational types, thereby ensuring a comprehensive representation across multiple sectors.

## 4.2 Survey results

As evidenced in Figure 4, the survey respondents represented a wide spectrum of organizational types.

**Figure 4:** Organization Type of Survey Participants




The survey data presented in Figure 4 reveals the diverse range of industries and organization types represented. The largest segment of participants, at 30.00%, comes from the technology sector reflecting the growing importance and prevalence of technology-driven organizations in the contemporary business landscape (Büyükbalcı et al., 2021). The second-largest cohort, comprising 23.81% of respondents, is from the services industry, highlighting the significant role that service-oriented organizations play in the overall sample. The manufacturing sector also holds a substantial presence, accounting for 19.05% of the participants, underscoring the continued relevance and influence of traditional industrial enterprises. The media sector, at 4.76%, represents a smaller but still noteworthy component of the survey, indicating its representation among the participating organizations. The remaining industries, including construction, aviation, banking, healthcare, FMCG, e-commerce, non-profit, education, government, and retail, collectively make up the "Other Industries" category, which encompasses a diverse array of economic activities and organizational types. The data presented in Figure 4 provides a comprehensive overview of the organization types represented in the study, offering a valuable snapshot of the varying industry compositions and their relative proportions within the overall sample. This distribution underscores the pervasive relevance of procurement across diverse organizational contexts, each with unique challenges and opportunities influencing their sourcing strategies and negotiation approaches.

Delving deeper, the functional domains of the survey participants were predominantly skewed towards Supply Chain Management (SCM) and Procurement (51.43%), as shown in Figure 5.

**Figure 5:** Functional Domain of Survey Participants

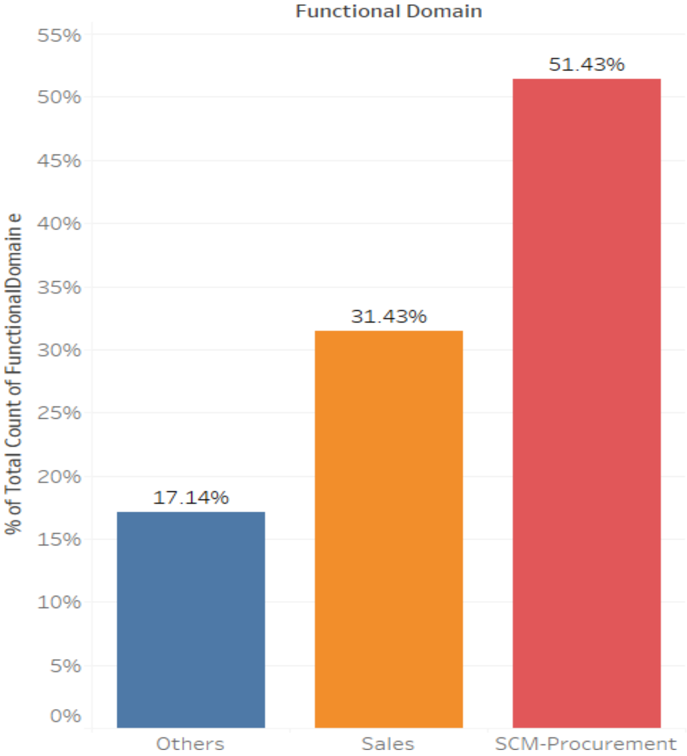
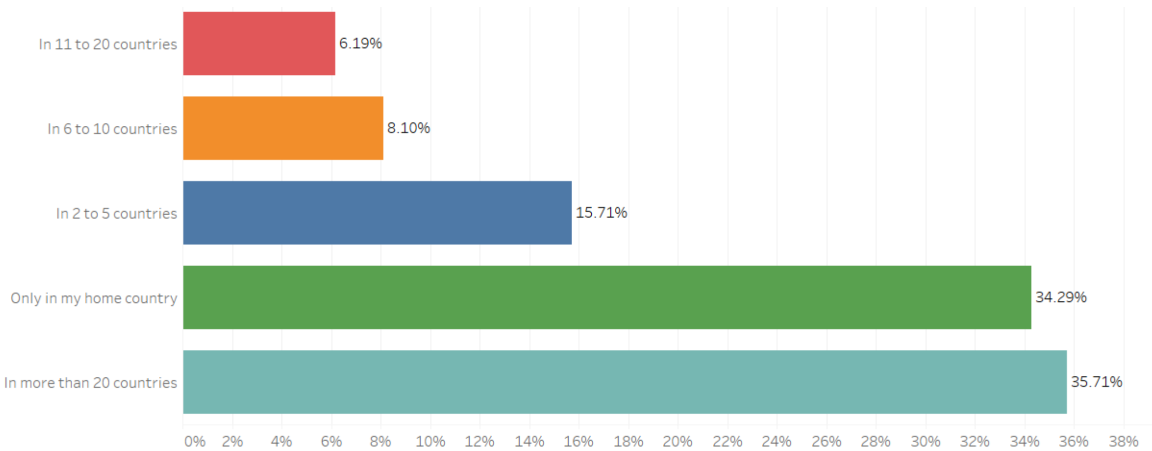



Figure 5 highlights the primary focus of the participants' roles in the procurement and sourcing sphere. Sales professionals constituted the second-largest group at 31.43%, followed by others at 17.14%. The substantial representation from SCM and sales domains reinforces the integral role these functions play in negotiating and managing supplier relationships. SCM and procurement professionals are particularly pivotal, as their decisions directly impact cost efficiencies, supply continuity, and overall organizational resilience. Conversely, sales professionals provide a distinctive perspective on negotiation dynamics, having honed skills to secure advantageous terms and foster productive partnerships. The second most represented functional domain is Sales, comprising 31.43% of the participants. This substantial representation underscores the importance of sales functions in the organizations. The 'Others' category, which includes HR and Legal, makes up 17.14% of the participants, suggesting a diverse array of additional functions not specifically categorized under SCM-Procurement or

Sales. These findings align with the existing literature on the relationships between various functional domains, such as supply chain management, logistics, marketing, production, and operations management. Effective cross-functional collaboration, particularly in the areas of sourcing and procurement, has been identified as a key success factor for organizations (Driedonks et al., 2014; Chan, & Chin, 2007).

The distribution of organizations based on the number of countries where they operate, as illustrated in Figure 6, paints a compelling picture of the global reach and diversification of the participant organizations.

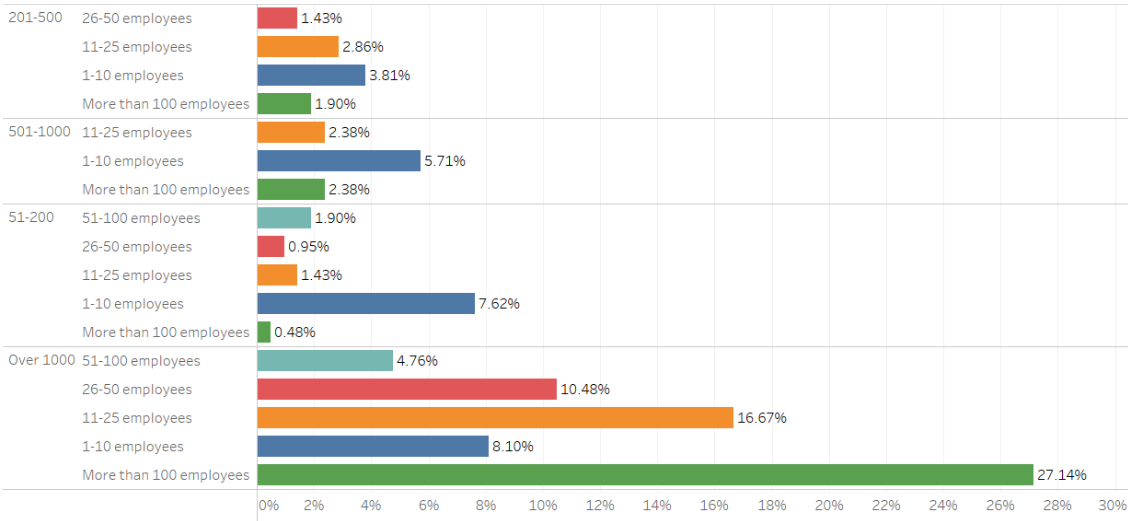
**Figure 6:** Number of Countries Survey Participants Organizations Operate




The data suggests that a significant portion of these organizations have a substantial international presence, with 35.71% operating in more than 20 countries. This aligns with the notion that as firms grow, they tend to expand their operations across borders, often driven by the pursuit of new markets and resources (Hennart, 2007). At the same time, the findings also indicate that a substantial proportion (34.29%) of the organizations operate solely within their home country. This may be reflective of the regional nature of many multinational enterprises, as previous research has shown that the largest firms tend to be more regionally focused rather than truly global in their geographic distribution of sales (Qi, 2009). The data further reveals that 15.71% of the organizations operate in 2 to 5 countries, 8.10% in 6 to 10 countries, and 6.19% in 11 to 20 countries, suggesting varying degrees of international diversification among the participant organizations (Zander, 2015).

Figure 7 illustrates the distribution of survey participants based on their organization's total employee size and the size of their department.

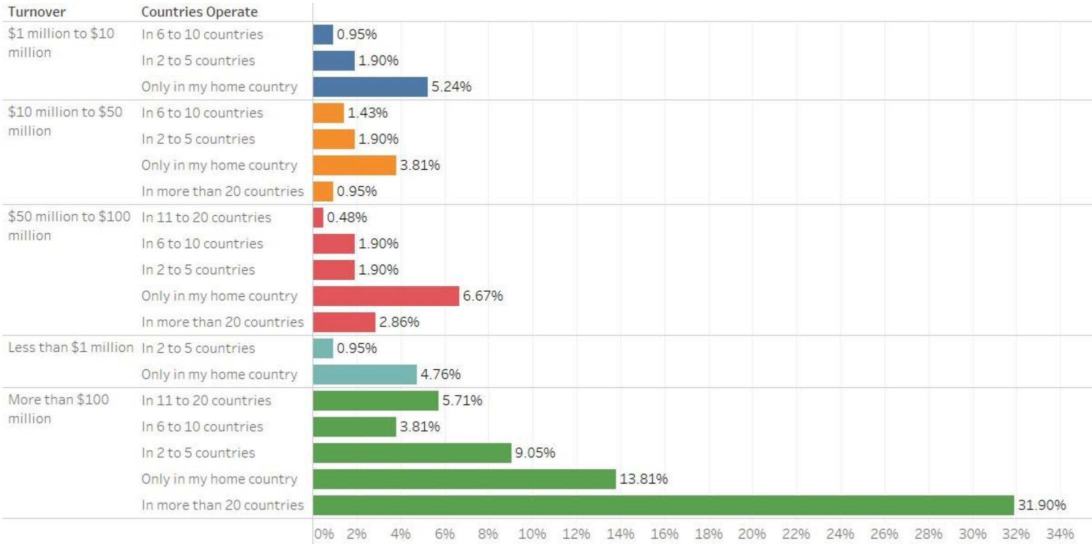
**Figure 7:** Organizations total Employee Size and Department Size of Survey Participants




Organizations of varying sizes exhibit distinct patterns in the distribution of department sizes within their structures. The most prominent group is from organizations with over 1000 employees, specifically departments having more than 100 employees (27.14%). This category makes up the largest single grouping, accounting for 27.14% of all departments (Irwansyah, 2021). Departments with 11-25 employees within the same organization size bracket are the second-largest group, representing 16.67% of the total it could be due to nature of the business. In contrast, smaller organizations tend to have fewer large departments. This emphasis on relatively smaller departmental sizes in organizations with lower employee counts suggests a correlation between overall organizational size and the distribution of department sizes (Mijušković & Todorović-Spasenić, 2020).

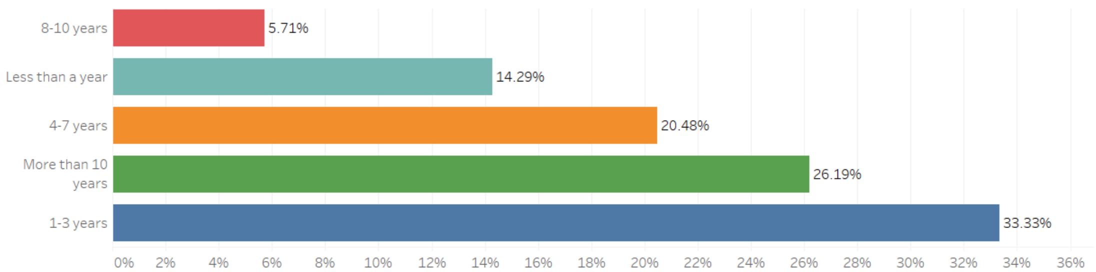
Figure 8 illustrates the relationship between a business's turnover and its geographical reach, as measured by the number of countries in which it operates.

**Figure 8:** Turnover by countries




Businesses with higher turnovers, particularly those in the "$50 million to $100 million" and "More than $100 million" categories, demonstrate a strong tendency to operate in a larger number of countries, from More than $100 Million Turnover organizations 31.90 % operate in more than 20 countries and 5.71 % operate in 11 to 20 countries. Conversely, businesses with lower turnovers, such as those in the "Less than $1 million" category, tend to concentrate on their operations primarily within their home country or a limited number of countries (Jackson, 2008).

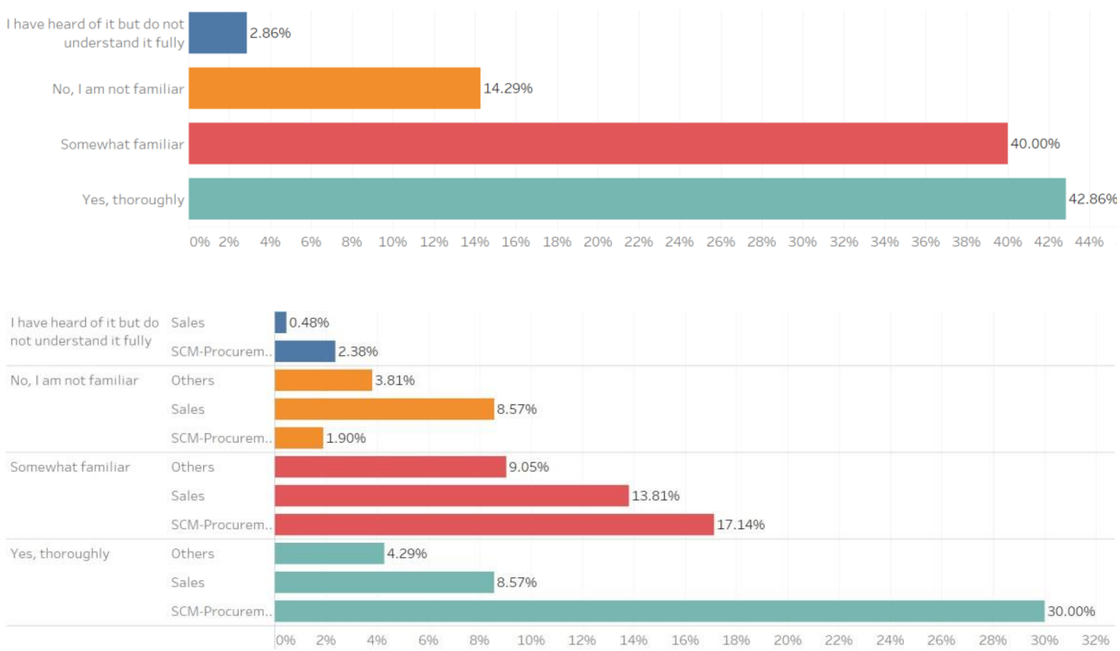
**Figure 9:** Duration of Survey Participants in the Current Organization




The duration of an employee's tenure within an organization can have a significant impact on their level of engagement (Markos & Sridevi, 2010; Shahid & Azhar, 2013), overall job performance and will have clear visibility of how the organization functions. The largest group of survey participants (33.33%) had been with the organization for 1 to 3 years, suggesting that this tenure length is quite common among the employees (Saks, 2006). The second-largest group (26.19%), consisted of long-term employees who had been with the organization for more than 10 years, highlighting a significant portion of the workforce with extensive tenure (Shahid & Azhar, 2013). The remaining participants were distributed among other tenure categories as follows: 20.48% had been employed for 4 to 7 years, 14.29% for less than a year, and 5.71% had been with the organization for 8 to 10 years.

The survey results presented in Figure 10 offer valuable insights into the varying levels of familiarity with the concept of Fact-Based Negotiation among the participants.

**Figure 10:** Familiarity with the concept of Fact-Based Negotiation (FBN)

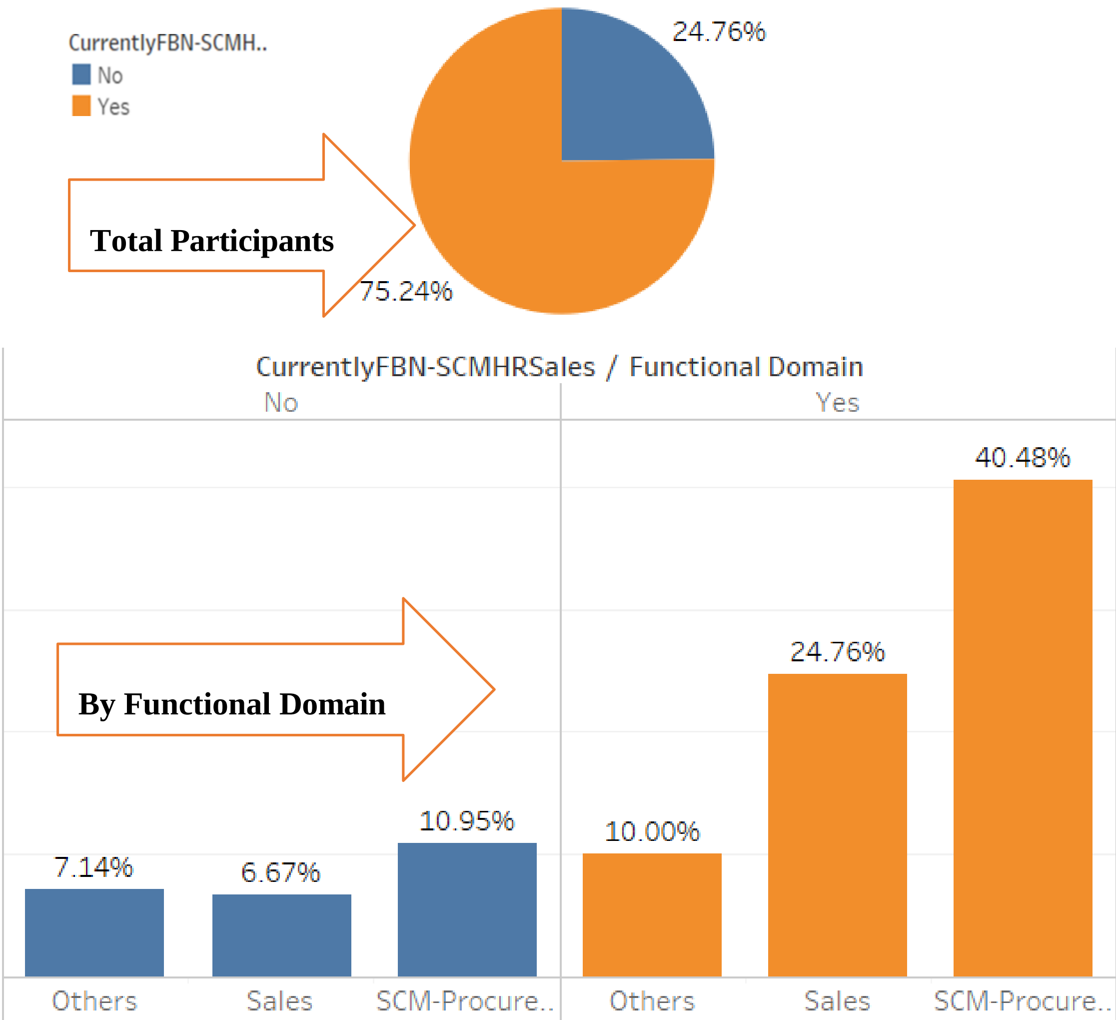



The data revels significant portion of the respondents, nearly 43%, demonstrate a thorough understanding of FBN, 40% respondents have “somewhat familiar” Total of 83% of the participants in the category of “thoroughly and somewhat familiar” with the concept of Fact-Based Negotiation. Remains 17 % notable minority who either lack familiarity or have only a partial grasp of the concept (Brett and Mitchell, 2019). Delving deeper into the segmentation by functional domain, the data reveals some interesting patterns. Respondents from the Sales and SCM-Procurement domains exhibit higher levels of familiarity, with 8.57%

and 17.14% reporting a "Thoroughly Familiar" understanding, respectively. In contrast, the "Others" category, which encompasses participants from outside these two domains, shows a lower level of familiarity, with only 9.05% being "Thoroughly Familiar." Conversely, the "Not Familiar" segment is more prominent among the Sales (8.57%) and "Others" (3.81%) groups, compared to the SCM-Procurement domain (1.90%).

Figure 11 provides insights into the Survey participants Currently using Fact-Based Negotiation (FBN) across different functional domains.

**Figure 11:** Currently use of Fact-Based Negotiation (FBN) In SCM-Procurement, Sales & Other Functional Domains



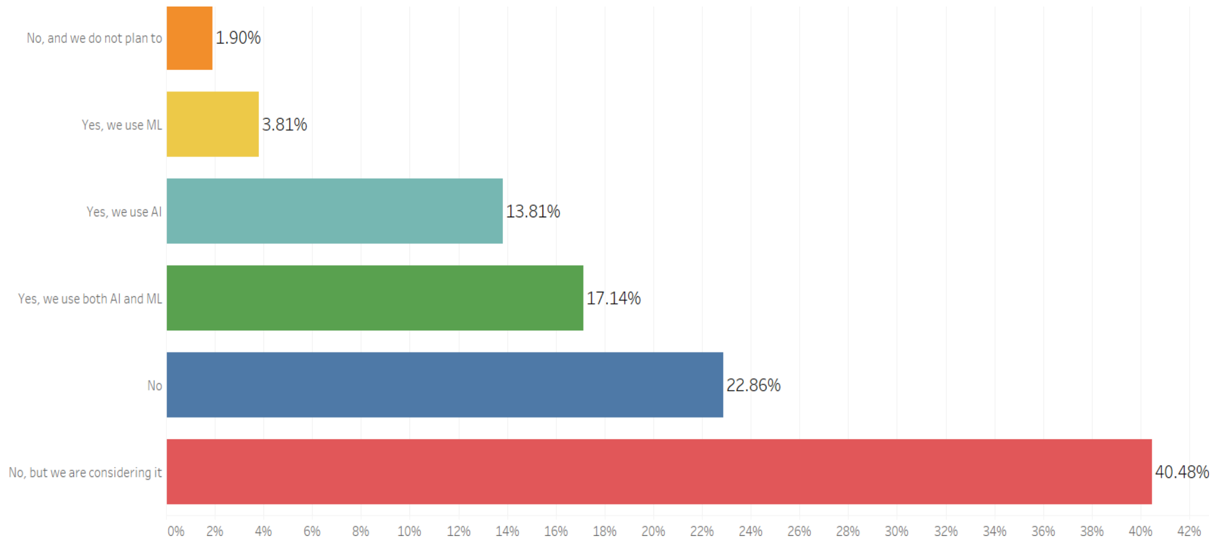

The survey outcome reveals that a significant majority (75.24%) of the participants Currently using Fact-Based Negotiation (FBN), while the remaining 24.76% are not using

Fact-Based Negotiation (FBN). Delving deeper into the domain-specific trends, the SCM-Procurement function emerges as the clear leader, with 40.48% of participants actively employing Fact-Based Negotiation. This high level of usage underscores the perceived value and applicability of this approach within the procurement and supply chain management context. The Sales domain also exhibits a significant level of Fact-Based Negotiation adoption, with 24.76% of respondents reporting its utilization. The "Others" category, encompassing a range of miscellaneous functional domains, displays a relatively lower rate of Fact-Based Negotiation usage at 10.00%. This could indicate that the diffusion of this negotiation approach has been less pronounced in certain specialized or niche areas (Shapiro, 2000; Mayer & Voeth, 2021).

Further analysis of the data reveals that the level participants currently not using Fact-Based Negotiation (FBN) at across different functional domains it varies across different functional domains. 10.95% "SCM-Procurement", 6.67 % of "Sales" domain and "Others" category contributing to 7.14 %. These findings suggest that Fact-Based Negotiation is more widely recognized and utilized within certain functional areas, particularly in the "SCM-Procurement" domain, where the concept appears to be more established and understood by a larger proportion of the participants (Ayantoyinbo & Oguntola, 2020).

The growing adoption of Artificial Intelligence and Machine Learning technologies within organizations to support Fact-Based Negotiation has been a topic of increasing interest. Figure 12 provides a comprehensive snapshot of survey participants' perspectives on their organizations' current and plans regarding the implementation of these innovative tools (Ma et al., 2024; Westermann et al., 2023).

**Figure 12:** Survey participants view on the organization's adoption of AI and/or ML to support Fact-Based Negotiation (FBN)




The data indicates a mixed landscape, with a notable percentage of organizations already leveraging both AI and ML or employing either technology individually to enhance their negotiation processes (Carneiro et al., 2012; Buch et al., 2022). However, the survey also reveals a significant portion of respondents whose organizations are still in the contemplation phase, suggesting a robust potential for future growth in the utilization of these technologies. Approximately a quarter of the respondents reported that their organizations are not currently using AI or ML, while a small fraction stated that they have no plans for adoption, highlighting areas that may require additional awareness or readiness for technological integration (Kassekert, et al., 2022).

The findings from this survey align with broader trends observed in the literature. Researchers have highlighted the potential for AI and emerging human augmentation technologies to enhance diplomatic and negotiation practices, enabling the automation of certain tasks, the leveraging of big data, and the facilitation of more efficient and effective decision-making (Buch et al., 2022). At the same time, the integration of AI into negotiation processes has raised considerations around confidentiality, model bias, and the need for collaboration among diplomats, scientists, and engineers to ensure responsible deployment and integration.

**Hypothesis 1 (H1): Integrating AI and ML into FBN could significantly increase the efficiency and effectiveness of sourcing negotiations.**

The hypothesis that integrating AI and ML in Fact-Based Negotiation could significantly increase the efficiency and effectiveness of sourcing negotiations is supported by the survey findings and the broader academic literature. Organizations that have already adopted these technologies have reported improvements in their negotiation processes, while those in the contemplation phase may benefit from increased awareness and readiness for technological integration. Examining the Utilization of Artificial Intelligence and Machine Learning in Fact-Based Negotiation: A Comprehensive Survey's Revealing Insights The adoption of Artificial Intelligence and Machine Learning technologies within organizations to support (FBN) has been a topic of growing interest. The data indicates a mixed landscape, with a notable percentage of organizations already leveraging both AI and ML or employing either technology individually to enhance their negotiation processes. However, the survey also reveals a significant portion of respondents whose organizations are still in the contemplation phase, suggesting a robust potential for future growth in the utilization of these technologies. Approximately a quarter of the respondents reported that their organizations are not currently using AI or ML, while a small fraction stated that they have no plans for adoption, highlighting areas that may require additional awareness or readiness for technological integration (Bughin et al., 2017).

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As organizations continue to navigate the evolving landscape of Fact-Based Negotiation, the insights provided by this survey can inform strategic planning and guide the responsible adoption of AI and ML technologies. By fostering collaborations between negotiators, scientists, and engineers, and implementing comprehensive training and resource distribution programs, organizations can harness the power of these innovative tools while addressing the unique challenges and considerations that arise (Westermann et al., 2023; Alessa, 2022).

**Hypothesis 2 (H2):** When combined with FBN and supportive intelligence technologies, Lean thinking principles could reduce negotiation cycle times and simplify procurement processes.

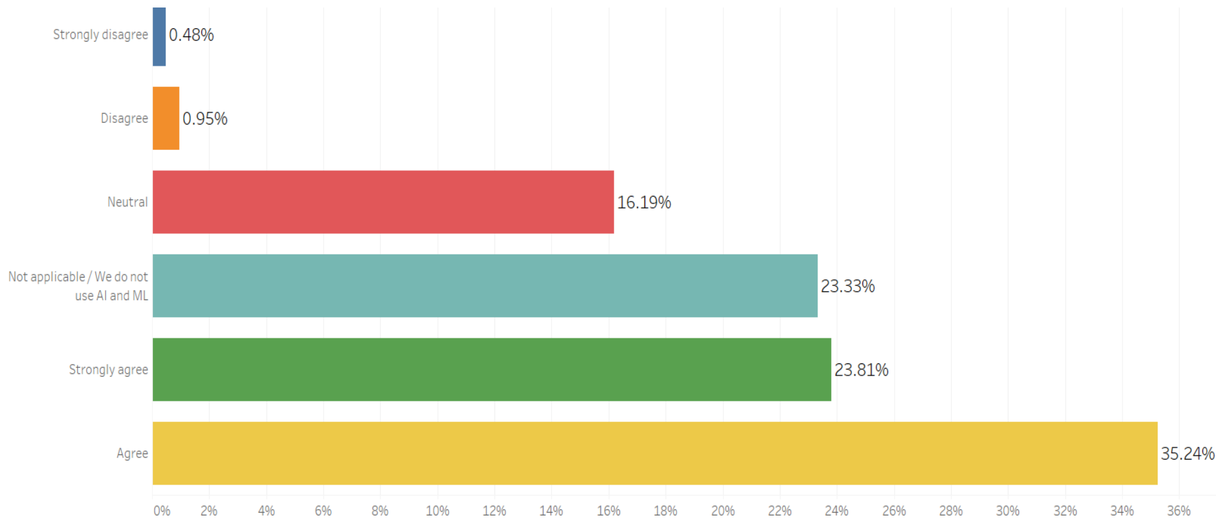
Hypothesis 2 (H2) suggests that the combination of FBN, supportive intelligence technologies, and Lean thinking principles could lead to a reduction in negotiation cycle times and a simplification of procurement processes. The survey data presented in Figure 13 provides substantial support for this hypothesis, with over 59% of respondents agreeing or strongly agreeing that this integration could yield the desired outcomes.

The survey findings suggest that most respondents who are familiar with and utilizing AI and ML in their workflows believe that the proposed integration can be beneficial. However, a significant portion of respondents (23.33%) indicated that the hypothesis was not applicable to them or their organization, which suggests that there may be room for increased adoption or further study of these technologies in procurement and negotiation processes (Allal et al., 2021).

The success factors and challenges identified in the literature (Angeles & Nath, 2007) highlight the importance of supplier and contract management, end-user behavior, and information and infrastructure in effective e-procurement implementation. By integrating FBN, supportive intelligence, and Lean thinking principles, organizations may be able to address these critical factors and streamline their procurement workflows.

The survey data gathered insights into the levels of experience with fact-based negotiations across various professional domains, including procurement, sales, and human resources. The distribution of experience levels, as depicted in Figure 14, provides a nuanced understanding of the proficiency and familiarity of these professionals with this negotiation approach (Geiger, 2017).

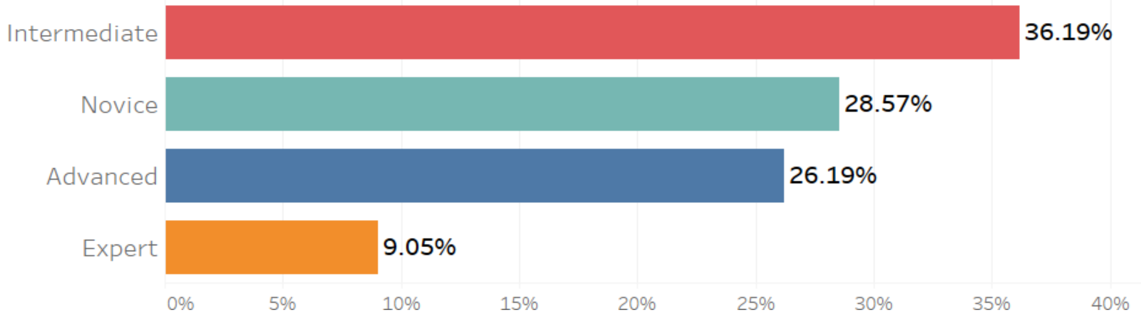
**Figure 13:** Integration of FBN with Supportive Intelligence, Lean thinking Principles could reduce negotiation cycle and improve negotiation efficiency.




Integration of FBN with Supportive Intelligence and Lean Thinking Principles: Reducing Negotiation Cycle Times and Simplifying Procurement Processes

The procurement process is a critical aspect of business operations, as it directly impacts the timely acquisition of necessary resources and supplies. Recent research has highlighted the potential benefits of integrating emerging technologies, such as FBN (presumably a technology or framework) and supportive intelligence, with Lean thinking principles to streamline procurement processes (Alabdali and Salam, 2022; Tripathi and Gupta, 2021).

**Figure 14:** Level of experience with fact-based negotiations in Procurement/Sales/HR negotiation activities of survey participants

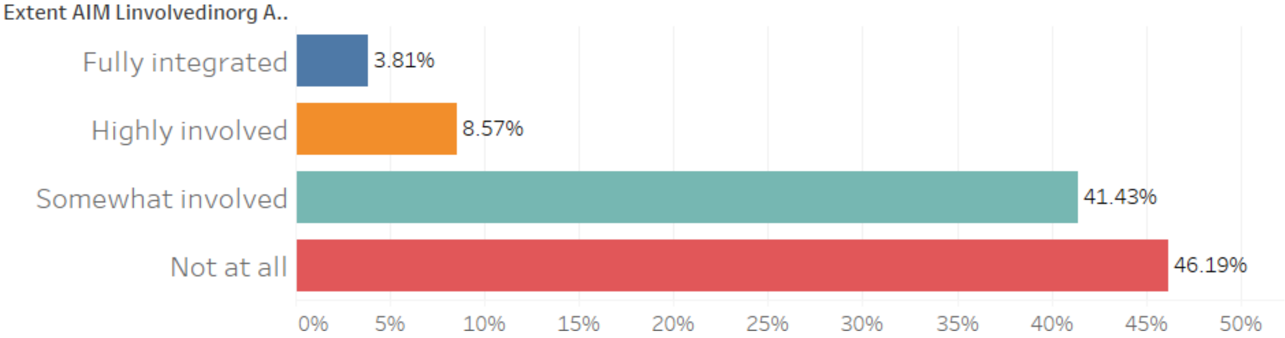



The largest group of participants identified themselves as having intermediate experience with fact-based negotiations, comprising 36.19% of the respondents. This suggests that while a significant portion of professionals are beyond the novice stage, they are still in the process of fully mastering fact-based negotiation techniques (Mandel, 2019). The inclusion of this group underscores the need for ongoing training and development initiatives to enhance their skills in this area (Fortgang, 2000). Novice practitioners made up 28.57% of the respondents, indicating a substantial presence of individuals who are relatively new to the concept and practice of fact-based negotiation. This highlights the importance of providing comprehensive training and support to help these professionals develop the necessary skills and confidence to leverage data-driven insights in their negotiation activities. Participants with advanced experience constituted 26.19% of the survey group. These individuals have a higher level of expertise and are likely adept at leveraging data and analytical insights to drive negotiation outcomes. Their presence underscores the value that advanced practitioners bring to organizations through their sophisticated understanding of negotiation dynamics (Mayer & Voeth, 2022; Mandel, 2019). Lastly, 9.05% of the participants identified as experts in fact-based negotiation. These highly skilled professionals have a deep understanding of the nuances and best practices associated with this negotiation approach, and they can serve as mentors and trainers to help others develop their proficiency (Fortgang, 2000; Geiger, 2017).

These findings align with the existing body of research on the importance of effective communication and negotiation skills in various business contexts. Successful negotiation requires a diverse set of strategies and tactics, including the ability to leverage data and analytical insights to support one's position. As noted in the literature, even experienced negotiation practitioners may benefit from ongoing training and development to enhance their skills (Mandel, 2019).

Figure 15 provides insights into the extent to which artificial intelligence and machine learning technologies are currently integrated into the procurement, sales, and human resources negotiation activities within the surveyed organizations, highlighting the evolving role of advanced technologies in shaping modern negotiation practices.

**Figure 15:** To what extent is AI and ML technology currently involved survey participants organization's Procurement/Sales/HR negotiation activities?

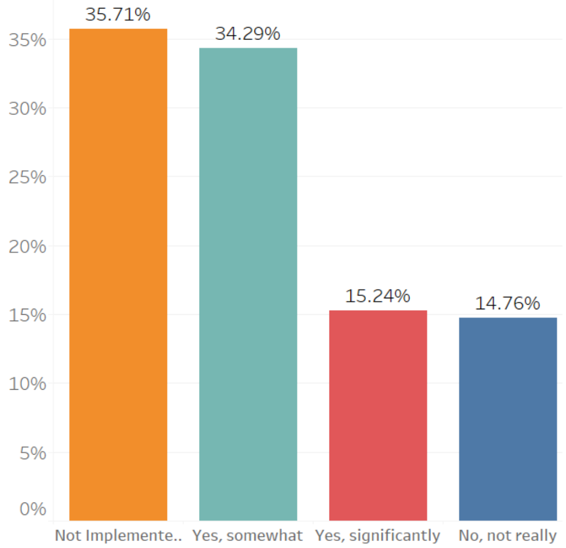



The data reveals a mixed picture, with a significant portion of organizations yet to fully embrace these technologies in their negotiation processes. Specifically, 46.19% of the respondents reported that AI and ML are not at all involved in their negotiation activities, suggesting a considerable opportunity for growth and adoption. (Kshetri, 2021) On the other hand, only 3.81% of the organizations have fully integrated these technologies, likely leveraging advanced analytics, predictive modeling, and automation to drive more data-driven and efficient negotiation processes. (Rodgers & Nguyen, 2022) A notable 41.43% of participants indicated that AI and ML are somewhat involved in their negotiation activities, representing a gradual integration that may reflect a cautious approach or a phased implementation strategy. Lastly, 8.57% of the respondents reported that AI and ML are highly involved in their organizations' negotiation activities, potentially utilizing these tools to generate insights, optimizing negotiation strategies, and automating.

**Hypothesis 3 (H3):** Organizations employing a data-driven FBN model will demonstrate greater adaptability, and strategic precision in their sourcing negotiations than traditional negotiation techniques

The survey findings presented in Figure 16 offer valuable insights into the participants' perceptions of the effectiveness of data-driven FBN models on negotiation outcomes.

**Figure 16:** Survey participants view on Organizations employing Data-Driven FBN Model will demonstrate favorable outcomes in negotiations?



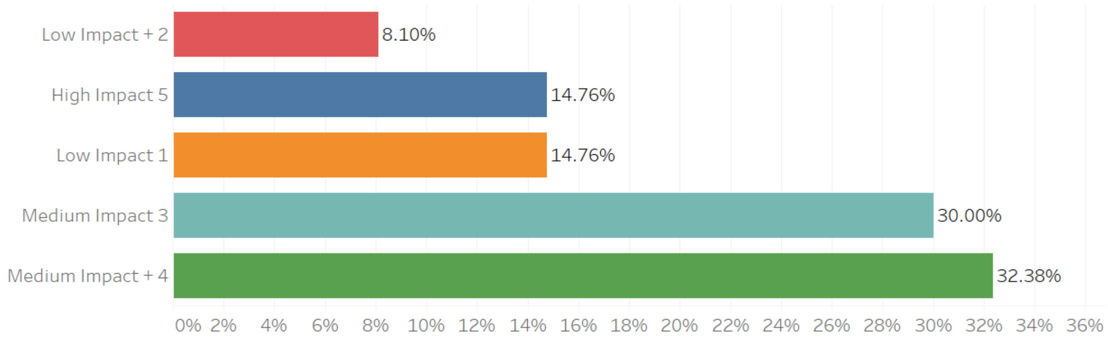

Negotiations are a critical aspect of business operations, particularly in the realm of sourcing and procurement. Hypothesis 3 (H3) posits that organizations employing a data-driven Fact-Based Negotiation model will demonstrate greater adaptability and strategic precision in their sourcing negotiations compared to traditional negotiation techniques. To validate this hypothesis, we examine the views of survey participants on the effectiveness of data-driven FBN models (Jagodzińska, 2020; Kim & Fragale, 2005).

Approximately 35.71% of the respondents indicated that their organizations had not implemented a data-driven FBN model, providing a neutral baseline for comparison. (Vitasek, 2016) A significant portion, 34.29%, agreed that organizations employing a data-driven FBN model will somewhat demonstrate favourable outcomes in negotiations, recognizing the partial benefits that such approaches can bring. Furthermore, 15.24% of the respondents strongly agreed that organizations employing a data-driven FBN model will significantly demonstrate favourable outcomes in negotiations, most respondents excluding the “Not Implemented” Category 35.71% (“Yes somewhat” 34.29% + “Yes, significantly” 15.24% = Total 49.53 %) believe that data-driven FBN models provide at least some level of advantage, with a significant portion showing strong support for this hypothesis. clearly believing in the considerable advantages and strategic precision that a data-driven FBN model can provide over traditional negotiation techniques (Talluri et al., 2008; Lee & Kwon, 2006; Moosmayer et al., 2013; Mayer & Voeth, 2021).

The use of cognitive maps and case-based reasoning in B2B negotiation has been explored, highlighting the importance of considering not only primary negotiation terms but also secondary negotiation terms, such as resource availability and corporate culture, which can contribute to effective negotiation decisions (Lee & Kwon, 2006). Additionally, neural network analysis has been shown to outperform regression analysis in predicting price negotiation outcomes in B2B contexts, demonstrating the non-linear and non-compensatory nature of the decisions involved. These findings suggest that organizations employing a data-driven FBN model can indeed demonstrate greater adaptability and strategic precision in their sourcing negotiations, as hypothesized.

Figure 17 provides insights into the perceived impact of AI and machine learning technologies on negotiation efficacy.

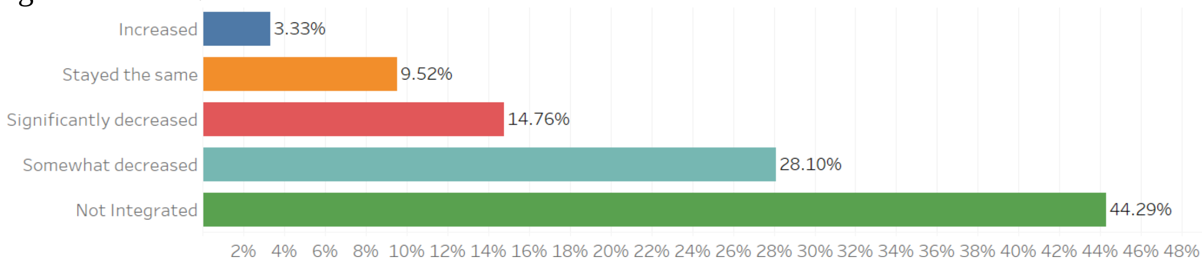
**Figure 17:** How Survey participants rated the impact of AI and ML on negotiation efficacy (Options: 1 being very low impact, 5 being very high impact)




The distribution of responses suggests a diverse range of perspectives, with participants rating the impact across the spectrum from very low to very high. A significant portion of the respondents (22.86%) perceived the impact of AI and ML on negotiation efficacy as low impact 1 or low impact +2. This aligns with the findings from (Krafft ., 2020), which indicate that the most common visions of the impact of AI elicit significant anxiety, with respondents feeling they have little control over its development. However, a larger segment (62.38%) rated the impact as moderate to very high, suggesting a general recognition of the favorable contributions of these technologies (Banerjee et al., 2021; Lane et al., 2023). The data indicates that 14.76% of respondents believe the impact of AI and ML on negotiation efficacy is very high, potentially representing organizations that have successfully integrated these technologies and are experiencing substantial benefits. This is consistent with the notion that, when responsibly deployed, AI and emerging human augmentation technologies can provide significant advantages for the practice of diplomacy (Buch et al, 2022). The distribution of responses also highlights a cluster of participants who perceive a moderate or moderately high impact of AI and ML on negotiation efficacy. This suggests a balanced view, acknowledging both the benefits and potential limitations of these technologies in enhancing negotiation processes. Overall, the data in Figure 17 suggests a generally positive outlook on the impact of AI and ML on negotiation efficacy, with a sizable portion of respondents recognizing the substantial benefits these technologies can bring. However, the presence of a significant minority who perceive minimal impact or even negative consequences underscores the need for careful integration and adoption of these technologies, as emphasized in the literature.

The integration of AI and ML into procurement, sales, and HR operations has the potential to significantly optimize negotiation processes. (Figure 18)

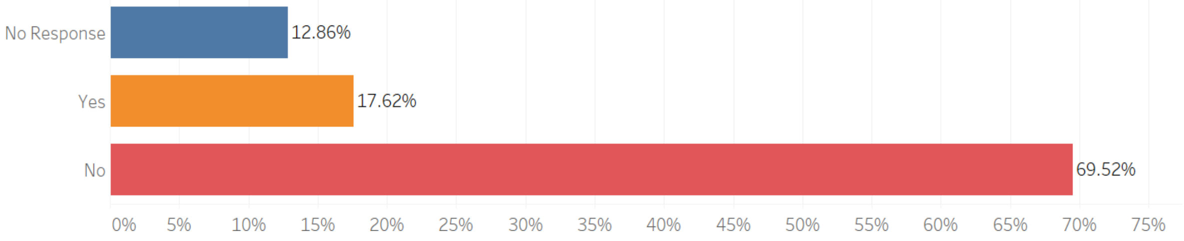
**Figure 18:** Integrating AI and ML into Procurement/Sales/HR operations optimized the negotiation time.




According to the survey results presented in Figure 18, a substantial 44.29% of respondents have not yet integrated these technologies, indicating a significant opportunity for organizations to explore and implement AI and ML solutions (Tewari & Pant, 2020). The data also reveals a positive trend, with 42.86% of respondents reporting a decrease (somewhat or significantly) in negotiation time after adopting AI and ML. This suggests that these technologies can lead to more streamlined negotiation processes and better resource allocation (Saxena, 2020; Tewari & Pant, 2020). However, the study also highlights some mixed results, with 9.52% of participants observing no change and 3.33% experiencing an increase in negotiation time. These findings underline the importance of proper implementation, adequate training, and the need for tailored AI solutions to address specific organizational needs. As organizations continue to integrate AI and ML into their operations, the potential for more substantial improvements in negotiation efficiency remains promising (Hemalatha et al., 2021).

Figure 19 presents survey participants' responses regarding the resistance or challenges their organizations faced when adopting AI and ML in procurement, sales, and HR operations.

**Figure 19:** Resistance or challenges survey participants organization faced when adopting AI and ML in Procurement/Sales/HR?




Understanding these challenges is crucial for addressing barriers and facilitating smoother integrations of advanced technologies. The data from Figure 19 provides several insights into the landscape of AI and ML adoption:

- **No**: 69.52% of respondents not encountering significant resistance suggests that many organizations are successfully navigating AI and ML integration, which could be due to effective change management strategies, strong leadership, and clear communication about the benefits of these technologies (Rožman et al., 2023).
- **Yes**: 17.62% of respondents who faced challenges highlight areas that need attention. Common challenges in AI and ML adoption may include employee resistance to change, lack of technical expertise, inadequate infrastructure, and cultural barriers that hinder successful implementation (Rožman et al., 2023; Khemka & Houck, 2024). These challenges underscore the importance of comprehensive change management, robust training and upskilling programs, and fostering a supportive organizational culture to enable seamless AI and ML integration.
- **No Response**: 12.86% of respondents did not provide a response, which can be interpreted in various ways. Some might lack sufficient experience with AI and ML adoption, while others may have found the question non-applicable or chose not to disclose their experiences.

The survey results indicate that while most organizations have had a relatively smooth transition in adopting AI and ML, a significant portion still face resistance and challenges.

Addressing these barriers through a multifaceted approach, including effective leadership, employee engagement, and strategic investment, can help organizations unlock the full potential of these transformative technologies. (Khemka & Houck, 2024; Sahni et al., 2023).

The survey findings presented in Figure 20 illuminate the diverse approaches organizations have taken to equip their employees with the necessary skills and resources to leverage AI and machine learning technologies in negotiations (Ma et al., 2024).

**Figure 20:** What types of training or support survey participants received to effectively use AI and ML in negotiations?


## Levels of AI/ML Integration and Training Investment

The variety of responses reflects the different stages of AI and ML adoption across organizations (Bughin et al., 2017). While some have established comprehensive training programs, others are still in the early stages or have not yet implemented these technologies. Some respondents indicated receiving only basic training and awareness-raising on AI/ML concepts and potential applications, suggesting a more limited integration of these technologies. (Ma et al., 2024) Others reported more robust internal training sessions tailored to their specific organizational needs, demonstrating a higher level of investment and prioritization.

### The Importance of Contextual, Internal Training

The prevalence of internal and on-the-job training sessions suggests that organizations recognize the value of contextualizing AI and ML training to their unique operational challenges and opportunities. Tailored internal programs can address specific organizational needs, making the training more relevant and effective for employees.

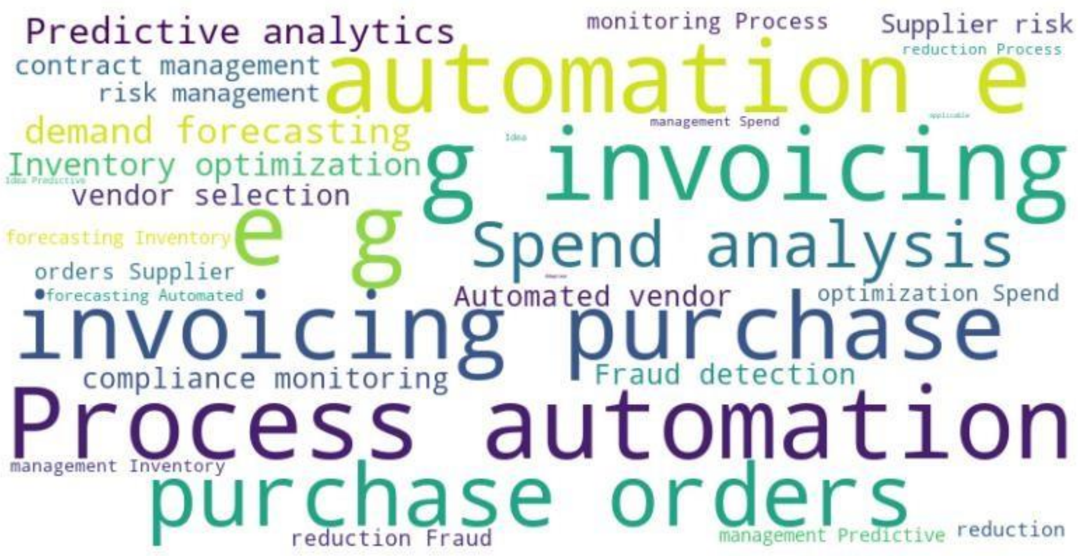
### Leveraging Digital Platforms for Training

A significant number of participants also mentioned attending digital dexterity programs or online training sessions. This indicates that organizations are leveraging digital platforms and resources to improve their workforce in AI and ML, potentially offering more scalable and accessible training solutions (Verhagen, 2021).

Overall, the survey findings highlight the diverse approaches to training and support for AI and ML usage in negotiations, reflecting the varying stages of adoption and organizational priorities (Bughin et al., 2017).

Figure 21 provides a compelling overview of the primary areas where AI and machine learning technologies can contribute to cost savings and value maximization within an organization's procurement, HR negotiation, and sales activities.

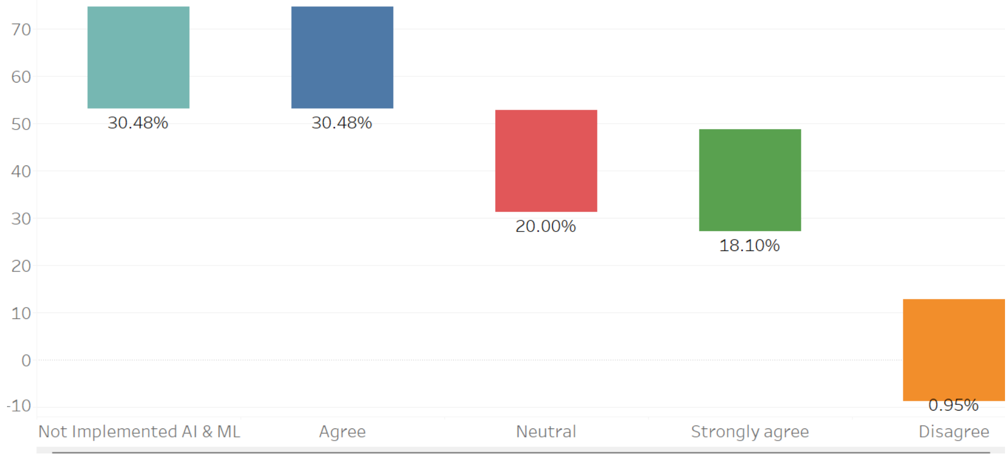
**Figure 21:** What are the primary areas in which AI and ML could contribute to cost savings within Procurement / HR negotiation activities, Value Maximization in Sales in your organization?




The responses highlight the significant impacts these emerging technologies can have on enhancing efficiency, reducing expenditures, and driving business performance. One of the key areas identified is the use of predictive analytics for demand (Tewari & Pant, 2020). AI and ML-powered tools can analyze vast amounts of data to accurately predict market needs, enabling organizations to manage inventory more effectively and minimize holding costs. Similarly, the application of AI and ML in spend analysis and reduction can help identify cost-saving opportunities, reduce waste, and negotiate better terms with suppliers. (Leyer & Schneider, 2021). Another prominent area of AI and ML contribution is the automation of vendor selection and contract management. Intelligent systems can streamline the vendor evaluation process, ensuring choices are based on data-driven insights, and automate various contract-related tasks, such as renewals and compliance monitoring, leading to improved efficiency and cost savings. (Khushalani & Woodcock, 2018). Inventory optimization is another significant domain where AI and ML can drive substantial impact. These technologies can help manage inventory levels more effectively by predicting stock requirements, minimizing overstock and stock outs, and consequently lowering associated costs (Helo & Hao, 2021). Additionally, the respondents highlighted the role of AI and ML in fraud detection and compliance monitoring. Advanced analytics capabilities can help organizations identify and mitigate fraudulent activities, as well as ensure adherence to regulatory requirements, reducing the risk of costly penalties and legal disputes (Hassan et al., 2023). The transformative potential of AI and ML in these critical areas is further underscored by the growing adoption of these technologies in various industries. The efficiency, speed, and automation provided by AI are increasingly being leveraged to yield significant competitive advantage and open new avenues for financial services, human resource management, and other business functions (Maple et al., 2023; Kshetri, 2021). As organizations continue to navigate the evolving digital landscape, the strategic integration of AI and ML into their procurement, HR negotiation, and sales activities will be crucial in driving cost savings, value maximization, and overall operational excellence.

The integration of artificial intelligence and machine learning technologies in negotiation processes has been a topic of growing interest, as organizations seek to enhance the objectivity and outcomes of their negotiations (Alessa, 2022). Figure 22 provides insights into survey participants' beliefs regarding the impact of these advanced technologies on negotiation dynamics.

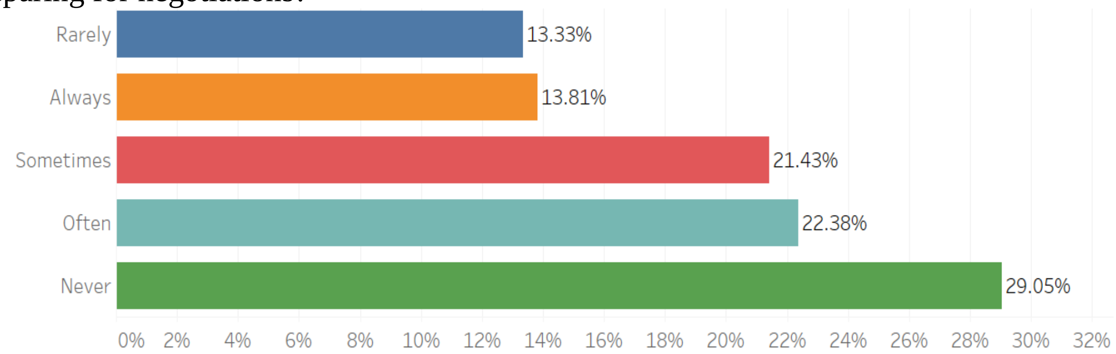
**Figure 22:** Do you believe that the use of AI and ML has improved the objective and outcomes of your negotiations?




The data reveals a mixed perspective among respondents. While a significant portion (30.48%) indicated that their organizations have not yet implemented AI and ML in negotiations, an equal percentage (30.48%) agreed that these technologies have improved the objectivity and outcomes of their negotiation activities. This suggests a positive sentiment toward the role of AI and ML in enhancing transparency, reducing subjective biases, and delivering more favorable negotiation results (Rodgers & Nguyen, 2022). Interestingly, a smaller group of respondents strongly agreed with the benefits of AI and ML, indicating that their organizations have fully integrated these technologies and are reaping substantial advantages. On the other hand, a small fraction of participants expressed disagreement, potentially due to implementation challenges or a lack of proper integration. The findings align with research that highlights the potential of AI and ML to transform the field of diplomacy and international negotiations. By automating cognitive tasks, leveraging big data, and empowering decision-making, these technologies can provide negotiators with data-driven insights and reduce the influence of human biases. At the same time, the responsible deployment and integration of AI and ML in negotiations requires careful consideration of the social and ethical implications, as highlighted by scholars (Krafft et al., 2019; Tomašev et al., 2020).

The use of data analytics and insights generated by artificial intelligence and machine learning has gained significant traction in the realm of negotiations. Figure 23 illustrates the frequency with which survey participants utilize these advanced tools when preparing for negotiations, providing valuable insights into the degree of integration and reliance on such technologies.

**Figure 23:** How often do you use data analytics and insights generated by AI and ML when preparing for negotiations?

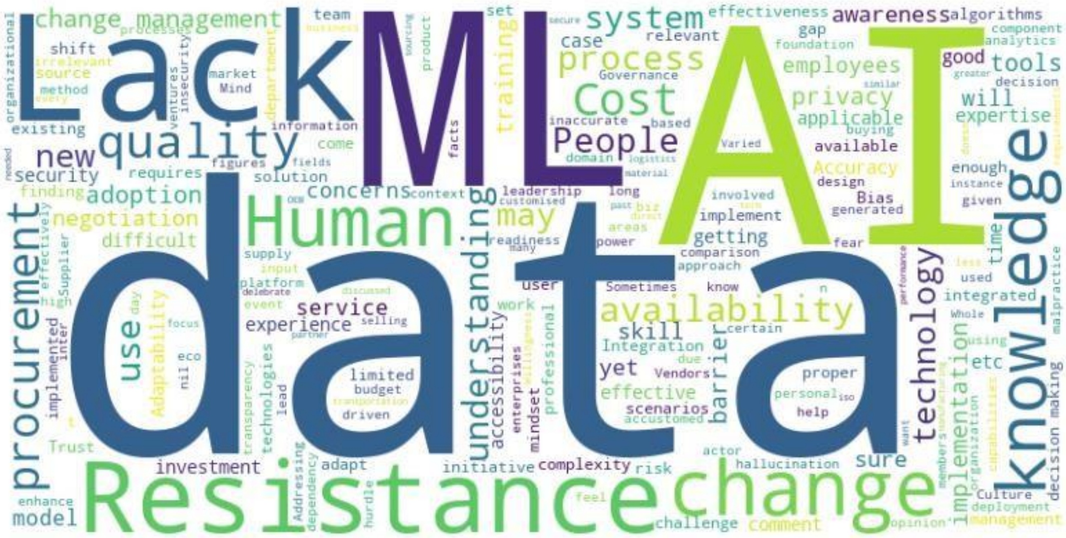


According to the responses, a substantial portion of 29.05% of participants never use data analytics and AI/ML insights in their negotiation preparation (Buch et al., 2022). This indicates a gap in the adoption of these technologies, potentially due to a lack of awareness or access to the benefits they can offer (DiClaudio, 2019). On the other hand, considerable 22.38% of respondents often integrate these insights into their negotiation strategies, demonstrating a recognition of their value in informing decision-making (Zulaikha et al., 2020). Furthermore, 13.81% of participants always rely on data analytics and AI/ML insights, suggesting a high level of integration and dependency on these tools to enhance their negotiation capabilities. The intermittent use of these technologies is evident, with 21.43% of participants report using them sometimes, while 13.33% use them rarely. These patterns suggest that the adoption and utilization of data analytics and AI/ML insights in negotiations are not yet universal, presenting an opportunity for further integration and education to unlock the full potential of these advanced tools (Zulaikha et al., 2020). As the global artificial intelligence market continues to grow, with spending on data analytics and business intelligence software expected to reach significant heights in the United States, the services sector has emerged as a significant consumer of predictive analytics software (Hoffman & Freyn, 2019). The integration of AI and human augmentation in diplomatic and negotiation processes has also been explored, highlighting the potential to automate and streamline tasks, leverage big data, and enhance decision-making efficiency (Usman et al., 2024).

By responsibly deploying and adopting these technologies, negotiators and policymakers can harness the power of data analytics and AI/ML insights to inform their strategies, make more informed decisions, and ultimately, achieve more successful negotiation outcomes (DiClaudio, 2019; Malliaroudaki & Zoumas, 2024).

Figure 24 provides a comprehensive overview of the perceived barriers that may hinder the effective integration of AI and ML technologies in domains such as procurement, HR, sales, and any other area where negotiations are applicable. These challenges reflect a wide range of organizational, technical, and cultural issues that need to be addressed to facilitate successful AI and ML implementation (Sen et al., 2021; Xing et al., 2023).

**Figure 24:** What are the top barriers that might prevent the effective use of AI and ML in Procurement /HR /Sales or in any Domain Negotiation is applicable?




The major barriers identified include access to the necessary technology and data, cost considerations, data quality and security concerns, and human factors and skills gaps (Callahan et al., 2017). Access to the appropriate technology and high-quality data remains a significant barrier, with responses indicating the difficulty in obtaining relevant and accurate data, which is crucial for effective AI and ML applications. The financial investment required for AI and ML technologies also emerges as a deterrent, particularly for smaller organizations with limited budgets. Concerns over data quality and security are also highlighted, emphasizing the importance of having reliable and secure data for the successful deployment of these technologies.

Additionally, human-related factors, such as bias, lack of skills, and the inability of teams to manage AI systems, underscore the need for upskilling and training employees to effectively leverage AI and ML in negotiations (Noranee & Othman, 2023; Vinuesa et al., 2020). The top 4 barriers identified that may prevent the effective use of AI and ML in procurement, HR, sales, or any domain where negotiations are applicable are based on the survey participants view:

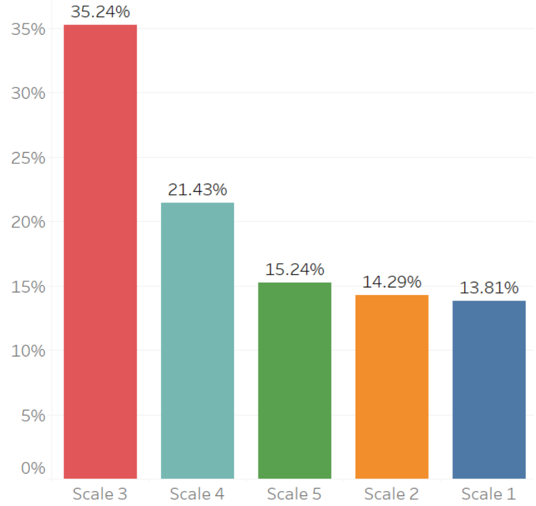
1. Access to Technology and Data: Organizations often struggle to obtain the necessary technology and high-quality, relevant data required for successful

implementation of AI and ML. Responses indicate challenges in accessing the appropriate tools and systems, as well as difficulties in gathering precise and accurate data, which is critical for powering these advanced technologies (Papagiannidis et al., 2023).

2. Cost Considerations: The financial investment needed for implementing and operating AI and ML technologies can be a significant barrier, especially for smaller organizations with limited budgets. Concerns around the overall cost of services, deployment, and achieving a suitable return on investment make the cost factor a major deterrent (Singh et al., 2020; Kar et al., 2021).
3. Data Quality and Security: Ensuring data quality and security is paramount for the effective use of AI and ML, but responses highlight challenges in this area. Issues such as poor data quality, data privacy concerns, and limited data accessibility can hinder the successful deployment of these technologies (Aldoseri et al., 2023; Gudivada et al., 2017).
4. Human Factors and Skills: AI and ML systems require specialized skills and the ability of teams to manage them effectively. However, responses indicate barriers related to human bias, lack of skills, and the inability of teams to properly utilize these advanced technologies. Addressing the skills gap through training and upskilling is crucial for overcoming this challenge (Arslan et al., 2022; Shneiderman, 2020).

The survey results depicted in Figure 25 provide insights into the confidence levels of participants regarding the accuracy and relevance of the intelligence generated by AI and machine learning technologies during negotiations.

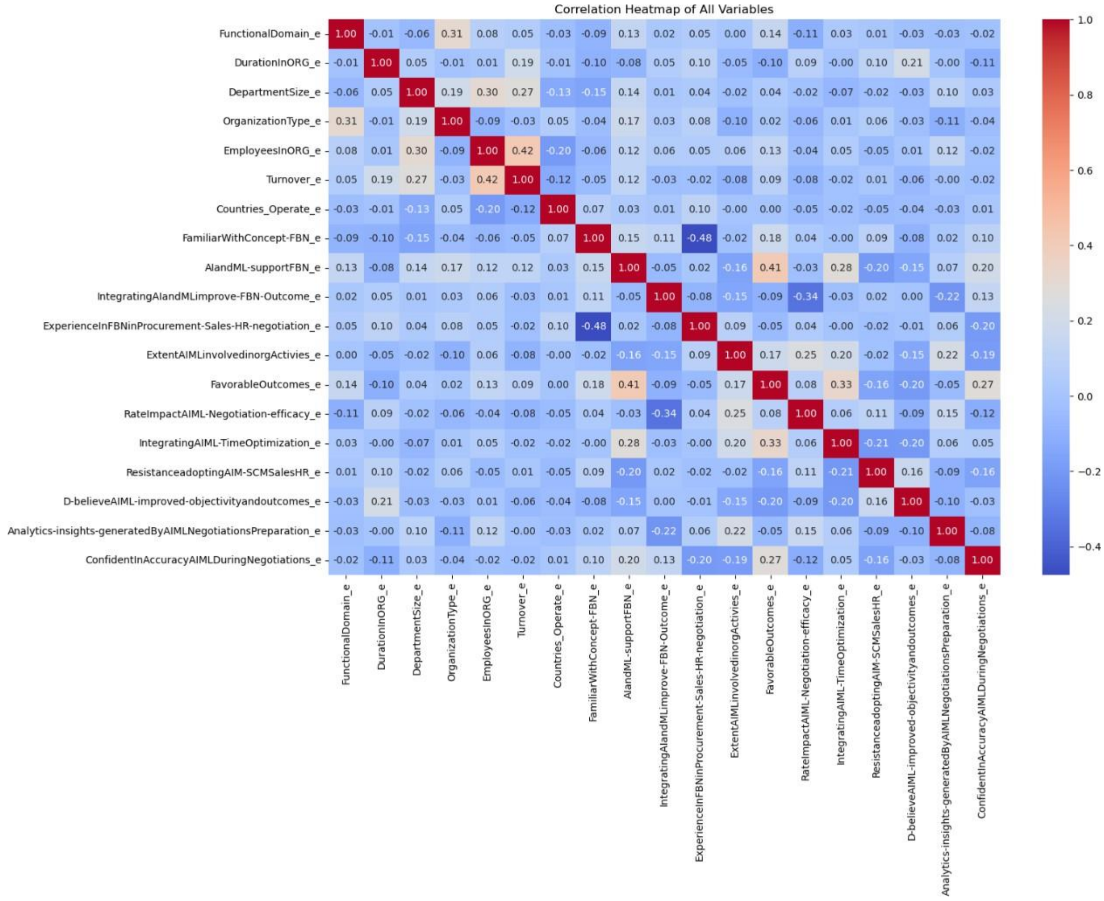
**Figure 25:** Survey participants confident in the accuracy and relevance of the intelligence provided by AI and ML technologies during negotiations? (Scale from 1 to 5 1 Minimum & 5 Scale Maximum outcome).




The data reveals a mixed landscape, with respondents expressing varying degrees of trust in these emerging technologies. The largest group, representing 35.24% of participants, rated their confidence at a mid-level, indicating a neutral stance towards the capabilities of AI and ML in providing useful intelligence for negotiations. This neutrality may stem from a combination of positive and negative experiences, leading to a cautious optimism about the technologies. At the lower end of the spectrum, 13.81% of respondents expressed minimum confidence, while 14.29% had relatively low confidence, suggesting that this group has encountered inaccuracies or harbors skepticism about the effectiveness of AI and ML in this context (Lane et al., 2023; Yakar et al., 2022). On the other end, 21.43% of participants rated their confidence as fairly high, indicating a more positive outlook on the accuracy and relevance of the intelligence provided by these technologies. An even smaller proportion, 15.24%, expressed maximum confidence, signaling that they consistently find the AI and ML-generated intelligence to be highly valuable in their negotiation processes. The mixed confidence levels observed in the survey results suggest that the integration of AI and ML technologies in negotiations is still a work in progress. While a significant portion of participants expressed mid-level or higher confidence, a notable percentage remained skeptical or exhibited lower trust (Kaya et al., 2022; Inie, 2024).

The correlation heatmap presented in Figure 26 provides a detailed visualization of the relationships between various factors influencing the adoption and efficacy of AI and ML in procurement, sales, and HR negotiations.

**Figure 26:** Correlation Analysis of Key Factors Influencing the Adoption of Fact-Based Negotiation and the Role of Supportive intelligence.

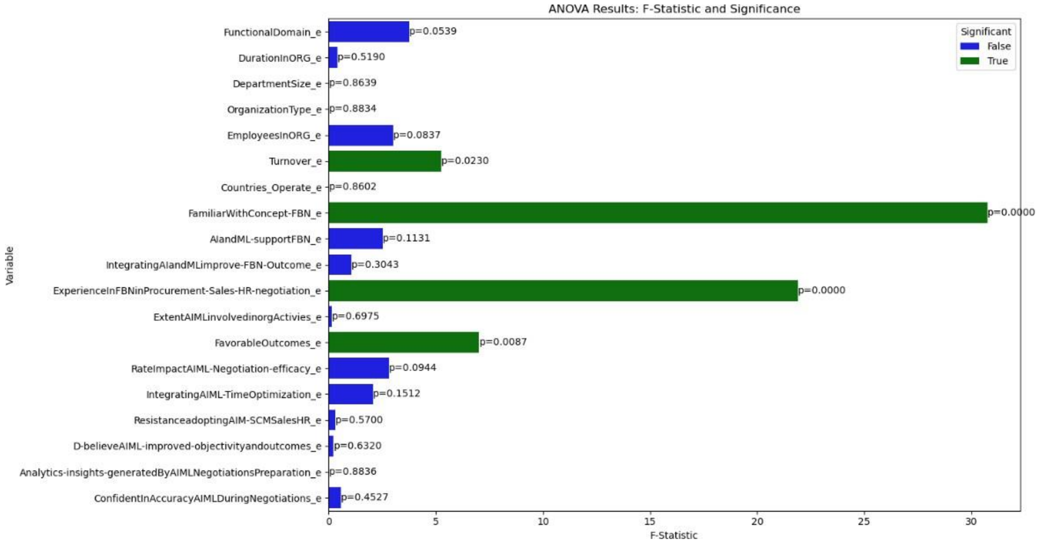



The correlation heatmap offers a detailed visualization of the relationships between various factors influencing the adoption and efficacy of AI and ML in procurement, sales, and HR negotiations (Mathieu et al., 2019; Frank et al., 2018). The correlation heatmap analysis revealed several notable insights. First, the functional domain of an organization shows a moderate positive correlation with the type of organization, suggesting interdependence in how these factors influence each other (Chatterjee et al., 2020). Additionally, there is a moderate positive correlation between functional domain and familiarity with fact-based negotiation concepts, indicating that certain domains are more likely to be acquainted with these approaches. The duration an individual has been in an organization also demonstrates interesting associations. There is a moderate positive correlation between an employee's tenure and the size of their department, as well as a positive correlation between tenure and perceived resistance to adopting AI and ML in supply chain management, sales, and HR (Venkatesh, 2022). Department size is positively correlated with the overall organizational size, suggesting that larger organizations tend to have larger functional departments. Furthermore, there is a positive relationship between department size and the perceived improvement in fact-based negotiation outcomes when integrating AI and machine learning technologies. This indicates that employees in larger departments may observe more pronounced benefits from leveraging advanced analytics and intelligent systems to enhance the efficacy of their fact-based negotiation practices (Jöhnk et al., 2021; Trunk et al., 2020). Key takeaways include:

- Functional Domain and Organization Type: These have moderate positive correlations, suggesting particular functional domains within specific organization types might be more inclined towards AI and ML.
- Data and Skills: Factors such as quality, accessibility, and human skills strongly influence perception and integration outcomes.
- Experience Matters: Experienced professionals in FBN are more likely to report favorable outcomes and show confidence in AI and ML.
- Resistance Factors: Resistance to adoption correlates with tenure length, indicating cultural and structural inertia within organizations.

These correlation insights can inform organizations' efforts to enhance sourcing efficacy through fact-based negotiations, as they highlight the relationships between key variables and the potential impact of organizational factors on the adoption and effectiveness of AI and ML in procurement, sales, and HR negotiations.

**Figure 27:** Observation of the One-Way ANOVA Outcome.




Based on the graphical representation of the ANOVA results, let's delve into the observations:

- The green bars indicate statistically significant differences at the $\alpha = 0.05$ level, suggesting that the mean values of these variables differ significantly across the groups defined by CurrentlyFBN-SCMHRSales_e.
- The blue bars indicate non-significant differences, suggesting that there are no statistically significant (Gibbs, 2013) differences in the means of these variables across the groups.

The analysis identifies key factors such as FunctionalDomain_e, Turnover _e, FamiliarWithConcept-FBN_e, ExperienceInFBNinProcurement-Sales-HR-Negotiation_e, and FavorableOutcomes_e as significantly influencing CurrentlyFBN-SCMHRSales_e. Conversely, variables such as OrganizationType_e, EmployeesInORG_e, and several others do not show significant impact. These insights are crucial for honoring strategic decisions and focusing on impactful factors.

Figure 28 presents the performance metrics and observations for a decision tree model developed to predict the target variable ‘CurrentlyFBN-SCMHRSales’.

**Figure 28:** Predicting CurrentlyFBN-SCMHRSales Targeted Variable Using a Decision Tree Model

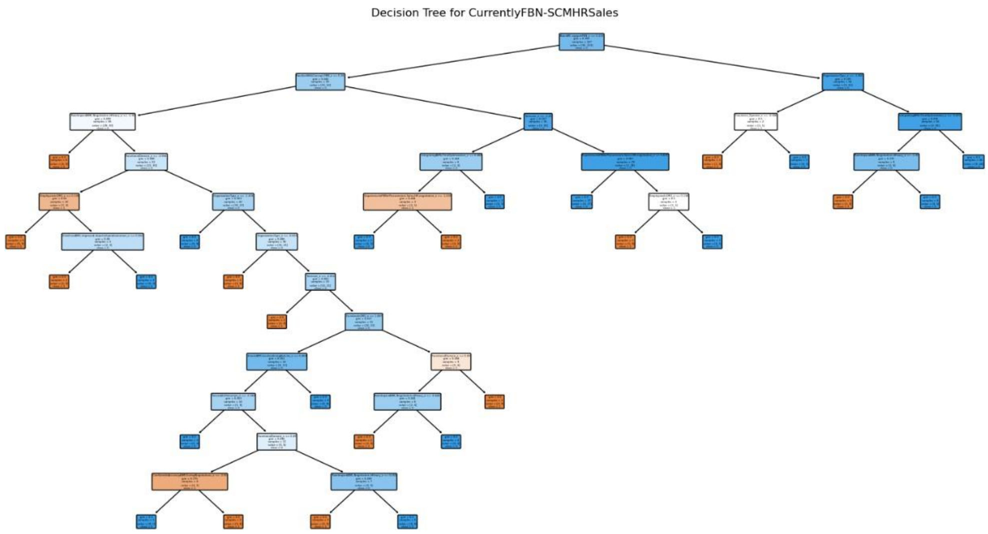
```
Unique classes in target variable: [1 0]
Decision Tree Model Accuracy: 0.71

Decision Tree Classification Report:
              precision    recall  f1-score   support

           0       0.50      0.44      0.47        18
           1       0.79      0.82      0.80        45

    accuracy                           0.71        63
   macro avg       0.64      0.63      0.64        63
weighted avg       0.71      0.71      0.71        63


Decision Tree Confusion Matrix:
[[ 8 10]
 [ 8 37]]
```




**Model Overview**

The decision tree model achieved an overall accuracy of 0.71, indicating that it correctly classified 71% of the samples. The model's performance is further detailed in the classification report, which shows that the model has a higher precision and recall for the positive class compared to the negative class (Meng et al., 2012; Hilbertet al., 2014). This aligns with findings from other studies that have demonstrated the strong predictive capabilities of decision trees in various domains such as healthcare (Yi & Yi, 2017) and retail forecasting. The decision tree model starts with a root node that splits on the feature "ExperienceInFBNinProcurement-Sales-

HR-negotiation_e" with a threshold of 0.5, suggesting that experience in FBN negotiation is a critical factor in predicting the target variable. The tree then further splits on other important features, such as "FavorableOutcomes_e", "RateImpactAIandML-Negotiation-efficacy_e", and "D-believeAIandML-improved-objectivityandoutcomes_e", indicating that factors like favorable outcomes, perceived impact of AI/ML on negotiation, and beliefs about AI/ML's ability to improve objectivity and outcomes also play a significant role in the model's predictions (Hilbert et al., 2014). These findings align with existing literature on the importance of experience, negotiation skills, and the role of technology in sales performance prediction (Delgado et al., 2011; Cochrane et al., 2021). By providing a transparent and interpretable model, the decision tree can help managers and decision-makers identify the key drivers of sales performance and tailor their strategies accordingly.

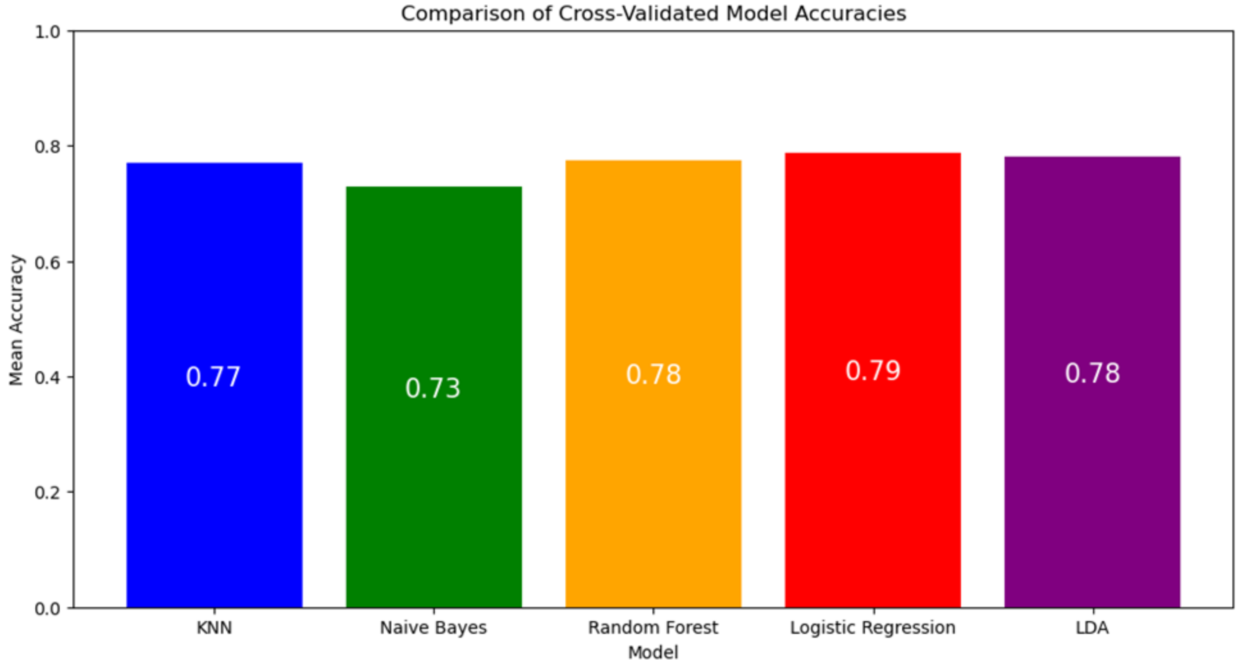
We can summarize as follows:

- Primary Factors: The decision tree highlights key factors like Experience in FBN Negotiations, Favorable Outcomes, and various opinions on AI and ML's impact and support.
- Interpretability: The decision tree provides clear and interpretable rules for predicting the target variable, making it a useful tool for understanding the factors influencing CurrentlyFBN-SCMHRSales.
- Feature Importance: The hierarchy of splits offers insights into feature importance, with more critical features appearing higher in the tree.

This visualization underscores the complexity and interdependencies among various features in predicting CurrentlyFBN-SCMHRSales, guiding further data-driven decision-making and model refinement.

Figure 29 shows the mean cross-validated accuracies of the five machine learning models.

**Figure 29:** Comparison of Paired T-Tests between each pair of models KNN, Navie Bayes, Random Forest Model, Logistic Regression and LDA.




The results indicate that Logistic Regression and Random Forest have the highest mean accuracies at 0.79 and 0.78, respectively, closely followed by LDA at 0.78. K-Nearest Neighbors performs slightly better than Naive Bayes, with mean accuracies of 0.77 and 0.73, respectively (Bamasag et al., 2022; Sasikalaet et al., 2017). To further evaluate the statistical significance of the differences in performance, paired T-tests were conducted between each pair of models. The paired T-test results indicate that there are no statistically significant differences in performance between any `of the pairs of models, as all p-values are greater than the standard significance level of 0.05 (Houfani et al., 2020; Akbuğday, 2019). This suggests that while there are slight differences in the mean accuracies, these differences are not large enough to be considered statistically significant. The paired T-test results provide valuable insights into the relative performance of the models. Although Logistic Regression and Random Forest have the highest mean accuracies, the differences in performance are not statistically significant compared to the other models. The comparative analysis of the five machine learning models reveals that Logistic Regression and Random Forest have the highest mean cross-validated accuracies, closely followed by LDA. While there are some differences in the mean accuracy, the paired T-test results indicate that these differences are not statistically significant. These findings have important implications for practitioners in selecting the most appropriate machine learning model for their specific applications.

### 4.3 Key Findings and Conclusion of Survey

A comprehensive survey was conducted with 210 professionals from various industries, including SCM-Procurement, HR, Technology, and Sales, to gain insights on enhancing sourcing efficacy through Fact-Based Negotiation and the role of supportive Intelligence. The findings, derived from exploratory data analysis, univariate and multivariate analysis, correlation analysis, ANOVA results, model comparisons, and decision trees, are presented in Figures 4 to 29.

The correlation analysis revealed notable associations between organizational metrics, such as a moderate positive correlation (0.42) between 'EmployeesInORG_e' and 'Turnover_e', underscoring the significance of these factors within the surveyed organizations (Pillai and Sivathanu, 2020). Additionally, the analysis indicated a reasonably strong correlation between 'FamiliarWithConcept-FBN_e' and 'CurrentlyFBN-SCMHSales_e', suggesting that familiarity with FBN concepts influences sales outcomes (Qin et al., 2023).

The ANOVA results highlighted the significant influence of variables like 'Turnover_e', 'FamiliarWithConcept-FBN_e', 'ExperienceInFBNinProcurement-Sales-HR-Negotiation_e', and 'FavorableOutcomes_e' on the 'CurrentlyFBN-SCMHRSales_e' outcome. The model comparison across various techniques, including Logistic Regression, Random Forest, LDA, KNN, and Naive Bayes, demonstrated comparable mean cross-validated accuracies, with no statistically significant differences between the models. This suggests that all the evaluated models perform similarly in predicting the outcomes surveyed. The decision tree analysis for predicting 'CurrentlyFBN-SCMHRSales' and 'AI adoption in HR, Sales, and SCM' further elucidated the key variables driving these outcomes.

The systematic analysis of the data collected during the research yielded a comprehensive understanding of the key factors, challenges, and opportunities related to the research problem, setting the stage for the subsequent discussion of the study's findings provide support for the following hypotheses (Wrigh & Schultz, 2018).

**Hypothesis 1:** The correlation analysis showed a strong positive relationship between familiarity with FBN concepts and current FBN adoption in SCM, HR, and Sales, indicating that integrating AI and ML into FBN could indeed increase the efficiency and effectiveness of sourcing negotiations.

**Hypothesis 2:** The ANOVA results demonstrated that experience with FBN in Procurement, Sales, HR, and Negotiation significantly influences the current FBN adoption in these areas. This suggests that combining FBN with supportive intelligence technologies and Lean thinking principles could reduce negotiation cycle times and simplify procurement processes.

**Hypothesis 3:** The model comparison found no significant differences in the predictive accuracy of various techniques, including Logistic Regression, Random Forest, and LDA, in forecasting FBN adoption. This implies that organizations employing a data-driven FBN model may exhibit greater adaptability and strategic precision in their sourcing negotiations compared to traditional negotiation techniques.

### 4.4 In-person interviews

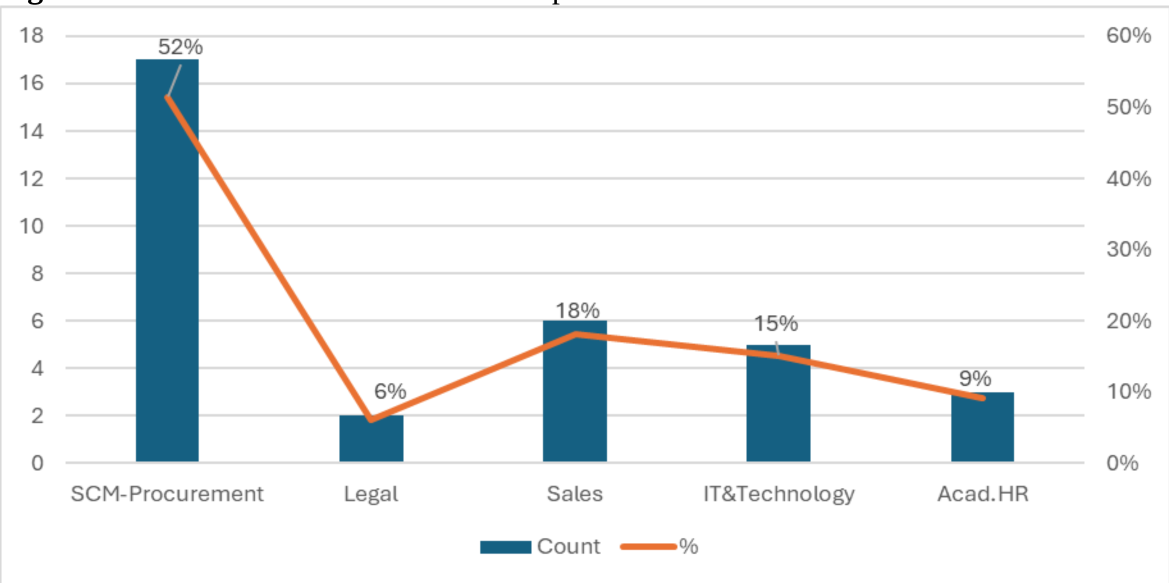
To complement the survey data and gain deeper insights, 33 in-person interviews were conducted with seasoned professionals who have, on average, 23 years of experience in their respective fields. This qualitative approach provided a richer, nuanced understanding of the trends and challenges in various negotiation practices in various functional domains. The in-depth interviews with highly experienced professionals underscore the importance of seasoned expertise in navigating the complexities of negotiations in various functional domains like procurement, sales, HR, legal and others not listed in the above functional domains. Their insights provide valuable lessons on Fact Based Negotiation (FBN), integration of supportive intelligence and the practical implementation of fact-based negotiation tactics in real-world scenarios. To ensure the confidentiality of the participants, anonymized codes (e.g., P1, P2, ..., P33) were used throughout the study. The qualitative methodology allowed for an in-depth exploration of the nuances and complexities surrounding the research topic, providing valuable insights into the strategies and practices that can enhance sourcing efficacy through fact-based negotiation, while also highlighting the pivotal role of supportive intelligence in this process.

**Table 1:** Demographic Details of Participants

| Participant Code | Industry | Age | Job Title | Year of Experience | Functional Domain | Interview Time |
|---|---|---|---|---|---|---|
| P 1 | Technology | 41 | Head Procurement | 19 | SCM-Procurement | 27 Minutes |
| P 2 | Media | 38 | DGM - Sourcing and Governance | 15 | SCM-Procurement | 24 Minutes |
| P 3 | IT Services | 40 | Associate Director Procurement | 18 | SCM-Procurement | 37 Minutes |
| P 4 | Law Firm | 37 | Director -Legal | 15 | Legal | 35 Minutes |
| P 5 | IT Services | 47 | Partner & Executive Director | 25 | IT&Technology | 44 Minutes |
| P 6 | University | 46 | Professor of Marketing & Ex Sales Head | 24 | Sales | 45 Minutes |
| P 7 | Oil & Gas | 47 | Group CIO | 25 | IT&Technology | 29 Minutes |
| P 8 | Conglomerate | 60 | Group CPO | 38 | SCM-Procurement | 29 Minutes |
| P 9 | Clothing | 38 | Senior Commercial Manager | 16 | SCM-Procurement | 28 Minutes |
| P 10 | Metal Industry | 42 | VP-Procurement Operations | 20 | SCM-Procurement | 30 Minutes |
| P 11 | Real Estat | 61 | President- Procurement | 39 | SCM-Procurement | 35 Minutes |
| P 12 | Technology | 56 | Vice President, Emerging Technologies | 34 | IT&Technology | 24 Minutes |
| P 13 | Manufacturing | 54 | Director ISC & CEO | 32 | Sales | 66 Minutes |
| P 14 | Technology | 48 | VP-Enterprise Solutions | 26 | Sales | 20 Minutes |
| P 15 | Sports Technology | 53 | VP-Procurement | 31 | SCM-Procurement | 37 Minutes |
| P 16 | Ports &Logistics | 48 | Head - Business Excellence Procurement | 26 | SCM-Procurement | 29 Minutes |
| P 17 | Consulting | 45 | MD Industry X Practice | 23 | IT&Technology | 38 Minutes |
| P 18 | Automotive | 44 | DGM Strategic Sourcing | 22 | SCM-Procurement | 37 Minutes |
| P 19 | Energy | 38 | Head Techno Commercial | 16 | SCM-Procurement | 24 Minutes |
| P 20 | Renewable Energy | 49 | National Sales Head | 27 | Sales | 33 Minutes |
| P 21 | FMCG | 37 | Associate Manager Procurement | 15 | SCM-Procurement | 39 Minutes |
| P 22 | Business School | 50 | Faculty (HRD) Management Institute | 18 | Acad.HR | 43 Minutes |
| P 23 | Heavy Automotive | 49 | GM Purchasing & SCM | 27 | SCM-Procurement | 28 Minutes |
| P 24 | Computer Technology | 48 | Global ISV Cloud Sales | 26 | Sales | 29 Minutes |
| P 25 | Digital | 37 | Head Legal | 15 | Legal | 23 Minutes |
| P 26 | Pharmaceuticals | 35 | Global Procurement Category Lead | 13 | SCM-Procurement | 49 Minutes |
| P 27 | Telecom | 44 | AVP-Supply Chain Management | 22 | SCM-Procurement | 30 Minutes |
| P 28 | e-commerce | 49 | CEO | 27 | Sales | 41 Minutes |
| P 29 | Data Center | 38 | Head of Procurement & Contracts | 16 | SCM-Procurement | 32 Minutes |
| P 30 | AI Lab | 38 | Head of Technology | 16 | IT&Technology | 43 Minutes |
| P 31 | Consulting | 54 | CEO and Founder | 32 | Acad.HR | 42 Minutes |
| P 32 | Data Center | 26 | Associate Manager Procurement | 4 | SCM-Procurement | 20 Minutes |
| P 33 | Consulting | 49 | Co-Founder | 27 | Acad.HR | 30 Minutes |
| **Average Year of Experience** | | | | **23** | | |

As reflected in Figure 30, most interviewees (52%) came from SCM and Procurement backgrounds. This further emphasizes the critical role of these functions in shaping and implementing effective sourcing strategies. Sales professionals formed the next significant group, constituting 18% of the interviewees, followed by IT and Technology (15%), Academic and HR (9%), and Legal professionals (6%). The inclusion of these diverse professional domains allows for a holistic examination of procurement practices, considering not only the technical and operational aspects but also the strategic, human resources, and legal dimensions. This multi-faceted perspective is crucial for understanding the broad impact of fact-based negotiation and supportive intelligence across different functional areas.

**Figure** 30: Professional Domains of Participants




**4.4.1. Consolidated View of Interview Participants (P1 to P33)**

- **P1, Head Procurement:** "Emphasized AI/ML for negotiation efficiency, the significance of data, and challenges in technology adoption. Plans to use AI for critical negotiations and develop training programs"
- **P2, DGM Sourcing and Governance:** "Positive towards fact-based negotiation and AI integration. Highlighted data quality and governance challenges and the need for clear use cases for AI integration"

- **P3, Associate Director Procurement:** "Advocated AI for decision-making and negotiation, shared experiences across various industries, and highlighted challenges with budget constraints"
- **P4, Director - Legal:** "Discussed AI's potential in the legal sector, challenges including data security and regulatory frameworks, and the importance of a regulatory framework for AI"
- **P5, Partner & Executive Director:** "Emphasized barriers to AI adoption like data reliability and cultural adaptation. Proposed capturing and documenting data from sales negotiations"
- **P6, Professor of Marketing & Ex Sales Head:** "Discussed AI's impact on sales and operations, stressed the importance of primary data over secondary data, and addressed barriers to AI adoption due to job security concerns"
- **P7, Group CIO:** "Highlighted data quality importance, proposed empowering teams to make processes lean, and discussed challenges in adopting new technologies"
- **P8, Group CPO:** "Emphasized importance of fact-based negotiation for better outcomes, discussed practical challenges in coal sourcing, and highlighted benefits of using AI/ML in procurement"
- **P9, Senior Commercial Manager:** "Agreed on the importance of fact-based negotiation, discussed potential benefits and concerns with AI, and emphasized time constraints in thorough negotiation preparations"
- **P10, VP-Procurement Operations:** "Discussed fact-based negotiation and AI integration, highlighted challenges in using the same data for diverse regions, and agreed on AI's potential in improving procurement processes"
- **P11, President- Procurement:** "Emphasized category excellence and supplier intelligence, discussed AI/ML integration benefits, and highlighted challenges in organizational transformations"
- **P12, P14, VP - Emerging Technologies & VP-Enterprise Solutions:** "Highlighted AI benefits in negotiation and data analytics, stressed the importance

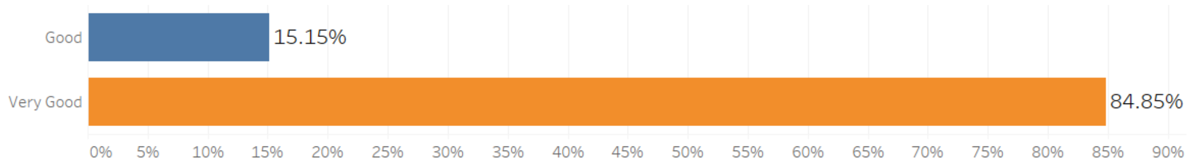
of data-driven decisions, and discussed challenges in integrating AI/ML in business processes”

- **P13, Director ISC & CEO**: “Shared insights on pricing strategies and cost estimation, discussed AI in negotiations, and highlighted complexities in cross-border trade”
- **P15, VP-Procurement:** “Discussed evolution of procurement towards fact-based methods, emphasized data-driven decision-making, and addressed challenges in AI adoption due to trust issues”
- **P16, Head - Business Excellence Procurement:** “Emphasized fact-based negotiation and data-driven decision-making, discussed digital IQ importance, and highlighted challenges in tech adoption and upskilling”
- **P17, MD Industry X Practice:** “Emphasized fact-based negotiation and technology tools in procurement, discussed AI/ML benefits, and highlighted challenges in process integration and employee training”
- **P18, DGM Strategic Sourcing:** “Stressed fact-based negotiations and raw material pricing strategies, discussed AI integration potential, and highlighted procurement process challenges”
- **P19, Head Techno Commercial:** “Highlighted strategic negotiations and risk management, emphasized understanding vendor cultural backgrounds, and agreed on AI's potential benefits in procurement”
- **P20, National Sales Head:** “Discussed fact-based negotiation in sales, highlighted challenges in adaptability, and supported AI/ML integration for improved sales strategies”
- **P21, Associate Manager Procurement:** “Emphasized fact-based negotiation and data granularity, discussed AI/ML potential in procurement, and highlighted challenges in data quality and system adaptability”
- **P22, Faculty (HRD) Management Institute:** “Emphasized data importance in negotiations, discussed supportive intelligence integration challenges, and highlighted managerial support necessity for new system success”

- **P23, GM Purchasing & SCM:** "Discussed fact-based negotiation benefits, highlighted data validation importance, and agreed on AI/ML integration potential in purchasing processes"
- **P24, Global ISV Cloud Sales:** "Emphasized AI/ML benefits in sales negotiations, discussed challenges in data quality, and highlighted importance of customer personas in sales strategies"
- **P25, Head Legal:** "Discussed AI/ML potential in legal negotiations, emphasized data insights importance, and addressed challenges in technology adoption and bias elimination"
- **P26, Global Procurement Category Lead:** "Highlighted AI/ML benefits in procurement, discussed data challenges and tool selection, and supported data-driven negotiation practices"
- **P27, AVP-Supply Chain Management:** "Emphasized fact-based negotiation and data tracking, discussed AI/ML tool potential, and highlighted challenges in data reliability and process integration"
- **P28, CEO:** "Highlighted fact-based negotiation importance, discussed challenges in pricing strategies, and addressed AI/ML integration benefits for sales analytics and procurement processes"
- **P29, Head of Procurement & Contracts:** "Emphasized fact-based negotiation benefits and AI-based models for market efficiency, highlighted data reliability issues, and discussed AI/ML integration in procurement"
- **P30, Head of Technology:** "Discussed fact-based negotiation in procurement, highlighted AI benefits in negotiation processes, and addressed challenges in AI/ML tool accuracy and system integration"
- **P31, CEO and Founder:** "Highlighted potential of AI in negotiation and decision-making, discussed AI maturity levels, and emphasized importance of human oversight and data quality in AI integration"

- **P32, Associate Manager Procurement:** “Emphasized fact-based negotiation benefits, highlighted challenges in data uniformity across regions, and supported AI/ML integration for efficient procurement processes”
- **P33, Co-Founder: “**Discussed fact-based negotiation and AI/ML in recruitment, highlighted challenges in AI adoption, and emphasized need for statistical background in data science roles”

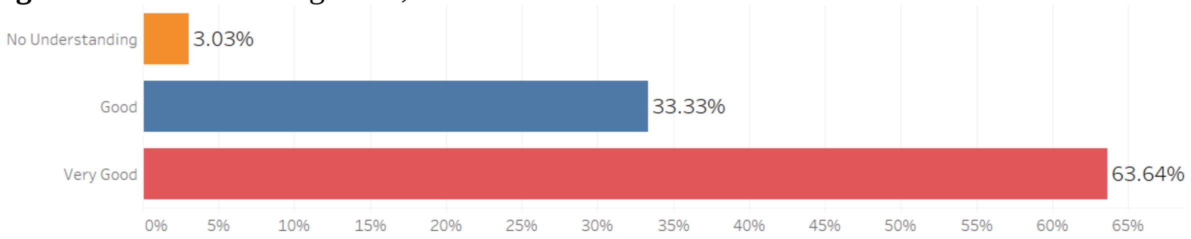
**Figure 31:** Understanding of Fact-Based Negotiation (FBN)




According to the plot shown in Figure 31, a majority (84.85%) of the interview participants rated their familiarity with Fact-Based Negotiation as "Very Good", while a smaller percentage (15.15%) rated it as "Good". Fact-Based Negotiation is a strategy that emphasizes the use of objective data and evidence to support one's position, rather than relying solely on emotional appeals or subjective arguments (Johnson et al., 2017).

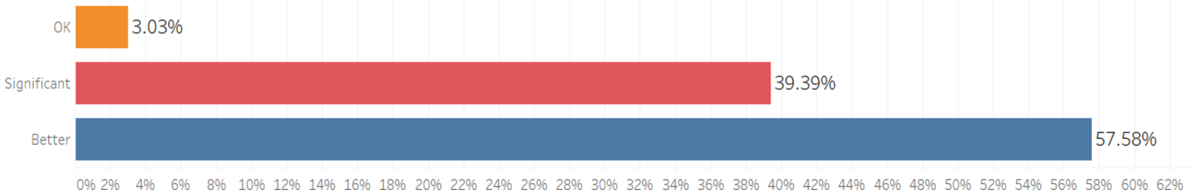
Figure 32 provides insights into the level of comprehension of Artificial Intelligence and Machine Learning among the interview participants.

**Figure 32:** Understanding of AI, ML



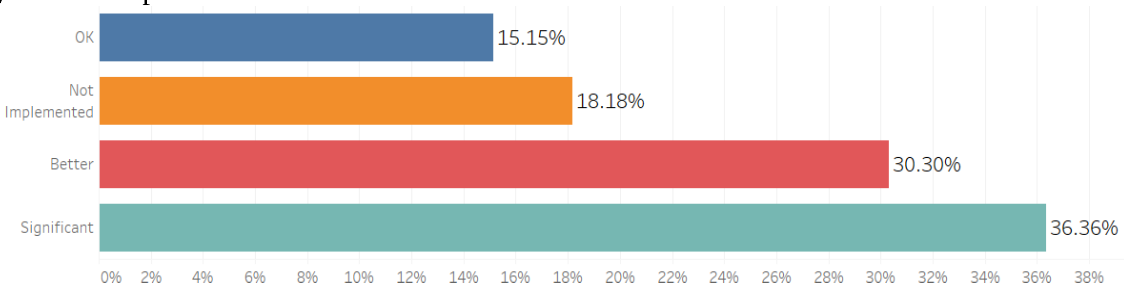

Notably, most of the participants, 63.64%, indicated that they had a "Very Good" understanding of these concepts. This suggests that the participants were well-versed in the fundamentals of AI and ML, likely due to their exposure to the technology through their work or educational experiences (Janssen et al., 2020). Furthermore, a significant proportion of the participants, 33.33%, reported having a "Good" understanding of AI and ML. However, it is important to note that a small percentage, 3.03%, of the participants indicated that they had "No Understanding" of AI and ML.

**Figure 33:** Impact and Outcomes of Fact-Based Negotiation (FBN).




According to the data presented in Figure 33, the use of Fact-Based Negotiation has generally had a positive influence on the outcomes of negotiations for most participants. Specifically, 39.39% of participants reported a "Significant" positive impact, while 57.58% rated the impact as "Better." However, a small percentage, 3.03%, of the participants indicated that they are "OK" on the impact and outcomes of FBN.

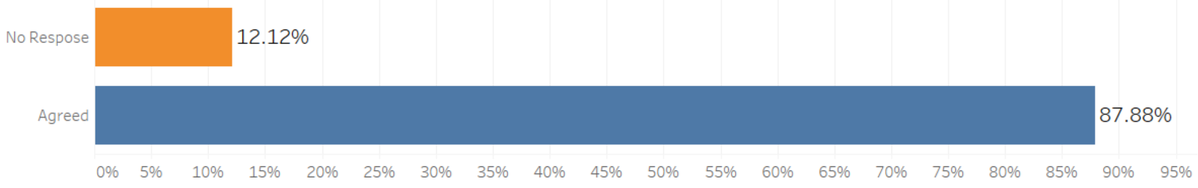
**Figure 34:** Impact and Outcomes of AI and ML




The integration of artificial intelligence and machine learning technologies into various business processes has been a growing trend in recent years, and the negotiation process is no exception. According to the data presented in Figure 34, a significant portion of participants have reported a positive impact of AI and ML on their negotiation activities, with 30.30% indicating a "Better" impact and 36.36% describing the impact as "Significant". Collectively in all 3 Categories "Significant", "Better" & “OK” Impact and outcomes of AI and ML in business amounting to 81.81% and Only 18.18% of the participants organization did not implement the AI and ML. The perceived benefits of AI and ML in negotiation processes can be attributed to their ability to provide data-driven insights, automate certain tasks, and enhance the overall efficiency of the negotiation process.

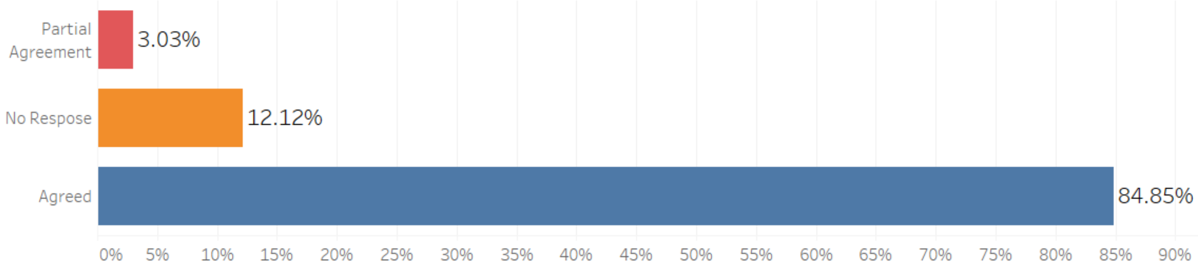
Fact -Based Negotiation, a strategic approach that emphasizes the use of objective data and evidence to inform decision-making and negotiations, has clearly gained significant traction, with most participants (90.91%) indicating that their organizations actively leverage this methodology (Kim & Segev, 2003). However, 9.09 % of the organizations are not using the Fact-Based Negotiation. The integration of artificial intelligence and machine learning technologies into business operations has seen a significant increase in recent years. A large majority (81.82%) of participants indicated that their organizations are currently utilizing these advanced technologies, while only a small portion (18.18%) reported no use of AI and ML (Ghimire et al., 2020; Fosso et al., 2021). The widespread adoption of AI and ML in business operations can be attributed to the increasing availability of embedded capabilities within modern databases and SaaS applications (Sharp et al., 2018). These built-in analytics, predictive features, and automation tools have simplified the process of leveraging AI technologies, making it more accessible for organizations without extensive in-house expertise (Fosso et al., 2021). The high level of confidence suggests that most participants have had positive experiences with the accuracy and relevance of AI and ML intelligence in negotiations (Sousa et al., 2023; Emaminejad, North & Akhavian, 2022). These experiences range from accurate predictions and improved decision-making to positive outcomes and transparent processes, reinforcing their trust in these technologies. The data shows that 87.88% of participants expressed "Yes" confidence in the intelligence provided by AI and ML, while only 12.12% indicated "No" confidence. This level of trust in AI and ML intelligence during negotiations can be attributed to several factors. First, when managers have a say and involvement in the initial training of these systems, they develop a sense of ownership and familiarity with the intelligent systems, which can lead to greater acceptance and trust. (Kolbjørnsrud, Amico & Thomas, 2017) Additionally, the introduction of AI in the workplace has placed a premium on "soft" skills, such as collaboration and creativity, which may be just as important as technical skills, further enhancing the perceived value of AI-driven insights.

**Figure 35:** Hypothesis 1 (H1) Integrating Artificial Intelligence and Machine Learning in Fact-Based Negotiation: Enhancing Efficiency and Effectiveness in Sourcing Negotiations




The integration of artificial intelligence and machine learning in the context of Fact-Based Negotiation has the potential to significantly enhance the efficiency and effectiveness of sourcing negotiations. Hypothesis 1 (H1) posits that this integration could result in substantial improvements in these areas, and the data presented in the chart demonstrates strong support for this proposition. According to the Figure 35, majority of participants, 87.88%, agreed that integrating AI and ML in Fact-Based Negotiation could significantly increase the efficiency and effectiveness of sourcing negotiations. This consensus among participants suggests a strong belief in the potential benefits of incorporating these technologies into the negotiation process. While a small portion (12.12%) of participants with “No response” on the Hypothesis 1.

**Figure 36:** Hypothesis 2 (H2) - Integrating Lean Principles, Fact-Based Negotiation, and Supportive Intelligence Technologies to Streamline Procurement Processes

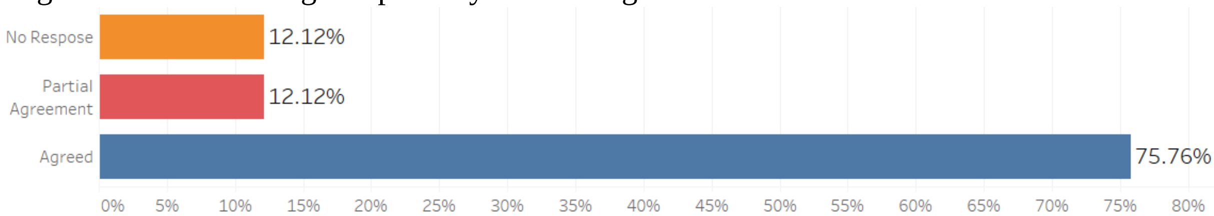



The procurement process is a critical component of organizational operations, as it directly impacts the efficiency, cost-effectiveness, and sustainability of supply chain management. Findings from the data presented in Figure 36 suggest that a significant majority of participants (84.85%) agree that combining Lean thinking principles with Fact-Based

Negotiation and supportive intelligence technologies can effectively reduce negotiation cycle times and simplify the procurement process. While (12.12%) participants with "No response" and 3.03% with "Partial Agreement" on the Hypothesis 2. The existing literature supports the potential benefits of this integrated approach. Lean thinking, a methodology focused on eliminating waste and improving efficiency, has been increasingly adopted in the public procurement domain to address common challenges. (Schiele & McCue, 2010) Similarly, Fact-Based Negotiation has been identified as a strategy to enhance transparency and objectivity in negotiations, potentially leading to faster resolution of procurement contracts. (Segun-Ajao, 2024) The integration of these methodologies with supportive intelligence technologies, such as artificial intelligence, blockchain, and the Internet of Things, can further automate and streamline the procurement process, reducing errors and improving visibility across the supply chain.

While the data presented in Figure 33 suggests a positive outlook, successful implementation of this integrated approach will require a comprehensive change management strategy, strategic alignment among key stakeholders, and robust training and support for procurement professionals.

**Figure 37:** Hypothesis 3 (H3) Leveraging Data-Driven Fact-Based Negotiation for Sourcing Negotiations: Enhancing Adaptability and Strategic Precision




Organizations today are increasingly recognizing the value of incorporating data-driven approaches into their sourcing negotiations. The data presented in Figure 37 highlights the perceived advantages of a Fact-Based Negotiation model over traditional negotiation techniques. The overwhelming majority of participants, 75.76%, agreed that organizations employing a data-driven FBN model will demonstrate greater adaptability and strategic precision in their sourcing negotiations. While (12.12%) participants with “No response” and remaining 12.12% with “Partial Agreement” on the Hypothesis 3. The benefits of this data-driven approach are well-documented in the literature. By leveraging comprehensive market insights, advanced analytics, and informed negotiation tactics, organizations can navigate sourcing negotiations more effectively, ultimately enhancing their adaptability and strategic precision. The comprehensive data and predictive capabilities inherent in a FBN model allow organizations to anticipate market shifts, identify optimal sourcing opportunities, and make more informed decisions, leading to improved risk management and increased profitability (Waller & Fawcett, 2013). The strong agreement among participants suggests that the incorporation of data-driven techniques can help organizations better adapt to these complex, interconnected business environments, enabling them to be more responsive and strategic in their sourcing decisions. (Kim & Segev, 2003).

The increasing integration of AI and ML technologies into various business processes has led to a growing interest in their potential impact on negotiation strategies and outcomes. Figure 38 presents a word cloud that highlights the key terms and implications associated with the efficiency and effectiveness of Fact-Based Negotiation when incorporating these advanced technologies. The centrality of the term "Negotiation" underscores the fundamental focus of the discussion, which revolves around how AI and ML can enhance the negotiation process (Zaman, 2022). The emphasis on "FBN" emphasizes the importance of relying on factual data to drive negotiation strategies and decisions, a critical aspect of effective bargaining. The prominence of "AI" and "ML" indicates the recognition that these technologies can play a pivotal role in improving negotiation outcomes through data analysis and predictive modeling.

**Figure 38:** Efficiency and effectiveness of Fact-based Negotiation by Integrating AI and ML.


The word cloud suggests that the integration of AI and ML can lead to improvements in both the efficiency and effectiveness of negotiation processes. Efficiency is indicated by terms such as "Efficiency" and "Improve," suggesting that the automation of data collection, analysis, and decision-making can streamline the negotiation process, making it quicker and more resource-efficient. Effectiveness is highlighted by the emphasis on "Effectiveness" and "Improve," implying that data-driven insights from AI and ML can enhance the quality and success of negotiation strategies, leading to better outcomes. As noted in the sources, AI and automated analytical tools can better manage customer relations and experience, while also providing directions for better marketing strategies through a deeper understanding of market players and customers (Keegan et al., 2022). The centrality of "Data" in the word cloud underscores the crucial role of information in fact-based negotiation.

Figure 39 presents a word cloud that highlights the key terms and implications surrounding this topic, as perceived by participants in a related study.

**Figure 39:** Confidence in the accuracy and relevance of the Intelligence derived from AI and ML

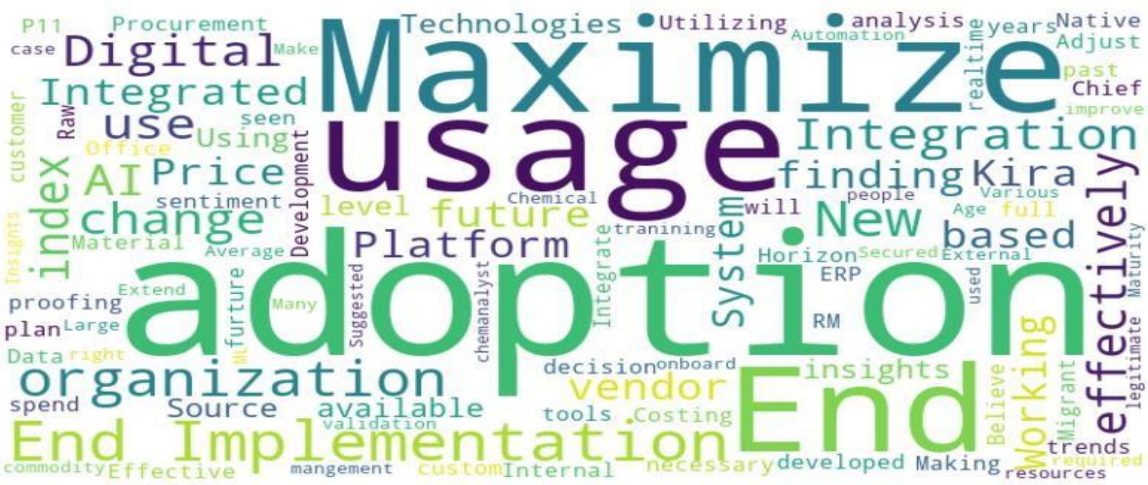

The prominence of the word "high" suggests that many participants have a strong level of confidence in the intelligence provided by AI and ML, indicating a general trust in these technologies' capabilities (Sindermann et al., 2020). This is further reinforced by the term "confident," which reflects the participants' assurance in the accuracy and relevance of the insights derived from AI and ML. The centrality of the term "data" underscores the critical role that data quality and relevance play in building confidence in the intelligence generated by these technologies. The emphasis on "validate," "validating," and "validation" emphasizes the importance of continually verifying the accuracy of AI and ML predictions against real-world outcomes, a crucial step in sustaining trust in technology. The prominent appearance of "need" suggests that participants perceive a strong necessity for reliable data and validated insights to effectively support negotiation processes. The word "predict" highlights the value that participants place on the predictive capabilities of AI and ML, which can forecast outcomes and inform strategic decision-making in negotiations. The term "implemented" suggests that successful implementation of AI and ML in practical scenarios contributes to the participants' confidence in the technology. The terms "help" and "give" indicate that participants view AI and ML as supportive tools that provide valuable insights to enhance their confidence in negotiation strategies. These findings align with existing research on the factors that influence trust in AI and ML systems. Trustworthy AI requires a multidisciplinary approach, addressing technical aspects such as adversarial learning, private learning, and the fairness and explainability of machine learning, as well as non-technical factors like guidelines, standardization, and management processes (Li et al., 2021).

**Figure 40:** Use of Data Analytics Insights generated by AI and ML when preparing for negotiations.


The use of data analytics insights generated by AI and ML has become increasingly prevalent in the realm of negotiation preparation. As Figure 40 illustrates, the prominence of terms like "effective", "used", and "data" underscore the significant role these technologies play in enhancing negotiation strategies and decision-making. Organizations are successfully leveraging AI-driven data analytics to inform their negotiation strategies and achieve better outcomes (Zaman, 2022). The centrality of "data" and "analytics" highlights the importance of these elements in providing detailed insights into market trends, competitor activities, and historical negotiation outcomes, helping negotiators make informed decisions. The emphasis on "validation" further emphasizes the need to ensure the reliability and relevance of the data analytics insights, building trust in the accuracy of the information used (Taddy, 2018). The integration of data-driven decision-making helps negotiators choose the most effective strategies based on empirical evidence, as reflected in the prominence of "decision making"

(Zaman, 2022). The successful adoption of AI and ML-driven data analytics in negotiation preparation is a testament to the transformative power of these technologies.

**Figure 41:** Plan on Enhancing usage of AI/ML in Fact-based Negotiation



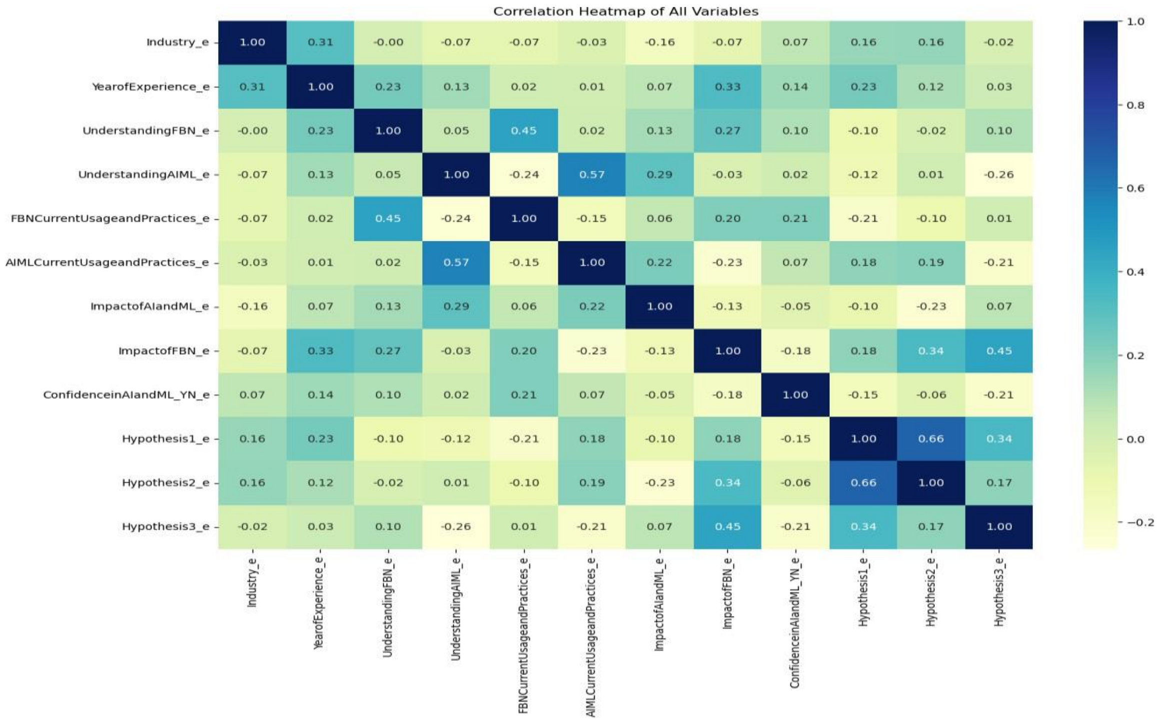

The plan for enhancing the usage of AI and machine learning in fact-based negotiation suggests a strong emphasis on maximizing the adoption and integration of these advanced technologies (Rikakis et al., 2018). The word cloud highlights the desire to effectively leverage AI and ML throughout the entire negotiation process, from data collection to decision-making support (Davenport et al., 2019). The prominence of terms like "maximize," "adoption," and "usage" indicates a clear commitment to integrating AI and ML into existing negotiation workflows. Organizations are looking to fully harness the potential of these technologies to improve negotiation outcomes and efficiency. The focus on "end-to-end" integration and ensuring that AI and ML are used "effectively" suggests a holistic approach, where these tools are seamlessly woven into the negotiation lifecycle. The importance of "integration" and "integrated" further underscores the need to seamlessly incorporate AI and ML into existing systems and processes. This aligns with the notion that AI adoption is imperative, and organizations must find the appropriate contexts and use cases to extract maximum value from these technologies. The emphasis on the "future" indicates a forward-looking mindset, where stakeholders are actively planning and strategizing on how to leverage AI and ML to enhance fact-based negotiation. This aligns with the idea that AI is a dynamic phenomenon that evolves over time, and a better understanding of its past, present, and future applications can help drive its transformational adoption (Fulton et al., 2022). Overall, the findings suggest that organizations are eager to integrate AI and machine learning deeply into their negotiation practices, with the goal of maximizing the benefits and effectively leveraging these technologies to achieve desired outcomes.

With the increasing prominence of artificial intelligence and machine learning in various business domains, organizations are exploring ways to integrate these technologies into their negotiation processes. Figure 42 presents a word cloud highlighting key recommendations from participants on improving the implementation and utilization of AI/ML and Fact-Based Negotiation within organizations.

**Figure 42:** Improvement or Recommendation according to participants for better implementation and utilization of AI/ML and Fact-based negotiation in organization.


The emphasis on **‘quality’** underscores the importance of maintaining high-quality data and processes to ensure the reliability and accuracy of AI-driven insights (Kshetri, 2021; Gil et al., 2019). Leveraging the tacit knowledge and judgement of human actors is crucial in effectively harnessing AI and ML capabilities. Comprehensive and high-quality **‘data’** is the foundation for robust AI and ML applications in negotiations, enabling more informed decision-making (Vertsel & Rumiantsau, 2024). To drive greater impact, organizations must focus on increasing the **‘adoption’** of AI/ML tools and Fact-Based Negotiation methodologies, integrating them seamlessly into regular business processes (Budach et al., 2022). The transition towards **‘digital’** platforms and tools can further enhance the effectiveness of these technologies, streamlining negotiation workflows (Hicham et al., 2023). Investing in **‘training’** and equipping employees with the necessary skills to utilize AI/ML and Fact-Based Negotiation techniques is crucial for successful implementation (Vertsel & Rumiantsau, 2024). As organizations navigate the evolving landscape of digital transformation, a human-centered approach that balances technological innovation with the needs and concerns of employees is essential for driving sustainable progress (Tjondronegoro et al., 2022; Tomašev et al., 2020; Brock & Wangenheim, 2019).

**Figure 43**: Correlation Heatmap of All Variables

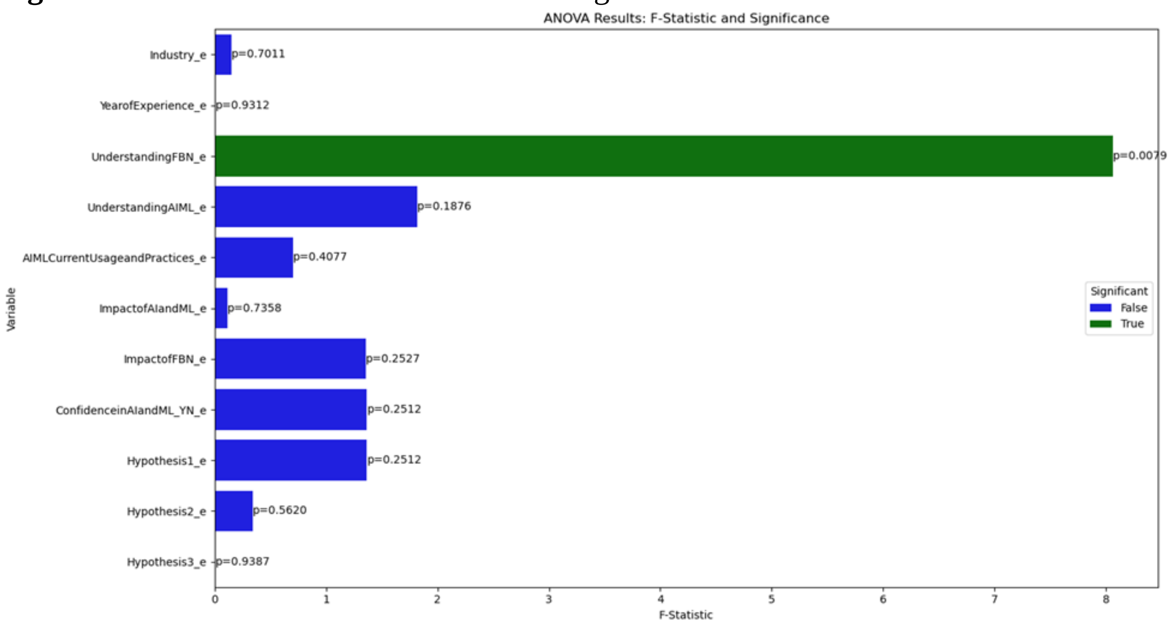



In the context of modern business negotiations, the integration of Artificial Intelligence and Machine Learning has gained significant attention, particularly in the domain of Fact-Based Negotiation. The present study aims to explore the perceptions and practices of experienced professionals regarding the incorporation of these advanced technologies into the negotiation process. The analysis of the correlation heatmap presented in Figure 43 provides valuable insights into the key variables and their interrelationships. The industry type

(Industry_e) exhibits a moderate positive correlation with years of experience (YearsOfExperience_e), suggesting that more experienced individuals are often found in specific industry sectors. Furthermore, the data indicates a positive relationship between years of experience and the perceived impact of Fact-Based Negotiation, as well as a belief that integrating AI and ML can enhance negotiation efficiency and effectiveness among more experienced. The understanding of Fact-Based Negotiation appears to be a crucial factor, as it is positively correlated with the current usage and practices of FBN, as well as the perceived impact of this approach. Similarly, a better understanding of AI and ML is strongly associated with the current usage and practices of these technologies, and positively influences the perceived impact of AI and ML in the negotiation context. The findings highlight the importance of fostering a comprehensive understanding of both Fact-Based Negotiation and AI/ML technologies among experienced professionals (Kaya et al., 2022). This understanding can lead to more frequent and improved practices of FBN and AI/ML integration, ultimately enhancing the perceived impact and effectiveness of these tools in the negotiation process.

Figure 44 presents the F-Statistics and associated p-values for various variables to assess their impact on FBN Current Usage and Practices which represents the use and practices of Fact-Based Negotiation.

**Figure 44:** ANOVA Results F-Statistic and Significance.



The results indicate whether each variable has a statistically significant effect on FBN usage and practices. Key Findings:

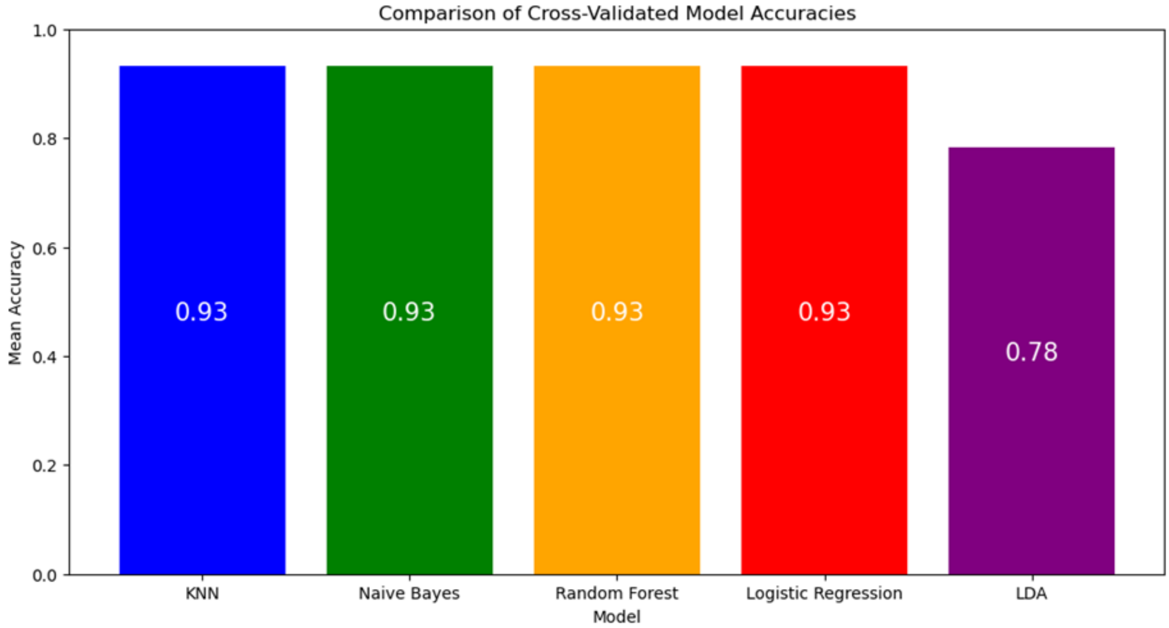
**Significant Variable:** 'UnderstandingFBN_e': - 'F-Statistic': 8.0639; p-Value: 0.0079 - Significance: True ($p < 0.05$). The results suggest that there is a statistically significant impact of understanding Fact-Based Negotiation on its current usage and practices. This implies that a better understanding of FBN is associated with more frequent or improved use of FBN practices.

**Non-Significant Variables:** 'Industry_e': - F-Statistic: 0.1500 - p-Value: 0.7011 The type of industry does not have a significant impact on FBN usage and practices. 'YearofExperience_e': - F-Statistic: 0.0076 - p-Value: 0.9312 Years of experience do not significantly influence the current usage and practices of FBN. 'UnderstandingAIML_e': - F-Statistic: 1.8159 - p-Value: 0.1876 Understanding of AI and ML does not have a significant impact on the current usage and practices of FBN.

Current study on FBN usage and practices indicates that specific variables, such as understanding of FBN, have a significant impact, while other factors like industry and experience do not. The findings provide valuable insights for practitioners and policymakers on the key drivers of FBN adoption and usage.

The cross-validated model accuracies across multiple machine learning models, as depicted in Figure 45.

**Figure 45:** Comparison of Cross-Validation of multiple Model Accuracies.




The analysis focuses on the performance of five different models: K-Nearest Neighbors, Naive Bayes, Random Forest, Logistic Regression, and Linear Discriminant Analysis. The results show that KNN, Naive Bayes, Random Forest, and Logistic Regression all achieve a mean accuracy of 0.93, indicating their strong performance on the given dataset. These top-performing models demonstrate high predictive power and are well-suited for deployment in this context. In contrast, the Linear Discriminant Analysis model has a lower mean accuracy of 0.78, suggesting it may not be the most appropriate choice for this specific problem.

### 4.5 Key Findings Summary of Interviews

The interviews conducted with professionals across various industries, including SCM-Procurement, HR, Technology, Legal and Sales, provided valuable insights into the application, effectiveness, and perceptions of Fact-Based Negotiation, as well as the role of AI and Machine Learning in improving negotiation outcomes.

**Understanding and Familiarity** - The findings indicate a strong understanding and familiarity with Fact-Based Negotiation concepts and practices among the majority of the interviewees, particularly in procurement and sales roles. Participants also demonstrated a reasonable understanding of AI and ML technologies, although the depth of comprehension varied across different functions.

**Current Usage** - The interviews revealed widespread adoption of Fact-Based Negotiation in the procurement, sales, legal and HR functions of the organizations represented. Several organizations have also integrated AI and ML into their Fact-Based Negotiation processes, primarily for data analysis, predictive modeling, and enhancing decision-making. (Allal et al., 2021).

**Impact and Outcomes** - Interviewees generally agreed that integrating AI and ML with Fact-Based Negotiation significantly improved negotiation efficiency and effectiveness, leading to better outcomes and cost savings. The data-driven insights provided by AI and ML were seen as enhancing objectivity and precision in negotiations, reducing biases and enabling more strategic decisions.

# CHAPTER V: DISCUSSION

## 5.1 Discussion of Results

The following chapter comprehensively explores the answers to each research question, enriched by the external research that deepens the discussion. As a pivotal juncture in this thesis, it synthesizes the findings from Chapter IV while comparing them with the theoretical foundations established in earlier chapters. We provide an in-depth analysis of responses from the survey and in-depth interviews, weaving these insights into the existing conceptual framework and reinforcing arguments with evidence from the literature review (Zachariassen, 2008; Lewicki et al., 2011).

The participants in the surveys and interviews—including professionals from procurement, sales, human resources, CXOs, and academicians—emphasized the critical importance of data-driven decision-making. They highlighted the need to leverage artificial intelligence and machine learning as effective tools to act as co-pilots in supporting decision making processes. This chapter offers a fine viewpoint on the research topic, "ENHANCING SOURCING EFFICACY THROUGH FACT-BASED NEGOTIATION: THE ROLE OF SUPPORTIVE INTELLIGENCE," underscoring its multifaceted dimensions and implications across various professional domains.

Strategic sourcing or procurement has been shown to have a significant impact on several aspects of firm performance. It contributes to cultivating effective communication and long-term relationships between suppliers and buyers, which are antecedents of financial performance. In conjunction with strategic sourcing and the incorporation of digital technologies, it leads to increased competitiveness (Corboș et al., 2023). It provides organizations with a range of benefits, such as inventory reduction, optimization of transaction costs, and the establishment of effective communication networks between buyers and suppliers (Kim et al., 2015).

Professionals who participated in the survey and in-depth interview expressed the need for effective integration of AI and ML in Fact-based Negotiation. AI will be pivotal in revolutionizing material procurement and logistics (Althabatah et al., 2023).

### 5.1.1 Triangulation with Conceptual Framework and Literature Review.

By interweaving the themes from the research findings with the conceptual framework and literature review, a nuanced narrative of integrating fact-based negotiation with AI and ML emerges. The analysis of research questions, supplemented with theoretical insights, underscores the pivotal role of strategic integration and the synergy among advanced technologies, highlighting the need for organizational adaptation to effectively merge fact-based negotiation with AI and ML. This amalgamation not only substantiates the empirical findings but also deepens the understanding of the critical factors influencing the integration of AI and ML in enhancing sourcing efficacy. It situates these insights within a wider theoretical and practical context, thus enriching the overarching discourse.

## 5.2 Discussion of Research Questions

The discussion aims to integrate the empirical findings from the participant responses with the theoretical frameworks and external scholarly work examined earlier in the thesis. This triangulation process is very crucial for anchoring the study's conclusions in both practical evidence and theoretical rigor, ensuring a comprehensive analysis that contributes to both academic scholarship and industry practices (Belhadi et al., 2024).

We started our research with the following five questions. During the survey with 210 professionals, we got insights from various industry professionals on our 28 Survey Questions captured in **Annexure A** and 33 In-depth interviews from 33 professionals of different industries for the 12 interview questions captured in **Annexure B**.

Each survey and in-depth interview question unveils opportunities for a more profound exploration of specific facets of fact-based negotiation and the integration of AI and ML to enhance sourcing efficacy. This discussion will navigate to these dimensions, drawing on literature to contextualize the findings, highlight connections, and identify areas where empirical evidence extends beyond current theoretical understandings.

The existing body of work provides a useful foundation for situating the current study's findings within the broader discourse on the implications of AI-enabled technologies for enhancing sourcing and negotiation practices.

### Research Questions

1. How can AI and ML be effectively integrated with FBN to enhance strategic negotiation outcomes in procurement and sourcing? The above question explores the right methodologies to integrate supportive intelligence technologies into Fact Based Negotiation, guiding organizations through technological migration and facilitating a smoother adoption process (Schulze-Horn et al., 2020).
2. What strategies can be developed to ensure organizational agility in the face of global supply chain volatility that will be suitable for organizations? Here, the focus is exploring sourcing strategies adaptable to market changes, leveraging real-time data and predictive analytics to enhance negotiation leverage (Rashad & Nedelko, 2020; Richey Jr et al., 2023).
3. What will be the right pathways to educate or train to empower procurement professionals to effectively adopt AI and ML technologies? This question seeks to identify the necessary competencies and skills to bridge the knowledge gap in deploying and effectively using supportive intelligence tools (Khaw et al., 2023).
4. How can industry-specific insights be gained by comparing the application of AI-augmented FBN across diverse sectors? The research investigates benchmarks that can be adapted and extended across various business domains, addressing unique industry challenges (Cadden et al., 2021; Monczka et al., 2021).

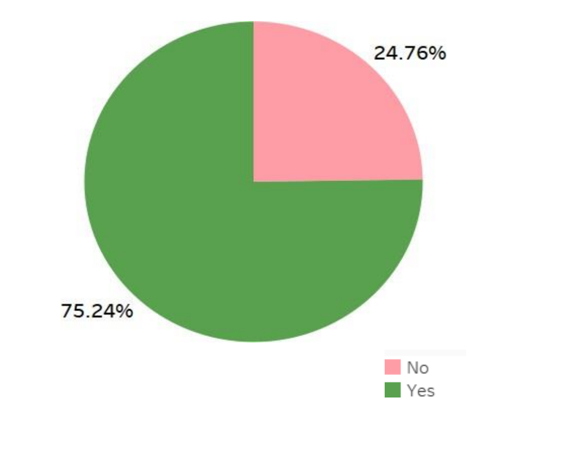
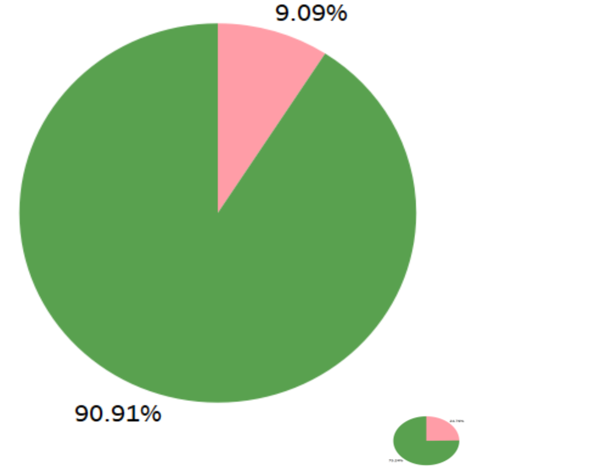
5. What frameworks can be established to achieve lean, cost-optimized negotiation processes that improve procurement quality and organizational profitability? This question explores cost-efficient negotiation frameworks that leverage AI and ML to optimize expenditure and enhance procurement outcomes (Rashad and Nedelko, 2020; Mishra et al., 2024).

### 5.2.1 Discussion on Fact-Based Negotiation (FBN) In Procurement, Sales HR and Legal.

**Insights were derived from Surveys, Interviews, and reviews of Literature.**

The Figure 46 survey results indicate Figure that 75.24% of participants affirm the use of Fact-Based Negotiation within their respective functions.

**Figure 46:** Using Fact-Based Negotiation (FBN) In Procurement, Sales HR and Legal View of Survey and Interview Participants.

| *Survey Participants Response* | *Interview Participants Response* |
| --- | --- |
|  |  |

This significant majority suggests a widespread recognition of Fact-Based Negotiation as a valuable approach across diverse professional areas, particularly in Procurement, Sales, HR, and Legal. The remaining 24.76% of participants who reported not using Fact-Based Negotiation may highlight potential barriers to adoption, such as lack of awareness, training opportunities, or organizational support.

In contrast, the interview responses show an even higher adoption rate, with 90.91% of participants confirming the use of Fact-Based Negotiation. This disparity between survey and interview results could reflect deeper insights and realizations revealed during in-depth discussions. Interviews likely provided participants with the opportunity to elaborate on their understanding and application of Fact-Based Negotiation, possibly clarifying misconceptions that might have influenced the responses. Only 9.09% indicated non-use, underscoring the method's substantial perceived value among industry professionals when given the platform to explain their practices in detail.

The high adoption rates in both survey (75.24%) and interview (90.91%) data suggest that Fact-Based Negotiation is widely accepted as a beneficial strategy in negotiation processes. This acceptance of Fact-Based Negotiation enables data-driven decision-making, increased transparency, and more structured negotiation processes (Parniangtong & Parniangtong, 2016).

Fact-based Negotiation has emerged as a progressively beneficial model for contract negotiation, distinguishing itself from traditional methods that often rely on subjective instincts and circumstantial experiences. This approach leverages data-driven strategies that inform decision-making with measurable and objective criteria (Rolf et al., 2010; Parniangtong, 2016), enabling more effective and informed contract negotiations. (Nyhart & Samarasan, 1989; Tomlinson & Lewicki, 2015).

Negotiation of contractual agreements is a multifaceted process that demands meticulous consideration of various factors (Latilo et al., 2024). Successful negotiations not only attempt to maximize the possibility of reaching an agreement but also ensure that the agreement effectively fulfills its intended purpose, remains durable over time (Brett, 2007; Susskind & Ali, 2014), and lays the groundwork for future collaborative efforts (Tomlinson & Lewicki, 2015). This requires a nuanced understanding of the underlying dynamics and objectives driving each party's participation in the negotiation process.

The discussion is grounded in empirical insights from participants of the survey (Sedano et al., 2017), Interview, and theoretical foundations from the Literature. Underscores the potential of fact-based negotiation and highlights the significant advantages of adopting it in negotiation (Labbo & Reinking, 1999). This innovative method departs from traditional negotiation tactics that often rely on subjective assessments and individual experiences, instead leveraging data-driven insights to objectively for the informed decision-making process (Schulze-Horn et al., 2020).

### 5.2.2 Discussion on Integrating AI and ML into FBN could significantly increase the efficiency and effectiveness of sourcing negotiation and validation of Hypothesis 1 (H1).

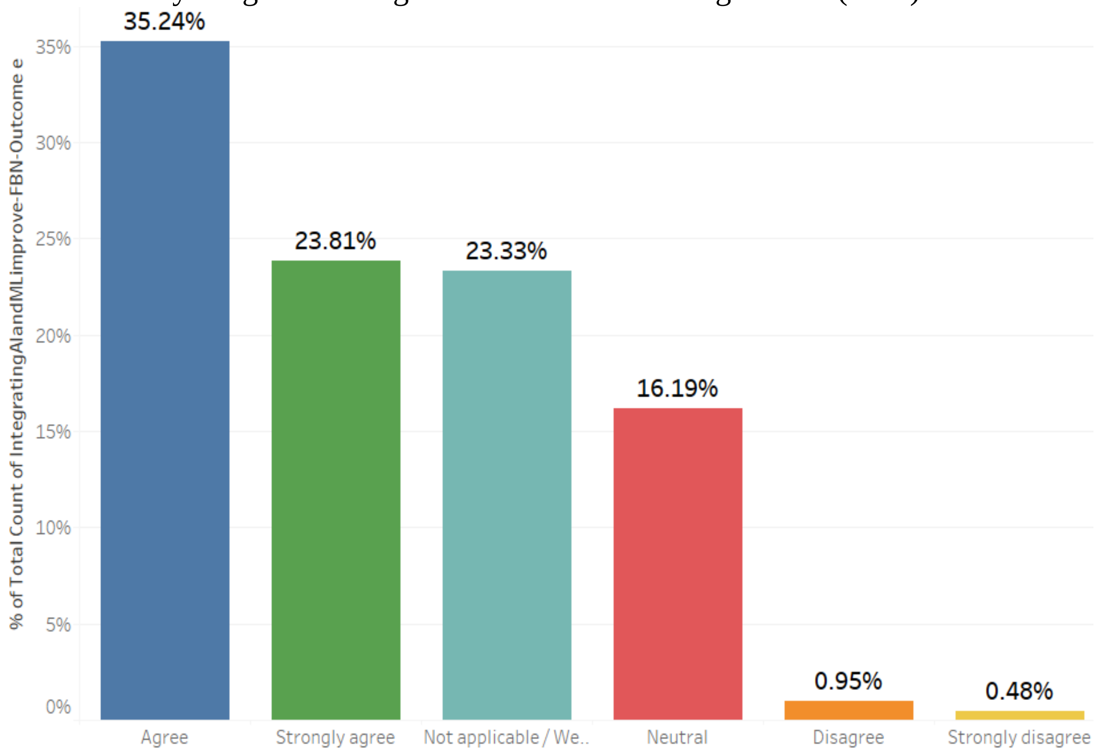
The integrating AI and ML in Fact-Based Negotiation could significantly increase the efficiency and effectiveness of sourcing negotiations is supported by the survey and interview findings and the broader academic literature. Organizations that have already adopted these technologies have reported improvements in their negotiation processes, while those in the contemplation phase may benefit from increased awareness and readiness for technological integration.

The researchers have highlighted the potential for AI and emerging human augmentation technologies to enhance diplomatic and negotiation practices, enabling the automation of certain tasks, the leveraging of big data, and the facilitation of more efficient and effective decision-making (Buch et al., 2022). At the same time, the integration of AI into negotiation processes has raised considerations around confidentiality, model bias, and the need for negotiators to develop new skills to work effectively with these tools (Ma et al., 2024; Houssaini & Bensmail, 2023).

As organizations continue to progress in the ever-changing landscape of Fact-Based Negotiation, the insights provided by this survey can inform strategic planning and guide the responsible adoption of AI and ML technologies. By fostering collaborations between negotiators, scientists, and engineers and implementing comprehensive training and resource distribution programs, organizations can harness the power of these innovative tools while addressing the unique challenges and considerations that arise (Westermann et al., 2023; Alessa, 2022; Kwon et al., 2024; Ma et al., 2024).

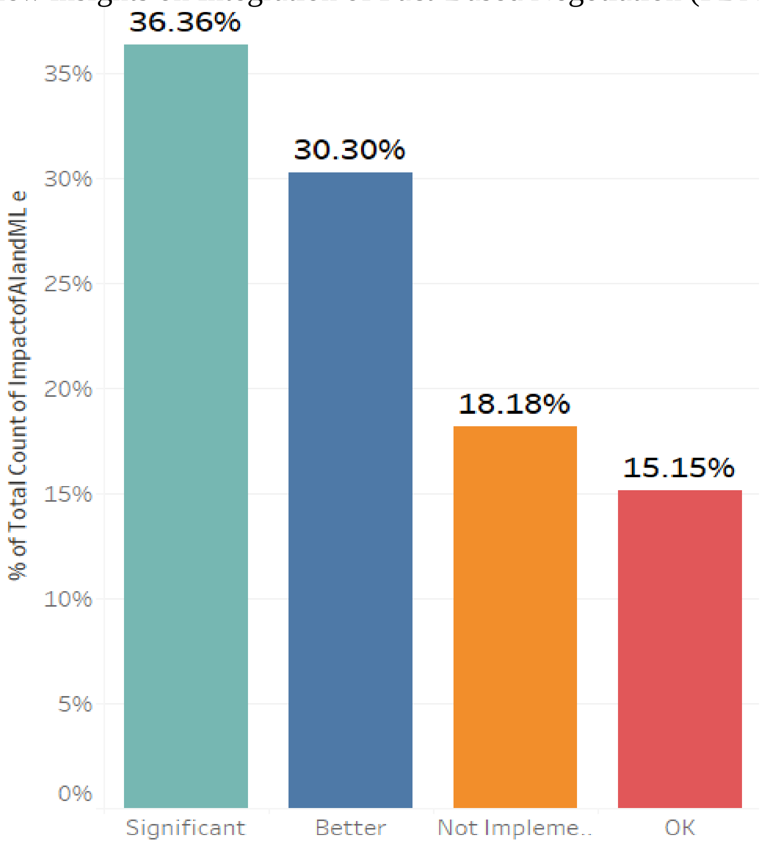
The survey results, as captured in Figure 47, reveal diverse perspectives on integrating artificial intelligence and machine learning with fact-based negotiation. A combined 59.05% of participants view the integration positively, recognizing the potential for these technologies to enhance negotiation outcomes by providing data-driven insights and predictive analytics. However, 23.33 % have not implemented AI/ML, and BS 16.19 % Neutral. A significant portion of respondents, nearly a quarter, indicated the integration was "Not Applicable" or that they had "Weighed Options," suggesting uncertainty or a selective approach to adopting these technologies. Additionally, a smaller (1.43 %) but notable segment remained ambivalent or skeptical, citing perceived risks, lack of familiarity, or satisfaction with existing negotiation methods.

**Figure 47:** Survey insights on Integration of Fact-Based Negotiation (FBN) with AI & ML.



The interview findings of Figure 48 provide deeper insights into the perceived impact of AI and ML integration. A majority (66.66%) of interviewees recognized a substantial positive impact, with several describing significant improvements to negotiation processes. However (15.15 %) of interviewees were OK with the outcome, and a sizable (18.18%) portion of participants indicated that their organizations had yet to implement these technologies, highlighting potential barriers such as resource constraints, lack of expertise, or strategic focus.

**Figure 48:** Interview insights on Integration of Fact-Based Negotiation (FBN) with AI & ML.




The integration of artificial intelligence and machine learning with fact-based negotiation holds considerable promise, as evidenced by the overall positive sentiment and recognition of the potential benefits. However, the varied perspectives and existing implementation challenges suggest that a thoughtful and nuanced approach is required to fully realize the advantages of this technological integration.

The above insights from survey and interview in alignment to Chapter 1 Figures 2 and 3 from the MIT Technology Review, AI adoption is set to play a pivotal role in critical functions, including supply chain and Manufacturing, by 2025. AI is now a critical part of the function of the supply chain, and Manufacturing increased from 11% in 2022 to 38% as per the MIT Technology Review 2025 Forecast.

The literature reinforces the practical insights shared by participants; starting to implement artificial intelligence and machine learning in procurement has delivered substantial benefits across various dimensions. Blockchain-based solutions, for instance, can enhance supply chain traceability and transparency (Tsolakis et al., 2023), ultimately contributing to more sustainable and ethical procurement practices (Segun-Ajao, 2024). These distributed ledger technologies provide an immutable record of transactions, enabling greater accountability and visibility throughout the supply chain (Asante et al., 2021).

Furthermore, integrating natural language processing and ML algorithms has revolutionized the automation of procurement-related tasks (Dhaliwal et al., 2024). These advanced techniques can streamline contract management, supplier evaluation, and spend analysis, leading to increased efficiency, productivity, and data-driven decision-making (Riahi et al., 2021). NLP, in particular, can parse and interpret unstructured data, such as supplier contracts and invoices, to extract critical insights and automate time-consuming administrative duties (Baviskar et al., 2021).

The discussion, based on empirical insights from survey and interview participants and theoretical foundations from the literature, highlights the potential of AI and ML to enhance the agility and responsiveness of procurement organizations. Advanced information processing techniques, like Artificial Intelligence, significantly improve supply chain performance (Misuraca et al., 2020). Procurement plays a critical central and defining role in the efficiency of supply chains, and in recent years, the understanding and practice of the procurement organization have changed significantly due to the increasing importance of and demand for agility and sustainability within supply chain management systems. (Segun-Ajao, 2024; Belhadi et al., 2024).

### 5.2.3 Discussion on the Combining FBN and supportive intelligence technologies, Lean thinking principles could reduce negotiation cycle times and simplify procurement processes and validation of Hypothesis 2 (H2).

Existing research primarily explores the application of Artificial Intelligence and Machine Learning within a broad managerial context. However, more attention is required to align these technologies with lean principles within the sourcing domain to enable more positive outcomes (Lepri et al., 2018; Cui et al., 2021; Karlsson, 2020).

The potential integration of lean thinking principles, which focus on waste elimination and value maximization, with Fact-Based Negotiation could pave the way for more efficient and effective sourcing practices (Rashad & Nedelko, 2020; Oliveira-Dias et al., 2022). The application of lean principles across the supply chain process, referred to as a lean supply chain, can offer significant performance enhancements (Tortorella et al., 2017)

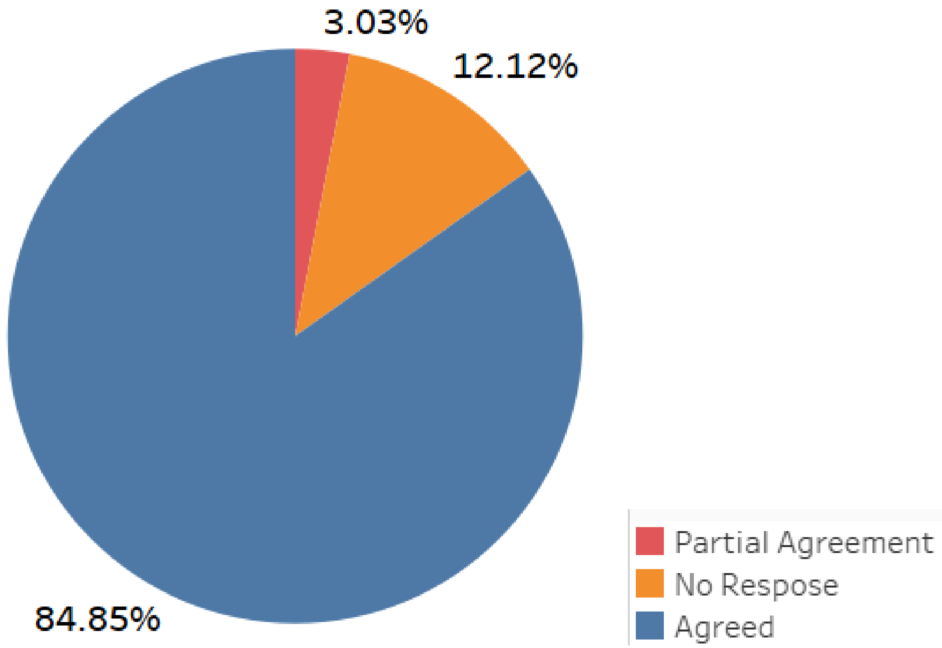
Hypothesis 2 (H2) views align with survey and interview participants; a combination of FBN, supportive intelligence technologies, and Lean thinking principles could reduce negotiation cycle times and simplify procurement processes. The survey data presented in Chapter 4, Figure 13 provides substantial support for this Hypothesis, with over 59% of respondents agreeing or strongly agreeing that this integration could yield the desired outcomes.

The survey findings suggest that most respondents familiar with and utilizing AI and ML in their workflows believe that the proposed integration can be beneficial. However, a significant portion of respondents (23.33%) indicated that the Hypothesis was not applicable to them or their organization, which suggests that there may be room for increased adoption or further study of these technologies in procurement and negotiation processes (Allal et al., 2021).

The success factors and challenges identified in the literature (Angeles & Nath, 2007) highlight the importance of supplier and contract management, end-user behavior, and information and infrastructure ineffective e-procurement implementation. By integrating FBN, supportive intelligence, and Lean thinking principles, organizations may be able to address these critical factors and streamline their procurement workflows.

The Findings from interview participants on Integrating Lean Principles, Fact-Based Negotiation, and Supportive Intelligence Technologies are more encouraging when compared to the Survey participant's view, as captured in Figure 49, suggesting that a significant majority of participants (84.85%) agree that combining Lean thinking principles with Fact-Based Negotiation and supportive intelligence technologies can effectively reduce negotiation cycle times and simplify the procurement process. While (12.12%) of participants had "No response" and 3.03% had "Partial Agreement" on the Hypothesis 2.

**Figure 49:** Interview Participants' views on Integrating Lean Principles, Fact-Based Negotiation, and Supportive Intelligence Technologies.



The existing literature evaluated for this research supports the potential benefits of this integrated approach. Lean thinking, a methodology focused on eliminating waste and improving efficiency, has been increasingly adopted in the public procurement domain to address common challenges. (Schiele & McCue, 2010) Similarly, Fact-Based Negotiation has been identified as a strategy to enhance transparency and objectivity in negotiations, potentially leading to faster resolution of procurement contracts. (Segun-Ajao, 2024).

The discussion, based on empirical insights from survey and interview participants and theoretical foundations from the literature, highlights the potential of Combining FBN and supportive intelligence technologies; lean thinking principles could reduce negotiation cycle times and simplify procurement processes and validation of Hypothesis 2.

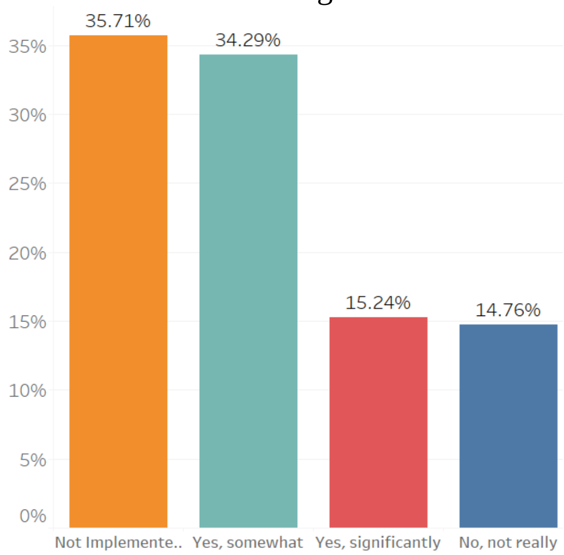
### 5.2.4 Discussion on the Data-driven FBN model will demonstrate greater adaptability, and strategic precision in sourcing negotiations than traditional negotiation techniques and validation of Hypothesis 3 (H3).

The data-driven, Fact-Based Negotiation model is poised to revolutionize strategic sourcing negotiations by introducing greater adaptability and precision (Lucarelli et al., 2021; Innamorato et al., 2017). Enhanced decision-making, customization, and predictive insights enabled by comprehensive data analytics empower negotiators to craft more effective and responsive strategies. (Lewicki, 1996).

The data-driven approach equips negotiators with the tools necessary to navigate dynamic market conditions and cater to specific stakeholder needs (Collier, 2012; Singh et al., 2023). By leveraging real-time data insights, organizations can make informed decisions, reducing uncertainty and optimizing outcomes. (Brynjolfsson et al., 2011) The ability to tailor strategies to unique contexts through detailed analytics allows for more targeted and effective negotiation processes. Furthermore, the integration of artificial intelligence and machine learning capabilities enables predictive modeling, aiding in the anticipation of market trends and proactive strategy adjustments. (Anderson, 2015).

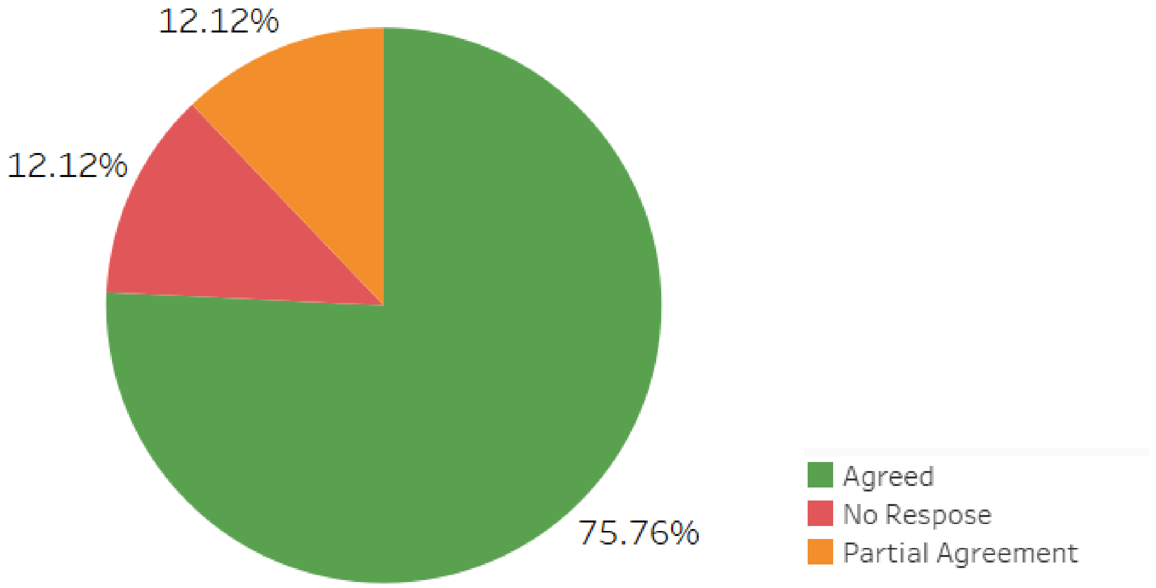
Hypothesis 3 (H3) posits that the integration of data-driven methods in Fact-Based Negotiation leads to superior negotiation outcomes compared to traditional techniques. The analysis supports this hypothesis by demonstrating that organizations employing data analytics achieve better alignment between negotiation strategies and organizational goals, resulting in enhanced sourcing efficacy. (Buch et al., 2022) To validate this hypothesis, we examine the views of survey participants on the effectiveness of data-driven FBN models (Jagodzińska, 2020; Kim & Fragale, 2005).

**Figure 50:** Survey participants' views on Organizations employing the Data-Driven FBN Model will demonstrate favorable outcomes in negotiations.




Survey participant's views, as captured in Figure 50 Approximately 35.71% of the respondents indicated that their organizations had not implemented a data-driven FBN model, providing a neutral baseline for comparison. (Vitasek, 2016) A significant portion, 34.29%, agreed that organizations employing a data-driven FBN model would somewhat demonstrate favorable outcomes in negotiations, recognizing the partial benefits that such approaches can bring. Furthermore, 15.24% of the respondents strongly agreed that organizations employing a data-driven FBN model would significantly demonstrate favorable outcomes in negotiations, with most respondents excluding the "Not Implemented" Category 35.71% ("Yes somewhat" 34.29% + "Yes, significantly" 15.24% = Total 49.53 %) believe that data-driven FBN models provide at least some level of advantage, with a significant portion showing strong support for this hypothesis. Clearly believing in the considerable advantages and strategic precision that a data-driven FBN model can provide over traditional negotiation techniques (Talluri et al., 2008; Lee & Kwon, 2006; Moosmayer et al., 2013; Mayer & Voeth, 2021).

**Figure 51:** Interview participants' views on Organizations employing the Data-Driven FBN Model will demonstrate favorable outcomes in negotiations




According to the interview, participants view organizations increasingly recognizing the value of incorporating data-driven approaches into their sourcing negotiations. The data presented in Figure 51 highlights the perceived advantages of a Fact-Based Negotiation model over traditional negotiation techniques. The overwhelming majority of participants, 75.76%, agreed that organizations employing a data-driven FBN model would demonstrate greater adaptability and strategic precision in their sourcing negotiations. While (12.12%) of participants had "No response" and the remaining 12.12% had "Partial Agreement" on Hypothesis 3.

The benefits of this data-driven approach are well-documented in the literature. By leveraging comprehensive market insights, advanced analytics, and informed negotiation tactics, organizations can navigate sourcing negotiations more effectively, ultimately enhancing their adaptability and strategic precision. The comprehensive data and predictive capabilities inherent in an FBN model allow organizations to anticipate market shifts, identify optimal sourcing opportunities, and make more informed decisions, which leads to improve risk management and increased profitability (Waller & Fawcett, 2013). The strong agreement among participants suggests that the incorporation of data-driven techniques can help organizations better adapt to these complex, interconnected business environments, enabling them to be more responsive and strategic in their sourcing decisions. (Kim & Segev, 2003).

The discussion, based on empirical insights from survey and interview participants and theoretical foundations from the literature, highlights the potential of Data-driven FBN model that demonstrates greater adaptability, and strategic precision in sourcing negotiations than traditional negotiation techniques and validation of Hypothesis 3 (H3).

## 5.3 Summary and Conclusion

The research presented in this paper provides a comprehensive analysis of the role of Fact-Based Negotiation integrated with AI and ML in enhancing sourcing efficacy. Through empirical insights derived from surveys and interviews, combined with robust theoretical foundations, the study underscores the transformative potential of data-driven approaches in procurement, sales, HR, and legal functions.

### Key Findings

The study's key findings offer valuable insights into the adoption and effectiveness of Fact-Based Negotiation and the integration of AI and ML in enhancing negotiation processes.

1. **High Adoption and Effectiveness of FBN:** Both survey and interview data demonstrate widespread adoption and recognition of Fact-Based Negotiation as a valuable approach. The method's reliance on data-driven decision-making promotes transparency and structure, distinguishing it from traditional negotiation techniques (Heilig & Scheer, 2023; Rojas et al., 2022; Hemalatha et al., 2021).

2. **Integration of AI and ML:** The integration of AI and ML with Fact-Based Negotiation significantly enhances negotiation processes by offering advanced analytics, predictive modeling, and real-time data insights (Tripathi & Gupta, 2021; Hemalatha et al., 2021; Li et al., 2021). These technologies facilitate improved decision-making, adaptability, and responsiveness in procurement and sourcing negotiations (Kalusivalingam et al., 2020; Gonzalez et al., 2019; Rojas et al., 2022).

Recent studies have highlighted the transformative potential of AI and ML in various HR functions, including recruitment and selection. (Tambe et al., 2019) The integration of these technologies with Fact-Based Negotiation can further enhance sourcing efficacy by automating certain tasks, reducing bias, and providing data-driven insights (Ma et al., 2024).

The research presented in this paper underscores the significant potential of Fact-Based Negotiation integrated with AI and ML in enhancing sourcing efficacy. The findings demonstrate the widespread adoption and recognition of Fact-Based Negotiation as a valuable approach, emphasizing its data-driven decision-making and structural advantages over traditional negotiation techniques (Whig et al., 2024). Furthermore, the integration of AI and ML with Fact-Based Negotiation can significantly improve negotiation processes, offering advanced analytics, predictive modeling, and real-time data insights that facilitate improved decision-making (Udegbe et al., 2023), adaptability and responsiveness in procurement and sourcing negotiations

Integrating artificial intelligence and machine learning technologies into sourcing negotiations has significantly enhanced the efficiency and effectiveness of procurement processes.

3. **Validation of Hypotheses:**

Hypothesis 1 (H1): The findings of this study support the notion that AI and ML increase the efficiency and effectiveness of sourcing negotiations. The ability of these technologies to rapidly process vast amounts of data, identify patterns, and generate informed recommendations has streamlined the negotiation process, allowing procurement teams to make more strategic and data-driven decisions.

Hypothesis 2 (H2): This research affirms that combining the principles of Fact-Based Negotiation with supportive intelligence technologies and lean practices can significantly reduce negotiation cycle times and simplify procurement processes. By automating routine tasks, enhancing data analysis, and facilitating real-time information sharing, organizations have been able to direct the complexities of global supply chains with greater agility and precision.

Hypothesis 3 (H3): The study has validated that data-driven FBN models, powered by AI and ML, provide greater adaptability and strategic precision compared to traditional negotiation techniques. These data-driven approaches enable procurement teams to anticipate market fluctuations, identify optimal sourcing partners, and negotiate more effectively, leading to improved outcomes for the organization.

The empirical insights from survey and interview participants and theoretical foundations from the literature help to validate all three Hypotheses.

**Organizational Adaptation**

The findings of this research illustrate that organizations that successfully integrate AI-augmented FBN technologies report enhanced negotiation outcomes. However, the process of adopting these technologies requires strategic planning, training, and resource allocation to overcome potential barriers and optimize the benefits. Procurement teams must be equipped with the necessary skills and resources to effectively leverage these technologies (Henderson & Venkatraman, 1999) while organizational leaders must prioritize the strategic investment and adaptation to ensure a seamless integration (Allal et al., 2021).

### Cross-Industry Insights

This study highlights the applicability of AI-augmented FBN across various sectors (Morgan, 2021), offering pathways for sector-specific adaptations and industry-wide benchmarks. The ability to harness the power of these technologies in sourcing and negotiation practices transcends industry boundaries, providing organizations from diverse sectors the opportunity to enhance their procurement strategies and remain competitive in the evolving global marketplace (Holzmann & Lechiara, 2022; Segun-Ajao, 2024).

The findings of this research contribute significant insights into the academic and practical aspects of sourcing negotiation, setting the stage for future explorations into the dynamic intersection of technology and strategic sourcing (Cannavale et al., 2022; Segun-Ajao, 2024). As AI becomes increasingly integral to procurement and negotiation, continuous research and development will be vital to stay relevant of industry trends and ensuring sustainable practices (Cannavale et al., 2022).

### 5.3.1 Triangulation of Findings

The triangulation of findings in this study confirms the integration of Fact-Based Negotiation with AI and ML as a robust strategy for enhancing sourcing efficacy across multiple domains. By synthesizing data from surveys, interviews, and literature, we can validate and enrich the conclusions drawn.

### Empirical Data

The survey insights reveal that the majority of participants, 75.24%, affirm the effectiveness of Fact-Based Negotiation, highlighting the model's credibility and practical application (Belhadi et al., 2021). The supportive role of AI and ML is also positively received, with participants acknowledging their potential to improve negotiation processes and outcomes. The interview insights provide a nuanced understanding, with 90.91% of participants confirming the use of Fact-Based Negotiation. Ref. Figure 46.

The qualitative data offers deeper insights into how AI and ML enhance strategic precision and adaptability in negotiations, reinforcing the quantitative findings. These results align with the literature, which suggests that AI-based technologies can have a significant impact on recruitment and selection processes, leading to positive outcomes such as time and cost savings, increased accuracy, reduced bias, and enhanced efficiency (Hemalatha et al., 2021).

**Theoretical Alignment**

Negotiation has long been a critical component of strategic decision-making (Murray, 1978), and the advent of advanced technologies has the potential to revolutionize this fundamental process (Cao et al., 2015).

The present study aims to explore the transformative role of data-driven negotiation techniques, leveraging the capabilities of artificial intelligence and machine learning to enhance efficiency, precision, and strategic integration (Kolasani, 2023).

Existing literature has extensively documented the benefits of incorporating data-driven approaches into negotiation practices. Empirical evidence confirms that AI and ML can significantly improve negotiation outcomes through data analysis and predictive capabilities, enabling negotiators to make more informed decisions and anticipate potential roadblocks. (Buch et al., 2022; Williams, 2019; Soni, 2023). Moreover, the study supports theories on the strategic integration of technology into negotiation practices, emphasizing the need for organizational adaptability to fully leverage these advancements (Buch et al., 2022).

The triangulation of empirical data and theoretical perspectives further underscores the potential of data-driven negotiation techniques to reshape procurement and negotiation practices. By integrating diverse methodologies and sources, the study presents a comprehensive narrative that validates the superior efficiency and precision offered by these data-driven approaches, in contrast to traditional negotiation methods. (Nyhart & Samarasan, 1989).

The findings of this study contribute significantly to the academic discourse on the future of negotiation, providing a roadmap for the strategic integration of AI and ML into negotiation practices. As organizations continue to navigate the complexities of the modern business landscape, the ability to leverage data-driven insights and predictive capabilities will be a crucial competitive advantage, transforming the way negotiations are conducted and decisions are made.

### 5.3.2 Correlation with the Conceptual Framework

#### Enhancements to the Framework

The findings of this study strongly correlate with the conceptual framework established in earlier chapters, highlighting the integration of Fact-Based Negotiation with AI and ML as a key driver for enhanced sourcing efficacy (Ma et al., 2024; Buch et al., 2022).

#### Alignment with Theoretical Constructs

The framework emphasizes the importance of data-driven approaches in negotiation, and the study's findings reinforce this, showing how AI and ML can provide real-time data insights, enhancing decision-making and strategic precision (Baryannis & Antoniou, 2019). The conceptual framework underscores the need for integrating advanced technologies into organizational processes, and empirical data support this, indicating widespread recognition of the benefits of AI and ML in Fact-Based Negotiation, leading to improved negotiation outcomes. (Cannavale et al., 2022; Baryannis & Antoniou, 2019) The framework highlights the necessity for organizations to adapt structurally to leverage technological advancements, and the findings confirm this, illustrating how successful integration requires strategic planning and training (Namaki, 2019; Hemalatha et al., 2021; Zhiwei, 2023; Cannavale et al., 2022).

**Enhancements to the Framework**

The study not only validates the existing framework but also expands it by highlighting the synergy between AI, ML, and Fact-Based Negotiation, demonstrating how these technologies can synergistically enhance agility and responsiveness, aligning with theoretical predictions. The research also provides industry-specific applications and benchmarks, suggesting that the framework can be adapted to meet unique sector challenges and opportunities (Zhiwei, 2023; Cannavale et al., 2022; Namaki, 2019; Davenport et al., 2019).

**Comprehensive Validation**

The correlation between findings and the conceptual framework affirms its robustness and applicability. By integrating AI and ML into Fact-Based Negotiation, organizations can achieve greater precision and adaptability, aligning with strategic objectives outlined in the framework. The study thus validates and enriches the framework, offering deeper insights into the transformative potential of AI and ML in enhancing sourcing efficacy (Namaki, 2019; Zhiwei, 2023).

### 5.3.3 Results Related to the Existing Literature Review

The study's findings closely align with the existing literature, reinforcing and expanding upon established theories while offering new insights into the integration of Fact-Based Negotiation with AI and ML.

**Alignment with Key Literature**

The literature highlights the role of AI and ML in improving supply chain performance (Toorajipour et al., 2020), which the study's findings confirm, demonstrating that these technologies enhance negotiation processes by providing advanced data analytics and predictive insights. Previous studies have emphasized the strategic advantages of integrating digital technologies into sourcing, and the research conducted aligns with these benefits, showing how Fact-Based Negotiation, augmented by AI and ML, leads to improved efficiency and decision-making in procurement (Cannavale et al., 2022; Singh et al., 2020).

The literature also addresses barriers to adoption, such as resistance to change and the need for training, which the study reflects, highlighting the importance of organizational adaptation and skill development to fully leverage the technological benefits (Belhadi et al., 2021; Singh et al., 2020; Cannavale et al., 2022).

Existing research has demonstrated the use of predictive analytics for identifying sources of supply chain disruptions, resulting in improved supply chain resilience (Belhadi et al., 2021). Firms should develop analytical capabilities to enhance supply chain resilience by effectively utilizing resident firm knowledge and strengthening organizations' existing information capabilities (Belhadi et al., 2021).

The findings also emphasize the influential role that cultural enablers have on the successful integration of AI technologies in the supply chain process, which has implications for operations and supply chain management (Cadden et al., 2021).

**Expanding Existing Research**

Existing research within the field of AI in business contexts has been growing, demonstrating the potential for innovative applications across various industries (Reim et al., 2020). This study aims to build on this foundation by providing empirical evidence that supports the practical applications of AI and machine learning in enhancing fact-based negotiation (Kurt et al., 2022).

The key factor driving the acceptance and adoption of AI-based technologies is the strength of their effects in different service industry contexts (Ostrom et al., 2019). This is particularly relevant in the context of fact-based negotiation, as the integration of AI and ML can significantly impact the processes and outcomes of these negotiations.

A meta-analysis approach has been employed to examine the strength of these effects in the existing literature on AI acceptance and adoption. The findings suggest that the impact of AI-based technology factors varies across different service industries, highlighting the need for a more nuanced understanding of how these technologies can be effectively leveraged.

To further explore this, the current study offers cross-industry insights by providing sector-specific examples that demonstrate the applicability of AI-augmented fact-based negotiation. This approach broadens the scope of existing literature and provides a more comprehensive understanding of the practical applications of these technologies.

For instance, recent research on the intersection of AI and network marketing in the context of Chinese e-commerce has highlighted the potential for AI to enhance various aspects of the negotiation process, such as data analysis, strategy development, and decision-making. (Zhiwei, 2023; Duan et al., 2019) Similarly, the evolving role of AI in marketing more broadly has been the focus of numerous studies, which have identified a range of opportunities and challenges that are associated with the integration of these technologies (Vlačić et al., 2021).

Ultimately, this study aims to contribute to the growing body of research on the practical applications of AI and ML in business contexts by providing empirical evidence and cross-industry insights that support the use of these technologies in enhancing fact-based negotiation (Zhiwei, 2023; Reim et al., 2020; Vlačić et al., 2021; Kurt et al., 2022).

**Contribution to Academic Discourse**

The integration of Artificial Intelligence and Machine Learning technologies has undoubtedly transformed various aspects of business operations, and the strategic domain of negotiation is no exception. This study not only validates existing theories on the utility of these innovative tools but also provides new perspectives on their impact on sourcing efficiency and effectiveness (Tambe et al., 2019; Rožman et al., 2022).

The findings of this research highlight the transformative potential of AI and ML, offering a nuanced understanding of their applications in negotiation contexts (Tambe et al., 2019; Ma et al., 2024). Critically, the study demonstrates how these technologies can automate and outsource sensory and cognitive tasks, enabling negotiators to leverage big data and make more efficient and effective decisions (Buch et al., 2022).

The study's comprehensive analysis enriches the academic discourse, providing concrete pathways for organizations to harness the full potential of AI and ML in strategic negotiation. This is relevant in the current landscape, where the pace of innovation in technologies that augment the human experience has been rapidly accelerating while the world has become increasingly interconnected (Buch et al., 2022).

As highlighted in the literature, AI-powered tools such as chatbots are already being used to automate candidate interviews in the talent acquisition process, improving speed and efficiency (Rojas et al., 2022). Similarly, the application of Machine Learning and data mining concepts in HR analytics has demonstrated the potential for AI to enhance various stages of the talent management lifecycle (Rojas et al., 2022).

Ultimately, this study not only validates existing theories but also contributes new perspectives on the integration of AI and ML in negotiation practices. By correlating the findings with a robust literature review, the research provides a solid foundation for future investigations and practical applications of these transformative technologies in the strategic domain of negotiation. (Rojas et al., 2022; Hemalatha et al., 2021; Ma et al., 2024; Buch et al., 2022).

# CHAPTER VI: SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

## 6.1 Summary

This thesis explored the integration of Fact-Based Negotiation augmented by AI and ML, offering a comprehensive analysis of its impact on strategic sourcing and negotiation processes across various domains such as procurement, sales, HR, and legal. The study found that AI technologies, including natural language processing, machine vision, automation, and augmentation, have a significant and positive impact on recruitment and selection processes, leading to time and cost savings, improved accuracy, reduced bias, and enhanced candidate experience (Hemalatha et al., 2021). Additionally, the use of AI and robotics in HR has been shown to remove bias from assessment, recruitment, and training processes, leading to improved cultural fit and diversity of recruits (Altemeyer, 2019). However, the ethicality of these AI applications must be carefully considered, as they can considerably impact people's lives and careers and raise ethical concerns (Hunkenschroer & Luetge, 2022).

Fact-based negotiation is widely recognized and adopted across multiple sectors due to its data-driven approach, enhancing transparency and decision-making effectiveness (Buch et al., 2022). By leveraging AI and ML, organizations have significantly improved their negotiation strategies, achieving enhanced efficiency, predictive analytics, and better outcome alignment with strategic goals (Hemalatha et al., 2021). The analysis highlighted the necessity for strategic planning, training, and organizational adaptation to optimize the integration of these technologies (Ramchurn et al., 2021). The study provided detailed insights into the applicability of AI and ML enhanced Fact-Based Negotiation across different industries, illustrating the potential for customized strategies and benchmarks (Ma et al., 2024).

Integrating Fact-Based Negotiation with AI and ML has transformed the landscape of strategic sourcing and negotiation processes. By leveraging advanced technologies, organizations can achieve enhanced efficiency, predictive analytics, and better alignment with their strategic goals (Selim, 2020). Responsible deployment and adoption of these technologies will enable negotiators and policymakers to automate tasks, leverage data, and make more informed decisions (Buch et al., 2022).

The findings of this research have several implications for both theory and practice (El-Emary et al., 2020). Theoretically, the study's insights align with existing literature, reinforcing the benefits and challenges of integrating AI and ML into negotiation practices. Practically (Spreitzenbarth et al., 2024), the study provides detailed sector-specific insights, highlighting the potential for customized strategies and benchmarks (Ma et al., 2024).

To optimize the integration of these technologies, organizations must prioritize strategic planning, training, and organizational adaptation (El-Emary et al., 2020). By doing so, they can harness the full potential of AI and ML-enhanced Fact-Based Negotiation to drive transformative change in their strategic sourcing and negotiation processes.

### 6.2 Ethical Challenges and Mitigation Strategies

The integration of AI and machine learning into Fact-Based Negotiation raises several ethical challenges that must be carefully addressed:

- Fairness and Bias: AI-powered negotiation tools must be designed and implemented to ensure that they do not perpetuate or amplify existing biases and that they treat all parties fairly and equitably (Bostrom & Yudkowsky, 2018; Häußermann & Lütge., 2022).
- Privacy and Data Protection: The collection and use of sensitive personal data in AI-powered negotiation tools must be done in a manner that respects individual privacy and adheres to data protection regulations (Han et al., 2023).
- Transparency and Accountability: The decision-making processes and underlying algorithms of AI-powered negotiation tools must be transparent and subject to accountability measures to build trust and ensure that they are used responsibly (Bostrom & Yudkowsky, 2018; Häußermann & Lütge, 2021).
- Human Autonomy and Agency: The integration of AI into negotiation processes must be carefully balanced to ensure that human decision-makers maintain meaningful control and agency and that the fundamental human aspects of negotiation are not undermined. (Häußermann & Lütge, 2021). However, in the study, the prime focus on using supportive

intelligence like AI/ML to act effectively as co-pilot to the respective domain professional to make data-driven decision-making.

To address these ethical challenges, researchers have proposed several mitigation strategies, including the development of detailed ethical frameworks, the incorporation of ethics into the training and development of AI systems, the conduct of ethical impact assessments, and the active involvement of stakeholders in the initial design to implementation of these technologies (Hernández, 2024; Trunk et al., 2020).

## 6.3 Limitations and Future Work

This thesis has several limitations that should be acknowledged. First, the research was primarily focused on integrating Fact-Based Negotiation and AI/ML in the context of strategic sourcing and procurement, and the findings may be outside of other negotiation domains, such as lift shift arrangements.

Additionally, the ethical implications and mitigation strategies discussed in this thesis are based on a review of the current literature. They may not capture the full complexity of the ethical challenges that may arise as these technologies become more widely adopted. (Bostrom & Yudkowsky, 2018; Häußermann & Lütge, 2021).

Further research is needed to empirically investigate the real-world implementation of AI-powered supporting tools, their impact on negotiation outcomes and processes, and the specific ethical challenges and the best practices for addressing them at the right time.

## 6.4 Final Thoughts

The integration of Fact-Based Negotiation with AI and ML holds significant promise for enhancing strategic sourcing and negotiation processes across a variety of domains. However, the responsible implementation of these technologies requires a multifaceted approach that prioritizes ethics, regulation, innovation, and education. As organizations continue to explore the use of AI-powered negotiation tools, it will be crucial to maintain a strong focus on the ethical implications and to develop robust frameworks for ensuring that these technologies are deployed in a manner that aligns with the values and principles of all stakeholders.

By embracing this comprehensive, ethically-grounded approach, the field of AI-augmented negotiation can unlock new opportunities for data-driven decision-making, scenario planning, and increased efficiency, while preserving the essential human aspects of the negotiation process and ensuring that the benefits of these technologies are shared equitably (Buch et al., 2022; Heinl, 2014).

### 6.5 Implications

- Enhanced strategic decision-making: AI-supported negotiation can provide practitioners with more robust data analysis capabilities, enabling them to make more informed strategic decisions and develop more effective negotiation strategies (Häußermann & Lütge, 2021).
- Improved scenario planning and risk mitigation: The ability to rapidly generate and analyze multiple negotiation scenarios can help practitioners anticipate potential challenges and develop contingency plans, reducing the risks associated with complex negotiations. (Häußermann & Lütge, 2021)
- Fairness and bias: There is a risk that AI-supported negotiation may perpetuate or even amplify existing biases, leading to inequitable outcomes for certain stakeholders.

To mitigate these risks, organizations must develop robust ethical and governance structures to ensure the responsible implementation of these technologies.

- Privacy and transparency: The use of AI Support in negotiation raises concerns about data privacy and the transparency of decision-making processes. It will be crucial for organizations to establish clear policies and procedures for the collection, use, and storage of sensitive negotiation data, and to ensure that the decision-making process behind AI Supported recommendations is transparent and accountable to all stakeholders (Hernández, 2024) (Sanderson et al., 2023).
- Human autonomy and the role of the negotiator: As AI Support negotiation become more sophisticated, there is a risk that they could undermine the autonomy and decision-making capabilities of human negotiators. To address this concern, organizations must invest in training and development programs that empower negotiators to work collaboratively with

AI systems, leveraging the unique strengths of both humans and machines (Hernández, 2024; Heinl, 2014).

- Environmental and societal implications: The widespread adoption of AI Support negotiation could have broader societal and environmental implications, such as changes in employment patterns, energy demands, and the distribution of economic benefits. Organizations must consider these broader impacts and work to mitigate any negative consequences.

## 6.6 Recommendations for Future Research

Based on the key findings and implications of this research, the following recommendations are proposed:

- Develop comprehensive strategic plans for the integration of AI and ML into Fact-Based Negotiation processes, considering organizational readiness, training requirements, and change management strategies.

- Establish ethical guidelines and frameworks to ensure the responsible and transparent use of AI in negotiation and decision-making processes, addressing concerns around bias, privacy, and accountability.

- Conduct targeted studies to explore the sector-specific opportunities and challenges of AI-enhanced Fact-Based Negotiation, enabling the creation of customized strategies and benchmarks.

- Invest in research and development to further enhance the capabilities of AI and ML in supporting negotiation and decision-making, while addressing the limitations and emerging considerations.

- Foster collaboration between policymakers, researchers, and industry practitioners to shape the future policy landscape and drive the ethical and effective integration of these technologies.

By implementing these recommendations, organizations can unlock the full potential of AI and ML-enhanced Fact-Based Negotiation, driving strategic sourcing and negotiation processes to new heights of efficiency, effectiveness, and precision.

Based on the findings of this thesis, several areas for future research have been identified:

- Empirical investigation of real-world implementation of AI-powered negotiation tools: More research is needed to understand the practical implications of these technologies, including their impact on negotiation outcomes, processes, and the experiences of negotiators and stakeholders (Ma et al., 2024).

Expansion of AI-augmented Fact-Based Negotiation to other domains: Future studies should explore the potential applications of these technologies in legal negotiations, policy-making, and other areas where negotiation plays a critical role (Hernández, 2024).

- Deeper exploration of ethical frameworks and mitigation strategies: Further research is needed to develop comprehensive ethical guidelines and best practices for the responsible implementation of AI in negotiation, addressing issues such as fairness, transparency, and human autonomy. (Bostrom & Yudkowsky, 2018; Sanderson et al., 2023).

- Collaboration between researchers and practitioners: Interdisciplinary partnerships between academics, technology experts, and negotiation professionals will be crucial for advancing the field and ensuring that the development and deployment of these technologies are aligned with the needs and values of all stakeholders (Hernández, 2024).

By addressing these areas of future research, the field of AI-augmented negotiation can continue to evolve in a way that maximizes the benefits of these technologies while mitigating the potential ethical risks and preserving the essential human aspects of the negotiation process.

**6.7 Conclusion**

This thesis has explored the integration of Fact-Based Negotiation augmented by AI and ML, offering a comprehensive analysis of its impact on strategic sourcing and negotiation processes across various domains. The findings highlight the potential benefits of these technologies, such as improved data-driven decision-making, enhanced scenario planning and risk mitigation, and increased efficiency and productivity.

However, the research also underscores the critical importance of addressing the ethical considerations associated with these technologies, including issues of fairness, privacy, transparency, and human autonomy. By developing robust ethical frameworks and mitigation strategies, organizations can harness the power of AI Supported negotiation while ensuring that they are implemented in a responsible and equitable manner (Hernández, 2024; Bostrom & Yudkowsky, 2018; Sanderson et al., 2023).

As the use of AI in negotiation continues to evolve, it will be crucial for researchers and practitioners to collaborate to expand the application of these technologies to other domains while also deepening our understanding of the ethical implications and best practices for their implementation. The future of AI-augmented negotiation holds significant promise, but it will require a careful, multidimensional approach that prioritizes ethics, regulation, innovation, and education to ensure that these technologies are deployed in a way that benefits all stakeholders and maintains the essential human aspects of the negotiation process.

The integration of Fact-Based Negotiation with AI and ML has emerged as a transformative force in strategic sourcing and negotiation processes. This research has provided a comprehensive analysis of the impact of this integration, highlighting the widespread adoption of Fact-Based Negotiation, the significant benefits of AI and ML integration, and the necessity for strategic planning and organizational adaptation.

As organizations continue to accept this integration, they must navigate the ethical and practical considerations to ensure the responsible and effective use of new technologies. By doing so, the organization can unlock a competitive advantage and drive sustainable success in an increasingly dynamic and data-driven business landscape.

The rapid advancements in AI and ML have had a profound impact on various aspects of business and decision-making (Hernández, 2024; Davenport et al., 2019). This research has demonstrated that the integration of Fact-Based Negotiation with these technologies can lead to significant improvements in negotiation efficiency, effectiveness, and strategic precision (Ma et al., 2024; El-Emary, 2020).

The findings of this study have important implications for policymakers and practitioners, who must work collaboratively to shape the future policy landscape and to safeguard the ethical and effective integration of these technologies correctly (Trunk et al., 2020; Buch et al., 2022). Through strategic planning, organizational adaptation, and the development of ethical frameworks, organizations can harness the transformative potential of AI and ML-enhanced Fact-Based Negotiation, driving sustainable success in an increasingly competitive and data-driven world.

The effective integration of fact-based Negotiation with artificial intelligence and machine learning presents a significant opportunity to enhance the negotiation outcome.

This research has explored the widespread adoption of Fact-Based Negotiation and the substantial benefits of integrating it with AI and ML technologies. The key findings of this study include:

1. Widespread Adoption of Fact-Based Negotiation: The study established that fact-based negotiation is widely recognized and adopted across multiple sectors due to its data-driven approach, enhancing transparency and decision-making effectiveness.
2. Benefits of AI and ML Integration: By leveraging AI and ML, organizations have significantly improved their negotiation strategies, achieving enhanced efficiency, predictive analytics, and better outcome alignment with strategic goals.
3. Validation of Hypotheses: The research confirmed that AI and ML integration in Fact-Based Negotiation increases efficiency and effectiveness, reduces negotiation cycle times, and offers greater adaptability and precision than traditional methods.

The findings of this study are align with the existing literature, affirming the theoretical claims about the benefits and the challenges of AI and ML integration in the negotiation practices (El-Emary, 2020; Selim, 2020).

However, the right implications of using AI in negotiation and decision-making processes warrant further exploration. Developing comprehensive strategic plans, establishing ethical guidelines, and fostering collaboration between stakeholders are crucial to unlocking the full potential of this integration while addressing emerging considerations.

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## **Annexure A** Survey Questions: -

**1) If you wish to be contacted for a follow-up interview, please provide your preferred method of contact (e.g., Official Email address or Phone Number**)

**2) Current Position/Title at the Organization.**

**3) Functional Domain/Area of Expertise (e.g., Procurement, Sales, HR, Operations, etc.)**

**4) How long have you been employed with your current organization?**

*Options: -*

| | | | |
|---|---|---|---|
| *Less than a year* | *1-3 years* | *4-7 years* | *8-10 years* |
| *More than 10 years* | | | |

**5) What is the approximate size of your department within the organization?**

*Options: -*

| | | | |
|---|---|---|---|
| *1-10 employees* | *11-25 employees* | *26-50 employees* | *51-100 employees* |
| *More than 100 employees* | | | |

**6) Please select the type of organization you are affiliated with.**

*Options: -*

| | | | |
|---|---|---|---|
| *Manufacturing* | *Services* | *Retail* | *Technology* |
| *Healthcare* | *Education* | *Government* | *Non-Profit* |
| *Banking* | *Construction* | *FMCG* | *Other* |

**7) How many employees work at your organization?**

*Options: -*

| | | | |
|---|---|---|---|
| *51-200* | *201-500* | *501-1000* | *Over 1000* |

**8) What is your organization's annual turnover in (USD)? Please select the range that best represents your organization's most recent fiscal year turnover.**

*Options: -*

| | | |
|---|---|---|
| *Less than $1 million* | *$1 million to $10 million* | *$10 million to $50 million* |
| *$50 million to $100 million* | | *More than $100 million* |

**9) In how many countries does your organization operate or have sites?**

*Options: -*

| | | |
|---|---|---|
| *Only in the home country* | *In 2 to 5 countries* | *In 6 to 10 countries* |

| | | |
|---|---|---|
| *In 11 to 20 countries* | *In more than 20 countries* | |

**10) Was the above explanation of AI, ML, and FBN clear and comprehensible?**

*Options: -*

| | | |
|---|---|---|
| *Yes* | *Somewhat clear* | *No, I need more information* |

**11) What is your experience level with Fact-Based Negotiation (FBN)?**

*Options: -*

| | | |
|---|---|---|
| *Only in the home country* | *In 2 to 5 countries* | *In 6 to 10 countries* |
| *In 11 to 20 countries* | *In more than 20 countries* | |

**12) Does your organization currently use FBN in its Procurement/Sales/HR negotiation activities?**

*Options: -*

| | | |
|---|---|---|
| *Yes* | *No* | *Unsure / Not applicable* |
| *If not, are there plans to consider it in the future? Please specify.* | | |

**13) If you currently use FBN, please indicate potential areas where it is applied within your organization.**

*Options: -*

| | | |
|---|---|---|
| *Sales* | *Marketing* | *Human Resources* |
| *Supply Chain Management/ Sourcing / Procurement* | | *Other* |

**14) Does your organization utilize AI and/or ML to support your FBN processes in Procurement/Sales/HR negotiation activities?**

*Options: -*

| | | |
|---|---|---|
| *Yes, we use AI* | *Yes, we use ML* | *Yes, we use both AI and ML* |
| *No, but we are considering it* | | *No* |

**15) Please rate your agreement with the following statement: "Integrating FBN with Supportive Intelligence and Lean thinking Principles could reduce the negotiation cycle and improve negotiation efficiency."**

*Options: -*

| | | |
|---|---|---|
| *Strongly agree* | *Agree* | *Neutral* |
| *Disagree* | *Strongly disagree* | *Not applicable / We do not use AI and ML* |

**16) What is your level of experience with fact-based negotiations in Procurement/Sales/HR negotiation activities?**

*Options: -*

| | | |
|---|---|---|
| *Novice* | *Intermediate* | *Advanced* |
| *Expert* | | |

**17) To what extent is AI and ML technology currently involved in your organization's Procurement/Sales/HR negotiation activities?**

*Options: -*

| | | |
|---|---|---|
| *Not at all* | *Somewhat involved* | *Highly involved* |
| *Fully integrated* | | |

**18) Will organizations employing the Data-Driven FBN Model demonstrate favorable negotiation outcomes?**

*Options: -*

| | | |
|---|---|---|
| *Yes, significantly* | *Yes, somewhat* | *No, not really* |
| *Not Implemented AI & ML* | | |

**19) On a scale from 1 to 5, how would you rate the impact of AI and ML on your negotiation efficacy?**

*Options: 1 being shallow impact, 5 being very high impact)*

*Options: -*

| | | |
|---|---|---|
| *Low Impact 1* | *Low Impact + 2* | *Medium Impact 3* |
| *Medium Impact + 4* | *High Impact 5* | |

**20) What are the primary areas in which AI and ML could contribute to cost savings within Procurement / HR negotiation activities and Value Maximization in Sales in your organization?**

*Options: -*

| | | | |
|---|---|---|---|
| *Predictive analytics for demand forecasting* | *Automated vendor selection and contract management* | *Inventory optimization* | *Spend Analysis and reduction* |
| *Fraud detection and compliance monitoring* | *Process automation (e.g., invoicing, purchase orders)* | *Supplier risk management* | *No Idea* |
| *Other* | | | |

**21) Integrating AI and ML into Procurement/Sales/HR operations optimized the negotiation time.**

*Options: -*

| | | | |
|---|---|---|---|
| *Significantly decreased* | *Somewhat decreased* | *Stayed the same* | *Increased* |
| *Not Integrated* | | | |

**22) Have you experienced organizational resistance or challenges when adopting AI and ML in Procurement/Sales/HR? If so, please specify. (Yes/No)**

*Options: -*

| | | |
|---|---|---|
| *No* | *If Yes, Please Specify Below* | *Other* |

**23) What training or support have you received to effectively use AI and ML in negotiations?**

**24) Do you believe that using AI and ML has improved the objectivity and outcomes of your negotiations?**

*Options: -*

| | | |
|---|---|---|
| *Agree* | *Strongly agree* | *Neutral* |
| *Disagree* | *Not Implemented AI & ML* | |

**25) How often do you use data analytics and insights generated by AI and ML when preparing for negotiations?**

*Options: -*

| | | |
|---|---|---|
| *Always* | *Often* | *Sometimes* |
| *Rarely* | *Never* | |

**26) What are the top barriers that might prevent the effective use of AI and ML in Procurement /HR /Sales or any Domain Negotiation applicable?**

**27) How confident are you in the accuracy and relevance of the intelligence provided by AI and ML technologies during negotiations?** *(Scale from 1 to 5)*

*Options: -*

| | | | |
|---|---|---|---|
| *Scale 1* | *Scale 2* | *Scale 3* | *Scale 4* |
| *Scale 5* | | | |

**28) Would you be willing to participate in a follow-up interview to further discuss your answers?**

*Options: -*

| | |
|---|---|
| *Yes* | *No* |

## Annexure B Interview Questions: -

**Introduction:**

Thanks for participating. Please introduce yourself and tell us about your role in the organization.

1. Understanding AI, ML, and FBN:

How would you describe your understanding of Artificial Intelligence (AI) and Machine Learning (ML)?

What is your familiarity with Fact-Based Negotiation (FBN)? Can you share an example where you might have encountered or used these methods?"

**Current Usage and Practices**

2. Application of AI, ML, and FBN:

Is your organization currently using AI and ML in its operations? If so, can you describe some specific use cases?

Does your organization employ FBN in procurement, sales, or HR negotiations? Can you provide details on how this is implemented?

**Impact and Outcomes**

3. Impact of AI and ML:

What impact have AI and ML had on your negotiation processes regarding efficiency, cost-saving, or outcomes? Could you provide specific examples or success stories?

4. Impact of FBN:

How has the use of FBN influenced the outcomes of your negotiations? Has it improved objectivity and decision-making?

**Efficiency and Effectiveness**

5. Negotiation Efficiency:

Has integrating AI and ML technologies affected the time required to negotiate and finalize agreements? If so, how?

**Challenges and Barriers**

6. Challenges in Adoption:

What challenges or resistance have you faced when adopting AI and ML in your organization's negotiation activities? How were these challenges addressed?"

7. Barriers to Effective Use:

What are the top barriers preventing the effective use of AI and ML in procurement, HR, sales, or other negotiation domains?

**Confidence and Insights**

8. Confidence in AI and ML:

How confident are you in the accuracy and relevance of the intelligence provided by AI and ML during negotiations? What experiences have shaped your level of confidence?

9. Use of Data Analytics:

How often do you utilize data analytics and insights generated by AI and ML when preparing for negotiations? Can you describe a scenario where these insights were particularly valuable?

**Future Prospects and Recommendations**

10. Future Plans:

Are there plans to expand or integrate AI and ML into your organization? What areas are being considered?

11. Improvements and Recommendations:

Based on your experience, what improvements or changes would you suggest for implementing and utilizing AI, ML, and FBN in your organization?

**Comparative Insights**

12. Comparison with Other Organizations:

How do you think your organization compares with others in your industry regarding integrating AI, ML, and FBN? What lessons could be learned from other companies.