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SOURCING EFFICACY – THE ROLE OF SUPPORTIVE INTELLIGENCE

Abstract

Purpose: Globalization has increased the importance of sourcing and procurement strategies and fact-based negotiation (FBN). Technological advances such as machine learning (ML) and artificial intelligence (AI) and their integration in FBN are significant transformative steps. The paper explores ML and AI's role in improving FBN processes that traditionally rely on data-driven perceptions.

Methodology: The research used in the paper used a multi-method approach with quantitative and qualitative elements. This research design was chosen to explore the complexity of integrating AI and ML in FBN and to obtain the impact this integration has on sourcing processes in different industries. The research results are based on a survey of 210 participants and 33 in-depth interviews.

Results: The research showed that companies use FBN and see it as a beneficial approach to increasing negotiation efficacy. AI and ML integration in FBN significantly improves the negotiation process since it provides predictive modeling and real-time data analysis.

Conclusion: The paper's results align with current scientific studies highlighting the opportunities and barriers to AI and ML integration in negotiation processes. Companies must prioritize planning, education and organizational alignment for further development and optimization of these tools. With this, it is possible to fully realize the possibilities that integrating AI and ML into FBN can bring to the transformation of sourcing processes and the company's competitiveness.

Keywords: Sourcing, Fact-Based-Negotiation, supportive intelligence, artificial intelligence, machine learning

1. Introduction

According to Vitasek (2016), sourcing has always been a significant pillar for any company wishing to achieve a competitive edge in the global market. There is a possibility that integrating artificial intelligence (AI) and machine learning (ML) into Fact-Based Negotiation (FBN) may enable the achievement of a competitive objective (Spekman et al., 1999). According to Shahzadi et al. (2024), AI will enhance the crucial functions of organizational supply chains and manufacturing industries. The forecast made by MIT Technology Review 2025 (2024) suggested that the implementation of AI in supply chain management and manufacturing will grow from 11% in 2022 to 38% by 2025.

The main competitive advantage of FBN is that it has been applied in other business units such as sales, HR, and legal, which leads to better overall negotiation results. The challenge of utilizing FBN to its fullest effectiveness is that it requires adequate management of internal and external data sources, which is often tedious and complicated. Supportive intelligence tools such as AI and ML can ease these processes and enable more accurate and effective decision-making (Allal-Chérif et al., 2020; Guida et al., 2023). The incorporation of AI and ML into FBN signifies a new era. These systems enable negotiators to conduct numerous data analyses to recognize patterns, make intelligence, enhance sourcing strategies, and assist decision-making (Lorentz et al., 2021).

Even though building contexts is crucial, AI-enabled estimations can predict counterparty behavior alongside fuzzy logic and other soft computing techniques that effectively enhance supply chain coordination (Shapiro, 2000). The sourcing agent with appropriate intelligence support tends to shift from classical negotiation methods towards cooperative negotiation strategies fostering precision and flexibility. This allows them to be more adaptive, which helps to generate better negotiating outcomes and achieve the company's profitability and competitive goals within the modern global business environment (Murray & Raynolds, 2007).

Thus, this paper aims to investigate the use of AI and ML techniques to enhance further FBN processes that were previously purely qualitative. The framework within which FBN is discussed is the organizational culture technology acceptance model. This constitutes the first part of the paper, which introduces FBN and its background. The second part of the paper deals with the research of AI and ML in the context of FBN. Lastly, the third part of the paper concludes and recommends further studies in this area.

2. Literature review

Companies face complex challenges in today's ever-evolving global market, highlighting the importance of effective procurement and sourcing strategies to remain competitive (Vitasek, 2016). Studies (e.g., Gates & Matthews, 2014; Ebner, 2017) highlighted the fundamental shift toward data-centric negotiation approaches and found that data is the new currency for delivering competitive sourcing outcomes. Traditional negotiation methods are increasingly being improved, and companies are adopting technology-driven strategies focusing on accuracy, efficiency, and strategic planning (Fasihullah et al., 2023). Technologies like AI and ML are important for this move in negotiation since they can analyze large datasets, quickly spot patterns and provide actionable insights and will help negotiations to enter the digital sourcing era (Allal-Chérif et al., 2020; Lorentz et al., 2021; Guida et al., 2023). Kelleher (2000) stated that supportive intelligence helps sourcing professionals in real-time data analysis for data-driven decisions, while traditional methods aim to help them use available resources strategically and capitalize on market opportunities.

The Technology Acceptance Model (TAM)

Sargolzaei (2017) concluded that the TAM predicts and explains user behavior regarding new technology acceptance in companies. TAM highlights perceived practicality significance in sourcing and practical drivers' technology adoption ease of use (Rahmi et al., 2018). The model suggests that if sourcing professionals see data-driven negotiation tools as easy and beneficial, they will use and utilize such systems (Luo et al., 2023). Frank et al. (2023) concluded that sourcing efficacy can be significantly enhanced when using data-driven insights for negotiation validation. Integration of supportive intelligence (e.g., AI, ML) can enhance sourcing efficacy (e.g., Allal-Chérif et al., 2020; Schulze-Horn, 2020; Guida et al., 2023). When these analytic tools are user-friendly and helpful in sourcing operations, sourcing professionals are more likely to adopt and effectively utilize them (Althabatah et al., 2023). Additionally, Gangwar et al. (2015) found that TAM can be integrated with studies on readiness for change and organizational culture to propose a complete attitude toward the technology adoption process in sourcing. Based on Rogers' (2003) diffusion of innovations theory, factors such as change readiness and organizational culture significantly impact the adoption of new technologies in sourcing (Sotelo & Livinghood, 2015).

Culture as an important factor in technology adoption

Adinew (2024) found that adopting new technology in companies is one of the most complex processes significantly influenced by a company's culture. Companies with a culture open to innovation and change (Steers et al., 2008) can implement AI and ML more successfully in their sourcing (Farayola, 2023). Vasiljeva et al. (2021) concluded that opinion toward AI differs among industries and that the three main factors influencing AI implementation are regulation, competition and top management's attitude toward this issue. The role of culture can also be seen in Lee et al. (2019), who stated that the implementation success of the new technologies needs alignment between new technologies requirements and the company's culture. Therefore, companies must create cultures aligned with evidence-based decision-making and continuous improvement to benefit from supportive intelligence (Shahzadi et al., 2024; Adinew, 2024; Guida et al., 2023). Allal-Chérif et al. (2020) found that this alignment can help integrate emerging technologies and maximize their positive impact.

The emergence and evolution of FBN

Helmold et al. (2022) stated that FBN developed as an increasingly beneficial contract negotiation model. It has distinguished itself from traditional methods that rely on instincts and experience. Parninagtong (2016) found that FBN leverages data-driven strategies for informing decision-making with objective and measurable criteria. At the same time, it enables more effective and informed contract negotiations (Tomlinson & Lewicki, 2015). Latilo et al. (2024) found that contract agreement negotiation represents a multifaceted process demanding different characteristics and considerations. To reach successful negotiations, it is necessary to ensure that the agreement satisfies both parties, fulfills its intended purpose, and remains durable over time (Sussking & Ali, 2014). It also creates the base for future collaboration efforts (Tomlinson & Levicki, 2015).

FBN leverages data-driven insights to ensure an objective and informed decision-making process compared to traditional negotiations that rely on individual experience and subjective assessment (Schulze-Horn et al., 2020). FBN enhances prospects for reaching agreements with more chances to endure the test of time and establish a better base for future collaboration (Nyden et al., 2013). This is done by grounding the negotiation process in verifiable and measurable criteria. Fiske et al. (2019) concluded that this approach allows negotiation parties to surpass intuition and anecdotal evidence and make informed decisions supported by analytical insights of quantifiable data. Finally, FBN is a progressive move toward a better-informed and sustainable approach to contract negotiations (Hămuraru & Buzdugan, 2024).

Streamlining trade-offs with intelligent support in FBN

The negotiation process often involves different and complex trade-offs in which decision-making needs to be considered in different aspects such as price, delivery terms, payment terms, service quality, etc. (Van der Rhee et al., 2009). Faratin et al. (2002) found these trade-offs familiar in negotiations, but the role of intelligent support, such as AI and ML, in enhancing these strategies has not yet been explored (Lin et al., 2023).

Since its emergence, AI has been seen as a tool that can significantly assist the negotiation process by offering insights to manage trade-offs more effectively (Schulze-Horn et al., 2020). Jarrahi (2018) stated that AI can be used for data analysis to identify the optimal balance between quality and cost that can help negotiators make decisions. Tafakkori et al. (2022) and Shrestha et al. (2019) concluded that AI can predict the impact of delayed deliveries and help negotiators make better decisions about costs and customer satisfaction.

ML is another supportive intelligence tool that can reduce the trade-off between delivery speed and cost in logistics and scheduling (Khedr, 2024). Kalasani (2023) stated that advanced algorithms learn from data and help negotiators create sourcing balance strategies. These algorithms can support negotiators in making decisions for accepting minor losses that could strengthen supplier relationships and secure supply chain reliability (Niranjan et al., 2021; Riahi et al., 2021).

With the help of supportive intelligence, negotiators can identify crucial trade-offs and develop innovative solutions (Singh & Mazumdar, 2017). This can help them streamline the negotiations and make informed decisions, balancing different criteria such as quality, price and customer satisfaction (Riahi et al., 2021). Previous studies showed that by integrating AI and ML in FBN, negotiators can leverage data-driven insights to make strategic choices for optimizing multiple objectives simultaneously. This approach supports negotiators in streamlining negotiations, resulting in more favorable outcomes that balance all stakeholders' needs and priorities.

Key elements of FBN in sourcing

In scientific papers, studies, and professional journals connected to sourcing, researchers and authors identified several key elements of FBN in sourcing that can be assisted and improved by supportive intelligence (Table 1).

Table 1 Key elements

Element	How and why
1. Cost breakdown analysis	A combination of AI, ML and Robotic Process Automation (RPA) enables cost breakdown analysis automation needed for support in FBN (Jha et al., 2021).
2. Zero-based costing	AI in handling zero-based costing improves productivity and creates a good start for negotiations (Timmermans et al., 2019).
3. Total cost of ownership (TCO)	RPA and AI help companies prepare TCO as a crucial part of optimizing a company's asset management strategies (Hosseini & Andersson, 2024; Bataev et al., 2020).
4. Value analysis	Value analysis implementation in FBN can increase the quality of construction projects and improve consumer satisfaction (Shelote et al., 2018).
5. The Best Alternative to a Negotiated Agreement and the Worst Alternative to a Negotiated Agreement	Adequate preparation and data gathering with the help of supportive intelligence is crucial for negotiators to achieve a better deal (Sebenius, 2017).
6. Sustainability	Companies can make more informed decisions and access sustainability factors within their supply chains with the help of supportive intelligence and e-procurement (Ramkumar & Jenamani, 2014)
7. Preparation	Accurate assessment of interest and possible agreements is significant for negotiation outcomes (Althabatah et al., 2023)
8. Concessions and compromise	Concessions and compromise are instrumental in reaching a mutually acceptable agreement, so the help of supportive intelligence is needed (Mwagike & Changalima, 2022).
9. Problem solving	An integrative approach allows negotiators to diverge from competitive strategies and focus on jointly overcoming obstacles (Boshrababi & Hosseini, 2021).
10. Decision making	Involves considering multiple scenarios and their potential outcomes, ensuring that decisions are grounded in data (Riggio & Saggi, 2015).
11. Persuasion	Articulating the value and rationale behind one's position, anchoring the negotiation on substantiated narratives and data (Ivey, 2023).
12. Agreement	An accurate assessment of interests and possible agreements, along with anticipation of potential contingencies and factors that may interfere in negotiation, are areas where supportive intelligence can help (Liu & Chai, 2015)

Source: Authors

AI and ML, as supportive intelligence, have their place in each key element of FBN sourcing. The literature review shows a significant link between supportive intelligence tools such as AI and ML and successful negotiation strategies (Karlsson, 2020). The use of AI and ML tools can help FBN analyze complex datasets and predict results, developing at the same time innovative strategies that are the result of modern sourcing (Heilig & Scheer, 2023). Collaboration between FBN and supportive intelligence assists informed decision-making and safeguards that negotiations are based on objective standards and mutual benefits (George et al., 2023). This approach links tradition and modern technology by mixing negotiation with data-driven preciseness. Thus, FBN and supportive intelligence such as AI and ML offer a comprehensive strategy for modern sourcing challenges. Together, they create an environment where sourcing professionals can balance efficiency with effectiveness when agreeing on contracts, which creates value and sustainability for the company in the long term.

3. Methodology

The research aims to provide an in-depth analysis of how AI and ML can support sourcing professionals in enhancing the effectiveness of FBN. A multi-method approach incorporating qualitative and quantitative elements was used for the research. This mixed-method design was selected to explore the intricate nature of AI and ML integration into FBN and to capture the impact of such practice across various industry sectors.

A purposive and snowball sampling strategy was used to create a research sample. The sample consisted of professionals representing the population in terms of industry, experience, role, and engagement with FBN, AI and ML technologies. Different organizational positions in the sample were needed to gather a wide range of insights into the applications, challenges, and opportunities of AI and ML in FBN.

The first part of the research was an online survey. To participate in the survey, respondents needed to have experience in sourcing and/or sales, engagement with AI and ML, and an organizational role. The survey included Likert-scale questions and open-ended responses to capture views (Allison et al., 2002) on FBN, AI, ML, challenges, and opportunities. The second part of the research included in-depth interviews with survey participants who expressed their interest in being contacted for the interviews. The interviews were designed to better understand their experiences and perceptions of AI and ML roles in FBN. The interview protocol consisted of structured and semi-structured questions.

An invitation to participate in a survey was sent to 450 professionals in various industries, of which 232 responses were received. Of these, 22 were incomplete and therefore excluded from the analysis. From the remaining 210 completed surveys, a sample of 33 professionals from the sourcing, sales, HR, and legal departments was created (i.e., 15% of the survey participants) to ensure a broad perspective. Data collected from surveys and interviews was analyzed with SPSS.

This research has several limitations, although the efforts to secure diverse samples from different industries and geographical locations to reach a fully representative cross-section of the sourcing professionals' population can be constrained. The second limitation lies in the sample size. In terms of considerable differences in practices and culture, the targeted sample size (210 surveys + 33 interviews) may not be sufficient for generalizing conclusions for companies' different sectors and sizes.

4. Research results and discussion

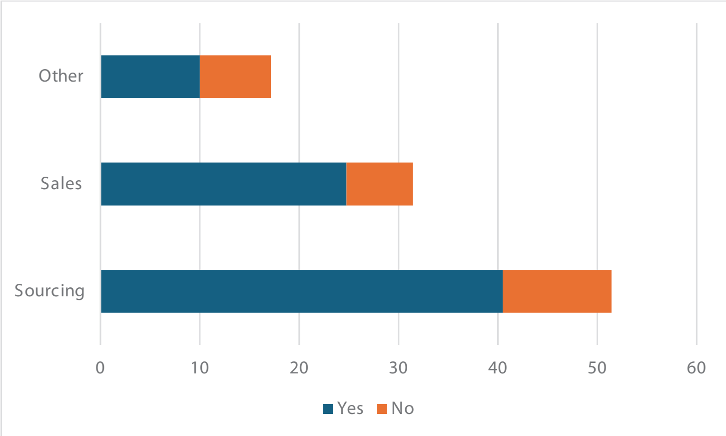
Survey results

A total of 210 completed survey responses were analyzed for this research. The largest segment of participants (30%) comes from the technology sector, which shows the prevalence of technology-driven companies in modern business (Büyükbalcı et al., 2021). The second largest segment comes from service industries (23.81%) and manufacturing sectors (19.06%). Regarding their company roles, most respondents work in supply chain management (51.43%) and sales (31.43%).

Companies involved in this research have a strong international presence since 35.71% operate in more than 20 countries, but on the other hand, a significant part (34.29%) operates only in their home country. The most significant segment of companies (67.15%) involved in the research have more than 1,000 employees, and their departments in most cases (40%) have more than 100 employees. The most involved companies (64.28%) have more than 100 million USD turnover; the highest share (49.6%) is in more than 20 countries worldwide. The duration of employment in the company can significantly impact the employees' level of engagement in the company (Markos & Sridevi, 2010). The largest share of respondents has been in the company for 1 to 3 years (33.33%), followed by long-term employees (26.19%) who have been there for more than 10 years.

When asked about familiarity with FBN, more than 83% of respondents are thoroughly and somewhat familiar with FBN. Figure 1 provides insights into the survey participants using FBN across different functional domains.

Figure 1 Current use of FBN in organizational functional domains

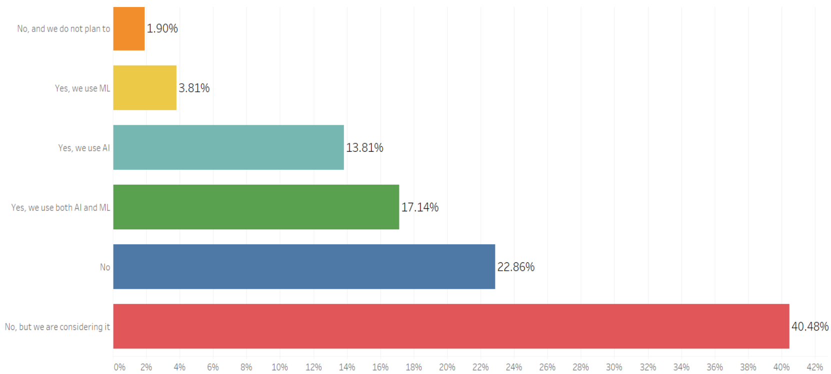


Source: Authors

Figure 1 shows that a significant share of respondents (75.24%) use FBN in their work. Within this group, most respondents come from sourcing (40.48%), followed by sales. These findings indicate that FBN is perceived as particularly applicable within these two functional domains of companies.

The increased adoption of AI and ML in FBN has been the subject of recent scientific studies (Westermann et al., 2023). Figure 2 shows survey participants' perspectives on their companies' plans for implementing these tools.

Figure 2 Adoption of AI and/or ML to support FBN



Source: Authors

Survey results reveal a mixed landscape: a significant proportion of companies are already using AI and ML, which is consistent with previous studies (Buch et al., 2022). It is important to state that a relatively significant share of respondents (24.76%) reported that their companies are not using nor do they plan to use AI and ML.

Respondents (59%) agree and strongly agree that integrating AI and ML could reduce negotiation cycle times and simplify sourcing processes. Their responses show that AI and ML integrated into FBN can help companies address critical factors (e.g., supplier and contract management, effective e-procurement implementation (Angeles & Nath, 2007)) and streamline their sourcing workflows. Research showed that a significant share of companies (46.19%) still need to involve AI and ML in their negotiations. However, when asked about the potential impact on negotiation results, almost a quarter of respondents (22.86%) perceived the impact of AI and ML as very low or low. This is aligned with findings by Krafft (2020), who indicated that most common visions of AI impact cause significant anxiety.

On the other hand, a large segment (62.38%) of respondents rated the impact as moderate to very high, which aligns with the research conducted by Lane et al. (2023). As a result of integrating supportive intelligence into negotiations, 42.86% of respondents reported a decrease in negotiation time. However, with the growing trend of AI and ML integration in company operations, the potential for substantial improvements in negotiation efficiency remains favorable (Hemalatha et al., 2021).

Since implementing supportive intelligence in FBN leads to changes in processes, it is necessary to understand the barriers and facilitate smoother integration of advanced technologies (Figure 3).

Figure 3 Types of training or support received to use AI and ML in negotiations effectively

Source: Authors

Results indicate that many companies faced resistance and challenges that must be addressed. Research participants indicated the following four barriers that may prevent the effective use of AI and ML in sourcing: (i) access to technology and data, (ii) cost considerations, (iii) data quality and security, and (iv) human factors and skills. One of the areas that can help is training and support during integration (Figure 4).

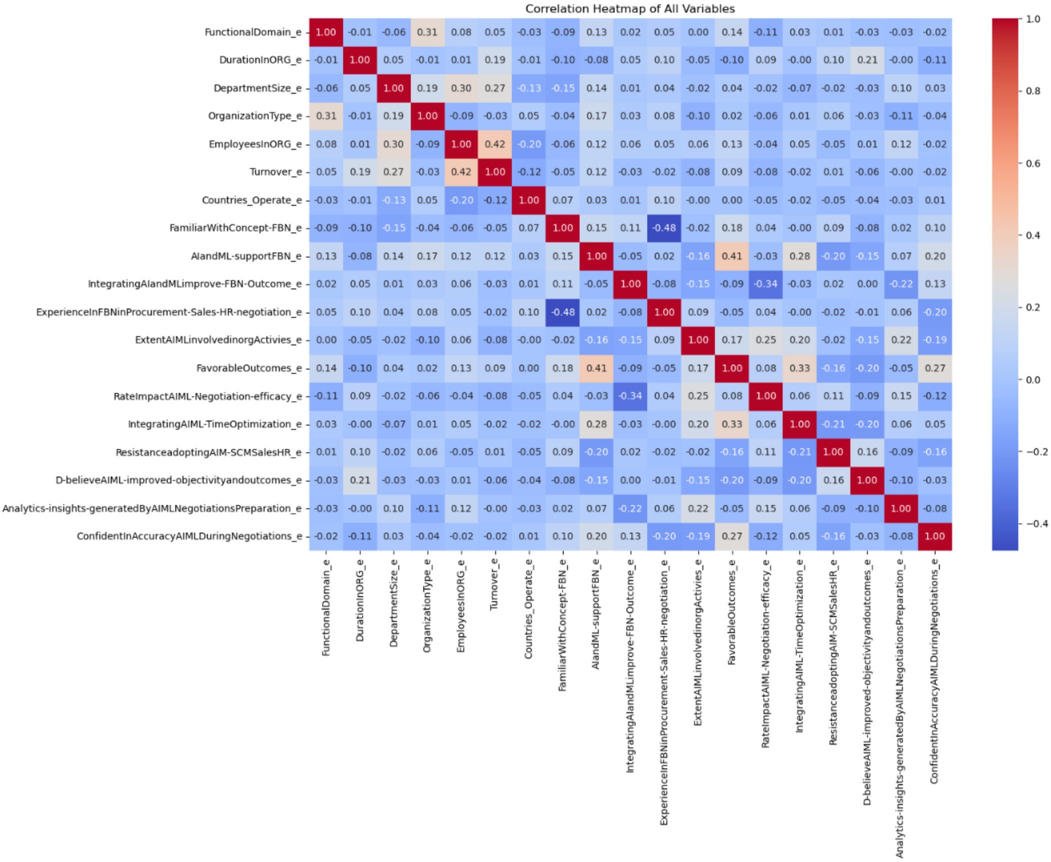
Figure 4 Types of training or support received to use AI and ML in negotiations effectively

Source: Authors

Some respondents indicated that they have received advanced training in AI and ML, while some are still in the early implementation phases or have not implemented those technologies at all. Training courses in some companies included basic information and awareness raising on AI and ML concepts, suggesting limited integration. In contrast, in other companies, the training was tailored to their specific needs, demonstrating a higher level of investment and prioritization, as found in research by Ma et al. (2024).

The correlation heatmap presented in Figure 5 shows the relationships between various factors influencing the adoption and efficacy of AI and ML in sourcing, sales, and HR negotiations.

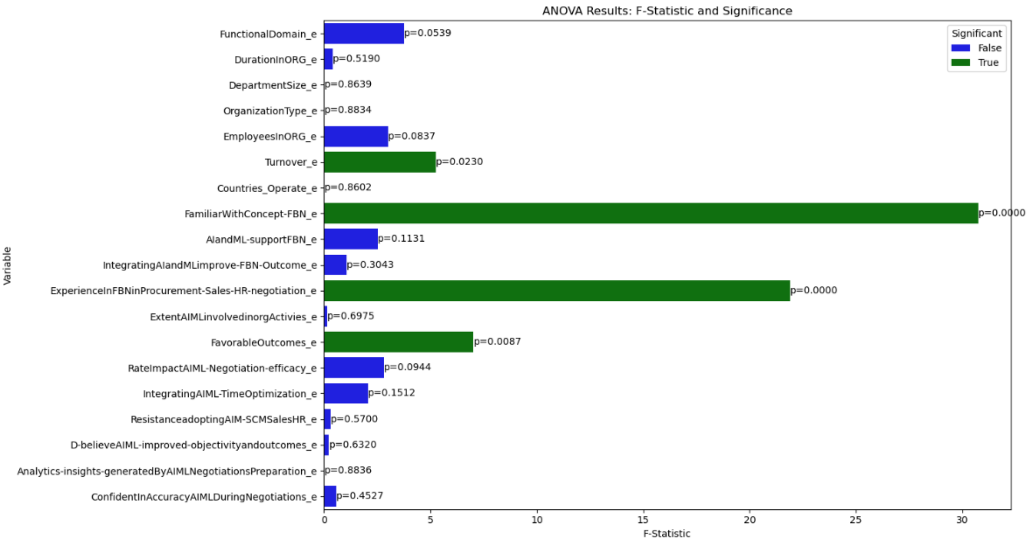
Figure 5 Correlation analysis of key factors influencing the adoption of FBN and the role of supportive intelligence



Source: Authors

Based on the correlation analysis, the heatmap showed that the functional domain of an organization shows a moderate positive correlation with the type of organization. A moderate positive correlation between functional domains and familiarity with FBN concepts indicates that certain domains are more likely to be acquainted with these approaches. There is a positive correlation between tenure and perceived resistance to adopting AI and ML in sourcing, sales, and HR. Furthermore, a positive correlation exists between the size of departments and perceived improvement in FBN results after AI and ML integration. This shows that employees in larger departments perceive greater value in leveraging advanced analytics and supportive intelligence in enhancing their FBN practices (Jöhnk et al., 2021). The correlation heatmap highlights that certain functional domains within specific organization types might be more inclined toward AI and ML. Factors like human skills, quality, and accessibility strongly influence perception and integration outcomes, and experienced sourcing professionals in FBN are more likely to report favorable outcomes and express confidence in using AI and ML. The correlation analysis showed a strong positive relationship between familiarity with FBN concepts and FBN adoption in sourcing, sales, and HR, indicating that integrating AI and ML into FBN could increase the efficiency and effectiveness of sourcing negotiations.

Figure 6 One-Way ANOVA outcome



Source: Authors

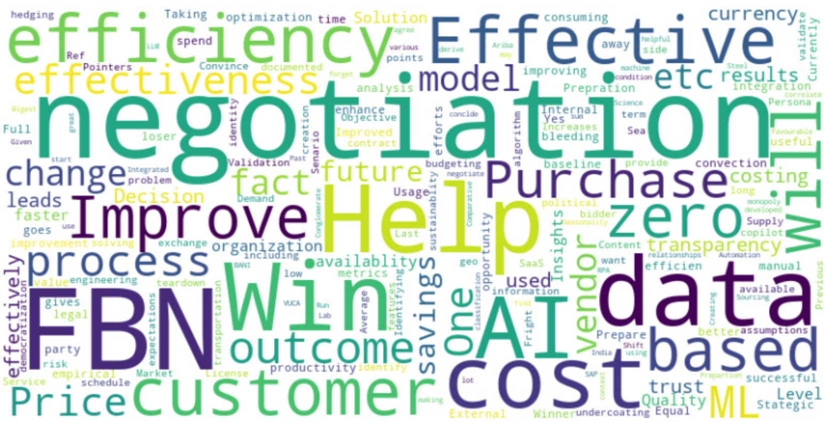
The ANOVA results highlighted the significant influence of variables like 'Turnover_e', 'FamiliarWithConcept-FBN_e', 'ExperienceInFBNinProcurement-Sales-HR-Negotiation_e', and 'FavorableOutcomes_e' on the 'CurrentlyFBNSCMHRSales_e' outcome. The ANOVA results demonstrated that experience with FBN in sourcing, sales, and HR significantly influences FBN adoption in these areas. This suggests that combining FBN with supportive intelligence technologies could reduce negotiation cycle times and simplify sourcing processes.

In-person interviews

To better understand the survey results, 33 in-person interviews were conducted with selected survey participants, who had an average of 23 years of professional experience. Most of them (52%) work in sourcing, followed by sales (18%) and IT (15%). Most of the participants are mid- and high-management members of their respective companies. The majority (84.5%) of participants are very familiar with the FBN concept, and more than two-thirds of participants reported the positive impact AI and ML have on their negotiation results, rating the impact as "better" or "significant". Interviewees expressed their confidence and trust in AI and ML during FBN because introducing 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. A significant share of participants, 87.88%, agreed that integrating AI and ML in FBN 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.

Figure 7 presents a word cloud with the key terms and implications associated with the efficiency and effectiveness of FBN with implemented AI and ML.

Figure 7 Efficiency and effectiveness of FBN with implemented AI and ML



Source: Authors

Figure 7 indicates that implementing AI and ML in FBN can improve both efficiency and effectiveness. The central position of the word ‘negotiation’ underlines the primary focus of the discussion, which revolves around how AI and ML can enhance the negotiation process. Efficiency is shown by terms such as ‘Efficiency’ and ‘Improve’, suggesting that data collection, analysis, and decision-making automation can improve 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 increase the quality and success of negotiation strategies, leading to better outcomes.

Figure 8 shows a word cloud with terms and implications related to confidence in the accuracy and relevance of information provided by AI and ML.

Figure 8 Confidence in the accuracy and relevance of the information provided by AI and ML

Source: Authors

The size of the word ‘high’ suggests that many participants have strong confidence in the information provided by AI and ML, which is consistent with findings by Sindermann et al. (2020). This notion is further reinforced by the word ‘confident’, which exhibits the participants’ assurance in the accuracy and relevance of insights gained from AI and ML. The central position of the word ‘data’ stresses the significant role that data quality and relevance play in building confidence in the information generated by these technologies. The emphasis on 'validate', 'validating', and 'validation' stresses the importance of continually verifying the accuracy of AI and ML predictions against real-world outcomes, representing an important step in sustaining trust in technology. The position of 'need' suggests that participants recognize a strong necessity for reliable data and validated insights to support negotiation processes effectively.

Figure 9 presents participants' opinions on the use of data analytics generated by AI and ML.

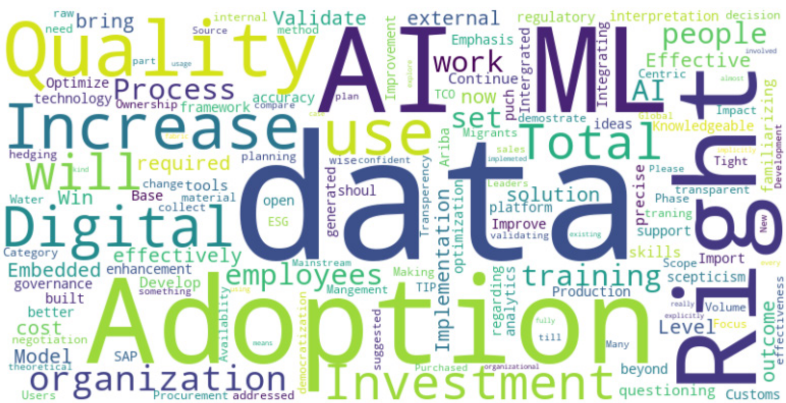
Figure 9 Use of data analytics generated by AI and ML for negotiation

Source: Authors

The status of words like 'effective', 'used', and 'data' in the above figure underline the significant role these technologies play in improving negotiation strategies and decision-making. 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 accent on 'validation' further stresses the need to ensure the reliability and relevance of data analytics, building trust in the accuracy of information, as seen in Taddy (2018).

Figure 10 presents participants' key recommendations for improving the implementation and utilization of AI/ML and FBN within companies.

Figure 10 Participants' proposals for improvement of better implementation and utilization of AI/ML in FBN



Source: Authors

The accent on 'quality' underscores the importance of maintaining high-quality data and processes to ensure the reliability and accuracy of AI-driven insights (Kshetri, 2021). Leveraging the tacit knowledge and judgment of human actors is crucial in effectively using AI and ML capabilities. Comprehensive and high-quality 'data' is the foundation for robust AI and ML negotiation applications, enabling more informed decision-making (Vertsel & Rumiantsau, 2024). To have a more significant impact, companies must focus on increasing the 'adoption' of AI/ML tools and FBN methodologies, integrating them seamlessly into regular business processes (Budach et al., 2022). A transition toward '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 FBN techniques is crucial for successful implementation (Vertsel & Rumiantsau, 2024).

5. Conclusion

Strategic sourcing significantly impacts several aspects of a company's performance. Sourcing results contribute to cultivating effective communication and long-term relationships between suppliers and buyers, which are antecedents of financial performance. A combination of strategic sourcing and digital technologies can increase company competitiveness. It provides companies with various benefits, such as inventory reduction, optimization of transaction costs, and establishing effective communication networks between buyers and suppliers.

FBN has emerged as an increasingly helpful model for contract negotiation, distinguishing itself from traditional methods that often rely on subjective judgment and circumstantial experiences. This approach leverages data-driven strategies that advise decision-making with measurable and objective criteria, enabling more effective and informed contract negotiations. In modern business negotiations, the integration of AI and ML has gained significant attention, particularly in FBN. Integrating AI and ML in FBN could significantly increase the efficiency and effectiveness of sourcing negotiation. Companies already adopting these technologies have reported improvements in their negotiation processes, while those in the observation phase may benefit from increased awareness and readiness for technological integration. Previous studies have emphasized the potential of AI and emerging human augmentation technologies for enhancing negotiation practices, enabling the automation of specific tasks, leveraging big data, and facilitating more efficient and effective decision-making. At the same time, integrating AI into negotiation processes has raised concerns about confidentiality, model bias, and the need for negotiators to develop new skills to work effectively with these tools.

Research results showed widespread adoption and recognition of FBN as a valuable approach. Integrating AI and ML with FBN significantly enhances negotiation processes by offering advanced analytics, predictive modeling, and real-time data insights. These technologies facilitate improved decision-making, adaptability, and responsiveness in sourcing negotiations. By automating routine tasks, enhancing data analysis, and facilitating real-time information sharing, companies can direct the complexities of global supply chains with greater agility and precision. These data-driven approaches enable sourcing teams to anticipate market fluctuations, identify optimal sourcing partners, negotiate more effectively, and, as a result, improve company outcomes.

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. Based on the key findings and implications of this paper, the following research recommendations are proposed: (i) develop comprehensive strategic plans for the integration of AI and ML into FBN processes, considering the company's readiness, training requirements, and change management strategies; and (ii) conduct targeted studies to explore the sector-specific opportunities and challenges of AI-enhanced FBN, enabling the creation of customized strategies and benchmarks.

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