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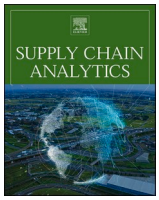

A text mining study of competencies in modern supply chain management with skillset mapping

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ABSTRACT

This study explores the skills and competencies required by modern supply chain management professionals, focusing on the shift toward advanced technological capabilities. We analyze job advertisements from a prominent Canadian employment platform using web scraping, natural language processing, and machine learning techniques, including Latent Dirichlet Allocation and Term Frequency-Inverse Document Frequency. The findings reveal that job postings primarily emphasize traditional operational skills such as logistics, inventory control, and customer relationship management. However, there is a noticeable underrepresentation of advanced technological competencies, such as machine learning, data analytics, and automation, which are increasingly critical in today's supply chain environment. This gap highlights the need for greater alignment between job market demands and supply chain management's evolving digital transformation landscape. The study identifies key themes, including technical, managerial, and soft skills integration, emphasizing adaptability, data literacy, and strategic decision-making. The results suggest a misalignment between the competencies highlighted in job advertisements and the skills necessary for managing the complexities of a digitalized supply chain. This research offers practical recommendations for industry leaders to refine hiring strategies, academic institutions to modernize curricula, and job platforms to better showcase emerging skill requirements. Addressing this gap is essential to equip supply chain professionals with the tools and expertise to meet the challenges of a technology-driven future.

1. Introduction

In today's globalized and technology-driven economy, effective supply chain management (SCM) is crucial for achieving supply chain (SC) efficiency and high service levels by ensuring the smooth flow of goods and services from producers through distributors to end consumers. Regardless of the industry or business segment, SCM success depends on three core elements: processes, people, and technology [1,14,25]. These three elements are pivotal in managing modern SCs, which are increasingly complex and interact with highly uncertain global systems.

Processes are central to SCM, encompassing the various activities, material flows, and operational stages - such as sourcing, manufacturing, transportation, and distribution—that must be coordinated to meet customer requirements efficiently. Effectively managing these processes leads to optimized resource utilization, reduced costs, and enhanced overall performance [53]. As SCs become more complex, organizations must ensure their processes are streamlined and aligned with evolving market demands.

Technology has become an indispensable element of modern SCM, transforming traditional operations through advancements in artificial intelligence (AI), machine learning (ML), automation, and big data analytics (BDA). These technologies enable greater efficiency and improved decision-making through data-driven strategies, essential for improving communication, coordination, and transparency within SCs [10,25]. With enhanced visibility across the SC, companies can minimize inventories, reduce costs, mitigate the bullwhip effect, and improve overall SC performance [34,61]. As technology evolves, SC professionals must adapt to these changes to maintain a competitive edge [3,5,50].

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The people dimension in SCM is equally critical, as the expertise of highly qualified professionals (HQPs) is essential for managing SC activities effectively. The crucial role of these HQPs cannot be overlooked, as their expertise is essential for the seamless execution of SC activities and the achievement of organizational objectives. However, as companies integrate advanced technologies into their SCM operations, the skills required to manage and sustain these operations are changing. SCM professionals are increasingly required to adapt by acquiring new competencies aligned with the digital economy's demands to make informed decisions, leading to tailored SC operations to meet client requirements and overall organizational goals [5,19,50]. While traditional SCM skills, such as logistics and procurement management, remain crucial, the growing reliance on technology has introduced a need for new proficiencies in data analytics, AI, ML, and process automation. These changes pose significant challenges for professionals who must navigate the complexities of digital transformation while ensuring the effective functioning of SC activities [18,50].

Navigating this technological shift presents challenges for professionals who must balance digital expertise with operational excellence. Industry reports consistently highlight changing SC skills from manual and cognitive tasks to social, emotional, and technological competencies. Companies need professionals with end-to-end SCM capabilities, data literacy, and strong decision-making skills as digital transformation redefines roles [3,13,20,50]. By 2055, half of tasks are expected to be automated, requiring reskilling, with 45 % of the workforce lacking the necessary skills. The 2022 Competencies of Canadian SC Professionals report stresses the importance of advanced techniques like ML for optimizing efficiency and aligning with strategic goals. This study is crucial in exploring and addressing the emerging skill requirements, mainly focusing on the competencies needed to operate effectively in technology-enabled SC environments [50].

Given the growing reliance on technology in SCM, this study aims to explore the emerging skill requirements for SCM professionals in technology-enabled environments. Specifically, this research aims to address the following questions:

1. What competencies are presently listed in job advertisements for SCM professionals, particularly those related to advanced technologies? This question aims to uncover the skills and proficiencies increasingly emphasized in the job market, mainly focusing on the shift toward technological competencies.
2. How can web scraping, ML, and natural language processing (NLP) be leveraged to identify and categorize competencies from job listings? This question explores a novel methodological approach by tailoring these techniques to the unique context of Supply Chain Management (SCM), a cross-disciplinary, complex, and evolving field. The focus is on applying web scraping and the integration of ML and NLP to uncover nuanced skill trends and emerging competency gaps in SCM job advertisements, providing scalable and actionable insights that extend beyond existing applications in other fields.
3. What patterns and trends can be discerned from the analysis of job advertisements, and what predictions can be made about future skills and competencies required in the SCM sector? This question seeks to leverage the predictive capabilities of ML and NLP to forecast the future trajectory of skills and competencies in the SC industry.

The study assesses the specific skills in high demand, identifies areas where skill improvement is needed, and pinpoints the current priorities for skill development within SCM. To address these questions, this study employs web scraping and NLP techniques to collect and analyze real-time job advertisements from indeed Canada (an online job portal). Web scraping allows the automated collection of large volumes of job postings, providing a dynamic and up-to-date view of the skills in demand across the SCM sector. Traditional methods such as surveys or interviews may only partially capture the rapid changes in job market trends, particularly in technology-driven and continuously evolving industries like SCM. By contrast, web scraping enables continuous monitoring of job advertisements, offering real-time insights into employer demands and emerging trends [29,43]. Once collected, job descriptions were analyzed using NLP techniques such as topic modeling and term frequency-inverse document frequency (TF-IDF) analysis. These techniques extract recurring themes, competencies, and skills from large, unstructured datasets [22]. NLP is uniquely suited for extracting insights from large, unstructured datasets like job descriptions or text-based information [28]. This study categorizes and identifies key themes in SCM competencies through topic modelling, providing insight into whether job requirements align with the people, process, and technology elements discussed earlier.

This paper provides a data-driven analysis of real-time job postings in SCM using web scraping, NLP, and ML techniques. By extracting and categorizing skill requirements, the study identifies a strong emphasis on traditional operational competencies such as logistics, inventory control, and customer relationship management, while revealing a limited representation of advanced technological skills, including machine learning, data analytics, and automation. These findings underscore a growing demand for cross-functional skills, highlighting the need for a workforce that can navigate the complexities of digital supply chains. The insights from this research contribute to industry, academia, and job platforms by informing curriculum development, talent acquisition strategies, and job market alignment with evolving SCM competencies.

2. Literature review

2.1. Evolution of the SCM profession

Historically, SCM primarily focused on functional skills such as logistics coordination, purchasing expertise, demand forecasting, and operations planning. Traditionally, SCM has involved the attainment of skills in outcompeting supplier relations, accurate stock, and management of inventories and distribution. These abilities focus on the economies of operation, physical and material distributions, and delivering value in well-coordinated SCs [16,21]. According to Flöthmann et al. [24], individual and organizational competencies such as network management, the performance of operations, and control of KPIs are also crucial in SCM. Beyond the fundamental tasks of the conventional SCM, technological advancement has impacted the SC and has assisted in defining the essential competencies of SCM [50]. Modern SCs necessitate a skill set mix derived from the application of digital technology. Therefore, when analyzing skill development, it is important to distinguish between new digital competencies that are important to promote data-driven decision-making in complex SC networks and traditional competencies to support the operational requirements.

Importantly, global shifts and rapid technological advancements demand highly skilled and knowledgeable supply chain professionals [21,27,46,58]. The COVID-19 pandemic further accelerated the adoption of digital technologies and emphasized the importance of SC visibility, requiring professionals to harness data-driven decision-making to enhance efficiency and adaptability in SCM. In today's globally integrated context, SCM practitioners must assume the roles of both strategic decision-makers and technology end users, leveraging data analytics and global experience to optimally manage SCs that increasingly confront pressing issues such as sustainability, risk management, and changing regulations [22,45,50]. Industry 4.0 technologies connect traditional linear value chains with ecosystems through digitization and automation. This transformation process requires technical skills, flexibility, integration, and problem-solving skills [19]. This implies that SCM practitioners continue to need technical skills, along with cultural, negotiation, and stakeholder engagement skills, to effectively manage interpersonal factors using advanced technology [22,50,55]. Combined with these soft skills, it ensures SCM's strategic importance and general

effectiveness [17].

To define the context historically, operational success and effective leadership in SCM required a full range of competencies. These competencies included expertise in SC functioning issues, psychosocial and management capabilities, inventory management, procurement and sourcing, logistic coordination, relationship management, and technology literacies, emphasizing efficiency, consistency, and reliability in SC operations [26]. Ellinger and Ellinger [21], reinforced by [2,60], further highlighted that additional complementary skills comprise teamwork, multifunctional experience, customer orientation, and analytics skills. In addition to integrating technological advancements and developing collaborative relationships in internal and external environments, SC managers must possess strong communication and leadership skills. Therefore, they must possess a broad skill set to manage the challenges of today's SC and go above and beyond to meet the expectations of employers in the logistics sector [6,50]. Behavioral SCM, which examines decisions based on beliefs, intents, and principles, is the driving force behind the increasing significance of soft skills in SCM compared to hard skills [7]. Even though the importance of acumen and soft skills is increasing, the logistics and SC sectors still heavily rely on well-trained and competent staff. However, the literature highlights a critical issue: the scarcity of sufficiently qualified supply chain managers to meet the demands of rapid industrial transformation. This underscores the urgent need to reorganize existing education and employment strategies while creating new opportunities to develop the digital skills and strategic capabilities required for success in the evolving supply chain landscape [33]. SC businesses must prepare for a revolution in SCM [32] and closely examine today's job descriptions to identify necessary changes [31,50].

The current demand for digital SCM skills necessitates that the knowledge associated with these skills aligns with emerging technologies. Solutions across SCs are revolutionizing AI, ML, big data, blockchain, and the Internet of Things (IoT). Anwar et *al.* [4] stress that these objectives (operation excellence, integration of digital technologies into SCM plans) are contingent on digital competencies, which are thus vital. Supply networks are now shifting to digitalization, and the SCM that employs advanced SCM must sift through vast amounts of data to influence critical business activities and trends. Hallikas et al. (2021) suggest that modern logistics specialists should possess data analytics, statistical modeling, demand forecasting, inventory optimization, and statistical modeling skills. In the same manner, automation and AI enhance mechanical processes and aid in predictive decision-making. Though automated technologies simplify processes, AI, ML, and advanced analytics identify SC disruptions [34]. Liu et al. [35] pointed out that the education of expertise regarding blockchain-based digital twins in SCM remains almost entirely unexplored. Blockchain plays a crucial role in product tracking, transportation documentation, and fraud prevention, ensuring the legitimacy and security of transactions, even when combined with traditional SCM strategies. Currently, integrating modern digital competencies with traditional SCM strategies remains a significant challenge. This involves reevaluating our positions in relation to technology, which has the potential to improve job quality. In their view, the professionals must orient themselves in two perspectives simultaneously, blending tactical knowledge and digital innovation, as digital competencies are required to meet distinct strategy SCM and demands the professionals to have.

2.2. SCM as an inter-disciplinary concept

Globalization and technology have transformed the corporate environment into an interconnected network of suppliers, enabling SCM to manage connections and synergy. SCM is characterized by integration and complexity, requiring real-time response to global expectations and challenges, such as transportation costs, international regulations, port strikes, geopolitical conflicts like the Russia-Ukraine war, pandemics such as COVID-19, social impact, trade barriers and more. Effective management of this interconnected SC network demands expertise across diverse domains such as strategy, information technology, marketing, operations, finance, psychology, industrial and mechanical engineering, international business, sourcing, and logistics. However, these disciplines often operate in silos, lacking cross-referencing and providing a limited perspective [2,9,23]. This highlights the need for holistic and multidisciplinary research, which brings together diverse perspectives.

For instance, natural science identifies the qualities, essential traits, and responses to physical or chemical processes in any material, offering critical input for sorting or reprocessing technologies in SCM. It also assesses compounds' environmental effects, produces input for mitigating them via manufacture, consumption, recovery, disposal, and absorption capacity, and performs life-cycle evaluations [48,52]. Engineering uses natural science results to design, build, and operate advanced structures, machinery, and recovery processes for SCM, focusing primarily on technological feasibility rather than economic viability. Further, management science bridges this gap by creating assessment frameworks and financial mathematical models to evaluate the economic and ecological performance of SC systems. Additionally, disciplines such as economics, sociocultural studies, and public policy further influence SC operations by addressing broader economic and societal dimensions.

Marketing and SCM can enhance their understanding of customer experience by leveraging the service-dominant logic of SCM's marketing and service ecosystem views [56]. Entrepreneurship theories within purchasing and supply discipline influence decisions on supplier selection (whether based on cost or innovation), supplier development (whether direct or third-party venture suppliers), and the acquisition and implementation of innovations for entrepreneurial projects. Sociology and marketing theories may address buyer-supplier role conflicts [39], while operations management or logistics help establish the capabilities of the global SC network.

However, these perspectives often focus narrowly on specific aspects. For example, operations management may optimize organizational strengths strategically but overlook potential risks, while a risk management lens in the same situation might highlight financial or network disruption risk without addressing organizational capabilities. Thus, integrating these diverse viewpoints can enhance the reliability and robustness of solutions, addressing these complexities and driving business performance and competitiveness.

2.3. Synergy of process, people, and technology

The most significant challenges in implementing IT are not technical but human. IT implementations can lead to failure because of a lack of user awareness, project management, and industry or firm culture. Such root causes evoke the notion that human endeavor in organizations relies on human communication. This diffusion of innovation paradigm is particularly attuned to the interaction of social factors, organizational culture, communication patterns, and information technology innovations. Perceived attributes of the innovation (relative advantage, complexity, compatibility), organizational factors (centralization, interconnectedness, system openness), communication channels (formalism, resource intensiveness), and leadership factors (management level support, opinion leaders), the adoption rate of technology by employees are many factors determining diffusion of innovation in SC IT solutions [47]. Enstroem et al. [22] also highlight the importance of skill development in the face of technological advancements and organizational change using the HI-TOP model. The study emphasizes the need for upskilling and reskilling, particularly in digital skills like data analysis and programming, driven by ICT, AI, and ML. It also stresses integrating soft and technical skills, fostering agile and adaptive abilities, and leveraging technology for personalized, remote learning. Merging data-centric methods with domain expertise is key to reducing decision-making ambiguity.

Institutional theory and stakeholder theory suggest that normative pressures prompt organizations to interact with their communities; in the context of SCM, it will include suppliers, employees, and customers to divide the cost-benefit of externalities. SCs provide platforms for collaboration, including upstream and downstream, addressing accountability by internalizing environmental and social externalities, harnessing critical resources, and emphasizing the quality of the relationship between SC partners as a crucial strategic mechanism for SSCM to reduce external uncertainties, thereby increasing the bottom-line results [37,38].

Thus, from the literature, it is evident that as SCM becomes more digital and data-driven, this research explores the balance between soft skills, such as communication, teamwork, and leadership - and hard skills in technology, data analytics, and process automation. Organizations must ensure that their workforce has operational expertise and can navigate complex technological ecosystems [22,50]. This research aims to contribute to the growing knowledge of SCM competencies by offering fresh insights into the skills and proficiencies required in a digitalized SC environment, offering valuable insights for businesses, educational institutions, and professionals seeking to prepare for the future demands of the SC industry.

Although existing literature on SCM competencies is extensive, there is a clear gap in research focusing on the digital transformation of the SC industry and its impact on required skills. Previous studies have primarily centred on traditional SCM competencies, such as logistics, procurement, and inventory management [16,26,33,58], while offering limited insight into the new skill sets necessary for professionals in digitally driven SCs (Bag & Rahman, 2023). Additionally, many existing studies rely on retrospective data or survey-based methodologies, which may not fully capture the real-time evolution of job market demands. Using web scraping and NLP, this study addresses this gap by providing real-time analysis of job advertisements, offering fresh insights into the skills and competencies shaping the future of SCM.

3. Research methodology

This section briefly reviews data collection, analysis, and visualization techniques and justifies the methodological choices. This research paper uses ML techniques to generate text-based, unstructured data insights. Specifically, the combination of web scraping, NLP, and ML was chosen to ensure scalability, precision, and relevance in extracting actionable insights.

As part of data mining, ML approaches involve extracting and analyzing large amounts of data to find patterns, trends, and insights for informed decision-making and performance improvement across various industries. It makes predicted judgements with the help of algorithms and data analysis [30,44]. ML, a subset of AI, can help identify patterns and discover relationships in large datasets. ML involves techniques like clustering, classification, and regression, which helps it find more complex patterns and expedites data mining more than a traditional method while maintaining data efficiency and effectiveness [15,49,57].

NLP, as an ML-based approach, can analyze text-based information and support advanced text analytics processes such as translation, summarization, sentiment analysis, entity recognition, and topic modeling. The ability of NLP to identify these patterns by evaluating extensive textual content enables organizations to recognize emerging trends early and address them proactively [40,42,51]. Topic modeling, in particular, helps identify document topics, organize and explore large textual datasets, and summarize key information. This process transforms raw data into actionable insights, allowing for straightforward interpretation and informed decision-making [36,59]. There are four common topic modeling techniques: Latent Semantic Analysis (LSA), Probabilistic Latent Semantic Analysis (PLSA), Latent Dirichlet Allocation (LDA), and the newer deep learning-based LDA2Vec. Among these, topic modeling using LDA is widely recognized as popular and effective [8]. This study employs LDA to analyze the job posting dataset effectively.

Through automated analysis and categorization of textual data from platforms like job boards, emerging SC trends and required industry skills can be uncovered. Moreover, ML algorithms can help identify key themes and industry priorities regarding the demand for specific competencies in the SC field. In conclusion, there are several advantages to identifying SC skill sets by integrating web scraping, ML, and NLP methodologies. This can help institutions make informed decisions about training and developing SC professionals to meet industry requirements.

This study utilizes a computer-assisted mixed methodology incorporating quantitative and qualitative methods to analyze the evolving competencies in job advertisements for SCM professionals. The combination of TF-IDF and LDA ensures a holistic analysis. TF-IDF quantifies skill prominence in job descriptions, while LDA reveals hidden themes, providing a nuanced understanding of how competencies are framed in job advertisements. To interpret the themes generated by LDA, this study applied thematic analysis, a qualitative research method that enables identifying and contextualizing patterns within textual data [41]. Thematic analysis was used to categorize the extracted topics into competency-related themes, ensuring that the results aligned meaningfully with SCM skill requirements. This qualitative approach complements the quantitative LDA modeling by adding contextual depth to the findings and enhancing interpretability.

3.1. Step 1 – data collection

This study used web scraping Python libraries (selenium, BeautifulSoup) to systematically retrieve and collect data about SCM-related job postings from indeed Canada. Using data from indeed Canada offers the advantage of standardized web pages, where job descriptions are consistently located under a specific HTML tag. This allows for the reliable extraction of detailed job requirements, including essential skills. Using Python libraries (selenium, BeautifulSoup), job titles, descriptions, locations, and other related information were extracted, ensuring the data's relevance and consistency. Extracted data was stored in CSV format for further analysis [12,54]. It is generally used in many fields to assess customer needs, describe products, jobs, and news articles, and research and collect business information. Based on such information, organizations can assess trends, decode the clients' preferences, and accordingly do pricing (iwebdatascraping, 2023).

Web scraping was chosen over traditional methods like surveys or interviews due to its ability to collect real-time, large-scale datasets that reflect current market demands and trends. Surveys, while valuable, may suffer from biases or lag in capturing evolving trends in dynamic fields like SCM. This approach ensures that the dataset is comprehensive and up-to-date, providing a robust foundation for analysis.

Information from multiple sources was compiled manually to identify SCM-related job titles (See Appendix 1), such as Indeed, Supply Chain Canada, APICS, and Council of Supply Chain Management Professionals (CSCMP), to create a comprehensive list of 47 SC positions. In the first step, predefined keywords were used to extract URLs containing relevant job postings, identifying 7910 URLs on job opportunities across Canada on April 25, 2024. The URL dataset was further analyzed for duplicates and missing URLs. The keyword search can lead to duplicate URLs that need removal. After removing duplicates, the URL list was redacted to 7401 unique URLs.

These URLs were used in the second step of the data collection process to download the job descriptions and other associated information, such as location and salary (if available). Data related to 6566 jobs were downloaded (out of 7401), as some URLs led to broken or

missing links (error 404[1]).

The dataset comprises essential attributes such as job titles (various roles and responsibilities within the field) and job locations (geographical perspective on where these opportunities are concentrated). Each job listing in the dataset is accompanied by a detailed job description, providing valuable insights into each role's specific duties, qualifications, and requirements. This detailed information is important to extract information about specific skills that companies look for in SCM roles.

3.2. Step 2: data-preprocessing

Data preprocessing is crucial for maintaining raw data quality, uniformity, and compatibility for subsequent analytical processes. This section outlines the data preprocessing steps to enhance the readability and reliability of extracted data from web scrapping of the SC-related job data. The preprocessing steps, such as detecting missing data, removing special characters, and stemming, were chosen to ensure that the data was standardized, structured, and ready for advanced analysis. For instance, tokenization and stop-word removal help focus on the meaningful content in the dataset by eliminating noise, enabling better results in NLP-based analyses like topic modeling.

- **Detecting Missing Job Descriptions**: As a first step in data preprocessing, identifying and dealing with incomplete or missing job descriptions is an important part of the process. Dataset integrity and interpretability are compromised when data is missing, increasing the risk of biased analysis and incorrect results. The data frame was checked for missing job descriptions to address this issue. No missing job descriptions were found (total jobs with complete descriptions = 6566).
- **Remove Special Characters and Regular Expressions**: To ensure uniformity and consistency within the textual data, special characters, symbols, and irregularities are removed using regular expressions. This process involves using the re.sub() function to substitute or eliminate non-alphanumeric characters, punctuation marks, and other artifacts that may hinder subsequent text processing and analysis. Standardizing the textual format mitigates potential discrepancies and facilitates more robust text mining and NLP techniques.
- **Convert to Lowercase**: Textual data are converted to lowercase to standardize the text and mitigate the impact of case sensitivity on subsequent analyses. By uniformly converting all text to lowercase, we ensure that words with the exact spelling but different cases are treated as identical entities, enhancing the accuracy and efficiency of text-based operations such as word frequency analysis, text classification, and sentiment analysis.
- **Remove Stop Words**: The next step is to remove the stop words. Stop words, commonly occurring words (such as the, he, she, I, etc.) that impart little semantic meaning or relevance to the overall context, are removed from the textual data using Python's Natural Language Toolkit (NLTK) library. Eliminating stop words such as articles, prepositions, and conjunctions allows for the reduction of irrelevant text and enables the focus on extracting important keywords and phrases that carry significant meaning. This approach enhances the effectiveness of text analysis tasks by prioritizing content-rich material and minimizing computational workload and duplicated data.
- **Remove Named Entities**: Additionally, proper nouns, organization names, and geographic locations were removed from the job description data to lessen the influence of named entities on subsequent analyses. Eliminating named entities, which frequently indicate unique entities or entities of interest rather than generic concepts, increases the text corpus's generalizability and neutrality. This makes text mining and topic modeling more exhaustive and objectified.
- **Stemming**: Next, words were reduced to their root or base form using stemming, which served to normalize them. While stemming decreases lexical variation, it increases consistency. Stemming removes affixes and suffixes to treat words with identical meanings as equal entities, reducing repetition and accelerating text-based analysis. For example, words that stem from "run," such as "running," "ran," and "runner," can be aggregated and compared more accurately within the dataset.
- **Tokenization**: The final step in text preprocessing is tokenization. It entails breaking up the preprocessed text into separate tokens or words. By breaking the text down into its most basic meaning units, tokenization makes it easier to do other text-processing tasks like feature extraction, semantic analysis, and document grouping. This step sets the stage for later text-based studies and ML applications by giving textual data an organized form that computers can easily manipulate and understand.

3.3. Step 3 – quantitative analysis – term frequency-inverse document frequency (TF-IDF) analysis and frequency counts

After data preprocessing, the next step involved analyzing the quantitative aspects of the job descriptions to identify the most mentioned skills and competencies in SCM job advertisements. These methods provided a data-driven understanding of the explicit demands for various skills in the industry. TF-IDF was chosen because it balances term frequency with its uniqueness across documents, ensuring that important but less common terms (e.g., advanced technical skills) are highlighted rather than overly generic terms like "management."

- **TF-IDF Analysis**: TF-IDF was applied to quantify the importance of specific terms across the job descriptions. This method highlights frequent but not overly common terms across all documents, allowing us to identify the key competencies that employers emphasize.
- **Frequency Counts:** To complement the TF-IDF analysis, frequency counts were used to identify the most frequently occurring terms across the job descriptions. This step provided a simple yet powerful quantitative measure of how often specific terms (e.g., "management," "supply chain," "logistics," "data") appeared in job postings. This analysis helped determine the overall focus areas within SCM job advertisements (e.g., operational vs. technical skills).

3.4. Step 4 - qualitative analysis: latent dirichlet allocation (LDA) and thematic interpretation

The qualitative analysis involved applying LDA, an unsupervised ML technique, to uncover underlying themes and patterns in the job descriptions. LDA was chosen for topic modeling because it effectively identifies hidden themes in large, unstructured datasets. Unlike earlier methods such as Latent Semantic Analysis (LSA), LDA incorporates probabilistic models that allow for a more nuanced clustering of terms into topics, making it particularly valuable for analyzing the diverse and multidisciplinary language found in SCM job postings. LDA2Vec, while advanced, is computationally expensive and less suited for analyzing smaller or medium-sized datasets, such as the 6566 job postings used in this study.

- **LDA for Topic Modeling**: LDA was used to model the hidden topics within the job descriptions. Although LDA is computational in nature, it provides qualitative insights by identifying clusters of terms that co-occur within job postings. These clusters, or topics, were

[1] https://www.ionos.ca/digitalguide/websites/website-creation/what-does-the-404-not-found-error-mean/

interpreted as representing broader themes or areas of focus in SCM roles.

- **Interpretation of Emerging Themes**: After generating topics with LDA, a qualitative review was conducted to provide context and meaning to the identified themes. Each topic was interpreted in relation to the broader goals of the research, focusing on how it aligns with the competencies required for digital transformation in SCM.

Ethical considerations: This study was conducted in compliance with ethical research standards and institutional guidelines. Since the data was collected solely from publicly available job postings and contained no personally identifiable information (PII), it was classified as non-human subject research. A consultation with the university's ethics review board confirmed that formal ethics approval was not required. Additionally, all company names were anonymized to maintain confidentiality, and data collection adhered to ethical web scraping practices, ensuring that only publicly available job-related information was extracted for academic analysis.

4. Results discussion and insights

This section explores the key findings from the quantitative and qualitative analyses, comprehensively discussing the results and their implications. The study identifies crucial trends in the competencies required for SCM professionals by exploring frequency counts, TF-IDF analysis, and LDA topic modeling. The insights provided align with the research questions, addressing the current demand for advanced technologies and traditional operational skills in SCM job roles. The discussion also highlights emerging skill gaps, especially in digital transformation. It explores the implications for industry stakeholders, educational institutions, and individuals seeking to develop careers in the evolving SCM landscape.

4.1. Quantitative analysis – TF-IDF and frequency count

4.1.1. Frequency distribution of job locations and job titles

The frequency analysis of SCM job advertisements by province reveals that Ontario dominates the job market, representing approximately 69 % of all SCM job postings (Fig. 1). This concentration is likely linked to Ontario's economic activity and its status as a key logistics hub, especially in regions such as the Greater Toronto Area. Alberta and British Columbia follow with 15.79 % and 5.72 %, respectively, with these provinces likely benefiting from diverse industries such as oil and gas, logistics, and technology sectors that drive SC operations.

The frequency analysis of job titles within SCM reveals a strong focus on operational roles such as Logistics Manager, SC Manager, and Operations Manager (Fig. 2). These roles emphasize the importance of leadership and management across various SCM functions, such as procurement, logistics, warehouse management, and production management. This underscores the complexity of SCM operations and the need for leadership at multiple levels. Interestingly, the data significantly includes managerial roles, suggesting that SCM operations are hierarchical and require leaders with both strategic and tactical capabilities. Roles such as Logistics Manager and Procurement Manager indicate a strong operational focus, while titles like General Manager suggest broader oversight roles, demonstrating the need for comprehensive management skills within the SCM sector.

4.1.2. TF-IDF analysis of job descriptions

The TF-IDF analysis of SCM job descriptions reveals the prominence of specific terms related to interpersonal skills and operational knowledge (Fig. 3). The term "work" has the highest significance, indicating the focus on skills and abilities directly tied to operational tasks. Other highly ranked terms, such as "team," "management," "customer," and "experience," emphasize the importance of interpersonal and managerial skills across SCM roles. These terms suggest that effective SCM professionals must excel in technical and operational areas, teamwork, client engagement, and management. The presence of terms such as "product," "business," "inventory," and "quality" indicates that SCM professionals are required to have strong competencies in product management, inventory control, and quality management—key operational aspects of SCM. Additionally, the inclusion of terms like "service," "operation," and "strategy" reflects a balanced demand for both tactical skills required for day-to-day SCM activities and strategic understanding necessary for higher-level decision-making.

While interpersonal and operational skills dominate the TF-IDF results, a further analysis focusing on technological skills reveals several key insights (Fig. 4). Terms such as "data," "information," and "analytics" point toward the growing importance of data-centric skills in SCM roles. However, specific analytical terms such as "predictive," "descriptive," "prescriptive," and "cognitive" are less frequent, indicating a possible

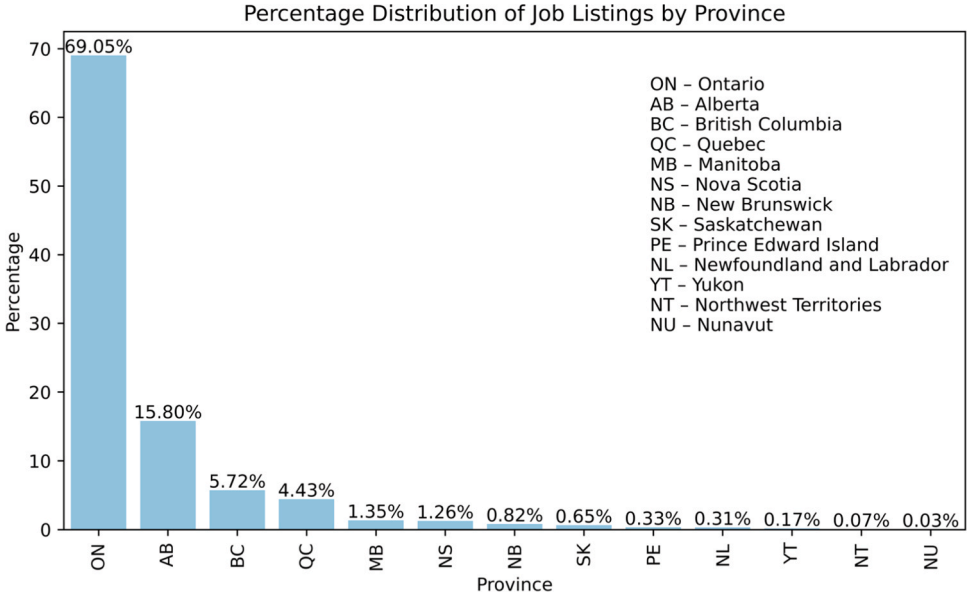

Fig. 1. Distribution of Job Listings by Province.

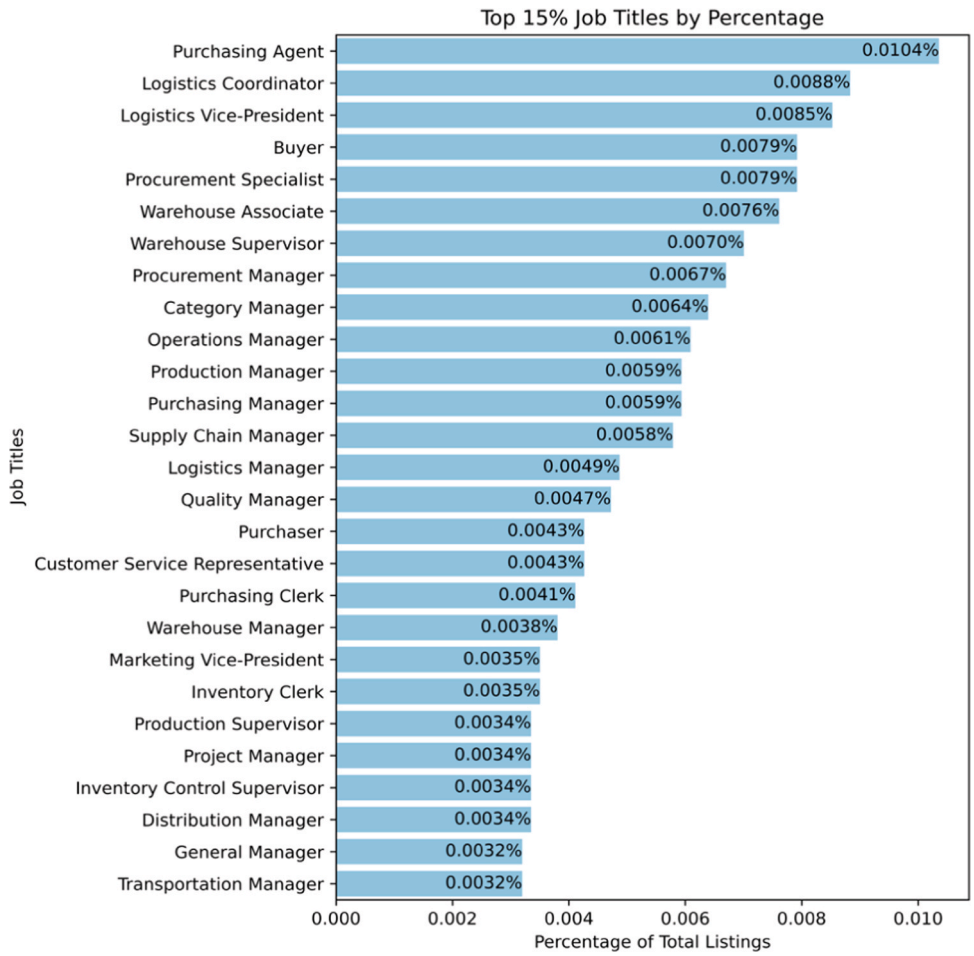

Fig. 2. Top 15 % job titles by percentage.

underemphasis on advanced data analytics skills in SCM job postings (Research Question 1). The relative lack of emphasis on advanced analytics suggests that many organizations may not fully understand the potential value of these skills or may not have the infrastructure to support them. This finding has significant implications for the industry, as companies that neglect to invest in advanced analytics and ML capabilities may miss opportunities for operational optimization, risk management, and innovation.

In exploring the technological competencies further, Fig. 5 shows that Excel remains the most commonly cited tool for data manipulation and analysis in SCM roles despite the availability of more advanced technologies. The dominance of Excel suggests that many SCM organizations continue to rely on familiar tools, possibly due to their widespread use and ease of integration into existing processes. However, the relatively lower frequency of more advanced tools such as Python, AWS, Power BI, and Tableau suggests an underutilization of advanced analytics tools and data visualization software. The under-representation of advanced tools like AI/ML technologies indicates a skill gap in the SCM workforce. Organizations that fail to invest in these technologies and train employees in their use may be less equipped to handle the complexities of modern SC operations, such as big data analysis, predictive modeling, and automation.

4.2. Qualitative analysis: latent dirichlet allocation (LDA) and thematic interpretation

In addition to the quantitative insights derived from frequency counts and TF-IDF analysis, the LDA analysis was conducted to uncover underlying themes and clusters within the job descriptions for SCM roles. A total of 10 topics were derived from LDA analysis, where topics from 7 to 10 yielded negligible relevance to job requirements in the SC profession. For example, topic 7 clustered various construction projects across different provinces, while topic 8 encompassed different French terms, among other incongruities. The outcomes of the LDA analysis (topics 1–6—Table 1) are presented in cluster forms, elucidating the top 20 relevant words for each cluster. The essence of cluster content is captured by assigning meaningful names based on the frequency of the top 20 words.

The LDA analysis addresses the second research question by demonstrating how unsupervised ML techniques, such as LDA, can extract meaningful themes from large volumes of unstructured text. Below, we discuss the six key clusters identified through LDA, which provide critical insights into the evolving skill sets required by SCM professionals.

4.2.1. Cluster 1 (professional development and workplace culture—people focus)

This cluster emphasizes the importance of career progression, employee well-being, and organizational culture within SCM roles. Terms such as “opportunity,” “career,” and “offer” reflect the focus on long-term professional development and growth opportunities provided by companies. The inclusion of terms like “company,” “culture,” and “community” highlights the growing emphasis on workplace culture, inclusivity, and diversity efforts within the SC domain. The terms related to employee benefits (e.g., “benefit,” “value,” and “committed”) suggest that companies in the SCM sector are keen on attracting talent by emphasizing both professional growth and a supportive work environment. This insight aligns with the industry’s broader focus on employee

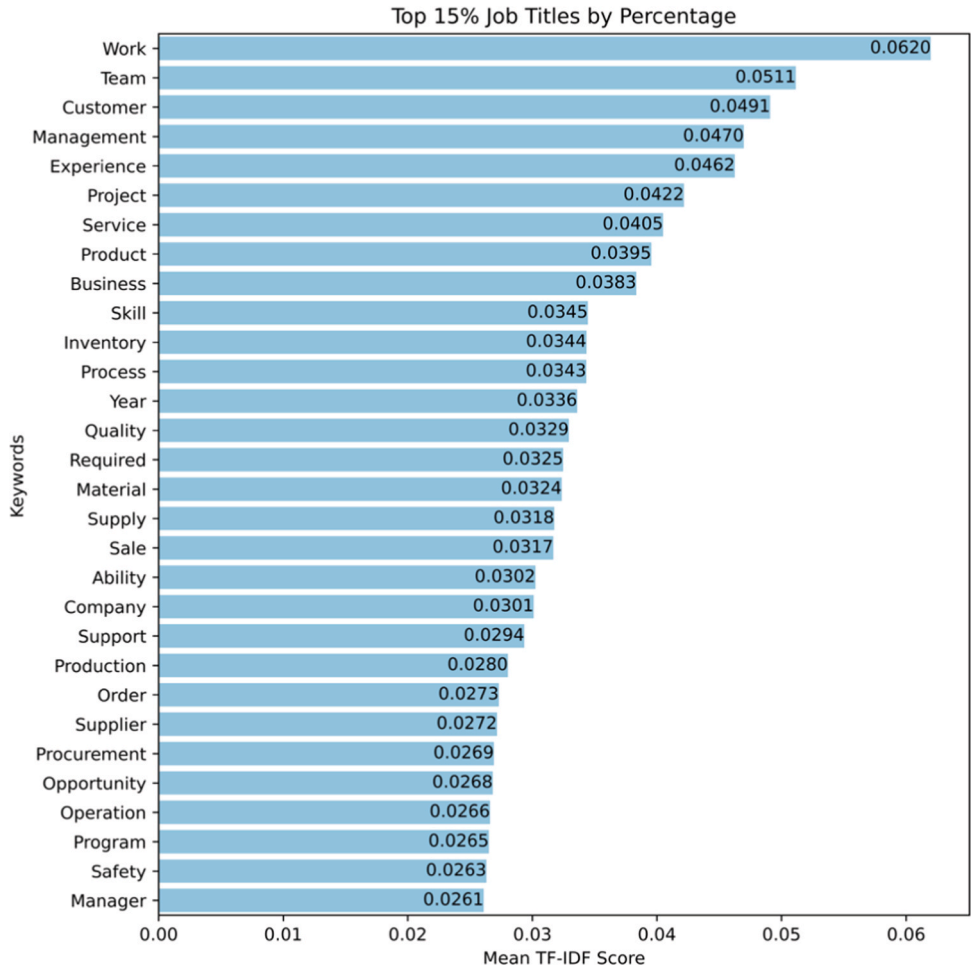

Fig. 3. Top 30 keywords by mean TF-IDF score.

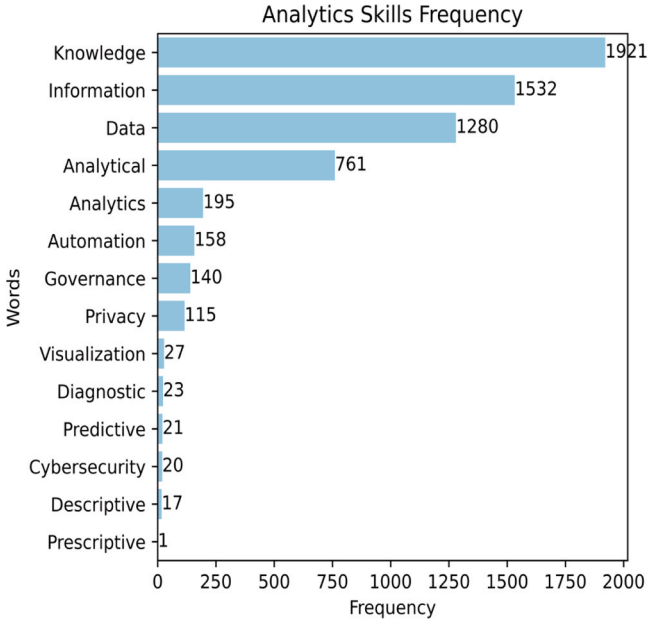

Fig. 4. Analytics skills frequency.

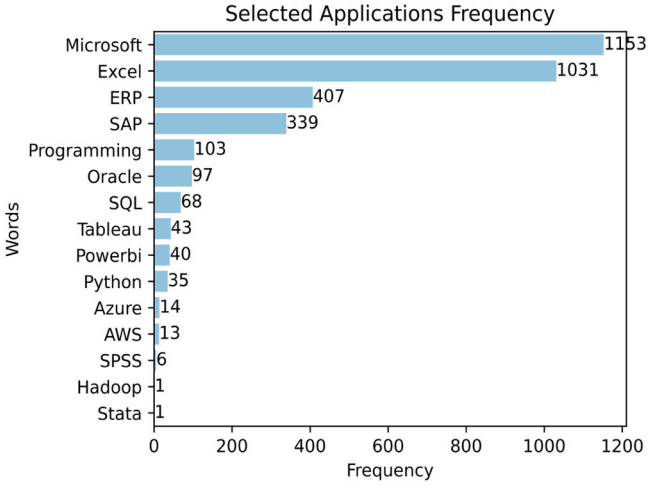

Fig. 5. Selected applications frequency.

retention and talent management strategies—crucial for maintaining a competitive edge in a dynamic SC landscape.

From people's perspective, this resonates with the resource-based view, suggesting that competitive advantages in SCM can be sustained through effective human capital management. Insights from cluster 1 reinforce the idea that SCM organizations see talent development as a way to future-proof their SC capabilities, an aspect highlighted by Birou

Table 1
Clusters and thematic interpretation.

Cluster Number	Thematic Interpretation	Relevant Words
1	Professional Development and Workplace Culture – People Focus	Team, People, Opportunity, Employee, Work, Disability, Candidate, Career, Committed, Benefit, Employment, Culture, Value, etc.
2	Operational and Logistics Management – Process Focus	Warehouse, Inventory, Work, Customer, Order, Location, Hour, Schedule, Job, Experience, Skill, Shipping, etc.
3	Strategic Supply Chain Management – Process and People Focus	Quality, Supply, Supplier, Improvement, Manufacturing, Production, Process, Management, Material, Cost, System, Purchasing, Performance, Compliance, Product, Procurement, etc.
4	Operational Excellence – Process, Technology, and People Focus	Sale, Business, Marketing, Category, Strategy, Product, Market, Team, Data, Customer, Strategic, Management, Relationship, Plan, Financial, etc.
5	Stakeholder Management – People and Process Focus	Service, Information, Position, Required, Work, Administrative, Job, Student, Public, Experience, Duty, Office, Record, Support, etc.
6	Project Management and Procurement – Process and People Focus	Procurement, Project, Planning, Transportation, Development, Management, Work, Environment, Infrastructure, Public, Technical, Related, Program, Transit, Contract, Client, etc.

& Van Hoek [11] and SCC [50]. Since COVID-19, the demand for people and digital skills in SCM has increased. This suggests that SCM leaders must also be adept at emotional intelligence and people skills to engage a more diverse and digitally enabled workforce.

4.2.2. Cluster 2 (operational and logistics management—process focus)

Cluster 2 centers on the operational demands and day-to-day responsibilities of SCM professionals, with a clear emphasis on logistics and inventory management. The prominence of terms like "warehouse," "inventory," "order," and "customer" indicates that managing physical goods and materials, particularly in warehousing and order fulfilment, are key operational competencies sought by employers in the SCM field. This highlights the importance of logistical capabilities that ensure smooth coordination of inventory levels, order processing, and warehouse operations. SC professionals are also expected to handle customer orders efficiently, ensuring inventory is managed correctly and shipments are timely and accurate. Customer order management is integral to the overall performance of the SC, linking the operational side of SCM with end-user expectations. Lastly, terms like "location," "shipping," and "schedule" emphasize the need for SCM professionals to be highly organized and capable of managing the movement of goods across various locations and meeting tight delivery schedules. The efficient coordination of shipping, transportation, and delivery processes is crucial to ensuring that SC operations run smoothly and customer demands are met.

Additionally, terms such as "work," "schedule," "job," "skill," "experience," and "hour" reflect the practical and job-specific expectations set by organizations for SCM professionals. These terms suggest that roles in this cluster are heavily focused on ensuring efficiency in daily tasks such as scheduling, managing work shifts, and overseeing the timely fulfilment of orders. Professionals must have the skills to effectively manage and coordinate these operations to meet organizational goals, particularly in fast-paced SC environments. These terms also suggest that employers are looking for candidates who bring technical expertise in areas such as inventory control and logistics and practical, hands-on experience in managing day-to-day SC activities.

4.2.3. Cluster 3 (strategic SCM—people and process focus)

Cluster 3 places a strong emphasis on the cross-functional nature of SCs, with a strong focus on planning, operational alignment with corporate goals and customer-centric approaches. The presence of terms like "quality," "supply," "improvement," "management," and "process" highlights the central role of operational efficiency and continuous improvement in SCM. These terms suggest that SCM professionals must possess comprehensive knowledge of various SC functions to align daily operations with broader organizational objectives effectively. Other terms such as "supplier," "procurement," and "material" reflect the importance of strategic sourcing and supplier relationship management. This highlights the process-driven focus of SCM, where companies seek professionals who can manage supplier networks, ensure the timely flow of materials, and mitigate risks through compliance and performance management. The presence of "system" and "cost" further underscores the need for operational and financial efficiency, signaling that companies value individuals who can optimize SC costs while maintaining high-performance levels.

From the people perspective, terms like "team" and "management" point to SCM roles' collaborative and leadership aspects. Effective leadership and teamwork are necessary for navigating the complexities of SC operations, ensuring that various functions—procurement, production, logistics—are aligned and work in unison toward achieving strategic goals. Including "relationship" and "customer" further emphasizes the importance of managing customer relationships, as maintaining customer satisfaction and fostering long-term relationships are key drivers of success.

This cluster also points out the integration of data-driven decision-making and financial oversight. Terms like "performance" and "compliance" can be related to process performance monitoring to meet regulatory and quality standards. These insights underscore the strategic necessity of SCM, providing organizations with useful guidelines on enhancing operational efficiency and gaining a competitive edge through continuous improvement and proactive management of supplier and customer relationships.

4.2.4. Cluster 4 (operational excellence—process, technology, and people focus)

Cluster 4 showcases how these professionals need to adopt a customer-focused, data-driven approach to remain competitive in today's fast-paced, technology-driven market environment by leveraging process, people, and technology aspects. The emphasis on terms like "sale," "business," "marketing," "financial," "plan," and "category" reflects a strategic approach to SCM where the focus extends beyond operational efficiency and touches on market-driven factors. These terms suggest that professionals in this area are expected to be adept at managing the commercial aspects of the SC, including product categories, market positioning, and customer segmentation. The inclusion of terms such as "strategy," "plan," and "team" points to the need for a cohesive, forward-looking approach where SCM professionals collaborate across functions to develop and execute comprehensive plans. The term "management" suggests that leadership skills are critical in aligning SC operations with broader business goals, while "relationship" highlights the importance of managing supplier and customer relationships to ensure smooth operations and long-term success. The presence of terms like "product," "market," "data," and "customer" underscores the increasing reliance on data-driven decision-making. SCM professionals must utilize insights from market data and customer feedback to forecast demand, optimize inventory, and align production with consumer needs. This also indicates a growing integration of technology into SCM, where analytics tools play a crucial role in shaping strategies and improving decision-making.

4.2.5. Cluster 5 (stakeholder management—people and process focus)

Cluster 5 emphasizes the importance of stakeholder management and information handling in a highly networked SC environment. "Service," "information," and "application" terms suggest that SC professionals in this domain are responsible for managing a wide range of internal and external information sources. This includes coordinating services and ensuring the right data is available to support operational decision-making. The inclusion of terms like "administrative" and "support" implies that SC professionals are expected to manage communication and provide support to various stakeholders, including public entities, customers, and internal teams, to ensure transparency and efficient workflow. Further, terms like "experience," "student," and "letter" reflect the importance of having relevant experience, especially for roles that might involve training or managing entry-level positions or internships within the SC. The inclusion of "record" and "duty" suggests a focus on maintaining accurate records and fulfilling administrative responsibilities essential to day-to-day SC activities. Additionally, the terms "job," "work," and "required" point to the practical requirements and qualifications necessary for these roles, underscoring that this cluster is grounded in the operational aspects of SCM, where experience, documentation, and organizational duties are paramount.

This cluster significantly focuses on people through stakeholder management and processes, ensuring that administrative and support tasks are handled efficiently. It highlights the importance of communication and documentation skills in SC operations, ensuring that the right information is conveyed and recorded for effective decision-making and seamless operations.

4.2.6. Cluster 6 (project management and procurement—process and people focus)

Cluster 6 underscores the complexity of project management and procurement responsibilities within SCM, emphasizing the need for strategic planning, team collaboration, and adherence to industry standards. Successful SCM professionals must be able to balance process efficiency with people management to achieve these goals. Terms like "project," "management," and "work" underscore the necessity of having strong project management skills, highlighting the ability to oversee multiple, interconnected SC activities from start to finish. Effective management in SC requires seamless coordination between various stakeholders, resources, and timelines. Other keywords like “experience,” “development,” and “program” are also associated with project management and program management aspects. This implies that professionals must possess skills in developing long-term procurement strategies that foster strong vendor relationships while ensuring timely and cost-efficient acquisition of goods and services.

Collaboration is key in project management and procurement, as reflected by terms such as "team," "client," “contract,” “community,” and "service." These terms suggest that customer satisfaction and teamwork are critical components of procurement processes. Successful SC professionals must work closely with internal teams, vendors, and clients to ensure that project outcomes align with customer needs and organizational objectives. Procurement and project management involve negotiating terms and conditions with suppliers, and project management requires engaging with various stakeholders, including the public and community, when relevant. Managing these relationships and ensuring compliance with contractual obligations are vital to SC operations. The inclusion of words like "process," "policy," and "technical" underscores the importance of adhering to established processes, policies, and technical standards within project management and procurement practices. These terms reflect the need for SC professionals to navigate regulatory environments and technical requirements while ensuring compliance and operational efficiency.

5. Conclusion and recommendations

The aim of the present study is to analyze skillsets at a broader industry level, focusing on the evolving demands within the SCM sector as a whole. It analyzed the wider competences needed in a digitally changed SCM context, connecting those of operational skills and advanced technology. This section builds upon the findings by addressing the core research questions, discussing managerial implications for various stakeholders, and situating these insights within the context of the broader literature on SCM, particularly in relation to the people, process, and technology framework.

5.1. Addressing the research questions

RQ1: The TF-IDF and frequency analysis findings reveal a notable imbalance in the competencies emphasized within SCM job descriptions. While process-driven skills—such as logistics, inventory control, and operational management—are prevalent, the focus on technology-driven skills remains underrepresented. Terms like “data” and “analytics” appear sporadically, but advanced technical skills like ML, Python, and data visualization tools are notably absent or minimally emphasized. This suggests that while organizations may understand the importance of digital transformation, job advertisements may not fully reflect the critical need for professionals with advanced technological competencies.

RQ2: Combining ML and NLP through techniques like TF-IDF and LDA allowed for efficiently categorizing critical themes in job advertisements. This approach effectively uncovered explicit (e.g., operational) and latent (e.g., professional development, stakeholder management) skills. Moreover, the unsupervised learning models (e.g., LDA) enabled us to identify deeper patterns in the data that manual analysis would likely miss, such as the imbalance between people, process, and technology-related skills. This method offers a scalable solution for job platforms like Indeed to provide more targeted insights for job seekers and employers.

RQ3: The data suggests a clear focus on process-orientated skills, such as logistics, project management, and compliance, as well as people skills, including leadership, collaboration, and customer relationship management. However, the demand for technical competencies—such as BDA, ML, and automation—appears to be under-represented. This may indicate an emerging skills gap, where the market’s growing reliance on advanced technologies (e.g., IoT, AI, ML) is not yet fully mirrored in the job market. In the future, we predict that the demand for these technical skills will surge as SCs become increasingly digitalized, leading to the need for upskilling and reskilling of SCM professionals.

5.2. Managerial implications for stakeholders

5.2.1. For industry leaders

The findings highlight a potential mismatch between the skills companies are advertising for and the skills needed to thrive in a digitally transformed SCM landscape. While process-oriented and people-centric skills are essential, the lack of emphasis on technology-driven skills may impede the full realization of data-driven SCs. This argument is also supported by the Supply Chain Canada Competencies Framework, which includes SC analytics, systems technology, and digital dexterity in foundational, functional, and integrative competencies and emphasizes technological capabilities. Similarly, the Association of Supply Chain Management (APICS) emphasizes technical skills as critical components of the SC Manager Competency Model. By integrating data acquisition and interpretation applications with comprehensive information analysis, individuals can assess the quality of their data and develop the critical thinking skills necessary to effectively solve problems, analyze data, and utilize recalled information. However, SC organizations need digital technologies according to their operational complexity, digital maturity, and organizational objectives. While smaller businesses may focus on foundational digital tools to optimize their processes, larger organizations require advanced skills for real-time decision systems and complete process visibility. Talent

acquisition approaches without emerging competencies prevent digital transformation from moving forward. Therefore, industry leaders need to reassess talent acquisition strategies and ensure job descriptions reflect the increasing need for technical proficiency in jobs. Additionally, structured upskilling and reskilling programs can be used to develop digital competencies within their internal workforce. Establishing industry-academia partnerships can further facilitate the alignment of training programs with evolving SCM needs. Furthermore, incorporating digital transformation roadmaps and AI-driven skill assessment tools can enhance workforce planning and future-proof SCM roles.

5.2.2. For academic institutions

Educational institutions should take note of the technological skills gap highlighted in the job advertisements. As the demand for advanced technical skills increases, academic programs in SCM should prioritize curriculum development that integrates advanced data analytics, AI, ML, and IoT applications in SCM. Partnerships with industries also help ensure graduates have the practical skills necessary to thrive in a digitally driven SC environment. The imbalance between people, process, and technology skills presents an opportunity for academia to bridge this gap through targeted educational initiatives. Moreover, academic institutions should develop short-term executive programs and certifications focused on emerging SCM technologies to enable continuous learning for professionals in the field. Utilizing job market analytics and AI-driven labor trend analysis, universities can dynamically adjust curricula to meet industry demands. Additionally, incorporating simulation-based learning and hands-on technology-driven case studies can further enhance students' preparedness for industry challenges.

5.2.3. For job advertisement platforms (e.g., indeed Canada)

job search platforms can leverage the insights from NLP and ML analyses by offering domain-specific competency mapping tailored to SCM. While platforms such as indeed already utilize ML for general recruitment purposes, such as candidate-job matching and hiring predictions. This paper provides unique insights into evolving SCM-specific skill requirements, particularly focusing on the under-representation of advanced technical competencies such as data analytics, automation, and AI/ML. The job recommendations can be refined by incorporating nuanced insights derived from topic modeling and trend analysis, encouraging them to include emerging technology-oriented skills that are increasingly critical in SCM. By doing so, employers can align job advertisements more closely with industry needs and digital transformation trends. Similarity for job seekers, the research outcomes can provide personalized skill development pathways, offering targeted suggestions based on the competencies identified in our analysis. This would help professionals stay competitive by highlighting key technical and strategic skills required in the evolving SCM landscape. Overall, these outcomes can help job search platforms to continuously adapt their services to the changing demands of the industry, ensuring that job advertisements remain aligned with the evolving technological landscape of SCM.

5.3. People, process, and technology perspective

The people, process, and technology framework serves as a helpful lens to view the current SC landscape. The data shows that while process and people skills are well-represented in job advertisements, technology skills are underemphasized.

1. People: The heavy focus on terms like "team," "customer," and "relationship" underscores the importance of people-centric skills. These findings align with the literature on the growing importance of soft skills in SCM, particularly as SCs become more customer-oriented and cross-functional. Birou & Van Hoek [11] highlight that post-pandemic SCM places greater emphasis on leadership and emotional intelligence to manage a more diverse and digitally enabled workforce.
2. Process: The prominence of terms like "logistics," "inventory," "order," and "supply" reflects the ongoing demand for process-related skills, which have traditionally been the backbone of SCM operations. Process optimization, risk management, and compliance continue to be vital, as also discussed in SC literature emphasizing operational excellence.
3. Technology: However, the lack of emphasis on technology-driven skills reveals a significant gap. The literature increasingly points to the digitalization of SCs, with technologies like IoT, AI, and ML transforming SCM operations. However, job advertisements still reflect a lag in fully embracing this shift. This suggests that while the industry is aware of the need for digital transformation, it has yet to integrate this fully into its talent acquisition strategies. As noted by Van Hoek et *al.* (2020), there has been an increase in the demand for digital skills in SCM since COVID-19, but this is not yet mirrored in job postings.

5.4. Future research direction

To address the technology gap, there must be a more deliberate integration of digital skills into both job advertisements and educational curricula. The industry must recognize that the future of SCM relies not only on process and people skills but also on the ability to harness technological advancements. As SCM becomes more data-driven, professionals who can leverage technologies like AI, ML, automation, and advanced data analytics will be critical to maintaining competitive advantage.

From a methodology perspective, some of the future research directions include:

1. Platform Dependency: The analysis relied exclusively on job postings from indeed Canada. Future studies should expand to other platforms like LinkedIn, Monster, or CareerBuilder to capture a more comprehensive set of job advertisements and compare if job postings are similar or different regarding skills.
2. Geographical Scope: The primary objective of this study was to provide a focused analysis of Canada's current SCM job market. Given Canada's distinct economic landscape, regulatory environment, and industry trends, analyzing data from this geographical context allows for more targeted insights relevant to Canadian employers, job seekers, and policymakers. The insights generated from Canadian job postings help highlight the specific competencies and trends pertinent to the unique characteristics of Canada's SC sector, which may differ from other countries. While the current study focuses on Canada to provide geographically relevant insights, future research can expand the scope to include global data, allowing for comparative analysis across different regions and industries. This would give a more comprehensive understanding of the global SC job market and could uncover international trends and best practices.
3. Limited Technology Skills Representation: While the LDA analysis captured a broad range of SCM skills, it did not highlight advanced data analytics, AI, or ML competencies in-depth. Further studies could investigate why these emerging skills are underrepresented in job advertisements despite the increasing demand for such expertise. Future research could utilize qualitative methods, such as interviews with hiring managers or SCM professionals, to comprehensively understand the skills required in contemporary SC roles.

CRediT authorship contribution statement

Enstroem Rickard: Writing – review & editing, Validation. **Kang Parminder Singh:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Bennett Owen: Visualization, Software, Resources. **Bhawna Bhawna:** Writing – review & editing, Validation, Resources, Investigation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. 1 - Keyword List Used for Web Scraping

KeyWordList =["supply chain", "production clerk", logistics coordinator", "production technician", "purchasing clerk", "load planner", "inventory associate", "inventory controller", "warehouse supervisor", "buyer", "category analyst", "procurement specialist", "logistics manager", "supply chain analyst", "export manager", "demand planner", "capacity manager", "quality manager", "production manager", "order picker", "supply clerk", "inventory control specialist", "replenishment manager", "materials manager", "plan manager", "demand manager", "vice president of supply chain", "purchasing agent", "sourcing specialist", "purchasing manager", "quality engineer", "commodity manager", "category manager", "sourcing manager", "supplier manager", "director of procurement", "fulfillment associate", "logistics specialist", "distribution specialist", "customer service representative", "route manager", "import manager", "warehouse manager", "logistics analyst", "distribution manager", "transportation planner", "director of transportation"]

Appendix A2. Description of Python Libraries for Reproducibility Purpose

Process Step	Libraries Used (Description)
Step 1 - Data Collection	**Requests** (used to send HTTP requests to get the URLs based on provided job search keywords)
1.1 Extract URLs for job listings from indeed Canada	**drop_duplicates** and **dropnan**(duplicate and empty URLs were dropped from the URL dataframe)
1.2 Drop duplicate and empty URLs	**BeautifulSoup** (library for parsing HTML and XML documents to extract data from web pages by navigating the HTML structure and searching for specific elements such as job description, title, etc.)
1.3 Extract job listings from the URLs	**pandas** (read CSV file and load to a data frame)
Step 2: Data-Preprocessing	**re** (remove punctuation characters (=,>,., !,?) from each element in the job description column of the data frame)
2.1 Text cleansing and parsing	**nltk** (used to filter out the stop words based on English dictionary)
2.2 Remove stop words	import nltk nltk.download('stopwords') from nltk.corpus import stopwords **nltk.tag** (is used for part-of-speech tagging, which assigns a part of speech (such as noun, verb, adjective, etc.) to each word in the text)
2.3 Remove named entities	**nltk.chunk** (is used for named entity chunking, which groups together words that form named entities such as person names, organization names, locations, etc.)
2.4 Stemming	**PorterStemmer** (PorterStemmer reduces each word to its root form. It uses linguistic rules and heuristics rather than a comprehensive dictionary.)
2.5 Tokenization	**word_tokenize** function is a part of the **nltk** Python library used to tokenize the cleaned text string into individual words or tokens.
Step 3: Exploratory Analysis	**genism** (Open-source Python library designed for topic modeling and document similarity analysis. It is used to analyze interview text
Topic Modelling and Visualization	corpora and extract meaningful patterns based on unsupervised ML tasks related to NLP)
3.1 Latent Dirichlet Allocation - LDA	from gensim.models import CoherenceModel model = gensim.models.LdaMulticore(corpus=corpus, id2word=id2word, num_topics=10, random_state=100, chunksize=1000, passes=10000, per_word_topics=True)
6. Topic Visualization	**pyLDAvis** (it creates interactive visualizations of topic models, particularly models generated by Latent Dirichlet Allocation (LDA) in the previous step)
7. Data analysis and visualization	**matplotlib.pyplot and seaborn** (2D data visualization)

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