The Future of Warehousing: Workforce Management Insights for Technology Adoption

by

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ABSTRACT

Warehouse automation is expanding rapidly as companies respond to rising e-commerce complexity, labor shortages, and pressure for faster deliveries. This study addresses technology adoption practices in modern warehouses from a workforce and labor management standpoint. A literature review and a structured survey of 322 warehouse technology decision-makers were conducted, identifying warehouse technology trends, main workforce-related challenges, relevant skills and gaps, training practices and their effectiveness, and emerging roles integration. Results show that firms with more extensive warehouse technology adoption plans follow recommended practices more closely and that effective training can reduce skills gaps. Effectively using a broader mix of training methods and integrating emerging roles enables warehouse technology transformation.

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TABLE OF CONTENTS

LIST OF FIGURES

1. INTRODUCTION

The adoption of warehouse automation is rapidly increasing, with investments in warehouse infrastructure exceeding $350 billion annually (Rodriguez Garcia, 2025). This surge is influenced by numerous trends affecting businesses. The growth of e-commerce combined with an expanding variety of SKUs brings increased complexity and volatility to supply chains (Ponce, 2023). Meanwhile, roughly 9 of 10 customers prioritize quicker home delivery. At the same time, labor shortages exacerbate operational challenges. In the U.S., there are approximately 1.8 available jobs per unemployed worker, which raises wages and operational expenses. Additionally, increasing land costs foster efficient use of space (Rodriguez Garcia, 2025).

In response to these concerns, there has been a significant proliferation of automation and digitalization solutions enabling businesses of all sizes to enhance their competitiveness. Flexible, scalable, and replicable technologies have emerged as crucial tools, providing smaller companies access to advanced automation, previously only feasible for larger corporations.

1.1 Motivation

As companies invest in the automation and digitalization of their logistics centers to meet omnichannel customers' expectations of fast delivery and high product availability, they frequently face challenges in selecting the right technologies, integrating them with existing systems, and ensuring they deliver the expected benefits.

In this context, the project sponsor, MIT's Omnichannel Supply Chain Lab, is motivated to investigate how companies can successfully adopt advanced technologies in modern warehouses. From a broader point of view, this research lab aims to understand how omnichannel distribution is reshaping supply chains in various aspects, such as strategies, warehousing, returns management, and artificial intelligence (AI) implications. They seek to provide practitioners with resources to meet new market demands by identifying current gaps and future trends. In particular, the Warehouse of the Future research line looks forward to understanding warehouses' role in the coming years and supporting the adoption of advanced technologies.

To determine how it can help, the lab needs to understand what the current process for implementing technologies in modern warehouses misses.

The motivation for this project stems from a preliminary review of over 60 diverse sources, encompassing academic studies, industry reports, and articles. Of those sources, 74% addressed workforce and labor management considerations when adopting warehouse technologies.

1.2 Problem Statement and Key Questions

As the literature review suggests, the core problem is that labor management is among the main barriers preventing warehouse technological transformation. There is a gap between what skills associates have and what they need to interact with new technologies (World Economic Forum, 2023, 2025). This gap requires developing an effective training strategy to upskill the workforce. Developing this new skill set requires defining new roles that must be identified and incorporated into the companies' structures. Our sponsor wants to develop a framework that helps companies overcome those challenges and adopt modern warehouse technologies.

In that context, the questions to be answered are:

- Are there any recommended practices for implementing warehouse technology from a workforce and labor management perspective?
- If so, do companies follow these practices?

1.3 Project Goals and Expected Outcomes

The primary goal of this project is to identify and assess the usage of recommended practices and strategies for implementing advanced technologies in warehouses from a workforce and labor management perspective. For that purpose, the project involves surveying warehouse managers to quantify the relevance assigned by companies to some sets of labor-related factors affecting technology adoption identified in literature. Those factors include skills requirements, training types and strategies, current and future roles, and already adopted or desired technologies.

Based on the literature review and the insights from the survey of practitioners, we will identify:

i. key skills and new emerging roles
ii. training and technology adoption common practices
iii. key challenges companies are facing when adopting technology from a workforce and labor management perspective

2. STATE OF THE PRACTICE

The following literature review synthesizes insights from multiple studies weighted by relevance, favoring newer insights to capture evolving trends. It addresses technological advancements, organizations' workforce-related challenges, necessary skills, training methods, and emerging roles. Mapping academic research on these factors is the first step toward contrasting practices in the literature with those in the real world. That comparison is conducted through a survey of warehouse managers, enabling conclusions and recommendations.

2.1 Technology Trends in Warehousing

Technological advancements continue to redefine warehouse operations, encompassing automation, digitalization, and artificial intelligence (AI). Automated storage and retrieval systems (AS/RS), conveyors, and robotics have improved space utilization, reduced manual labor and errors, and enhanced operational efficiency (Tikwayo & Mathaba, 2023). Automated guided vehicles (AGV), robotic arms, and inventory drones are other examples of transformative technologies (Sheffi, 2023). Additionally, collaborative robots (cobots) and autonomous mobile robots (AMRs) now work alongside human workers, handling tasks such as goods transport and picking, which increases flexibility and productivity (Sodiya et al., 2024).

On the digital side, traditional systems such as warehouse (WMS) and labor management systems (LMS), as well as radio frequency identification (RFID), are being complemented with the use of mobile devices and the introduction of cutting-edge improvements. Advanced sensing, algorithms, and computer-aided vision have further improved the precision of automated solutions like robotic arms, raising accuracy from 60–70% in 2019 to current levels of 80–90 % (Guthelius & Theodore, 2019; MIT News, 2024). These advancements support collaborative work environments by enabling robots to efficiently handle repetitive or physically demanding tasks (Guthelius & Theodore, 2019). Meanwhile, digital twins and the Internet of Things (IoT)-enabled devices enhance operational transparency, enabling real-time tracking, system communication, and virtual representations of warehouses. This technology facilitates better monitoring, simulation, and process optimization (Sodiya et al., 2024; Rodriguez Garcia & Agmoni, 2024). Vision-directed picking systems and augmented reality (AR) overlays have also emerged, improving accuracy in inventory management and reducing the training curve for complex tasks (Ellithy et al., 2024).

AI- and machine learning (ML)- powered tools are pivotal in analyzing vast datasets, streamlining decision-making, optimizing inventory management, and enabling predictive analytics (Bari, 2023). Generative AI facilitates document creation and workflow optimization (World Economic Forum, 2024).

Automation and digitalization decrease reliance on manual labor, enabling workers to focus on value-added tasks such as data analysis and sustainability (Gutelius and Theodore, 2019; Rodriguez and Agmoni, 2024). Predictions indicate that 33% of tasks related to reasoning, decision-making, and data processing will be automated by 2030, with the rate rising to 42% in the retail and wholesale sectors. This shift necessitates new workforce skills, innovative training methods, and roles that blend operational expertise with technical proficiency (WEF, 2025). By understanding these dynamics, businesses can address skill gaps, adopt advanced technologies, and maintain competitiveness in global markets.

2.2 Workforce and Labor Management Challenges

Through the literature, we have identified several workforce and labor management issues related to the adoption of warehouse technologies. Firstly, the literature underscores the need for reskilling existing workers to handle complex automation systems or acquire managerial skills for tech-based environments, and the increased demand for specialized talent derived from automation and robotics. In addition to training the current workforce, the growth in demand for talent implies a need to recruit skilled personnel capable of managing complex systems. In other words, organizations face challenges related to talent shortages and a skills gap in the workforce and have difficulties in talent acquisition and retention (Rodriguez Garcia & Agmoni, 2024).

Moreover, Guthelius and Theodore (2019) highlight the impact of technological changes on labor forces, such as job displacement, resulting in workers' resistance to change. While the WEF (2025) report suggests that retraining initiatives are vital to smooth transitions, as most companies are implementing them, McKinsey (2020) reports that 6 of 10 companies' learning and development strategies are temporally disconnected from the business strategy, suggesting the misalignment between training programs and evolving job requirements. Lastly, McKinsey (2018) discusses the financial burden companies face when investing in upskilling and reskilling their workforce to handle the adoption of new technologies.

2.3 Addressing the Skills Gap

Integrating advanced technologies into warehouse operations requires significant workforce adaptation. Studies highlight the increasing demand for technological proficiency, problem-solving skills, and adaptability. Digital proficiency, particularly in AI and data analysis tools, is essential for operating automated systems such as e-commerce fulfillment centers that rely on real-time data (Hoquelet, 2020; WEF, 2025). Analytical thinking has emerged as a top priority, with 79% of logistics service providers (LSP) identifying it as critical for future growth. Human-robot collaboration demands adaptability and creative problem-solving to ensure effective interaction with intelligent systems in dynamic environments (Guthelius & Theodore, 2019). Although not core skills today, knowledge of computing and cybersecurity is an increasingly relevant technical capability for future supply chains (WEF, 2025).

While technical skills are crucial, soft skills like communication and leadership remain valuable. LSPs are seeing increasing demand for talent management by 2030 (WEF, 2025).

However, skill instability is a pressing concern, with 39% of current skills projected to become obsolete by 2030, and the skills gap remaining the predominant barrier to transformation across industries and economies (WEF, 2025). Gaps persist despite efforts to reskill workers, particularly in technical expertise required for operating intelligent machines and analyzing data outputs (Bari, 2023; WEF, 2025). Companies struggle to find talent with a blend of operational expertise and technological literacy, underscoring the need for proactive workforce strategies (Rodriguez Garcia & Agmoni, 2024).

Understanding these skill gaps involves identifying critical skills across roles, exploring strategies for reskilling, and aligning workforce capabilities with technological demands. Addressing these gaps is vital for effectively equipping the workforce to meet future challenges.

2.4 Training and Upskilling Methods

Effective training strategies play a pivotal role in bridging the skills gap. Blended learning approaches have gained prominence, combining traditional on-the-job training with advanced digital tools like augmented reality (AR) and virtual reality (VR). AR glasses visually guide workers, enabling safer and more efficient task execution, while VR simulations provide immersive environments for developing technical skills (Grandi et al., 2023; Bari, 2023). McKinsey & Co. (2020) advocates for “learning journeys,” a mix of online platforms, simulations, and workshops, to equip workers with skills for emerging technologies.

However, financial constraints, limited skilled labor, and uneven technology adoption challenge workforce adaptation (Hoquelet, 2020; Grandi et al., 2023; Tikwayo & Mathaba, 2023). Partnerships with educational institutions and tailored training programs are necessary to address these barriers (Amazon, 2023; Rodriguez Garcia & Agmoni, 2024). While traditional workshops and in-person training remain valuable for learning foundational skills, they are less adaptable to rapidly changing technological landscapes (Hoquelet, 2020; Bari, 2023). Conversely, digital platforms offering on-demand training provide flexibility, allowing workers to acquire skills at their own pace (Sleezer et al., 2014). Pre-job training, employer-sponsored apprenticeships, and continuous learning initiatives have also proven effective (Alibaba, 2024; Sodiya et al., 2024). For example, Amazon's apprenticeship programs and Alibaba's training platforms showcase comprehensive practices in workforce development (Amazon, 2023; Alibaba, 2024).

Employers increasingly prioritize reskilling and upskilling efforts to align with evolving technological landscapes. According to the World Economic Forum (2025), 85% of companies plan training programs to ensure workers' skills stay relevant. However, only 41% of companies transition staff from declining roles to growth areas, highlighting an opportunity for improvement (WEF, 2025).

2.5 Emerging Roles in Warehousing

Automation, digitalization, and AI reshape warehouse roles, shifting traditional manual responsibilities toward technology-enabled tasks. For example, the Amazon Career program trains workers to become robot maintenance engineers (Amazon, 2023). WMS analysts are common in warehousing today (Extensiv, 2021), and roles like forklift operators and inventory control clerks are evolving to require interfacing with automated systems (Ellithy et al., 2019). Emerging positions, such as automation technicians and specialists, focusing on designing, implementing, and managing automated systems, and roles in AI oversight and data-driven decision-making are gaining prominence (Walmart, 2024; Bari, 2023). For example, IT Support Engineers are one of the open positions at Amazon jobs for their new cutting-edge warehouse in Shreveport (Amazon.jobs, 2025). Other roles that are in demand include Senior Manager of Warehouse Automation & Technology (Chobani, 2025) and Supply Chain Transformation Manager (Intellectual Capital Resources, 2025); the latter, while not directly related, includes responsibilities like formulating customer-centric planning and fulfillment strategies, which affect warehouse operations.

As businesses adapt, sectors like retail and wholesale evidence the emergence of specialized roles, including AI and ML specialists, data scientists, and digital strategy experts. These roles demand advanced technical expertise and the ability to oversee interactions between human workers and intelligent systems (Gutelius and Theodore, 2019; World Economic Forum, 2025). For example, the employment of data scientists is projected to grow 36% from 2023 to 2033, much faster than the average for all occupations (U.S. Bureau of Labor Statistics, 2023). Understanding the dynamics of these emerging roles involves analyzing automation's impact on traditional positions and exploring strategies for transitioning staff to growth areas.

3. METHODOLOGY

This project involved surveying warehouse technology decision-makers to quantify the relevance assigned by companies to some sets of labor-related factors affecting technology adoption. This chapter starts with a brief introduction to the core elements of the survey process. Secondly, the survey's structure is described, showing how it is tied to these core elements. Next, the target audience and promotion strategy are presented, followed by the response rate and demographics after the survey's deployment. The final section of this chapter explains the data processing and analysis stage, including a clustering approach.

3.1 Methodology Selection

A structured survey was developed to quantify the perceived relevance of workforce-related factors in warehouse technology adoption. Responses from 322 qualified professionals were analyzed using Python, statistical methods, and clustering to identify patterns across roles, industries, and regions.

A survey methodology was well-suited for this study, as it enables the systematic collection of information about perceptions, behaviors, and practices from a broad range of supply chain professionals involved in workforce and technology adoption decisions in warehousing. Prior studies on supply chain risk perception (Villena et al., 2018), supplier responsibility (Villena et al., 2020), and technology disappointment cycles (Sodhi et al., 2022) have successfully used surveys to capture demographic insights and contextual variations. Moreover, in the context of warehouse transformation, surveys offer a robust approach to analyze differences across organizational roles, technology maturity levels, and strategic pathways (Kembro & Norrman, 2022).

3.2 Survey Structure

We defined the survey's goal as quantifying the relevance to practitioners of the practices found in the literature and from different workforce perspectives, and to measure whether they are implementing them or not. The four key concepts for achieving that objective were technology adoption, skills gap, training, and role change. The *technology adoption* concept focused on the types of technologies companies adopted, encompassing automation, digitalization, and AI. The technology adoption concept also involved the labor-related challenges faced in this process. The *skills gap* concept asked respondents about the impact of technology adoption on generating skills gaps and the relevance of the new skills needed (upskilling priorities), such as digital skills, analytical and creative skills, and human-robot collaboration. To tackle the topic more accurately, we incorporated the perspective of frontline workers and warehouse managers, as workers were closer to physical technologies (automation), and managers were closer to new digital tools. The *training* concept inquired about the importance of different types of training and their effectiveness in coping with upskilling requirements, comparing tech-enabled, on-demand, or tailored approaches with traditional ones (classrooms, in-person, one-size-fits-all). The *roles* concept investigated current roles in warehousing and to what extent new skills contributed to forming new roles. These roles featured abandoning manual tasks for data- and analytics-focused ones, and the emergence of AI and ML specialization.

The technical aspects of the survey process are summarized as follows: The target population was warehouse-related managers or higher roles, and warehouse technology decision-making managers or higher roles. We devised a poll that took 8 to 10 minutes to complete and prioritized closed-ended questions to encourage the greatest number of responses. With the same objective, we used an online engine to distribute it (Qualtrics). To ensure the anonymity of respondents, we only asked about the industry, the number of employees in the company, the annual company revenue, the number of years of experience, their role and managed functions, and the regions where the company operates. We used the World Bank regions for grouping. These regions were East Asia and Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, North America, South Asia, and Sub-Saharan Africa (World Bank, 2023). To create the scale for the number of employees, we considered a simplified group of categories from the ones used by the U.S. Census Bureau (2021). Appendix A includes the complete survey questionnaire.

3.3 Survey Deployment

The survey was published in February 27, 2025, and promoted through MITx MicroMasters in Supply Chain Management's monthly newsletter, LinkedIn posts, and emails, tracking the source. These sources were strategically selected to reach the intended respondents and minimize responses from individuals outside the target audience, thereby protecting the quality of the survey results. Appendix B includes links to the promotional initiatives. Additionally, an external vendor panel group was engaged to support response collection.

Through these sources, we reached the target audience of warehouse managers and/or logistics and supply chain professionals with decision-making power over warehouse technology adoption. By April

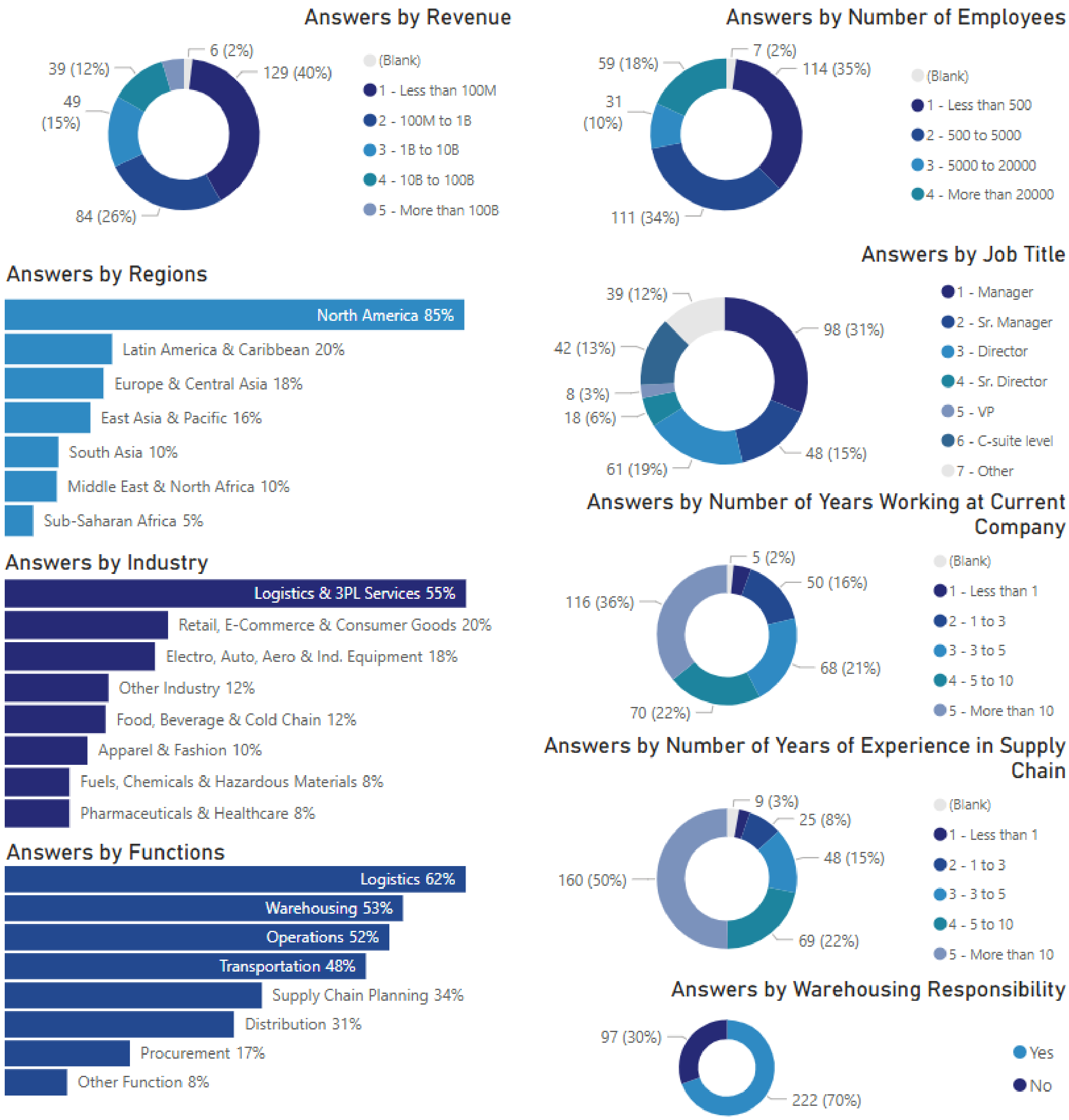
8, 2025, we had collected 480 answers, reaching a representative sample to conduct our analysis. Table 1 displays a summary of the finished response rate by source. We received 480 answers in total, but after cleaning the data, only 322 were completed and valid responses. Responses labeled “False” in the table were incomplete, and those under “True” were completed.

Table 1. Responses by source and finish status

Finished	False		True		**Total**
Sources	Count	%	Count	%	**Count**
Total	**158**	**33%**	**322**	**67%**	**480**
Panel	29	10%	253	90%	**282**
Newsletter	68	72%	27	28%	**95**
LinkedIn	51	65%	28	35%	**79**
Direct emails	6	33%	12	67%	**18**
Other	4	67%	2	33%	**6**

Figure 1 presents charts illustrating respondent demographics for the 322 valid answers. Single-choice demographic data are in donut charts, whereas multiple-choice demographics (for example, the regions where the respondent's company operates) do not sum up to 100% and are displayed using bar charts. The sample mostly consists of North American respondents; most work at companies with fewer than 5,000 employees and revenues below $1 billion per year. More than half work primarily in Logistics & 3PL Services. Half have over 10 years of supply chain experience, and a similar share hold logistics, warehousing, operations, or transportation roles. Managers and directors comprise the largest job title segments, with nearly 70% having direct warehousing responsibilities.

Figure 1. Demographics dashboard (revenue is in US dollars)



3.4 Data Analysis

This section presents the data preprocessing steps and describes the clustering process used and the clusters that were obtained.

3.4.1 Data Preprocessing

Data analytics required previous data transformation and pre-processing of the online survey service's raw database. First, multiple-choice and matrix question-type answers had to be converted into separate data columns. One-hot encoding was employed for that purpose, using Python coding. This technique transformed cells containing multiple answers into binary columns indicating an option’s presence (1) or absence (0). Following the one-hot encoding, additional data preprocessing was conducted using an analytical platform. This phase focused on developing custom analytical calculations and visuals to enable a precise interpretation of the survey data. These steps enabled the development of a dynamic dashboard to facilitate the data analysis. The 158 incomplete responses from Table 1 were filtered at the dashboard level.

After identifying the most insightful data from a general standpoint, the study included an in-depth analysis of demographic data cuts to understand the key differences among populations, and whether there are decisions that lead to better overcoming the labor-related challenges of technology adoption.

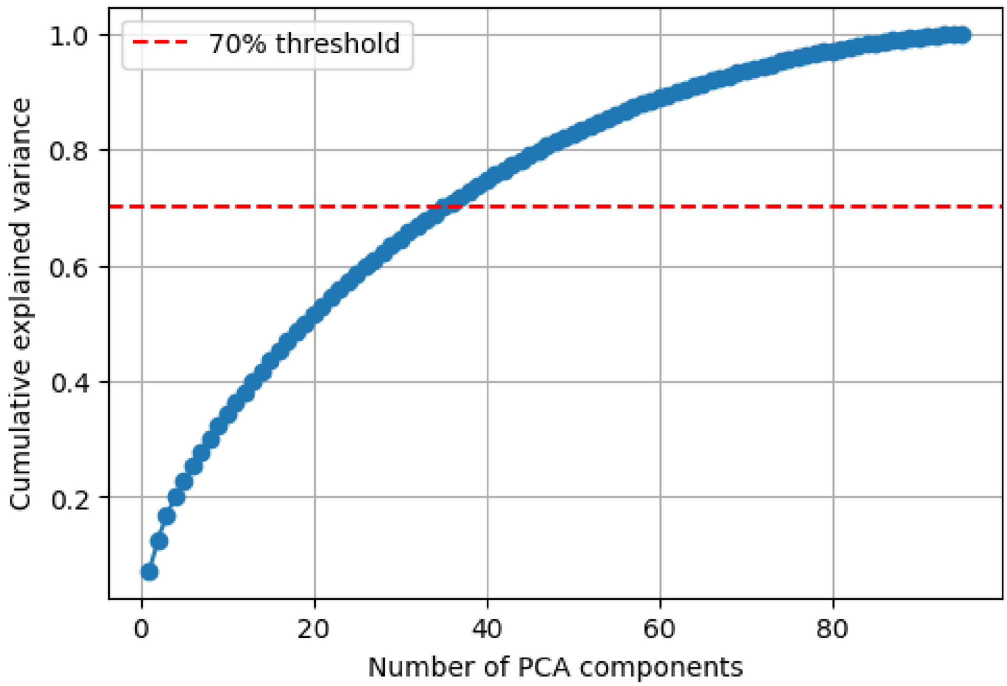
3.4.2 Clustering

We also used clustering techniques over the survey answers to investigate underlying patterns in the data and capture more insights. For that purpose, features that served solely as identifiers or demographic descriptors were removed, as were repeated question items. Multiple-choice questions probing perceived effectiveness or challenge were recoded into binary flags to collapse ordered categories into “high versus low” indicators. All remaining categorical responses were label-encoded to treat every feature numerically.

With 95 features (dimensions) remaining, principal component analysis (PCA) was applied to project the data into a lower-dimensional space. Figure 2 shows the cumulative explained variance in the dataset as a function of the number of components in the PCA, and a reference threshold of 70% of explained variance. As shown in the figure, retaining the first 30 to 50 components preserved 70 to 80% of the signal while using fewer features and filtering out noise and multicollinearity, thus enabling more stable and computationally efficient clustering. With this in mind, we assessed using a range of 30 to 60 principal components in five clustering techniques, and a range of cluster numbers, using a common 4-

metrics composite score to choose the best performance configuration as explained in the next paragraph. This procedure led to using the first 30 principal components to obtain the highest clustering quality. Appendix C contains the list of the first 30 principal components.

Figure 2. Cumulative explained variance per principal component

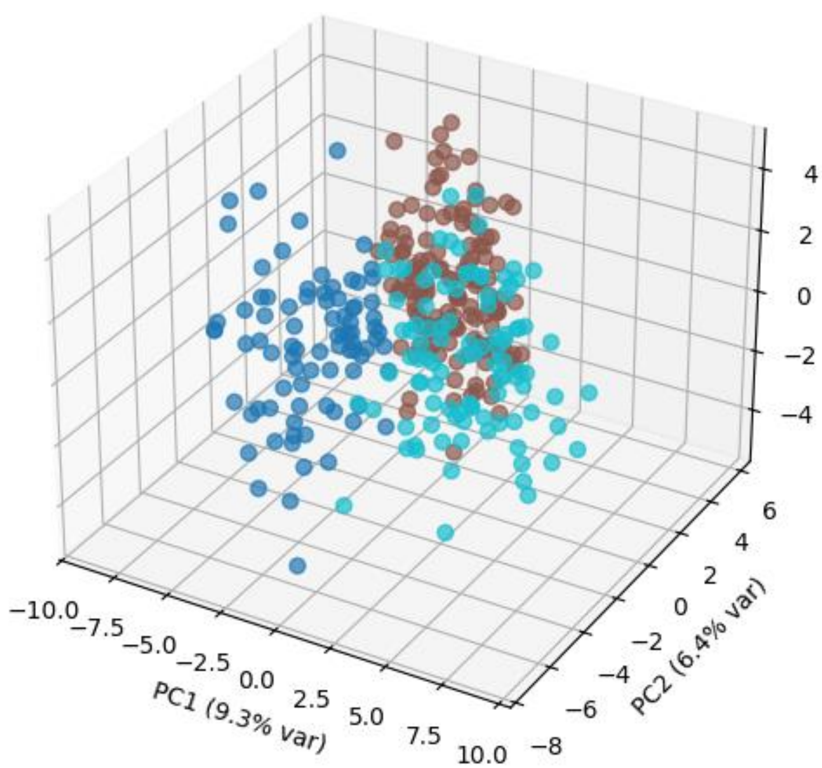


Five clustering paradigms were evaluated in a systematic grid search. The partition-based K-Means algorithm and its hierarchical Ward-linkage analogue seek compact, roughly spherical clusters. Gaussian mixture models (standard and Bayesian variants) assume the data arise from combining multiple Gaussian distributions, allowing for more flexible, possibly overlapping clusters. Finally, HDBSCAN, a density-based method, identifies clusters of varying densities and relegates sparse observations to noise. For each technique, the key hyperparameter (K for the partition and mixture models, minimum cluster size for HDBSCAN) was shifted over a small range, and only those configurations producing a cluster with 16 or more observations (5% of full answers) were retained to ensure interpretability.

Cluster quality was assessed along four complementary metrics. The silhouette score quantifies how similar each observation is to its cluster compared to its nearest neighboring cluster (higher values indicate clearer separation). The Calinski–Harabasz index evaluates the ratio of between-cluster to within-cluster dispersion (higher is better), while the Davies–Bouldin index measures average cluster similarity (lower is better). Lastly, an R^2-style explained variance metric captures the fraction of total variance accounted for by the clustering. Each metric was min–max scaled to [0, 1], the Davies–Bouldin index was inverted (so that larger is uniformly better), and the four scaled scores were averaged into a single composite score. The configuration achieving the highest composite score was deemed optimal. Appendix C contains tables with all the cluster paradigms and configurations and their scores.

Our best solution was obtained with K-Means partitioning into three clusters on the first 30 principal components. Its raw performance values were as follows: silhouette = 0.081, Calinski–Harabasz = 28.25, Davies–Bouldin = 2.94, and explained-variance R^2 = 0.15. Although the absolute silhouette score is modest, indicating only slight separation between clusters, the Calinski–Harabasz index and inverted Davies–Bouldin score rank this scheme highly relative to the alternatives, suggesting that the clusters are reasonably compact and distinct. The explained variance of 15% confirms that three clusters capture a partial but meaningful fraction of the overall survey variability. Taken together via the composite metric (≈ 0.81 on a 0–1 scale), these values imply that this three-cluster solution, while not defining perfectly separable groups, provides the most balanced and interpretable segmentation available in this dataset. Figure 3 plots the selected clusters as a function of their three principal components.

Figure 3. Selected K-Means clusters as a function of their three principal components



3.4.3 Clustering Results

The three clusters obtained were named Clusters 0, 1, and 2. Cluster 0 comprises roughly one-third of the answers, and Cluster 1 one-quarter. Cluster 2 is the largest, with 42% of the answers, as shown in Table 2.

Table 2. Answers by cluster

Cluster	Answers	%
0	104	32%
1	84	26%
2	134	42%
Total	**322**	**100%**

Cluster 0 was characterized by respondents from companies with a worldwide presence above the mean, and working in varied industries, also above the average. Three-quarters of the respondents had at least five years of supply chain experience. More than half were at director level and above, and therefore hold a greater proportion of functions than other respondents, with roughly four out of five having direct warehousing responsibilities. These respondents worked in larger companies, with two out of five having over $1 billion in annual revenue and one-quarter having more than 20,000 employees.

Cluster 1 comprised almost 40% more respondents from companies operating in regions outside North America than the mean, and those respondents work in comparatively more industries. While the majority are employed by logistics and 3PL companies, this cluster also included a considerable proportion of retail and food organizations, in addition to other industries. However, there were a low number of respondents from electronics, automotive, aerospace, and industrial equipment. This cluster exhibited the lowest years of supply chain experience, with 1 out of 5 respondents having just 3 or fewer years of experience. Only one-third were directors or above, therefore managing fewer functions, and only half directly oversee warehousing. Half of the respondents work in companies with annual revenues below $100 million and 500 employees or fewer. Roughly one-quarter work in companies with annual revenues below $1 billion dollars and up to 5,000 employees.

Cluster 2 included respondents from companies that are mainly concentrated in North America. The majority are working in Logistics & 3PL Services. Electronics, automotive, aerospace, and industrial equipment have average representation, and retail and food have a lower presence. While they were slightly more involved with transportation functions than their counterparts in Clusters 0 and 1, more than 7 out of 10 still had direct warehousing responsibility. Even though the respondent profile in this cluster had similar years of experience to those in Cluster 0, their job titles and companies' sizes resonated more with those in Cluster 1. The cluster respondents were mainly experienced supply chain professionals, in middle-management positions. Most also work in companies with annual revenues of up to $1 billion, but with a larger number of employees than Cluster 1.

4. RESULTS AND DISCUSSION

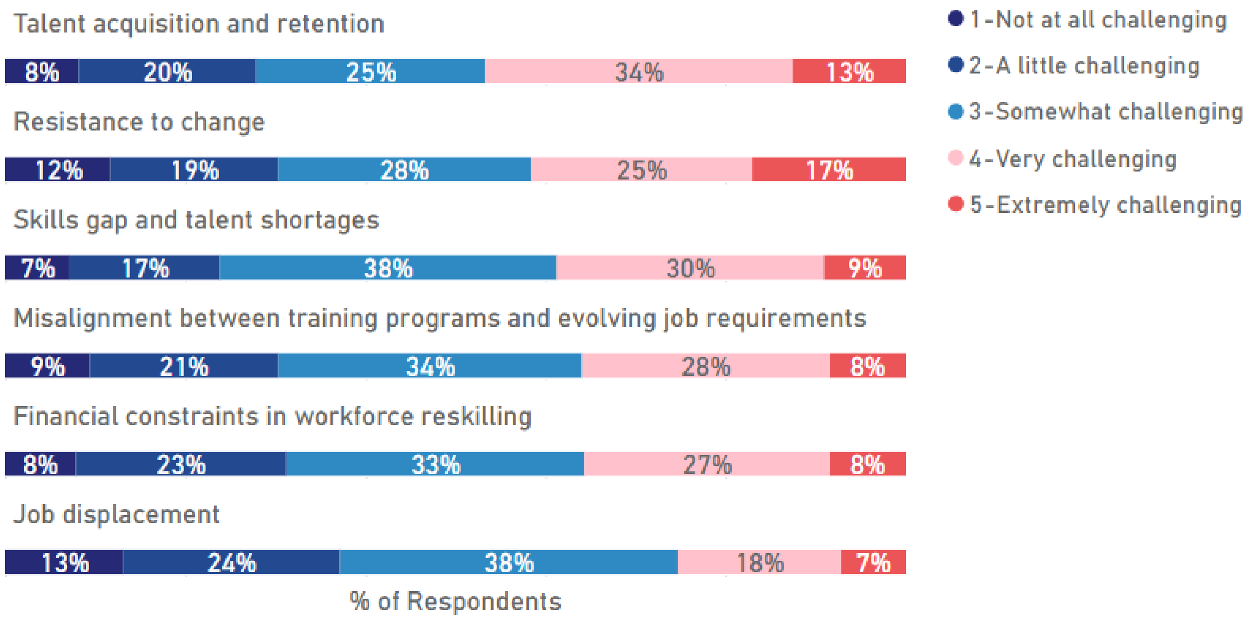
The first subsection presents the overall insights (Section 4.1). Section 4.2 delves deeper into demographic-specific insights, examining factors such as region, industry, company size, job titles, and tenure. Section 4.3 explores distinctive insights generated by the clustering analysis, identifying three respondent groups with different workforce readiness and approaches to warehouse technology adoption. Lastly, we integrate these empirical insights with findings from our literature review, discussing workforce readiness implications for warehouse technology adoption to answer our research questions (Section 4.4).

4.1 Main Results

Our survey reveals insights across five essential topic areas: workforce-related challenges, technology adoption, skills readiness, training effectiveness, and the integration of emerging roles. Each topic provides key insights into companies' preparedness and strategic approaches toward technological transformation in warehouse operations.

The first topic is workforce-related challenges. Figure 4 shows how survey respondents rate six common workforce challenges in warehouse operations, using a five-point scale from "not at all" to "extremely" challenging. Talent acquisition and retention stand out as the most formidable challenge, with the greatest share of respondents marking it as very or extremely difficult. Close behind is resistance to change, rooted in established work habits and company culture, and rated as the most extreme challenge. Skills gaps and talent shortages complete the top three. The mismatch between training programs and evolving job requirements, which also rank as major hurdles, and financial pressures on workforce reskilling emerge as other significant barriers, falling slightly behind skills gaps. Lastly, concerns about job displacement are comparatively fewer, suggesting that most see it as less severe.

Figure 4. Workforce-related challenges in warehouse technology adoption (N=322)

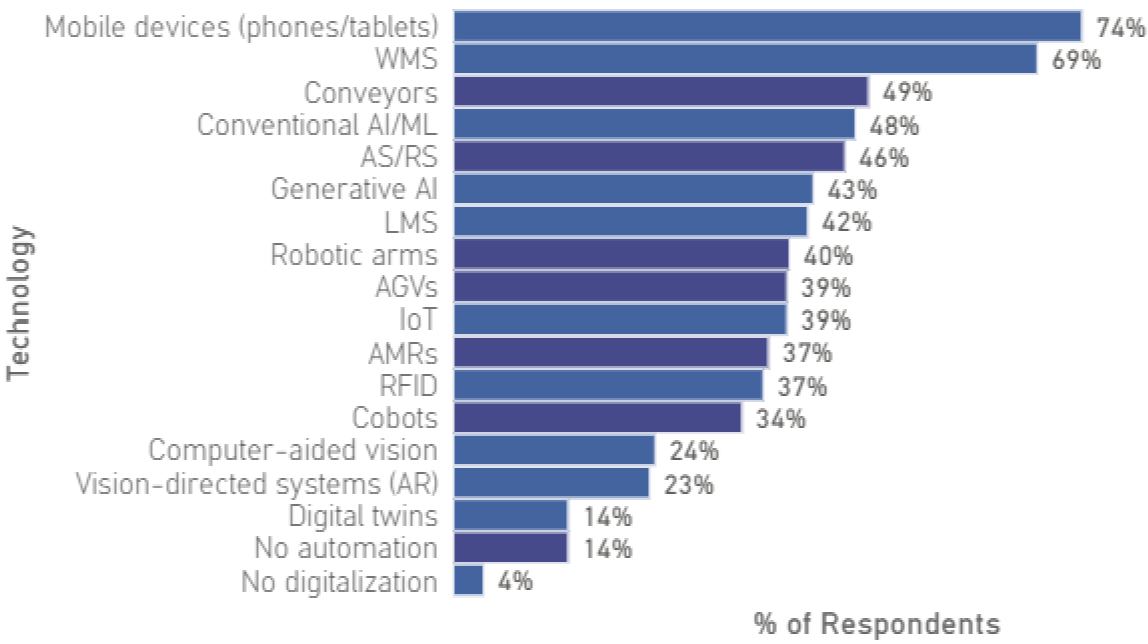


The second topic is technology adoption itself. The chart in Figure 5 shows the proportion of warehouses that already use or plan to deploy a range of digital (lighter blue) and automation (darker blue) technologies over the next five years. Over this period, most warehouses plan to lean on mobile devices and robust warehouse-management systems, while nearly half will have conveyor belts and/or automated storage-and-retrieval systems. Notably, interest in AI is growing steadily, and many companies' roadmaps are adopting conventional AI and newer generative AI tools to optimize inventory management, streamline operations, and support decision-making.

A mid-tier of respondents plans to implement labor-management systems, or roll out robotic arms, autonomous guided vehicles, IoT solutions, autonomous mobile robots, and RFID tagging, and many are considering cobots. An important takeaway regarding automation is that AGVs, AMRs, and cobots are very close to traditional/more rigid systems like AS/RS systems, while they did not even exist ten years ago. Also, robotic arms (which rely on AI similar to AMRs) are pretty common.

By comparison, advanced vision tools (computer-aided and augmented reality, or AR) appear on fewer plans, and digital-twin implementations remain relatively niche. Digital twins are still the least implemented solution, probably due to their complexity in building an overall solution. Lastly, only a small minority foresee staying with no further automation or digitalization.

Figure 5. Technology used or planned to be used in warehousing in the next five years (N=322)

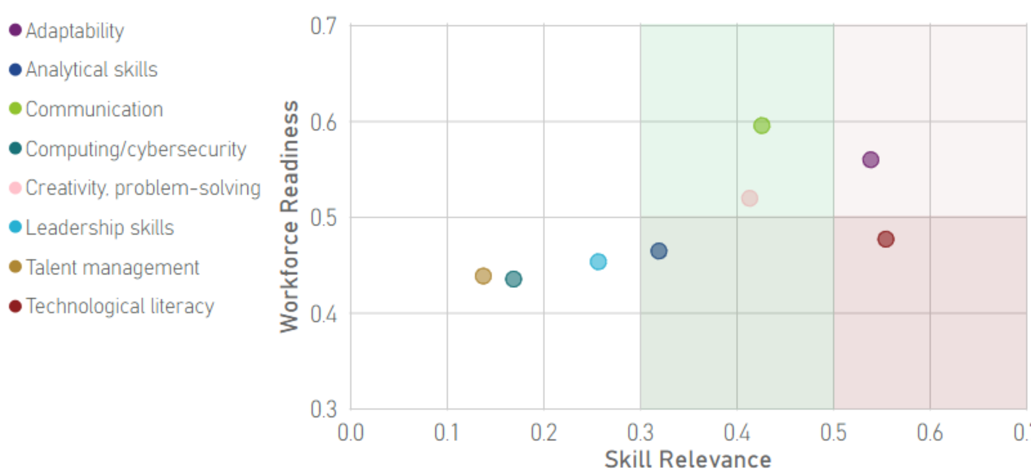


The third topic is workforce skill readiness. Survey participants have answered two questions about each of eight key workforce skills. They did that for two groups, frontline workers and warehouse managers. The first question is how relevant the skill will be for warehouse work over the next five years, and the second is what share of their workforce already possesses that skill. To better analyze skills, workforce readiness is converted from those "share" responses into a single readiness score, which weights each survey response using a midpoint value and averages across respondents. The weights are 0.05 for "Less than 10%," 0.30 for "10% or more but less than half," 0.50 for "50%," 0.70 for "More than half but less than 90%," and 0.95 for "90% or more." Then each skill's average relevance (x-axis) is plotted against its readiness estimator (y-axis) so that skills in the upper-right quadrant are both highly relevant and well covered today, and those in the lower-right are highly relevant but show the biggest readiness gaps.

To make it easier to spot the largest skill gaps, the chart is overlaid with three vertical bands: low relevance (<0.30), moderate relevance (0.30–0.50), and high relevance (>0.50). The moderate and high-relevance bands are each cut by a horizontal readiness line at 0.50. This creates five interpretive zones: On the far left sit all low-relevance skills; in the center lie moderate-relevance skills, split into those where readiness is above versus below the 0.50 benchmark; and on the right are seen high-relevance skills, likewise divided into well-prepared (upper) and underprepared (lower) groups. The leftmost band groups all skills whose relevance falls below 0.30 and is not bisected by the readiness line. When a skill is that low in importance, it is treated as a single "low-priority" category regardless of how ready the workforce already is. In other words, any skill in the left band sits outside the respondent's organization's urgent focus. The middle band captures skills of moderate importance, i.e., those that will matter but are not critical, and is split by the 0.50 readiness line into areas where training largely meets demand (upper middle) versus where it begins to lag (lower middle). By contrast, the right band contains the highest-priority skills for the next five years: Its upper section shows the handful of critical skills where the workforce is already reasonably prepared, while the lower right highlights the most urgent gaps—those vital capabilities that remain underdeveloped and should be the focus of immediate upskilling efforts.

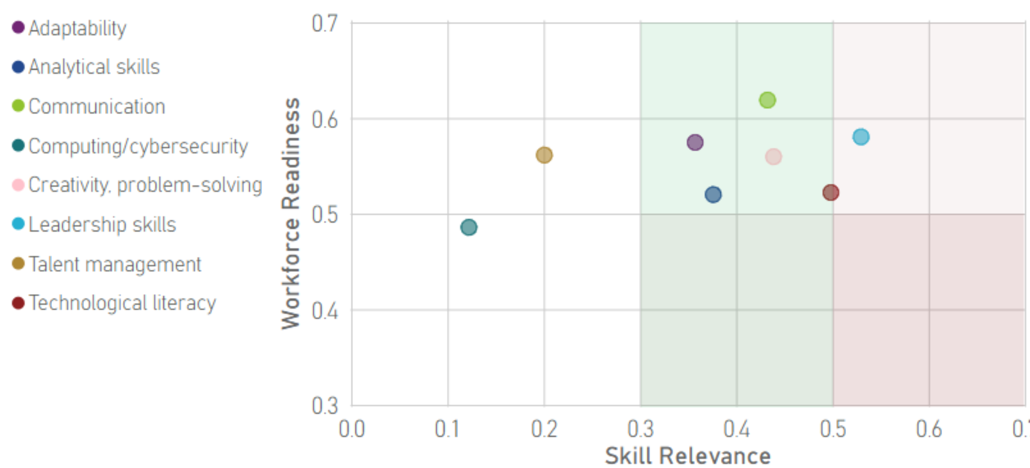
Plotting results for frontline workers, Figure 6 shows that technological literacy sits in the lower-right "high-relevance/under-prepared" zone, making it the most urgent upskilling need for the next five years. Adaptability follows in the upper-right "high-relevance/well-prepared" band, a relevant capability where the workforce already shows an acceptable readiness. In the moderate-relevance middle band, analytical skills fall just below the 0.50 readiness threshold, an important skill with a modest gap. While communication and creativity/problem-solving lie above that line, indicating these valuable skills are already well covered. Finally, computing/cybersecurity, and understandably, leadership skills, and talent management occupy the leftmost low-priority band, as they are not deemed critical in the near term, regardless of current readiness. As a takeaway, redirecting training efforts toward technological literacy could bring a greater impact.

Figure 6. Skills relevance for warehouse workers over the next 5 years and their readiness (N=322)



A similar analysis is done among the warehouse managers from the skills chart in Figure 7. In the high-relevance band (>0.50 on the x-axis), leadership skills and technological literacy sit above the 0.50 readiness line, so no highly relevant managerial skill is deemed underdeveloped. Moving left into the moderate-relevance band (0.30–0.50), adaptability, communication, creativity/problem-solving, and analytical skills also clear the readiness cutoff, indicating warehouse managers already command these important capabilities. Even in the low-priority band (<0.30 relevance), computing/cybersecurity and talent management meet or slightly exceed the 0.50 benchmark, showing that secondary skills are also adequately covered. By overlaying three vertical relevance zones with a horizontal readiness line at 0.50 through the moderate and high areas, the chart shows that managers today are seen as acceptably equipped across every relevant skill for the next five years.

Figure 7. Key skills relevance for warehouse managers in the next five years and their readiness (N=322)

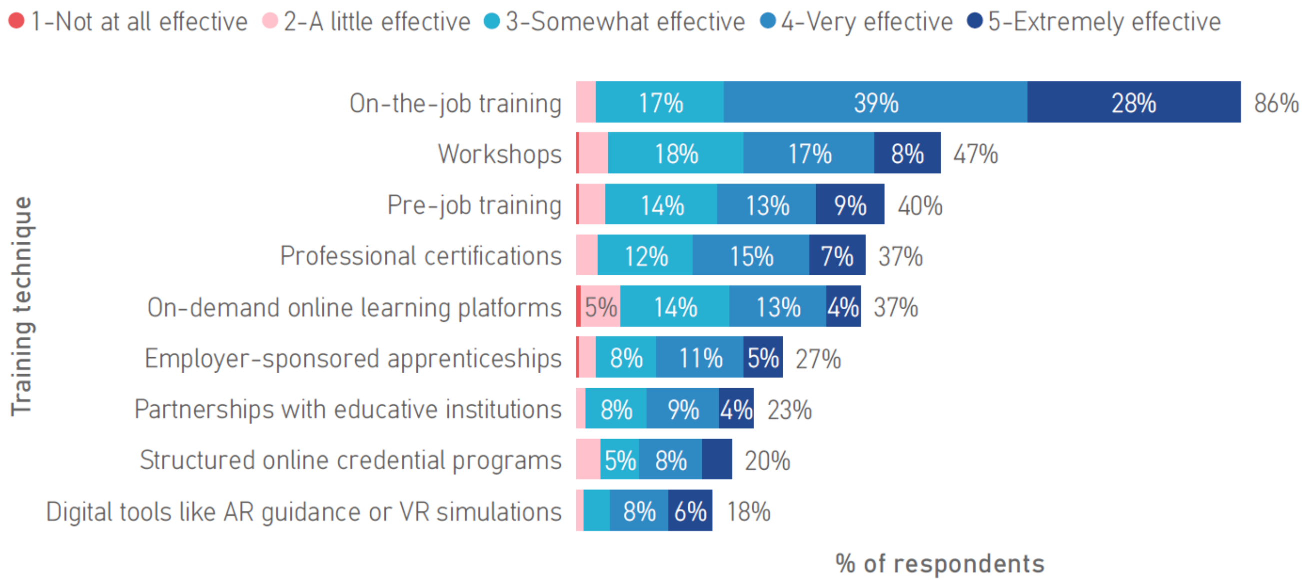


In fourth place comes training effectiveness. The bar chart in Figure 8 shows how widely each of the nine surveyed common training techniques is used in warehouses (total percentage at right) and how users rate their effectiveness (color segments summing to that total). Most companies rely on on-the-job training, and respondents almost always find it helpful. Workshops are also common and generally work well.

Some firms utilize pre-job training, professional certifications, and on-demand online learning platforms, with different effectiveness. Pre-job and certifications often work well, but on-demand learning is proportionally the least effective technique.

Company apprenticeships reach fewer people, and feedback on them is mixed. Finally, partnerships with schools, structured online programs, and AR/VR tools are the least common options, and those who try them have varied views on how well they work. Interestingly, AR and VR have a high proportion of very/extremely effective responses while being the least used, suggesting companies should explore this more.

Figure 8. Training preferences and effectiveness (N=322)



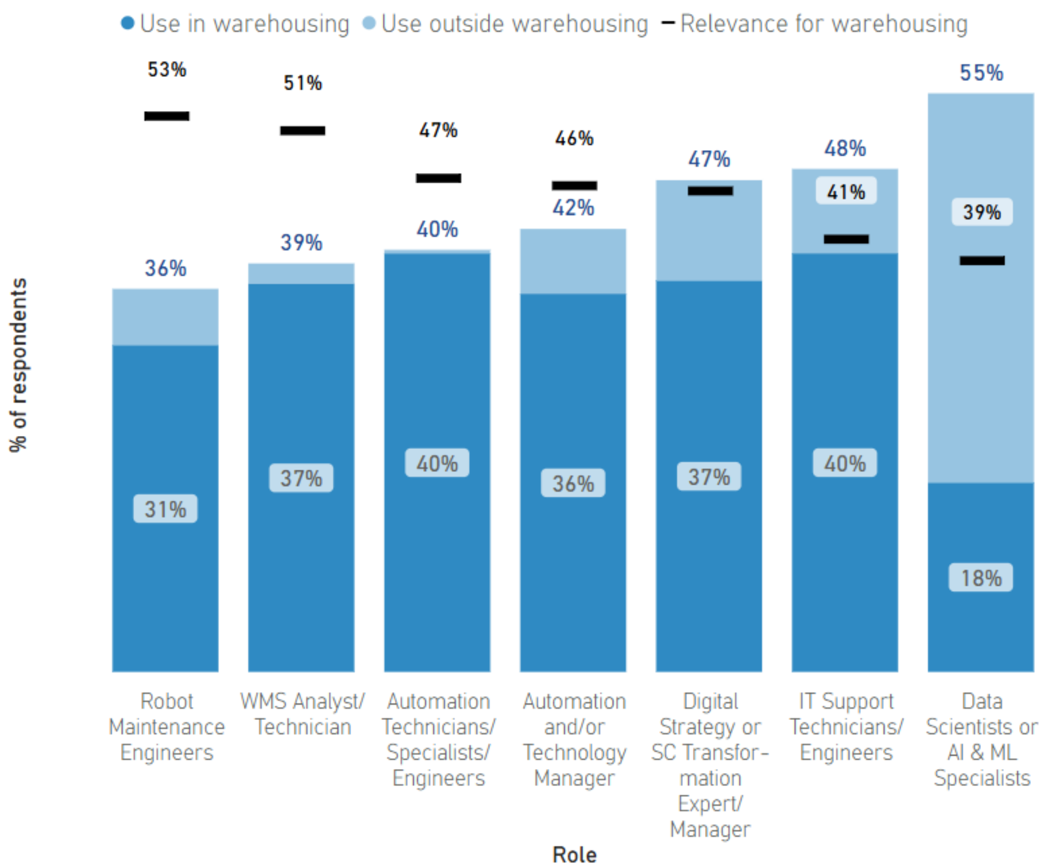
Finally, the last topic is the integration of emerging roles. In Figure 9, the bar chart compares seven specialist roles by where they are used in the organization (inside the warehouse or elsewhere) and how many survey respondents say each role is relevant to warehouse operations. For each role, the darker blue segment shows the share of companies that have it directly in their warehouses, the light blue segment shows the additional share deployed elsewhere in the company, and the line marks the portion of respondents considering it important for warehousing.

At the top of the relevance are robot-maintenance engineers and WMS analysts/technicians—roles firms deem critically important, yet only about one in three work on the warehouse floor. This represents the largest mismatch between perceived importance and in-warehouse staffing. Just below them, automation technicians achieve higher deployment rates in warehouses but still fall well short of the value companies place on them.

In the mid-range, automation/technology managers and digital-strategy or supply-chain transformation experts exhibit similarly wide gaps: firms expect these roles to be relevant over the next five years, yet their on-floor presence remains markedly lower than their conferred importance.

Further down, IT support technicians/engineers come closer to alignment, with warehouse staffing more aligned with their relevance score. At the bottom of the relevance ranking, data scientists and AI/ML specialists show the smallest importance rating but one of the largest shortfalls in warehouse deployment. Despite growing organizational interest, they remain largely absent from day-to-day operations.

Figure 9. New roles' use and relevance to warehousing (N=322)



In sum, our survey pictures where companies stand in preparing for warehouse transformation. First, workforce challenges are dominated by talent acquisition and retention, with resistance to change and skills gaps close behind. Second, in technology adoption, mobile devices and WMS dominate current deployments; mid-tier automation such as conveyors, AS/RS systems, and modern solutions like AGVs, AMRs, cobots(all of which did not even exist ten years ago), and robotic arms are rapidly growing; AI-driven tools are on most roadmaps; and digital twins remain the least implemented, likely due to their integration complexity. Third, skill-readiness analysis encounters technological literacy as the most urgent gap, while adaptability, analytical thinking, and communication are comparatively well covered. Fourth, training efforts are centered on on-the-job training, followed by workshops, and both are highly valued. Pre-job courses and certifications are also effective, but on-demand online learning proves the least effective approach. Interestingly, AR/VR tools, despite being the least adopted, receive a high share of very/extremely effective ratings. Finally, emerging roles show in-warehouse shortfalls: robot-maintenance engineers and WMS analysts/technicians top the relevance ranking yet are staffed on only about one-third of floors; automation technicians perform better but still lag importance; IT support roles approach parity; and data scientists and AI/ML specialists, despite lower warehouse relevance ratings, exhibit one of the largest on-floor gaps even as they proliferate elsewhere in organizations.

4.2 Results Based on Demographic Factors

The following sections summarize key demographic insights in our five areas: workforce challenges, technology adoption, skill readiness, training strategies, and emerging roles. Each topic reveals patterns by company size, region, and industry. Appendix D includes numerous figures supporting this analysis.

4.2.1 Key Challenges

The top three challenges remain the same across different company sizes. Talent acquisition and retention are the number one challenges for most companies, regardless of their income level. They are followed by resistance to change in most cases, showing the highest proportion of extreme challenge across segments. Close is the skills gap and talent shortages, even in the second place among the largest companies. An interesting finding, as shown in Figure D2, is that mid-sized companies find more financial constraints in the workforce reskilling than smaller ones, who struggle more with the misalignment between training programs and evolving job requirements. Larger companies have proportionally more very/extremely challenging answers, with companies between 10 and 100 billion in revenue being the most challenged. The largest companies, above 100 billion, still experience strong talent acquisition/retention difficulties and skill gaps and face considerable resistance to change, but mostly find few financial constraints and have better training program alignment. Lastly, job displacement is a minor concern for most respondents.

Regional differences show that companies operating in North America (NA) face fewer barriers than those outside, reflecting greater cultural readiness for change. Figure D1 shows that more than half of the companies outside NA experience very/extreme resistance to change, being the most relevant barrier for most regions. Half the companies also experience very/extremely challenging skill gaps and talent acquisition/retention difficulties. Misalignment between training and jobs is also concerning, as 2 of 5 companies outside NA find it very/extremely challenging. Financial constraints, though, are not as important even for companies outside NA and Europe; they happen to be stronger inside NA, even over skills gap/talent shortages. Talent acquisition remains the main challenge for NA companies, followed by resistance to change and financial constraints in workforce reskilling.

The pace of technological advancement of the sector and its complexity also influence the workforce barriers companies encounter. As shown in Figure D3, logistics and 3PL operators report a smaller share of very/extremely challenging workforce issues than companies in other industries when rolling out new warehouse technologies. Although finding and keeping skilled staff remains a big problem, other obstacles are noticeably less severe than in the remaining sectors, and even resistance to change or skills gaps fall from the top 3 for these companies, giving their places against financial constraints and training misalignment. Non-logistics companies face a higher combination of workforce barriers when adopting warehouse technologies. Roughly half of respondents outside the logistics sector assess first resistance to change and closely second talent acquisition as very/extremely difficult, and a considerable portion of respondents are concerned about skills gaps, training-program misalignment, and limited reskilling budgets. For example, the most critical workforce constraints appear in electronics, automotive, aerospace, and industrial equipment, where a large majority rated every single barrier as very/extremely challenging.

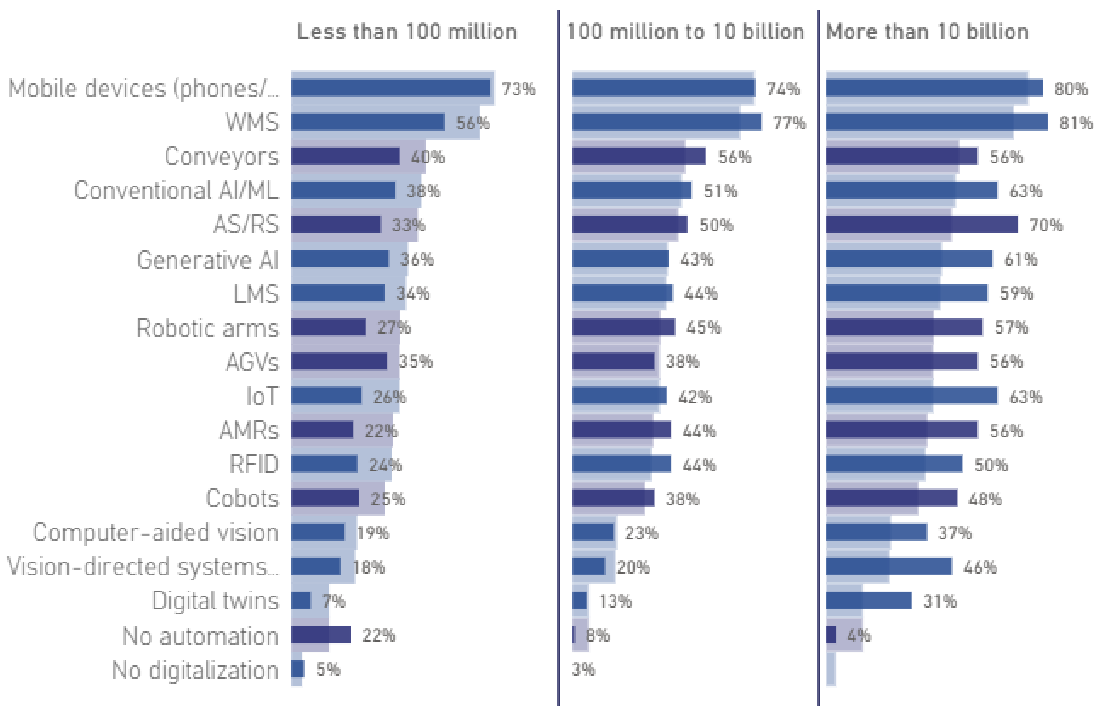
In short, the three principal pain points (finding and keeping talent, overcoming resistance to change, and closing skills gaps) hold at every revenue level. Mid-sized firms feel budget pressures for reskilling more impactfully, while smaller companies fight most with making training relevant. Larger enterprises report the heaviest concentration of very/extremely challenging responses overall, even as they benefit from stronger funding and better program alignment. Geographically, North American organizations encounter fewer severe barriers than their counterparts elsewhere. By sector, logistics and 3PL providers face relatively fewer barriers beyond talent acquisition (financial constraints and training misalignment complete their top three challenges), whereas non-logistics industries, and especially electronics, automotive, aerospace, and industrial equipment companies, mostly rate almost every workforce obstacle as very or extremely challenging.

4.2.2 Technology Adoption

Figure 10 illustrates the technologies used or planned to be used in warehousing by revenue segments. Each figure’s chart compares the in-warehouse adoption rate of each technology for a given revenue band (the solid bars) against the overall industry average (the transparent bars on the back).

Overall, the trend is clear: as companies grow, they steadily plan to adopt new technologies. Smaller firms lag the average, mid-sized companies converge on it, and the biggest players surpass industry adoption levels across all warehouse automation tools assessed. In the smallest companies, those under one hundred million in revenue, solid bars almost always appear below the transparent average. They use basic tools like mobile devices and WMS at rates close to the mean, when advanced automation systems and other digitalization initiatives remain low, and a considerable portion is adopting no automation in the next five years. As revenue climbs into the mid-range (one hundred million to ten billion), the solid bars begin to catch up. Core technologies like conveyors, conventional AI/ML, and AS/RS move closer to or even above the average. Although the gap narrows, companies in this band are still behind the overall mean on the newest tools, such as digital twins, vision-directed solutions, and AR. In larger enterprises, the solid bars rise well above the transparent benchmarks for every technology. Mobile devices, WMS, and AI/ML become nearly universal on the floor, and even digital twins and vision systems exceed their population averages.

Figure 10. Technologies used or planned to use in warehousing by revenue segments (Less than 100 million, N=129; 100 million to 10 billion, N=133; more than 10 billion, N=54)



Appendix D Figure D4 provides a deeper analysis of the previous charts in more revenue segments. Those charts show that almost every company above 100 billion is planning to integrate AI/ML into warehousing, and that the largest companies are using the most cutting-edge technology in at least half of the cases (vision systems and digital twins).

Another significant demographic for technology adoption is the industry segment, as seen in the Appendix D, Figure 5. From those charts, in logistics and 3PL services, all technologies but AGVs and digital twins exceed the mean, with those two being almost at the average. In contrast, for all except logistics and 3PL services, particular technologies fall short of the previous group. Where logistics firms push above the average, the all-except logistics and 3PLs solutions group only reaches (or even falls below) the mean in digital tools like mobile devices, both forms of AI, and LMS, and in automation solutions like cobots.

However, the previous situation has its nuances by sector. Non-logistics companies in the electronics, automotive, aerospace, and industrial equipment segments stand above the average for nearly every technology except RFID. These companies consistently exceed the sample mean, marking them as frontrunners in warehouse tech uptake, especially for automating with AMRs, AGVs, robotic arms, and implementing digital tools as AI and IoT. Similarly, food, beverage, and cold chain outpace the mean on almost all technologies, leading in WMS, conveyors, LMS, and robotics. In retail, e-commerce & consumer goods, it is the opposite, and most technologies fall below the average. Only a handful of mechanized solutions, such as conveyors and AS/RS, or AGVs, cross the mean, giving this sector a profile of broad under-adoption compared to the average. Finally, apparel and fashion exhibit a mixed picture. It climbs above the mean line for most innovations, especially leading in conveyors, robotics, and RFID, plus IoT, but notably encounters far below for AI-enabled warehouses.

Concisely, warehouse technology uptake rises steadily with company size: the smallest firms trail the industry average on nearly every tool, mid-sized businesses converge on it, and the largest enterprises outpace it. Sector by sector, logistics and 3PL providers lead on most systems, while non-logistics companies lag in technologies like AI and cobots. Among those latter companies, though, high-tech manufacturing (electronics, automotive, aerospace) and food & beverage stand out as frontrunners, retail and e-commerce are found well below the average, and apparel & fashion shows a mixed pattern of strong automation and digitalization but weak AI-driven perspectives.

4.2.3 Skills Readiness

With slight variations, most demographic factors almost do not alter the skills profiles. Technological literacy emerges as the central workforce skill gap for workers across company roles, sizes, and industries, shaping technology adoption outcomes. Across company sizes, for example, technological literacy consistently lags behind other warehouse workers' skills. As shown in Appendix D, Figure D8, for companies with over 100 million annual revenues, readiness in technological literacy remains the core skill gap affecting the effective use of complex systems. Only the smallest firms perceive their workers outside the critical readiness/relevance zone (the low-right quadrant in the skills charts). Consistent with their under-average adoption plans, they value an adaptable labor force slightly more than the tech-savvy one needed to move beyond basic warehouse systems.

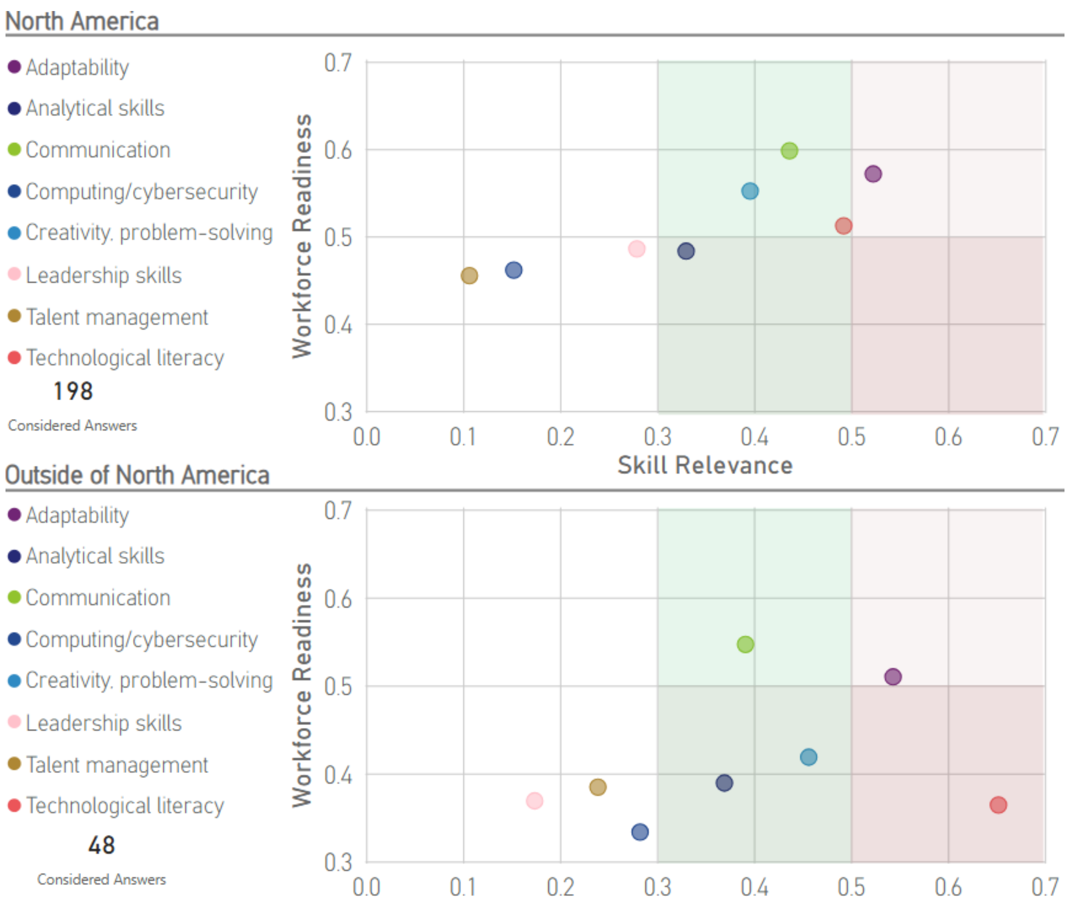
Furthermore, industries have nuanced readiness profiles, but relevant skills do not change considerably. Sectors like electronics and automotive exhibit stronger technological and soft skills, aligned with the sector's maturity and strong technology adoption plans. On the contrary, retail/e-commerce, and apparel and fashion show workers have, in general, weaker capabilities, adding adaptability to the critical zone with technological literacy. This correlates with their less/mixed technological adoption plans described above.

In addition, the region is indeed an insightful demographic factor. As shown in Figure 11, workers in companies with operations outside North America (including Europe) are assessed to have a critical technological literacy readiness and wider skill gaps in general. These regional differences could explain the intensity of challenges in these regions. Conversely, companies present in North America almost show parity in technological literacy readiness/relevance for frontline workers, although it remains the main priority. Regional differences also affect warehouse managers, unlike other demographic factors. Warehouse managers outside North America (including Europe) have deficits in technological literacy and creativity, problem-solving, and lower skills readiness in general. This further reinforces the heavier barriers evidenced.

Lastly, computer and cybersecurity skills are consistently underestimated across all demographic cuts for frontline workers and warehouse managers, despite the criticality of avoiding cyberattacks for supply chain reliability. Surprisingly, talent management is another least relevant skill for both groups, despite talent acquisition and retention being the main challenges for this sample's respondents.

In brief, demographic splits by role, size, or industry barely alter the overall skills picture: technological literacy is the one clear, consistent gap for warehouse workers everywhere. Even the largest firms struggle most with tech knowledgeability, while the smallest place relatively more weight on adaptability. High-tech manufacturing sectors are doing best, whereas retail, e-commerce, and fashion workers routinely fall short on overall skills. Regionally, organizations outside North America exhibit wider readiness gaps even in managers, underscoring heavier barriers in those markets. Across all groups, computer/cybersecurity and talent-management abilities remain surprisingly underprioritized despite their strategic importance.

Figure 11. Key workforce skills' relevance for warehouse frontline workers in the next five years and their readiness for companies in/outside North America (NA) (only in NA, N=198; only outside NA, N=48)



4.2.4 Training Strategies

Across every category, whether by revenue, region, or industry, on-the-job training stands out as the undisputed top training technique of warehouse upskilling. It is the most widely used almost everywhere and earns the strongest "very" and "extremely" effectiveness ratings. Workshops are consistently the next ones in use and effectiveness: nearly every group leans on them, and most users report they work well.

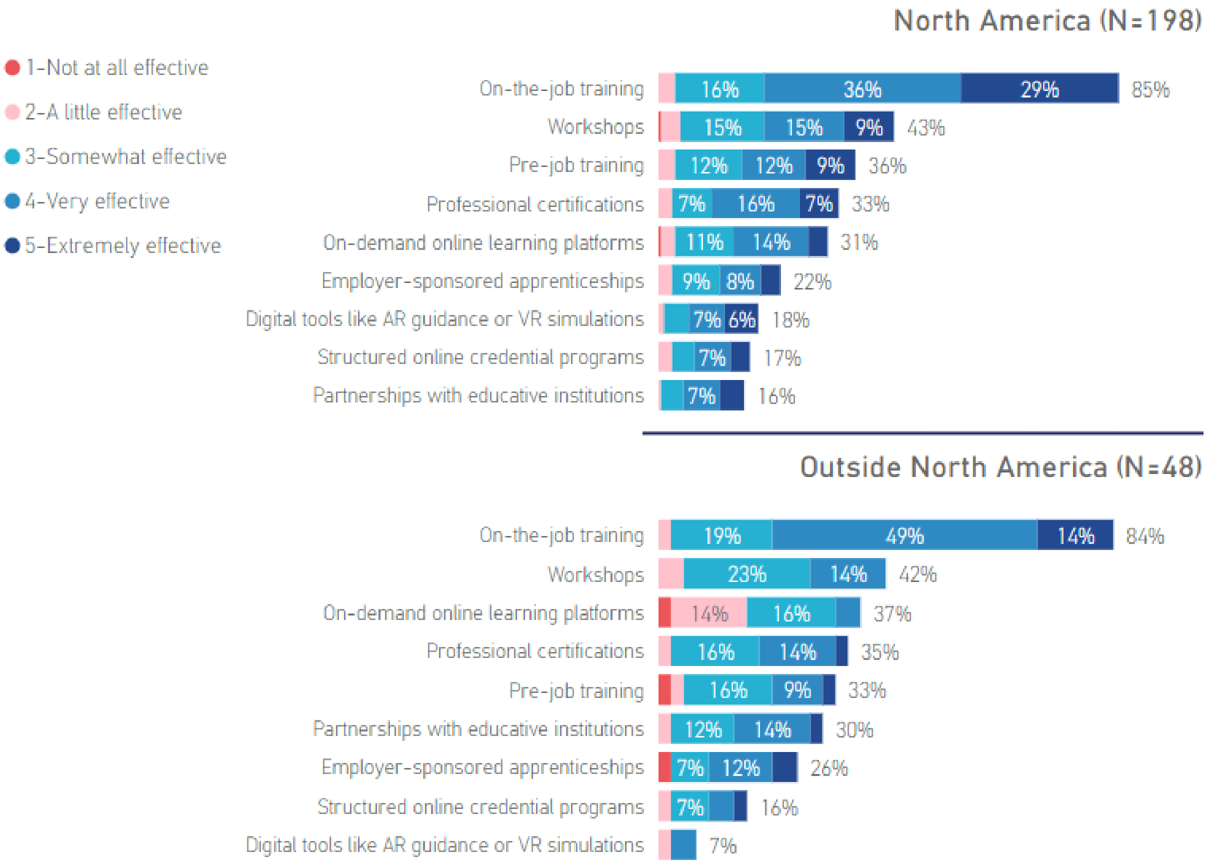
When we look at company size, smaller firms rely almost exclusively on on-the-job training and workshops, with little adoption of other methods. Appendix D, Figure D11 shows that as organizations grow, they steadily broaden their training strategies: mid-sized companies add professional certifications, pre-job courses, and on-demand platforms to their mix, while the largest companies also embrace apprenticeships, structured e-learning tracks, and AR/VR pilots. In those big players, the newer digital techniques still sit behind the main methods in adoption and perceived impact, but they have proportionally increased.

On a regional level, following the previous section distinction, in Figure 12 we split companies into those purely inside North America and those outside. Both rely strongly on on-the-job training, followed by workshops, but in third place, companies outside North America lean more on online learning than those in North America. However, their use carries moderate or little effectiveness, or even ineffective results. In general, these companies use a similar level of training techniques to companies in North America, but with a consistently lower overall effectiveness, correlating with less skilled workforces as seen in the previous section. Finally, companies outside North America show extremely low use of AR/VR tools to assist training.

Then, analyzing by sector, logistics and 3PL providers report a broad use of every common technique beyond the basics, and they generally find them effective (see Appendix D, Figures D12 and D13). This sector surpasses other industries, even with the most innovative initiatives, like AR/VR tools. Only with structured online credential programs does this sector lag most others. In contrast, retail and e-commerce rely almost entirely on on-the-job training, with few utilizing certifications or other programs. High-tech manufacturing (electronics, automotive, aerospace) mirrors the largest companies adopting many methods with solid satisfaction levels, like professional certifications, apprenticeships, and structured online credential programs. Food, beverage, and cold-chain players lie between those extremes: slightly weaker on on-the-job training, strong on pre-job courses and workshops, and modest in the remaining techniques. Apparel and fashion firms show the narrowest set of tools in use and the most modest effectiveness feedback, relying primarily on workshops alongside their core on-the-job sessions.

In summary, no matter the context, hands-on training leads the training strategies, and workshops often follow closely. Growth in company size and high-tech or warehouse-specialized industries correlates with greater diversification into certifications and e-learning, though none of those newer approaches have yet displaced learning by doing on the warehouse floor. Overall effectiveness is consistently lower outside North America, correlating with less skilled workforces.

Figure 12. Training preferences and effectiveness in/outside North America



4.2.5 Emerging Roles

Revenue scale, geographic region, and industry sector influence the gap between the specialist roles organizations say they need in their warehouses and the ones they have. As companies scale, their ability to embed strategic roles directly into warehouse operations evolves. Appendix D, Figure D14, evidences a clear pattern across revenue bands: smaller firms tend to lack relevant emerging roles, while larger enterprises are increasingly capable of integrating these specialists. At the lower end of revenue, roles like data scientists, AI/ML experts, automation managers, and even WMS analysts are often housed outside the warehouse, somewhere in the organization. This results in a gap between perceived relevance and actual warehouse staffing. In contrast, as company size grows, these gaps narrow. Medium and large firms steadily move IT support, WMS technicians, and robot-maintenance engineers into operational settings, reducing their reliance on central or corporate functions. By the highest revenue tier, most roles show near-complete alignment between stated importance and physical presence in the warehouse.

Geographic differences further influence how organizations incorporate these roles. As per Appendix D, Figure D15, across the regions, companies outside North America show the largest overall disconnect between the roles they need and what they staff on the warehouse floor. In North America, gaps are present but comparatively smaller: the biggest shortfalls are in robot-maintenance engineers and data scientists, and to a lesser extent, automation managers and WMS analysts. Outside North America, however, almost every one of those roles sits much below its relevance line, especially digital-strategy leads, robot/automation technicians, and WMS analysts.

Industry-specific patterns also emerge. Appendix D, Figure D16, shows that high-tech manufacturers (including electronics, automotive, aerospace, and industrial equipment) demonstrate the strongest alignment between relevant roles and staffing. Here, relevance and presence nearly converge across all roles. Retail shows moderate gaps in robot/IT engineers and automation managers. Sectors like food, beverage & cold-chain, and apparel & fashion reveal wider disparities, particularly for data scientists and digital-strategy managers, although these roles are already present outside warehouses. Surprisingly, despite displaying a higher percentage of modern roles used in warehouses than most industrial sectors, logistics and 3PL providers exhibit the largest average gap between relevance and staffing. They give roughly 10 more percentage points to most roles than their counterpart. Most specialist roles must be developed for them, as these firms often lack them in other organizations' functions. The one exception is data science and AI, where some external bench strength exists.

A final point worth highlighting is the consistent outlier behavior of data scientists. This role is generally adopted at higher rates across revenue bands, geographies, and sectors than its stated relevance suggests. However, this adoption remains heavily concentrated outside the warehouse. The result is a persistent opportunity: organizations already recognize the value of data science, but few have fully leveraged it in operational settings. Data scientists are present within the business, even among the smallest companies, but are underutilized in warehouse contexts.

In sum, as companies grow, they progressively close the gap between the specialist roles they declare essential and the actual incorporation of those jobs on the warehouse floor. North American firms tend to include these roles more fully than companies elsewhere, which show larger disconnects across all positions. Among industries, high-tech manufacturers achieve the closest match between relevance and staffing, retail and e-commerce exhibit moderate shortfalls for core engineering roles, and food, beverage & cold chain, and apparel & fashion reveal the widest disparities despite having many experts in corporate functions. Logistics and 3PL providers display the greatest average gap, lacking most modern roles concerning the higher relevance the sector confers to them compared to other industries. Across every dimension, data scientists stand out as persistent outliers, widely hired but rarely placed in warehouses, highlighting a clear opportunity to use existing analytics talent in the warehouse context.

4.3 K-Means Clustering

The clustering analysis described in Section 3.4 identified three distinct company profiles. To understand how companies of these different profiles experience workforce and technology trends in warehousing, in this section, the same five dimensions, workforce challenges, technology adoption, skill relevance vs. readiness, training effectiveness, and emerging role integration, are examined for each of the three clusters described. Appendix E contains figures for these 3 clusters.

Recalling from Section 3.4, about one-third of responses fall in Cluster 0, one-quarter in Cluster 1, and the largest share (42%) in Cluster 2. Cluster 0 respondents come from large, globally diversified firms (two-fifths with over one billion US dollars in annual revenue) and tend to be senior (directors or above), highly experienced in supply chain (75% have 5 or more years), and nearly 80% oversee warehousing directly. Cluster 1, by contrast, skews toward smaller companies (half under 100 million US dollars in annual revenue and less than 500 employees), a heavy mix of 3PL, retail, and food firms operating more outside North America, and a less experienced, less managerial cohort (only one-third directors, 20% with less than 3 years' experience). Cluster 2, the largest group, draws mainly North American logistics and 3PL with high-tech industry incumbency professionals whose experience levels mirror Cluster 0 but whose roles and employer sizes align more closely with Cluster 1: mid-management positions in companies generally up to 1 billion in revenue (but with more employees than Cluster 1), with over 70% having direct warehousing responsibility.

The greatest intensity of workforce challenges, especially around talent acquisition, skills shortages, and resistance to change, is reported by respondents in Cluster 0. Nevertheless, these companies are pioneers in digital and automation technologies: nearly all have deployed advanced WMS and mobile devices, and most use IoT, AI/ML, conveyors, AS/RS systems, and robotic arms on the warehouse floor. Modern digital tools like generative AI and digital twins are also more common here than elsewhere, and they strongly use or plan to use computer-aided systems. This group also shows the closest match between which skills matter most and how prepared the workforce is in all but technological literacy. For this group, tech literacy exceeds the relevance of the average population, but remains underdeveloped, especially among workers. Adaptability, managers' leadership, analytical thinking, communication, and problem-solving all score high on relevance/readiness. When developing talent, they consistently use a broad spectrum of training with major good results, reflecting a balanced blend of traditional and tech-enabled learning. They all favor on-the-job training and workshops, supplemented by on-demand online learning platforms and professional certifications in most cases, when a great portion also leverages pre-job training, structured online credentials, apprenticeships, and partnerships. They are also pioneering AR/VR. Reflecting their emphasis on innovation, these firms have staffed emerging roles way above the mean, with roughly half of the companies having all the modern roles assessed working on their warehouses. However, these companies naturally confer higher relevance than the mean to incorporating emerging roles in warehousing and therefore still have not closed the gap for roles like automation managers, robot-maintenance engineers, WMS analysts, and data scientists (data scientists are the only that, as in general, are present elsewhere in their organizations).

By contrast, Cluster 1 respondents, small firms with a narrower geographic scope, dominated by 3PLs, and seconded by incumbents in retail and food, experience moderate workforce barriers. Talent retention and skills gaps are still top concerns, but resistance to change is larger here than in Cluster 0, climbing to the first place. They standardize on WMS and mobile devices, and match the average in conveyors, but are more cautious about advanced automation (robotic arms, AS/RS) and digital technologies (AI, IoT, RFID). Less than 1 in five plans to add automation, and one in ten plans to use no digital tools. Skill readiness critically lags relevance, with all skills deeply underdeveloped, technological literacy being the worst, in both workers and managers. Practical, hands-on learning dominates here: on-the-job training is generally rated effective, followed not closely by pre-job training and workshops, digital tools, and formal certifications, all receiving low effectiveness scores. There is a noticeable gap in role implementation in the warehouse against their relevance, for all the assessed emerging roles in this cluster. Automation managers or digital-oriented roles are found elsewhere in the organizations, but technical positions such as WMS analysts, robot engineers, and automation specialists are lacking considerably.

Cluster 2, predominantly low revenue, more headcount, North America–focused, and centered on logistics/3PL services with high-tech industry incumbency, and few retail or food respondents, reports workforce challenges at slightly lower intensity. Talent acquisition and retention are their main barriers; meanwhile, resistance to change and skills gaps are less challenging than for other firms, and they are slightly more worried about training misalignment and financial limits. Technology adoption is even lower than the previous cluster across almost all the assessed options. A fairly strong deployment of mobile devices contrasts with more cautious use of all other technologies. Again, roughly one in five companies will not adopt warehouse automation in the next five years. Conversely, most skills are well developed here, especially adaptability in workers, leadership in managers, and communication in both. Technological literacy is not as relevant as the prior three for this group, although in general, well-developed together with analytical skills, and creativity. On-the-job training remains the training method of choice, while these firms use even less varied training strategies than the previous cluster. However, they consistently have better results than cluster 1. While they have a similar role relevance profile to cluster 1, and similar gaps overall, all but one of the emerging roles assessed (robot maintenance engineers) often remain in the companies but outside warehouse operations.

Finally, some similarities across all clusters include that job displacement concerns are always fewer, and that knowledgeability on cybersecurity and talent management skills always have low relevance.

In short, cluster 0 (large, globally minded firms) faces the most arduous workforce challenges yet leads in both technology deployment and emerging roles, using diverse training methods to bridge skill gaps effectively. Companies in this cluster confer extremely high relevance to workers' technological literacy in correlation with their ambitious technology adoption plans. Cluster 1 (smaller, regionally diversified 3PL, retail, and food operators) struggles most with change resistance and skill underdevelopment, relies almost exclusively on basic training, and performs poorly in the remaining low-utilized training techniques, and should train/hire and integrate associates in nearly all modern roles. Cluster 2 (low-revenue, North American logistics specialists) encounters moderate barriers, shows conservative tech adoption but stronger baseline skills and training outcomes despite relying on traditional on-the-job training, and maintains expertise in emerging roles company-wide, even as those experts are outside the warehouse.

4.4 Discussion

This discussion explicitly addresses the key research questions and the three expected outcomes based on the literature review and empirical findings from the survey data.

4.4.1 Key Research Questions

Are there any best practices for implementing warehouse technology from a workforce and labor management perspective?

The literature identifies several recommended practices: systematically assessing and addressing skill gaps, proactively recruiting specialized talent capable of managing complex systems, developing tailored reskilling and upskilling programs to transition staff to technology-enabled roles, and integrating advanced training techniques, including digital and immersive learning (AR/VR simulations) to reduce training curves (Amazon, 2023; Ellithy, 2024; McKinsey, 2020; Rodríguez & Agmoni, 2024; WEF, 2025).

If so, do companies follow these practices?

Survey data indicate mixed adherence to these practices. Large global companies (like in Cluster 0) largely follow these recommendations, extensively using advanced training methods and successfully integrating relevant emerging roles within their warehouses. In correlation with this, these companies show ambitious technology adoption plans. Conversely, smaller or more regionally focused companies (like Clusters 1 and 2) frequently exhibit gaps in following these practices, characterized by fewer training methodologies, lower technology adoption rates, and less integration of specialist roles within operational contexts. Thus, adherence to these practices significantly varies based on company size and geographic reach.

4.4.2 Expected Outcomes

Key skills and new emerging roles

From the literature review, critical skills identified include technological literacy, adaptability, and creative problem-solving to foster human-robot collaboration, analytical thinking as LSPs' priority, emergent knowledge of computing and cybersecurity needs, and soft skills like communication, leadership skills, and an increased demand for talent management facing 2030 (Guthelius and Theodore, 2019; WEF, 2025).

Survey data partially aligns with these insights from the warehousing standpoint. It highlights technological literacy as the most urgent skill gap across nearly all companies and roles, its relevance increasing with growth in technology adoption profiles. The results validate the relevance of workers' adaptability, analytical skills, communication, creativity/problem solving, and warehouse managers' leadership skills. Based on the relevance/readiness chart devised in this study, it was possible to assess that workforces are, generally, well-positioned in all the aforementioned skills, except for technological literacy. However, this has its nuances by industry, with high-tech manufacturers leading in readiness and retailers and fashion lagging, and by regions, with companies outside North America showing especially low figures even for their managers. Finally, the analysis also helped to conclude that even though the

WEF includes computing/cybersecurity and talent management as emerging skills for supply chain and logistics by 2030, the surveyed companies confer these skills low relevance for warehousing in the next five years.

The literature highlights that roles such as robot-maintenance engineers, automation technicians, WMS analysts, AI/ML specialists, and data scientists are emerging strongly (Gutelius and Theodore, 2019; Extensiv, 2021; Amazon, 2023; Walmart, 2024). Data scientists, for example, are expected to grow faster than the average occupation in the current decade (U.S. Bureau of Labor Statistics, 2023). Other roles in demand include IT support engineers, warehouse automation and supply chain transformation leads, and digital strategy experts (Amazon, Chobani, ICR, 2025). However, statistics show that only 41% of companies transition staff to emerging roles (WEF, 2025).

Our survey validates emerging roles such as robot-maintenance engineers, WMS analysts, and automation specialists/managers, rated highly relevant by roughly half the respondents on average, meanwhile, the remaining ones are, in general, less relevant for warehouse operations. However, it also underscores that they often appear insufficiently staffed directly within warehouses, except among larger global firms (like Cluster 0), validating the WEF statistic of low transition. It is important to clarify within warehouses, given that respondents declare their presence elsewhere in their companies for some of these absent roles in warehouse operations. The clearest example is data scientists, a role with major presence in other areas of the companies (following growth predictions), in which most companies could leverage internal capabilities on warehouse favor.

Training and technology adoption common practices

The literature emphasizes the use of tailored training strategies to bridge skills gaps: blended learning approaches combining on-the-job training with AR/VR tools; “learning journeys” with a mix of online platforms, simulations, and workshops (McKinsey, 2020; Bari, 2023; Grandi et al., 2023). Other effective initiatives are partnerships with educational institutions, pre-job training, and apprenticeships (Alibaba, 2024; Sodiya, et al., 2024). Academics say the effectiveness of these training techniques may depend on financial constraints and the company's overall inclination toward adopting new technologies, limiting workforce skill levels (Hoquelet, 2020; Grandi et al., 2023; Ticwayo & Mathaba, 2023).

Survey data demonstrate widespread reliance on on-the-job training for over eight out of ten companies, with effective results most of the time. At half that number are workshops. Other techniques are less commonly used, reflecting a significant gap between ideal and common practices, which decreases with company size. Mid-sized companies use more pre-job training, online platforms, and certifications, and the largest leading companies are diversifying their strategies to include them all, even AR/VR solutions.

However, training effectiveness does not follow the same pattern as adoption. The survey results show that lower skill readiness is indeed associated with lower training effectiveness, and vice versa. Nevertheless, in this sample, skill readiness is not necessarily dependent on company size, but on industry or regional nuances. Furthermore, when comparing clusters 1 and 2, for example, they reunite companies of a similar size and technology adoption profiles and use of training, but with extremely uneven workforce skills. While both rely on basic training, cluster 2 shows good training outcomes and better skills readiness, and cluster 1 has a greater proportion of little effective training or even ineffective (especially with online learning), and poor skills readiness. Therefore, we cannot check the literature suggestion that financial resources and technological expertise affect training quality.

Concerning technology adoption trends, the literature addresses numerous warehouse automation and digitalization technologies and the rising use of AI. Among modern automation, stand out AS/RS, conveyors, AGVs, robotic arms, cobots, and AMRs (Tikwayo & Mathaba, 2023; Sodiya et al., 2024). Digital systems include WMS, LMS, RFID, mobile devices, computer-aided vision, digital twins, IoT, AR (Guthelius & Theodore, 2019; Sodiya et al., 2024, Ellithy et al., 2024). AI involves conventional ML analytics and Generative AI (Bari, 2023; WEF, 2024). WEF (2025) predicted that 33% of decision-making and data processing tasks would be automated by 2030, increasing to 42% in retail and wholesale.

Our survey validates strong adoption of foundational digital tools, notably WMS and mobile devices. It also confirms that conveyors and automated storage-and-retrieval systems (AS/RS) are widely adopted or planned technologies. AI tools, particularly generative AI, are also seeing increasing inclusion in companies' future roadmaps.

However, our results reveal substantial variability in adoption across company size. Smaller companies demonstrate cautious deployment strategies, often limiting themselves to basic digital and mechanized solutions. Mid-sized firms show greater openness but still trail in implementing more sophisticated technologies like digital twins, AR, and advanced vision systems, which remain relatively niche despite literature projections. By contrast, larger companies, particularly those above $10 billion in annual revenue, consistently exceed industry averages, with widespread adoption of advanced automation (e.g., robotic arms, AGVs), digital innovations (IoT, generative AI), and even emerging tools like digital twins. Their strong alignment with the literature underscores the role of financial capacity in enabling advanced technology integration.

Sector and regional differences add further nuance. High-tech manufacturers and logistics providers are clear frontrunners, while retail, e-commerce, and fashion sectors fall below average. Similarly, companies operating in North America show higher adoption and fewer barriers, whereas firms outside the region face greater resistance and skill constraints. Thus, these findings contribute to the literature by supporting overall adoption trends while adding nuance, highlighting that adoption is far from uniform and is significantly shaped by structural and contextual factors such as company size, industry, and region.

Key challenges companies are facing when adopting technology from a workforce and labor management perspective

The literature identifies several workforce and labor-management challenges related to warehouse technology adoption, notably skill gaps, resistance to change, talent acquisition and retention difficulties, financial constraints in workforce reskilling, misalignment between training programs and evolving job requirements, and concerns regarding job displacement due to automation (Gutelius & Theodore, 2019; WEF, 2025; Ellithy et al., 2024; Tikwayo & Mathaba, 2023; Sodiya et al., 2024).

Our survey strongly validates several of these challenges. Specifically, talent acquisition and retention emerge as the most significant barrier overall, rated highly challenging across company sizes, sectors, and regions. Resistance to change is closely related and similarly important, reflecting entrenched work practices and cultural inertia, consistent with the literature's emphasis on human-centered obstacles during technological transformation. Likewise, skills gaps and talent shortages rank prominently, confirming expectations that technological advancement continues to outpace workforce readiness, particularly in the critical area of technological literacy among frontline workers.

However, the data also reveal that these workforce challenges, while prevalent and intense, do not appear to constrain companies' technology adoption plans. Even organizations reporting high difficulty in managing talent and change, such as those in Cluster 0, exhibit high percentages of automation and digitalization technologies implemented or in rollout plans. This suggests that while labor challenges may increase the complexity of implementation, they are not serving as a deterrent to pursuing warehouse technology upgrades.

Survey results also reinforce the literature's emphasis on financial constraints for workforce reskilling and misalignment between training programs and evolving job requirements. Notably, mid-sized firms felt financial pressures most seriously, whereas smaller companies struggled to align training to new skill demands. Larger companies typically reported fewer financial constraints, better aligning well-funded training initiatives with workforce development needs.

Conversely, our findings challenge the literature's concerns around job displacement due to automation. Respondents consistently rated job displacement as the least severe challenge, suggesting a relative confidence that automation augments rather than replaces labor in warehouse contexts. However, because our survey sample was drawn primarily from managers rather than frontline associates who may perceive the threat of displacement more acutely, this result may reflect a managerial perspective and be further explored with associate-level input.

5. CONCLUSION

This study examined recommended practices for adopting warehouse technology from a workforce and labor management lens through a literature review and survey of warehouse decision-makers. This work assessed technology adoption by firms and identified critical skills, training methods, emerging roles, and key challenges. It revealed that talent acquisition and retention, change resistance, and skills gaps are the most intense workforce obstacles, yet job displacement concerns remain minimal in our sample.

Larger, global companies align closely with recommended practices, employing a broad mix of foundational and advanced technologies, immersive training techniques (including AR/VR), and on-floor staffing of emerging roles such as robot-maintenance engineers and WMS analysts. In contrast, smaller or regionally focused firms rely primarily on basic digital technologies, like mobile devices and WMS, and traditional training, with few specialist roles in warehouses.

Technological literacy emerged as the most urgent skill gap. Adaptability, analytical thinking, and managers' leadership skills are relevant and better covered overall. Emerging roles such as robot maintenance engineers, automation technicians, and WMS analysts were validated as highly relevant, yet, following predictions, inadequately staffed within warehouses, especially outside larger firms.

Overall, the findings underscore that company size and resources drive alignment with recommended practices: those with greater capacity not only adopt advanced technologies but also invest in targeted training and on-site expertise to bridge workforce gaps.

5.1 Management Recommendations

Building on the conclusion, this study's recommendations for companies planning to adopt technologies in warehouses are as follows:

- *Emphasize upskilling technological literacy:* Establishing dedicated training programs focused specifically on the digital tools and automation systems in use or planned to adopt would accelerate implementations and prepare the workforce to operate efficiently.
- *Use targeted training and combine traditional methods with digital solutions:* Combine traditional hands-on methods (on-the-job coaching, workshops) with digital solutions (e-learning platforms, AR/VR simulations) tailored to each role's needs. This mix accommodates different learning styles and allows companies to train in the upcoming technologies.
- *Align training programs with evolving job requirements:* Implement regular training audits tied to the technology roadmap, ensuring courses and certifications evolve alongside new system rollouts or process changes. Engage cross-functional teams, including IT, HR, and operations, to update curricula and maintain relevance as roles shift from manual tasks to technology-enabled responsibilities.
- *Integrate emerging roles to mitigate resistance and enhance effectiveness:* Place specialists, like robot-maintenance engineers, WMS analysts, and automation technicians, directly on the warehouse floor to create the operational muscle to manage, not just deploy, an increasingly sophisticated technology ecosystem..
- *Leverage internal capabilities, especially when resources are constrained:* Engage other departments by inviting their experts, such as data scientists, IT specialists, or process engineers, into warehouse projects to fill skill gaps and ensure new technologies are applied effectively.

5.2 Future Work

While this study offers valuable insights into workforce readiness and labor-management challenges in warehouse technology adoption, it presents some limitations that suggest directions for future research. First, its scope is limited to workforce-related factors, excluding financial, technical, or systems integration perspectives that could influence adoption. An integral analysis would provide a more holistic view of warehouse transformation. Second, while the study identifies associations between, for example, training strategies and skills readiness, it does not establish causation. Experimenting with causal inference techniques would mathematically establish whether specific actions or factors cause improvements. Third, the sample is predominantly composed of North American respondents, with limited representation from some sectors and regions, which may restrict the generalizability of findings. Expanding the geographical scope would help better understand the big picture. Finally, survey responses are subject to bias and varied interpretations of terms like “effectiveness” or “relevance.” Interviews at the plant-floor level would complement and validate the conclusions of this academic work.

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APPENDICES

APPENDIX A

This Appendix provides the full survey questionnaire.

Welcome!

I'm Milton Lavia, a Graduate Candidate in the Massachusetts Institute of Technology (MIT) Supply Chain Management Master's Program. This survey is part of my Master's research and is done in collaboration with the MIT Center for Transportation and Logistics (CTL) Omnichannel Supply Chain Lab. The goal of this survey is to understand how companies are thinking about adopting and incorporating new technologies into modern warehouses.

This survey is anonymous. Your responses will be used for research purposes only. You may skip any questions you do not wish to answer and you may quit the survey at any time. If you have any questions, please reach out to me at mlavia16@mit.edu.

If you wish to proceed with the survey, please click the "Start Survey" button below.

Companies face different challenges when they adopt new technologies in their warehouses. Please rate how challenging each item below is for your company when adopting new warehouse technologies.

	Not at all challenging	A little challenging	Somewhat challenging	Very challenging	Extremely challenging
Skills gap and talent shortages	○	○	○	○	○
Financial constraints in workforce reskilling	○	○	○	○	○
Job displacement	○	○	○	○	○
Resistance to change	○	○	○	○	○
Misalignment between training programs and evolving job requirements	○	○	○	○	○
Talent acquisition and retention	○	○	○	○	○

Which modern automation technologies do you use or plan to use in your warehouses in the next 5 years? Please select all that apply from the following automation technologies.

- ▢ Conveyors
- ▢ There's flexibility in my ways to collect data
- ▢ Automated guided vehicles (AGVs)
- ▢ Collaborative robots (Cobots: semi-autonomous assistance in person-to-goods picking)
- ▢ Autonomous mobile robots (AMRs: for autonomous goods-to-person picking)
- ▢ Robotic arms (for loading/unloading, packing/unpacking, picking, and/or labeling)
- ▢ None

Which modern digital technologies do you use or plan to use in your warehouses in the next 5 years? Please select all that apply from the following digital technologies.

- ▢ Mobile devices (phones/tablets)
- ▢ Warehouse management system (WMS)
- ▢ Radio frequency identification (RFID)
- ▢ Labor management systems (LMS)
- ▢ Internet of Things (IoT)-enabled devices
- ▢ Vision-directed systems / Augmented reality (AR)
- ▢ Computer-aided vision
- ▢ Digital twins
- ▢ Traditional artificial intelligence (AI) and machine learning (ML)
- ▢ Generative AI
- ▢ None

Thinking about the next 5 years, for companies that wish to integrate new warehouse technologies, which skills are most critical for FRONTLINE WORKERS to have? Please mark the top 3 key skills for frontline workers from the list below.

- ▢ Technological literacy (ability to use technology, including AI)
- ▢ Analytical skills
- ▢ Adaptability
- ▢ Creativity, problem-solving
- ▢ Communication
- ▢ Leadership skills
- ▢ Talent management
- ▢ Knowledgeable about computing/cybersecurity

Now thinking about your current warehouse workforce, roughly how many of your FRONTLINE WORKERS possess each of the following skills?

	Less than 10%	10% or more but less than half	50%	More than half but less than 90%	90% or more	Don't know
Technological literacy (ability to use technology, including AI)	○	○	○	○	○	○
Analytical skills	○	○	○	○	○	○
Adaptability	○	○	○	○	○	○
Creativity, problem-solving	○	○	○	○	○	○
Communication	○	○	○	○	○	○
Leadership skills	○	○	○	○	○	○
Talent management	○	○	○	○	○	○
Knowledgeable about computing/cybersecurity	○	○	○	○	○	○

Thinking about the next 5 years, for companies that wish to integrate new warehouse technologies, which skills are most critical for WAREHOUSE MANAGERS to have? Please mark the top 3 key skills for warehouse managers from the list below.

- ☐ Technological literacy (ability to use technology, including AI)
- ☐ Analytical skills
- ☐ Adaptability
- ☐ Creativity, problem-solving
- ☐ Communication
- ☐ Leadership skills
- ☐ Talent management
- ☐ Knowledgeable about computing/cybersecurity

Now thinking about your current warehouse workforce, roughly how many of your WAREHOUSE MANAGERS possess each of the following skills?

	Less than 10%	10% or more but less than half	50%	More than half but less than 90%	90% or more	Don't know
Technological literacy (ability to use technology, including AI)	○	○	○	○	○	○
Analytical skills	○	○	○	○	○	○
Adaptability	○	○	○	○	○	○
Creativity, problem-solving	○	○	○	○	○	○
Communication	○	○	○	○	○	○
Leadership skills	○	○	○	○	○	○
Talent management	○	○	○	○	○	○
Knowledgeable about computing/cybersecurity	○	○	○	○	○	○

Does your company use any of the following training techniques or tools? Please select all that apply.

☐ Pre-job training

☐ On-the-job training

☐ Employer-sponsored apprenticeships

☐ Workshops

☐ Professional certifications

☐ Structured online credential programs (e.g. MITx MicroMasters in SCM)

☐ On-demand online learning platforms (e.g. Udemy and LinkedIn Learning)

☐ Partnerships with educative institutions

☐ Digital tools like AR guidance or VR simulations

Please rate how effective you think each of the following training techniques or tools is within your company.

	Not at all effective	A little effective	Somewhat effective	Very effective	Extremely effective
Pre-job training					
On-the-job training					
Employer-sponsored apprenticeships					
Workshops					
Professional certifications					
Structured online credential programs (e.g. MITx MicroMasters in SCM)					
On-demand online learning platforms (e.g. Udemy and LinkedIn Learning)					
Partnerships with educative institutions					
Digital tools like AR guidance or VR simulations					

Indicate if these roles are relevant to warehousing and if they are present in your organization or warehouses. Please mark all that apply.

	This role is relevant for warehousing	This role is used in my organization, outside of the warehouses	This role is used in my organization's warehouses
WMS Analyst/Technician			
Data Scientists or AI & ML Specialists			
Automation Technicians/Specialists/Engineers			
Robot Maintenance Engineers			
IT Support Technicians/Engineers			
Automation and/or Technology Manager			

Digital Strategy or Supply Chain Transformation Expert/Manager	☐	☐	☐

Q0b **In which industries does your company work?** Please mark all that apply.

- ☐ Retail, E-Commerce & Consumer Goods
- ☐ Food, Beverage & Cold Chain
- ☐ Pharmaceuticals & Healthcare
- ☐ Apparel & Fashion
- ☐ Electronics, Automotive, Aerospace & Industrial Equipment
- ☐ Fuels, Chemicals & Hazardous Materials
- ☐ Logistics & 3PL Services
- ☐ Other

Q24 **What is the number of employees in your company?**

- o Less than 500
- o 500 to 4999 employees
- o 5000 to 19999 employees
- o More than 20000 employees

Q25 **What is your company's annual revenue in US dollars?**

- o Less than 100 million
- o 100 million to 1 billion
- o 1 to 10 billion
- o 10 to 100 billion
- o More than 100 billion

Professional experience:

	Less than 1 year	1 to 3 years	3 to 5 years	5 to 10 years	More than 10 years
Number of years working at current company	○	○	○	○	○
Number of years of experience in supply chain	○	○	○	○	○

Which of the following better describes your position or role?

▼ Manager (1) ... Other (8)

Which function(s) do you manage? Please mark all that apply.

- ▢ Supply Chain Planning
- ▢ Warehousing
- ▢ Logistics
- ▢ Procurement
- ▢ Operations (8)
- ▢ Transportation
- ▢ Distribution
- ▢ Other

Q18 **In which of these regions do you have warehousing operations?** Please mark all that apply.

- ▢ East Asia & Pacific
- ▢ Europe & Central Asia
- ▢ Latin America & Caribbean
- ▢ Middle East & North Africa
- ▢ North America
- ▢ South Asia
- ▢ Sub-Saharan Africa

Are you responsible for warehouse operations?

o Yes

o No

APPENDIX A

This Appendix provides the survey promotion links.

1. MITx Micromasters in Supply Chain Management's February 2025 newsletter

- https://mailchi.mp/mit/monthly_oct_2022-1639106?e=496eea033a

2. LinkedIn posts:

- https://www.linkedin.com/posts/milton-lavia_mit-survey-looking-for-insights-from-activity-7301260601106845696-S4xJ?utm_source=share&utm_medium=member_desktop&rcm=ACoAAEiiGigBVfZwFIX1QOPURrmLULUueIZVcEg

- https://www.linkedin.com/posts/mrodgarcia_hi-everyone-i-am-inviting-my-followers-activity-7303017622655123456-gJQ4?utm_source=share&utm_medium=member_desktop&rcm=ACoAAEiiGigBVfZwFIX1QOPURrmLULUueIZVcEg

- https://www.linkedin.com/posts/mit-supply-chain-management-masters-programs_supplychain-supplychainmanagement-mastersdegree-activity-7307502284282736640-2O-m?utm_source=share&utm_medium=member_desktop&rcm=ACoAAEiiGigBVfZwFIX1QOPURrmLULUueIZVcEg

- https://www.linkedin.com/posts/eva-ponce_warehousing-logistics-supplychain-ugcPost-7308106509446492160-js4n?utm_source=share&utm_medium=member_desktop&rcm=ACoAAEiiGigBVfZwFIX1QOPURrmLULUueIZVcEg

APPENDIX C

This Appendix provides clustering technical details.

Table C1 summarizes the five clustering methods tested and the parameters tuned before obtaining the best-performing combination. Table C2 shows the best individual and composite scores obtained for each method, at the best hyperparameter configuration for them. Table C3 lists the first thirty principal components (PC), explaining two-thirds of the variance when summed.

Additionally, each original variable in the dataset is associated with a coefficient in each PC. By picking the variable with the highest coefficient in each PC, it is possible to identify the top feature contributing to each principal component's linear combination. Table C3 also includes these top contributing features.

Table C1. Clustering methods hyperparameter tuning summary

Method	**Parameters**											
	Clusters / components				Principal components				Gamma			
	Name	From	To	Best	From	To	Interval	Best	From	To	Interval	Best
KMeans	n_clusters	2	11	3	30	60	10	30	-	-	-	-
GMM	n_components	2	11	3	30	60	10	30	-	-	-	-
BayesianGMM	n_components	2	11	3	30	60	10	30	-	-	-	-
Hierarchical	n_clusters	2	7	2	30	60	10	30	-	-	-	-
KPrototypes	n_clusters	2	12	2	30	60	10	30	0.25	1	0.25	0.25

Table C2. Clustering methods' best scores

Method	**Best scores**				
	Silhouette	Calinski–Harabasz	Davies–Bouldin	R^2	Composite
KMeans	0.0812	28.2485	2.935	0.1505	0.8032
GMM	0.0766	27.7082	2.9757	0.148	0.7784
BayesianGMM	0.0735	27.0835	3.0294	0.1452	0.7551
Hierarchical	0.0886	23.0521	2.841	0.0672	0.6974
KPrototypes	0.0776	23.2579	3.5974	0.0678	0.5903

Table C3. Principal components (PC) used in clustering, and the top contributing feature

PC	Variance explained (%)	Top contributing feature description
PC1	9.34	Warehouse managers' readiness in communication skills
PC2	6.44	Frontline workers' readiness in technological literacy
PC3	4.47	Automation Technicians/Specialists/Engineers relevance for warehousing
PC4	3.5	Data Scientists or AI & ML Specialists' presence in organizations
PC5	2.93	Use of on-the-job training
PC6	2.65	Use of digital tools like AR guidance or VR simulations
PC7	2.45	Use of pre-job training
PC8	2.23	Use of professional certifications
PC9	2.09	Relevance of communication for frontline workers
PC10	1.98	AGVs’ use or plan to use in the next five years
PC11	1.93	Use of partnerships with educational institutions
PC12	1.84	Automation Technicians/Specialists/Engineers’ use in warehousing
PC13	1.78	Relevance of leadership skills for warehouse managers
PC14	1.74	Effectiveness of workshops
PC15	1.69	Challenging rate of misalignment between training programs and evolving job requirements
PC16	1.64	Relevance of adaptability for frontline workers
PC17	1.58	Digital Strategy or Supply Chain Transformation Expert/Manager presence in organizations
PC18	1.54	WMS Analyst/Technician presence in organizations
PC19	1.48	Use of pre-job training
PC20	1.45	Use of structured online credential programs
PC21	1.42	Use of digital tools like AR guidance or VR simulations
PC22	1.38	Use of professional certifications
PC23	1.35	Relevance of adaptability for warehouse managers
PC24	1.29	Relevance of creativity and problem-solving for warehouse managers
PC25	1.27	Relevance of computing/cybersecurity for warehouse managers
PC26	1.25	Relevance of computing/cybersecurity for frontline workers
PC27	1.22	Relevance of computing/cybersecurity for warehouse managers
PC28	1.21	Challenging rate of job displacement
PC29	1.16	AGVs’ use or plan to use in the next five years
PC30	1.14	Mobile devices’ use or plan to use in the next five years
	67.44	

APPENDIX D

This Appendix provides figures supporting section 4.2.

List of figures in Appendix D

Figure D13. Workforce-related challenges when companies operate in/outside North America

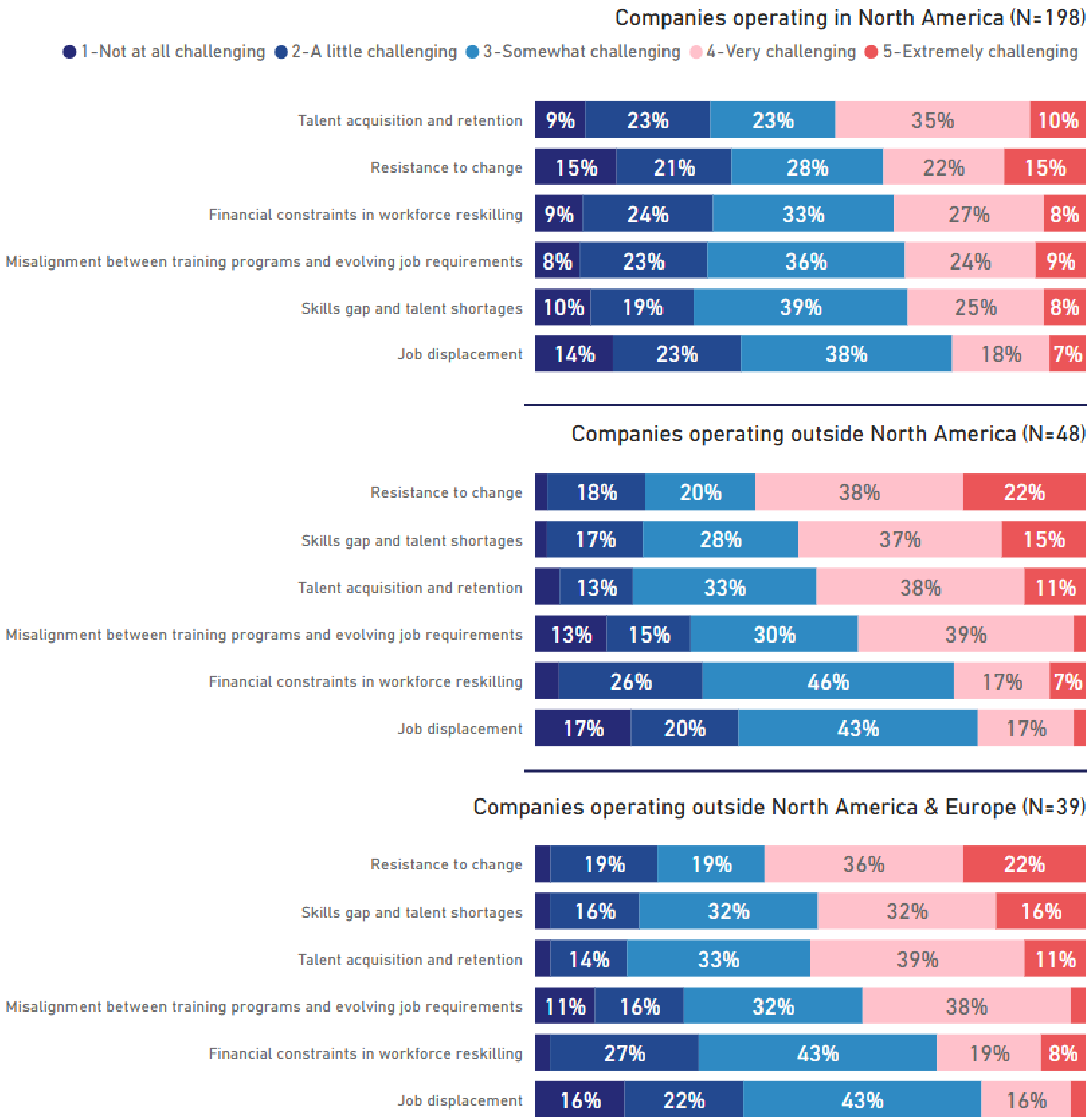


Figure 14. Workforce-related challenges in warehouse technology adoption by annual revenue in US dollars

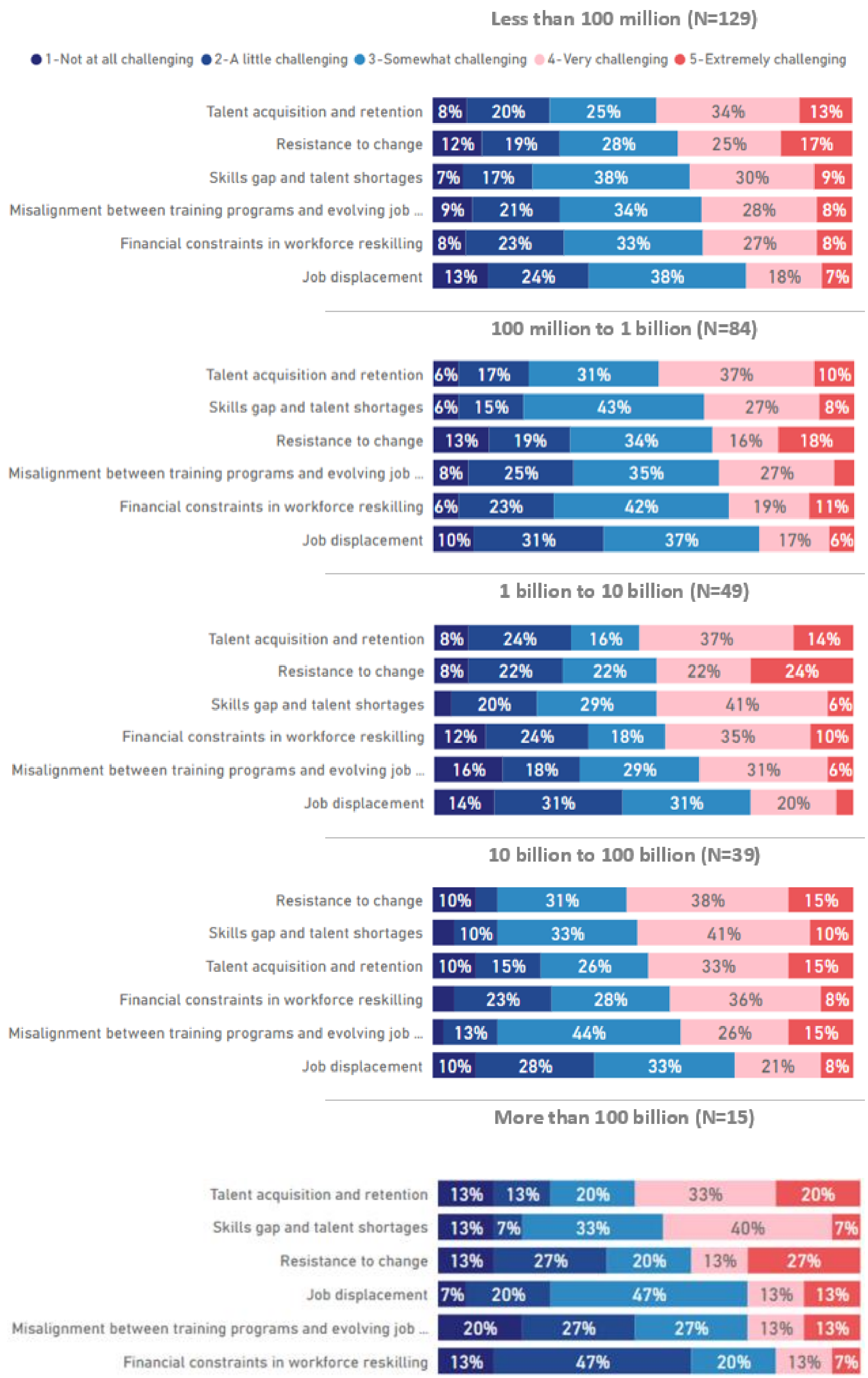


Figure 15. Workforce-related challenges in/outside logistics and 3PLs services, and for pure electronics, automotive, aerospace, and industrial equipment companies

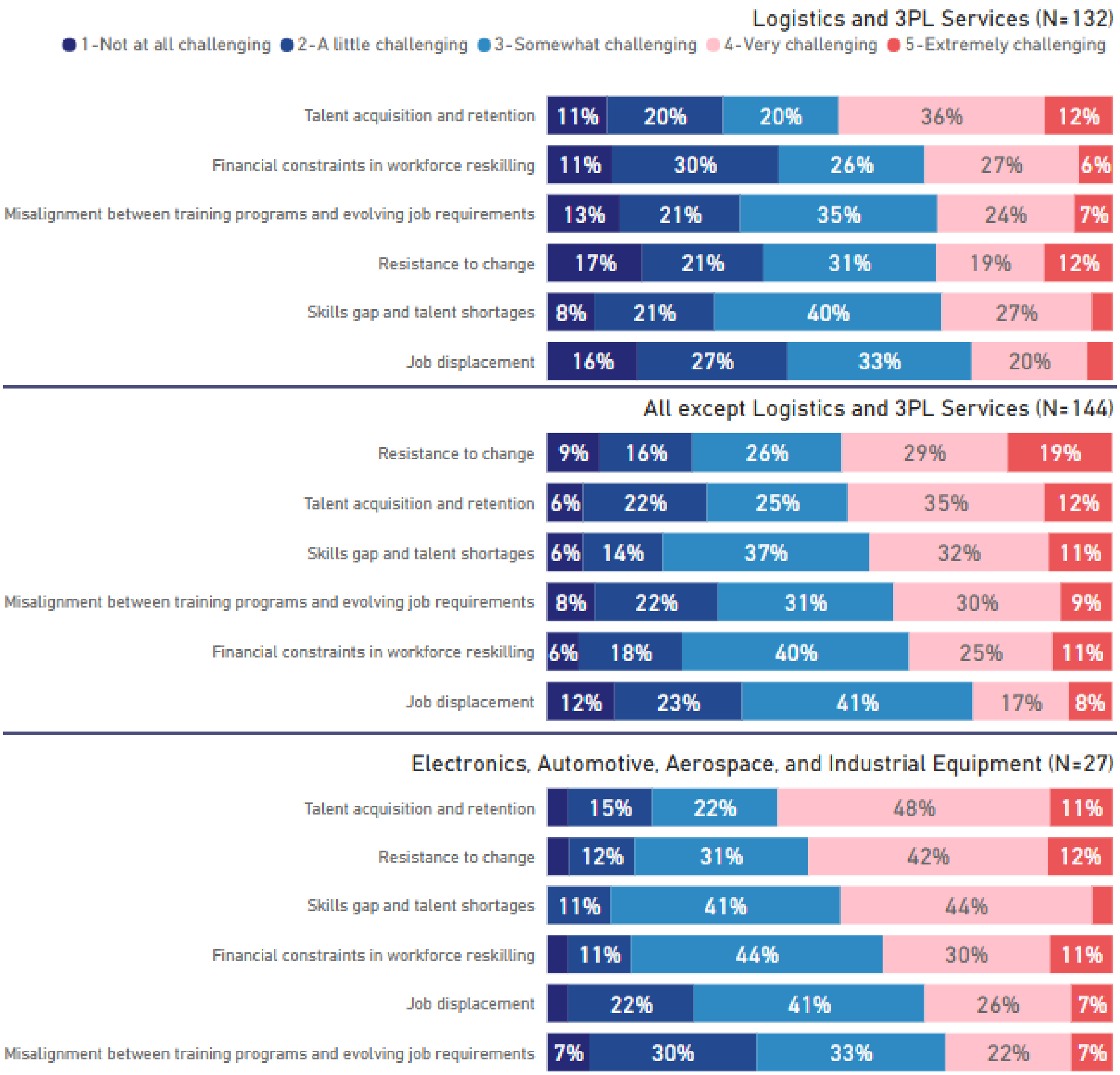


Figure 16. Technology adopted or planned to adopt in the next five years by annual revenue in US dollars (Less than 100 million, N=129; 100 million to 1 billion, N=84; 1B to 10 billion, N=54; 10 billion to 100 billion, N=39; more than 100 billion, N=15)

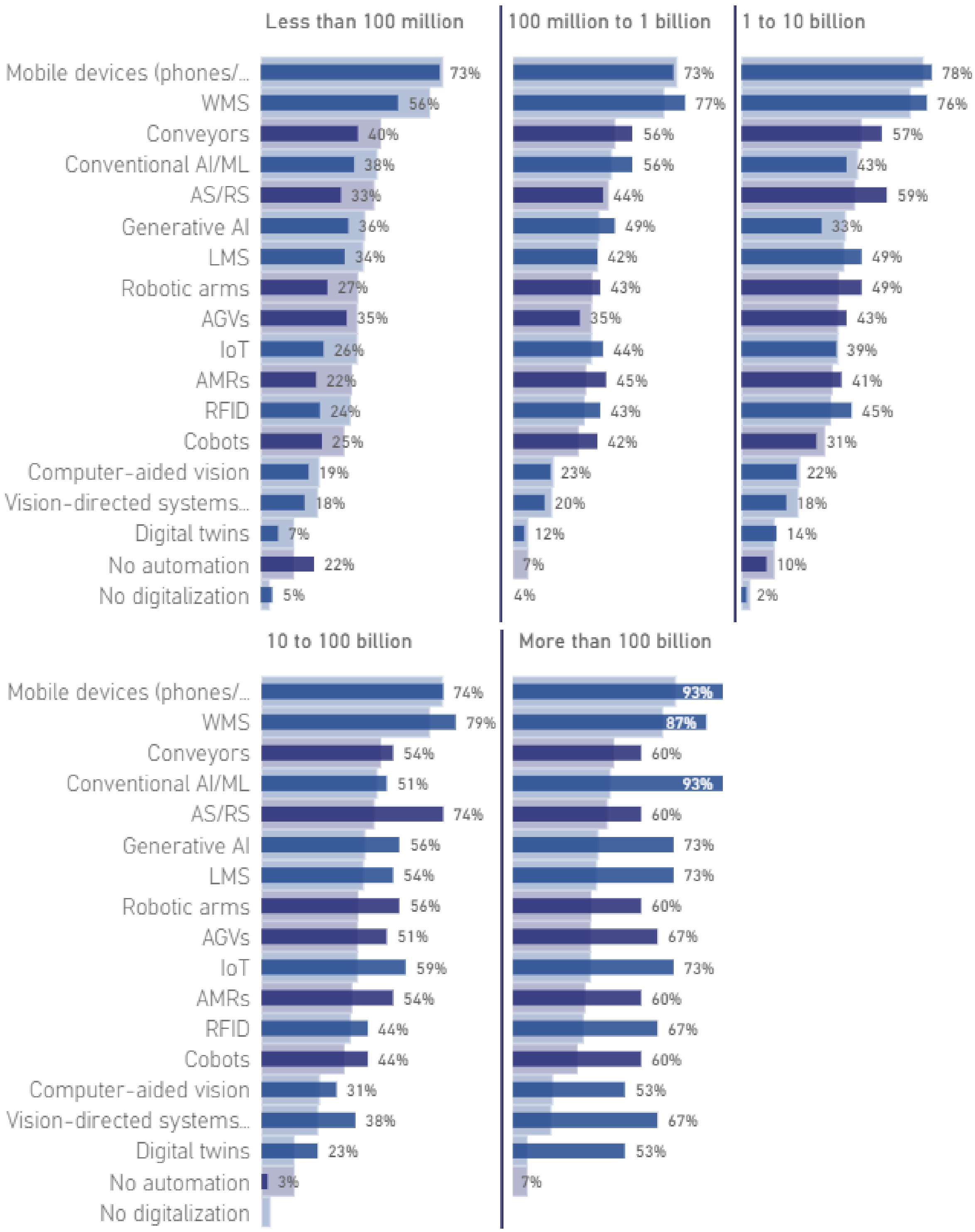


Figure 17. Technology adopted or planned to adopt in the next five years by sectors where companies work, not-exclusively (Logistics and 3PL services, N=178; non-logistics and 3PLs services, N=144; electro, automotive, aerospace, and industrial equipment, N=38; retail, e-commerce & consumer goods, N=34; apparel and fashion, N=14; food, beverage, and cold chain, N=27)

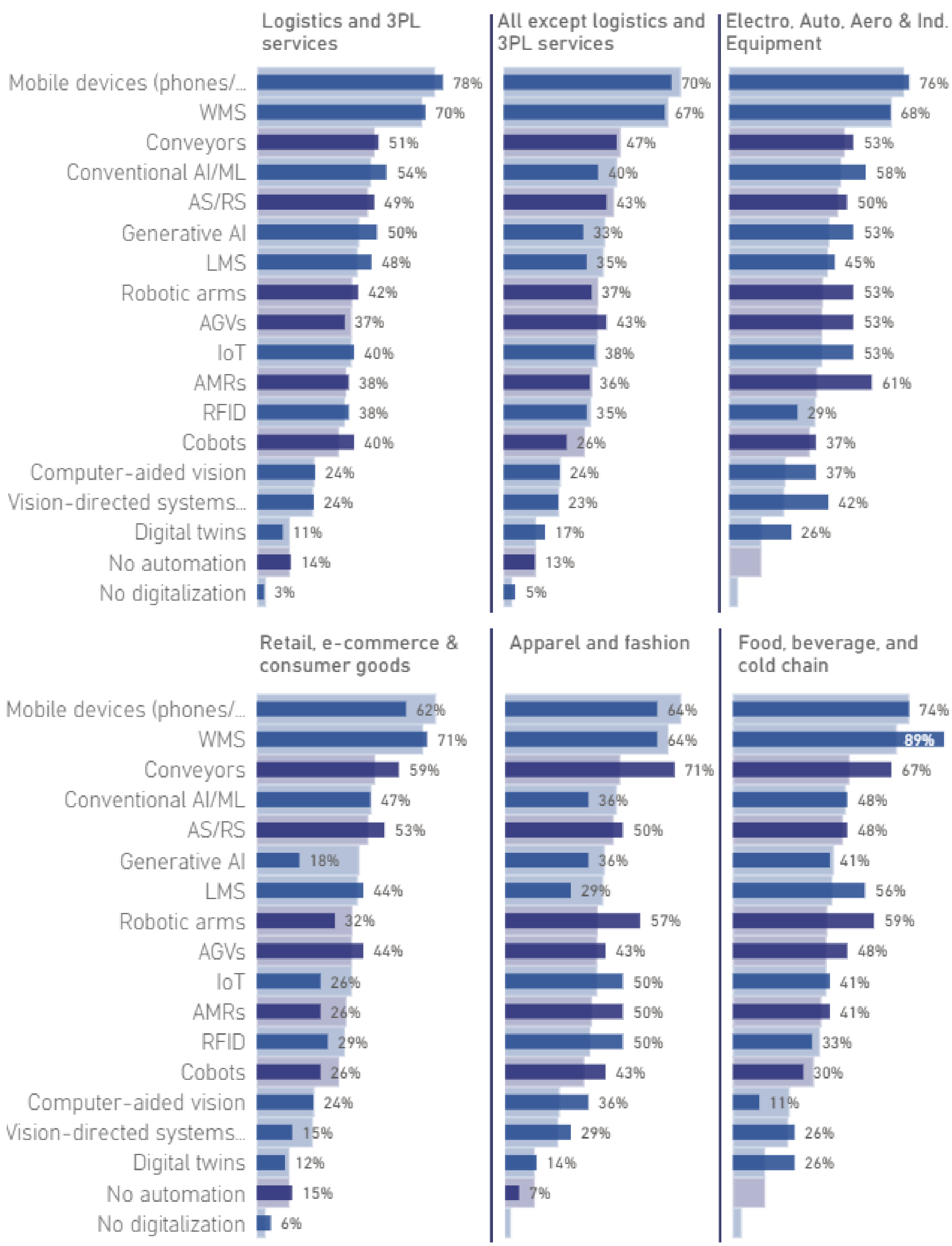


Figure 18. Key workforce skills relevance for warehouse frontline workers in the next five years and their readiness by annual revenue in US dollars (Less than 100M, N=129; 100M to 1B, N=84; more than 1B, N=103)

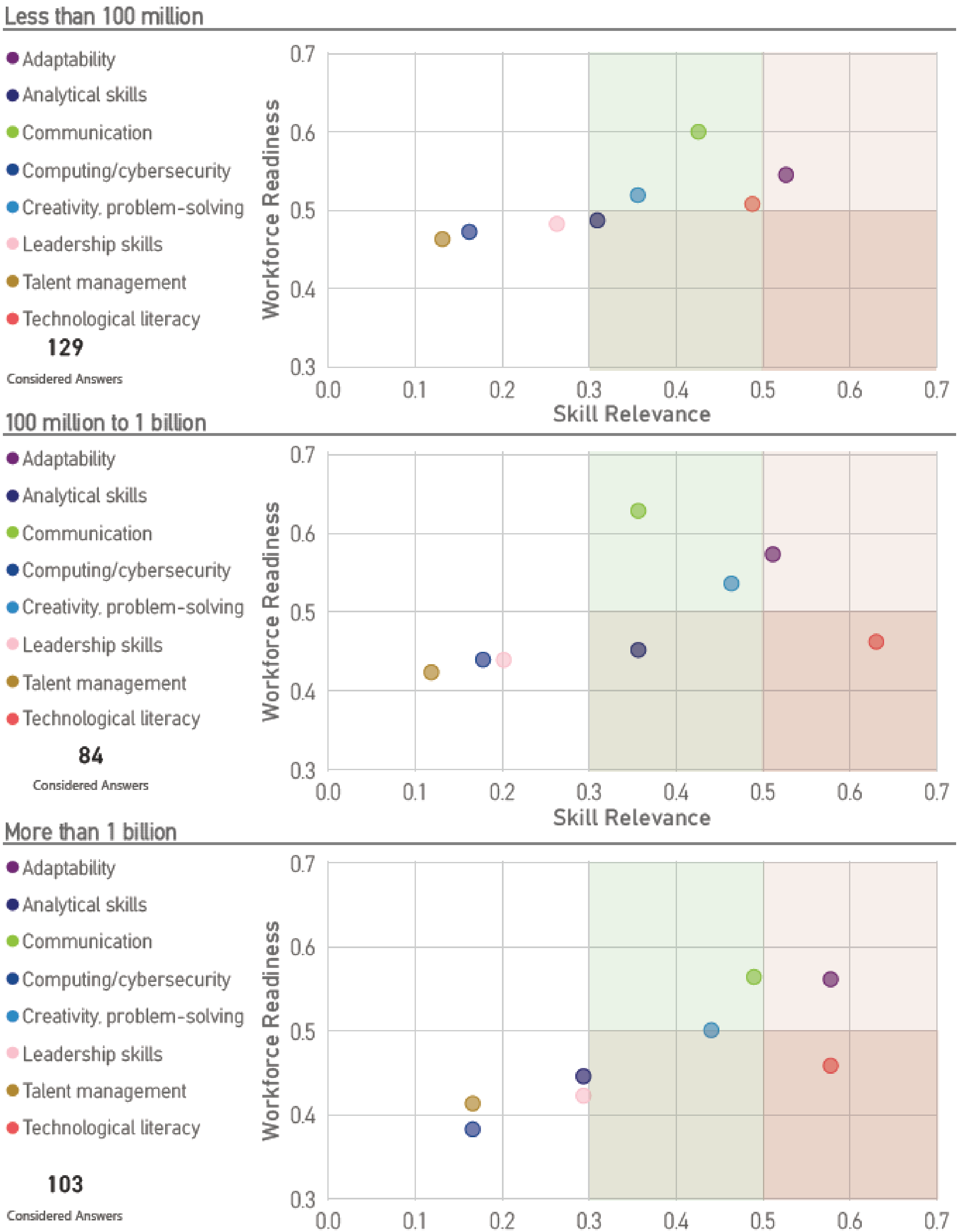


Figure 19. Key workforce skills relevance for warehouse frontline workers in the next five years and their readiness for the main industries they operate in (Logistics and 3PLs, N=178; All except logistics and 3PLs, N=144; of those, Electronics, Automotive, Aerospace, and Industrial Equipment, N=38)

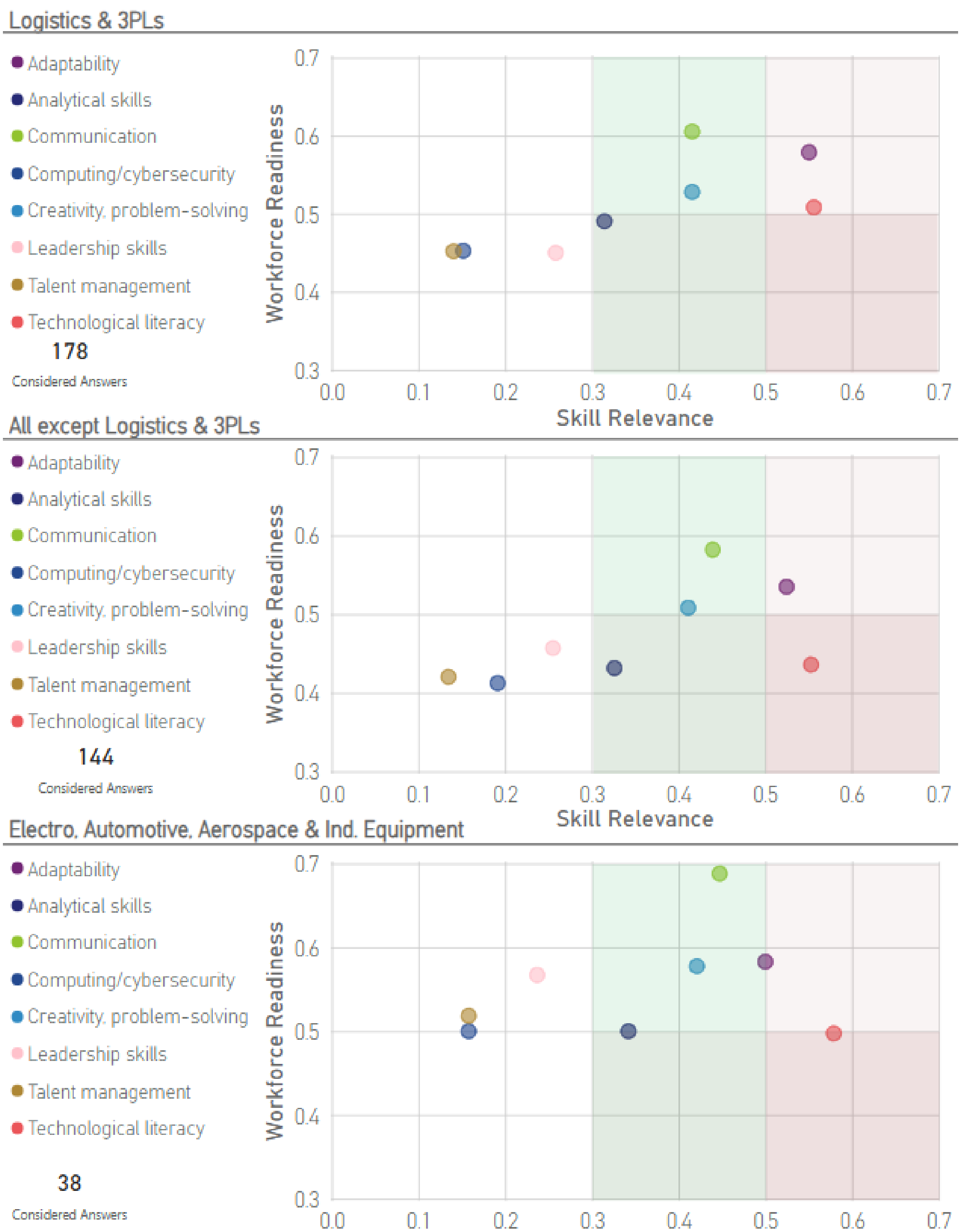


Figure 20 (cont.). Key workforce skills relevance for warehouse frontline workers in the next five years and their readiness for the main industries they operate in (non-logistic/3PLs in: Retail, e-Commerce, and Consumer Goods, N=34; Apparel and Fashion, N=14; Food, Beverage, and Cold Chain, N=27)

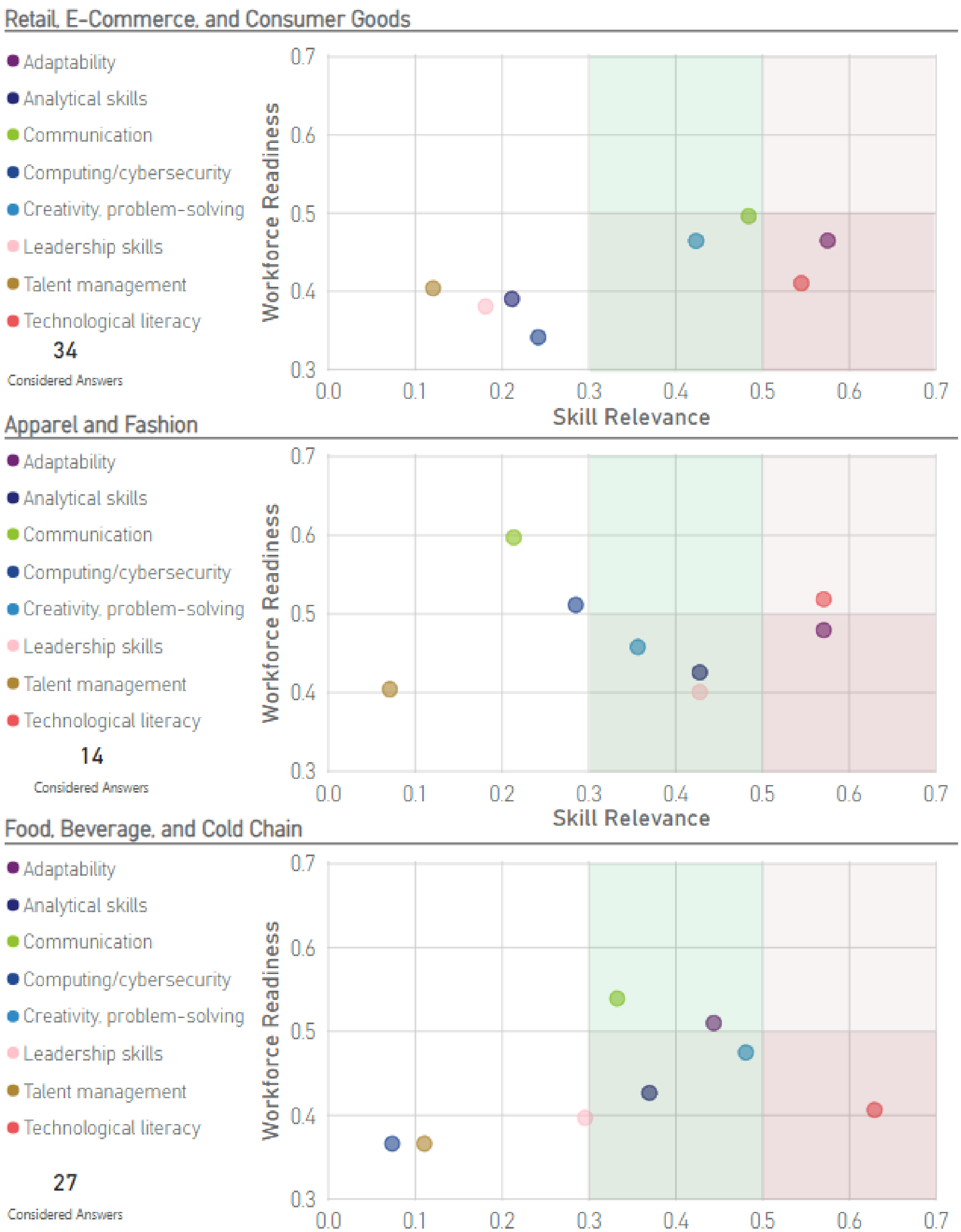


Figure 21. Key workforce skills relevance for warehouse managers in the next five years and their readiness by annual revenue in US dollars (Less than 100M, N=129; 100M to 1B, N=84; more than 1B, N=103)

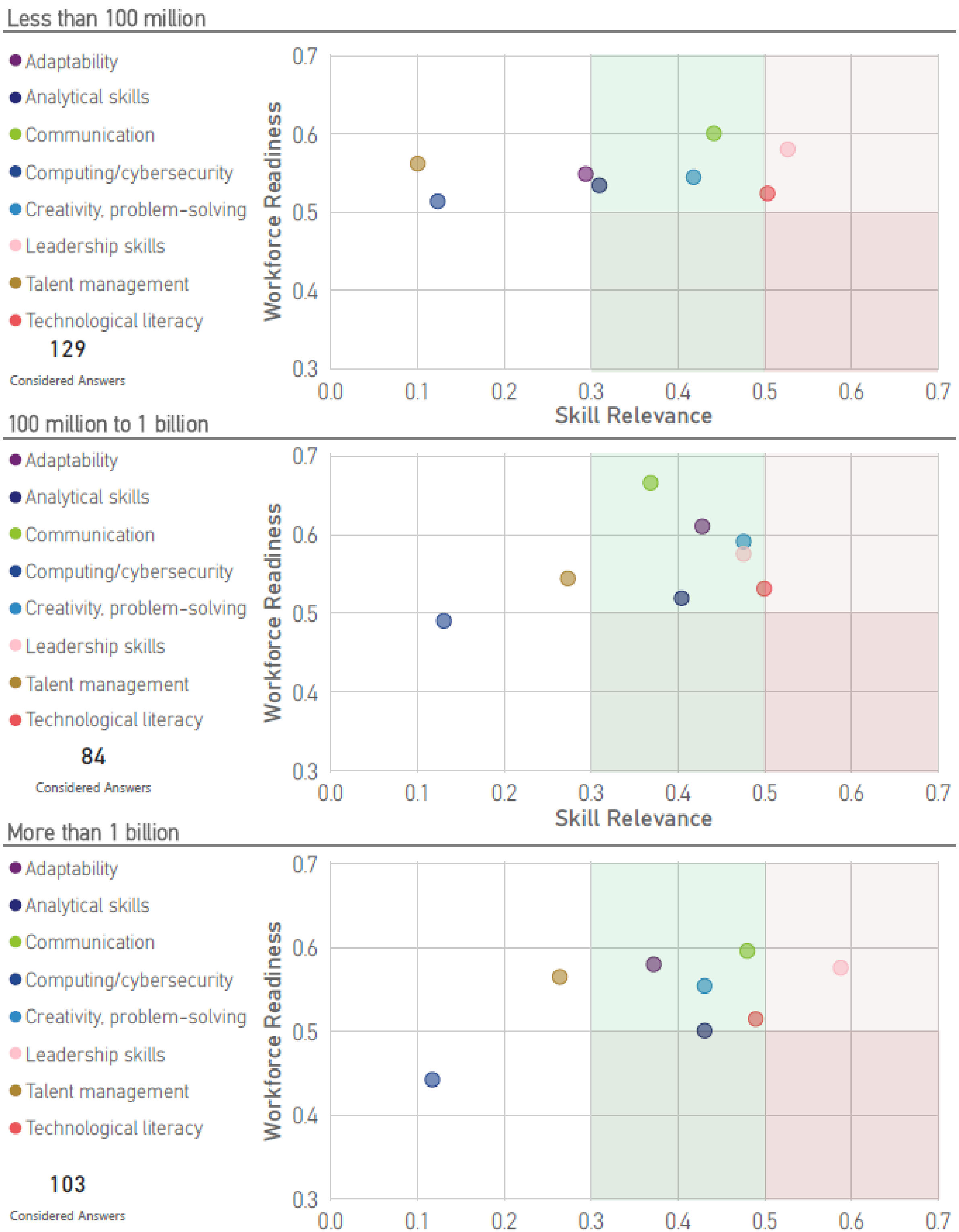


Figure 22. Key workforce skills' relevance for warehouse managers in the next five years and their readiness for companies outside North America (N=48)

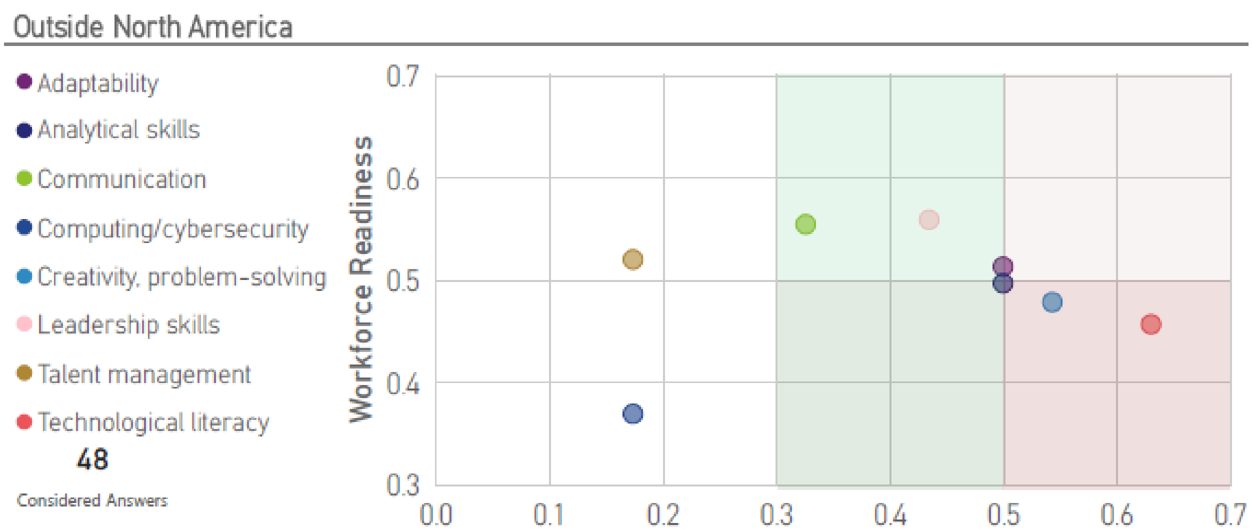


Figure 23. Training preferences and effectiveness by revenue

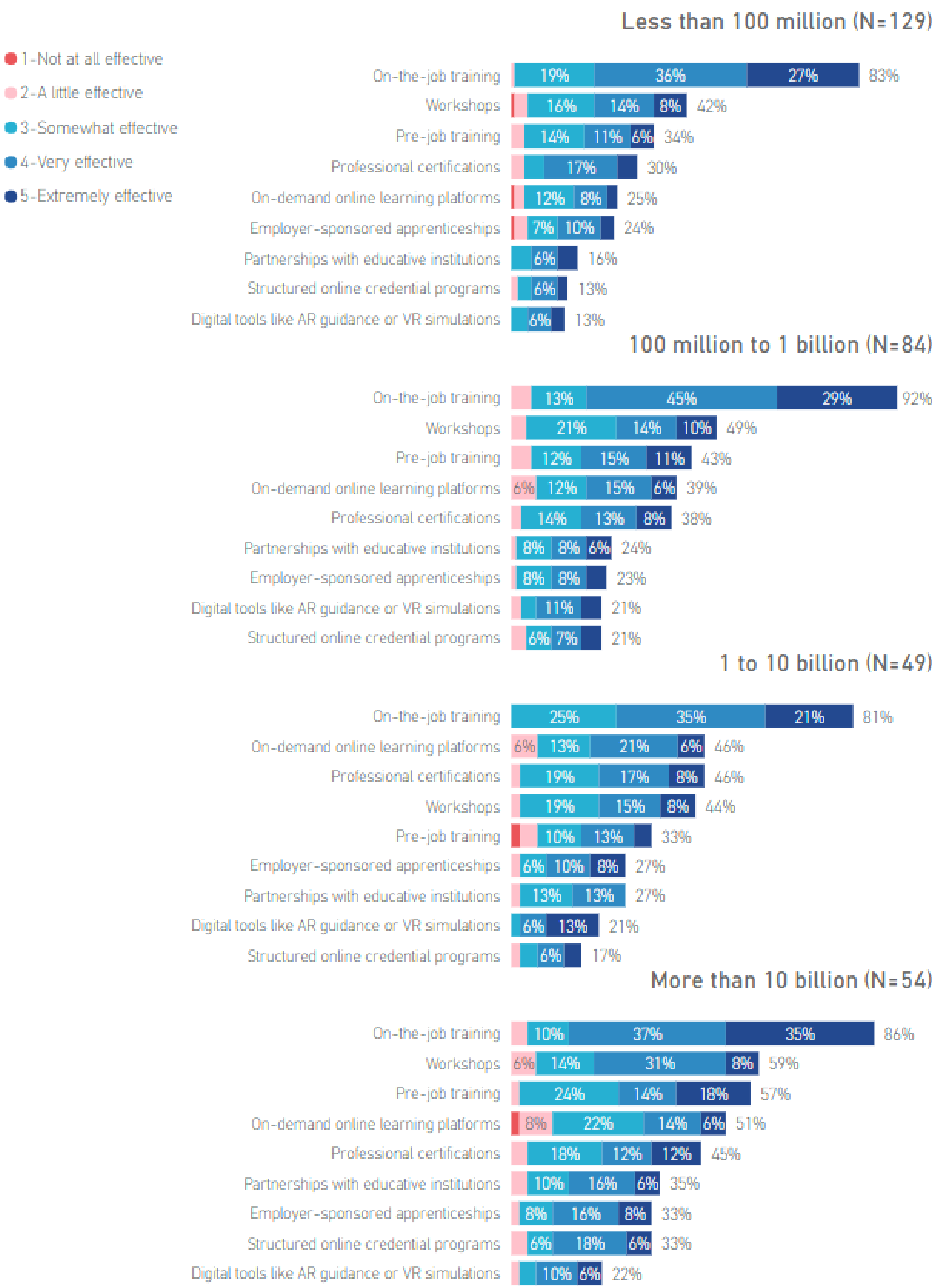


Figure D124. Training preferences and effectiveness by industry

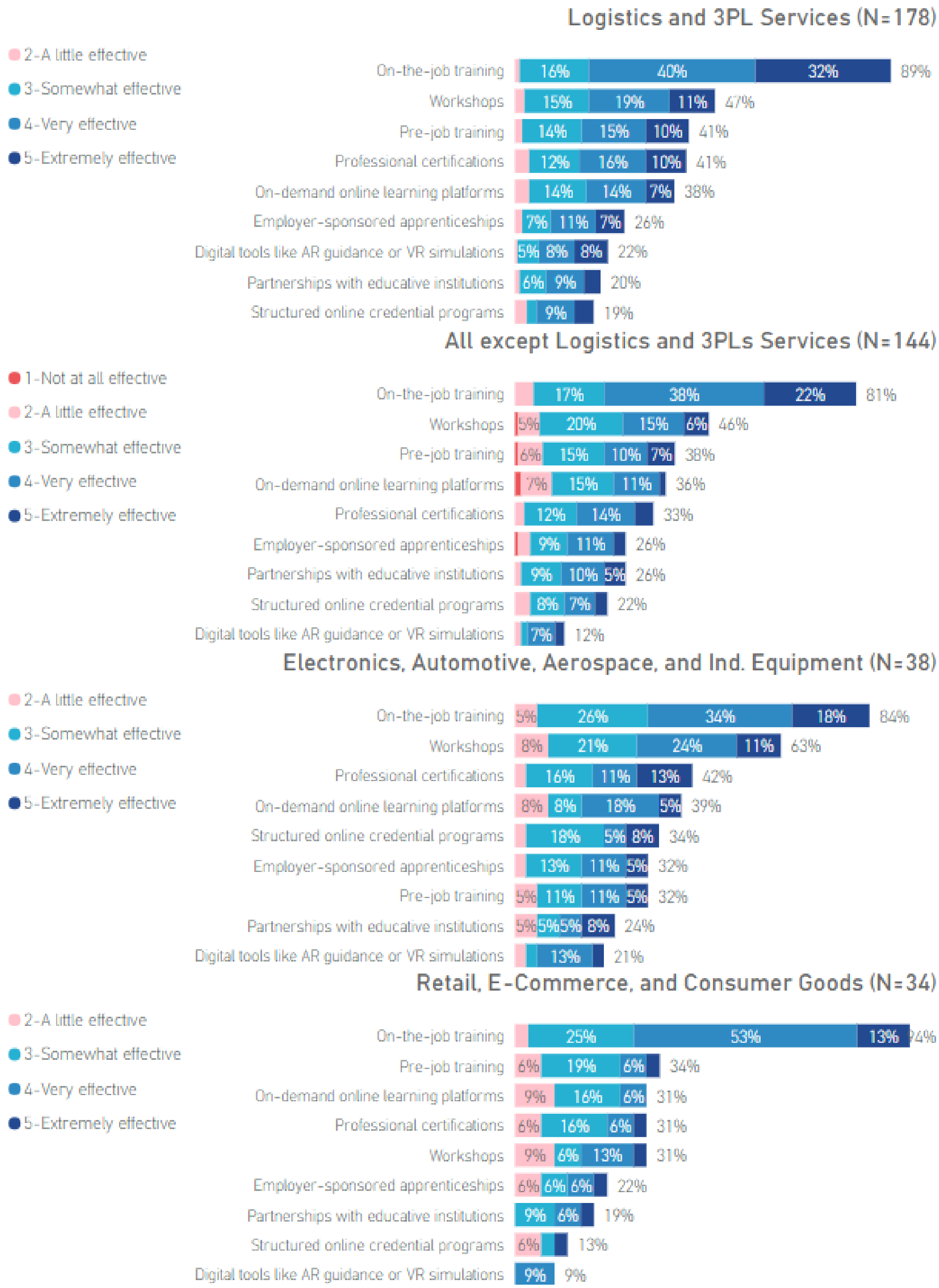


Figure 25. Training preferences and effectiveness by industry (cont.)

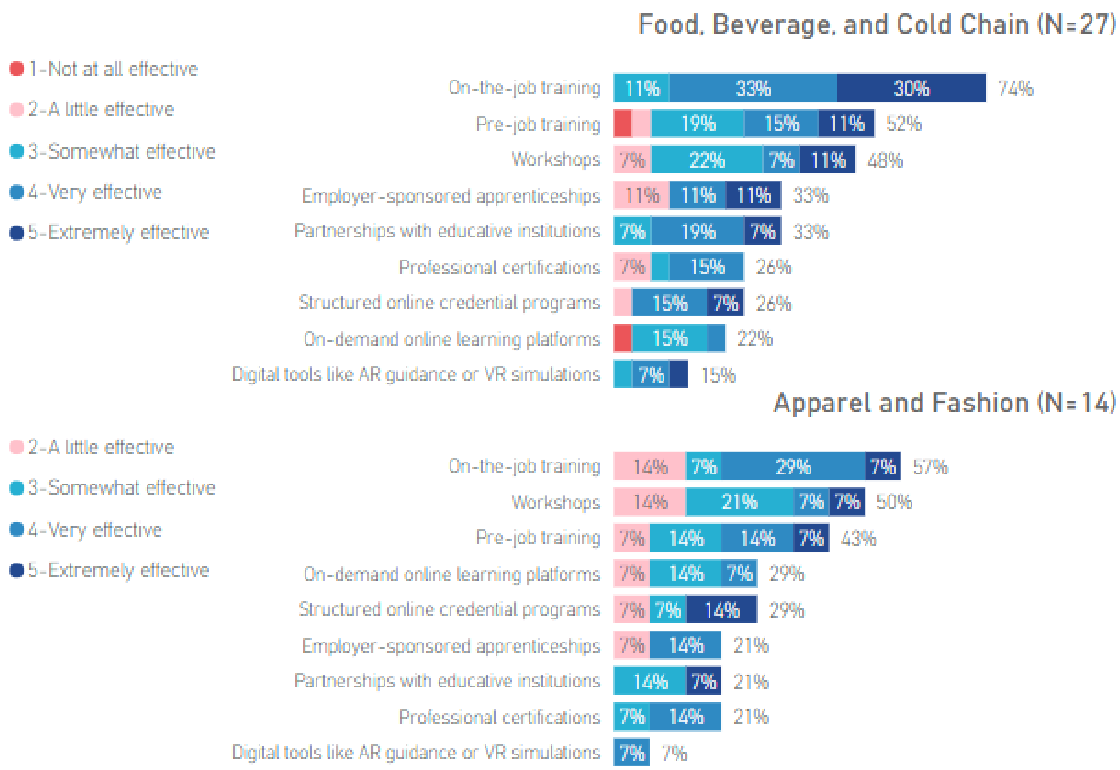


Figure 264. New roles' use and relevance to warehousing by revenue in annual dollars (Less than 100M, N=129; 100M to 1B, N=84; 1B to 10B, N=49; 10B to 100B, N=39; more than 100B, N=15)

Figure 27. New roles' use and relevance to warehousing in/outside North America

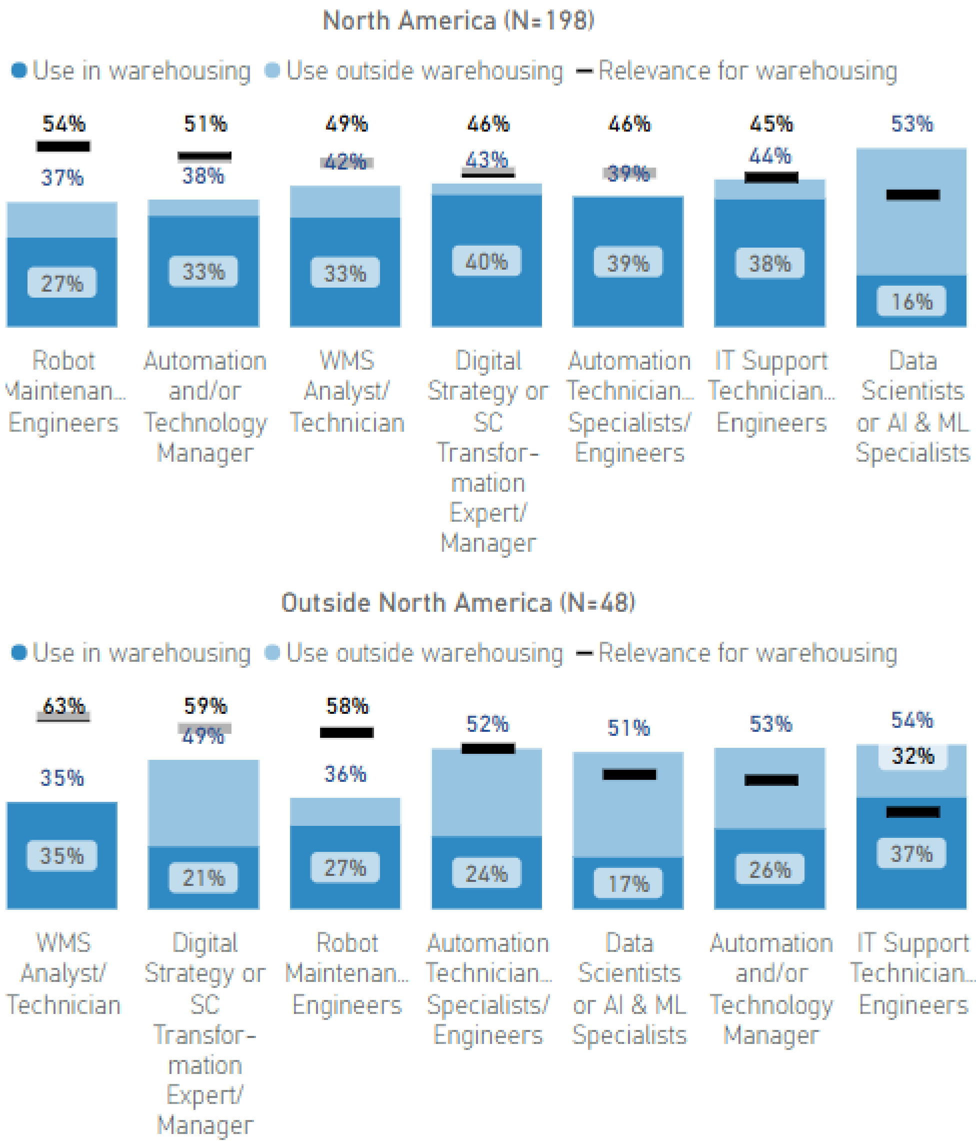


Figure 28. New roles’ use and relevance to warehousing by sector

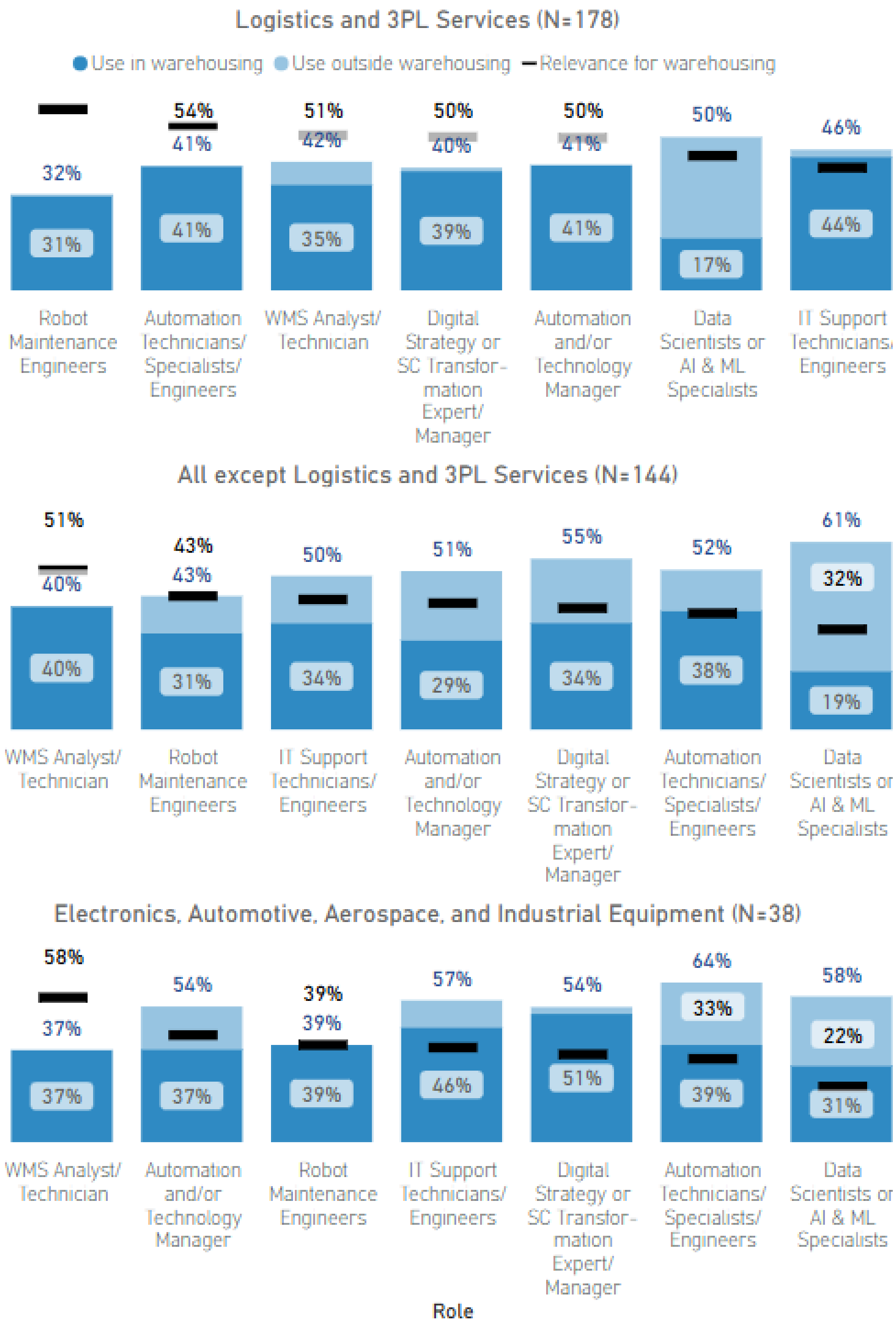
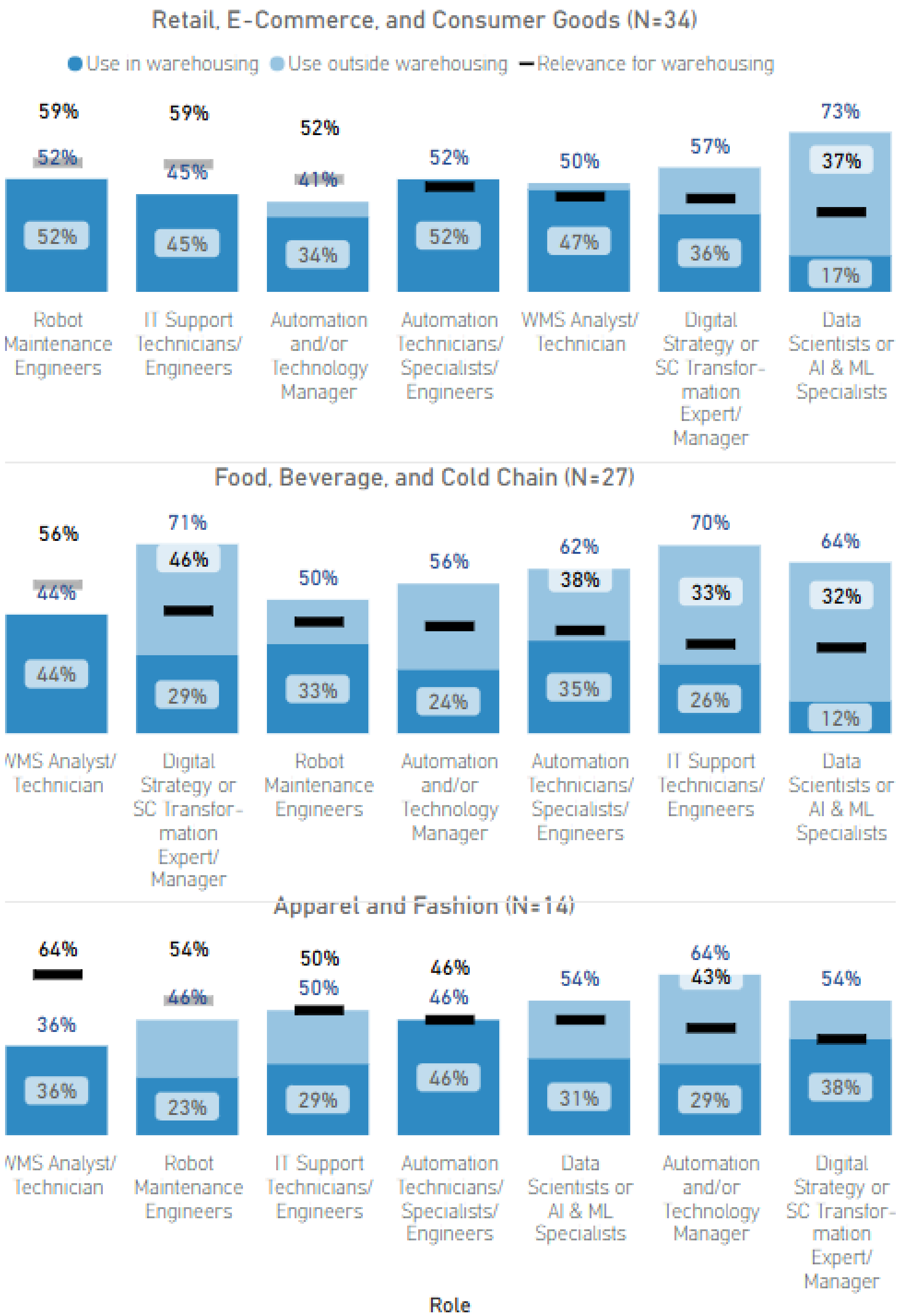


Figure 29(cont). New roles' use and relevance to warehousing by sector



APPENDIX E

This Appendix provides figures supporting section 4.3.

List of figures in Appendix E

Figure E1. Cluster 0 demographics (N=104; revenue in US dollars)

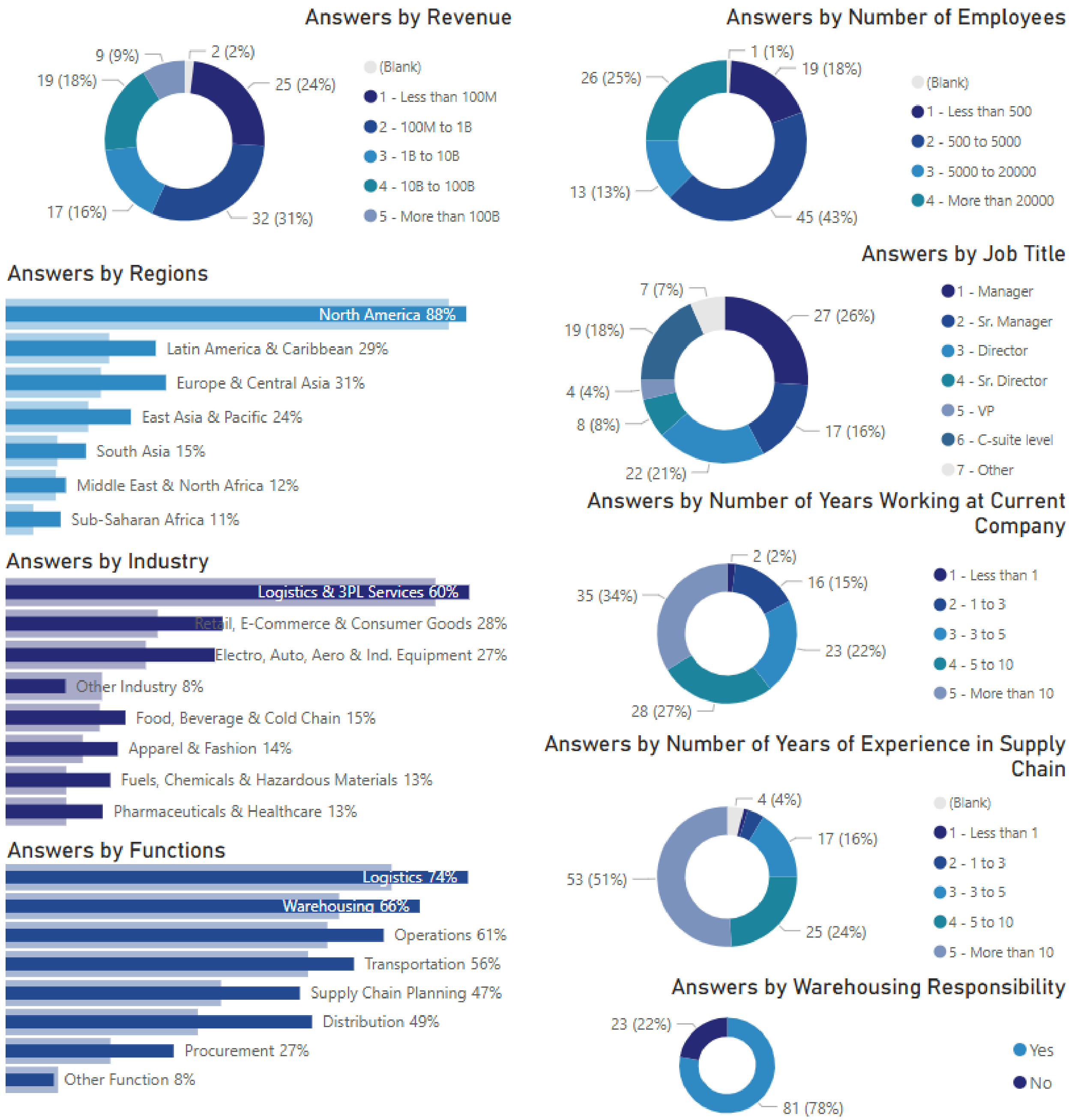


Figure E2. Cluster 1 demographics (N=84; revenue in US dollars)

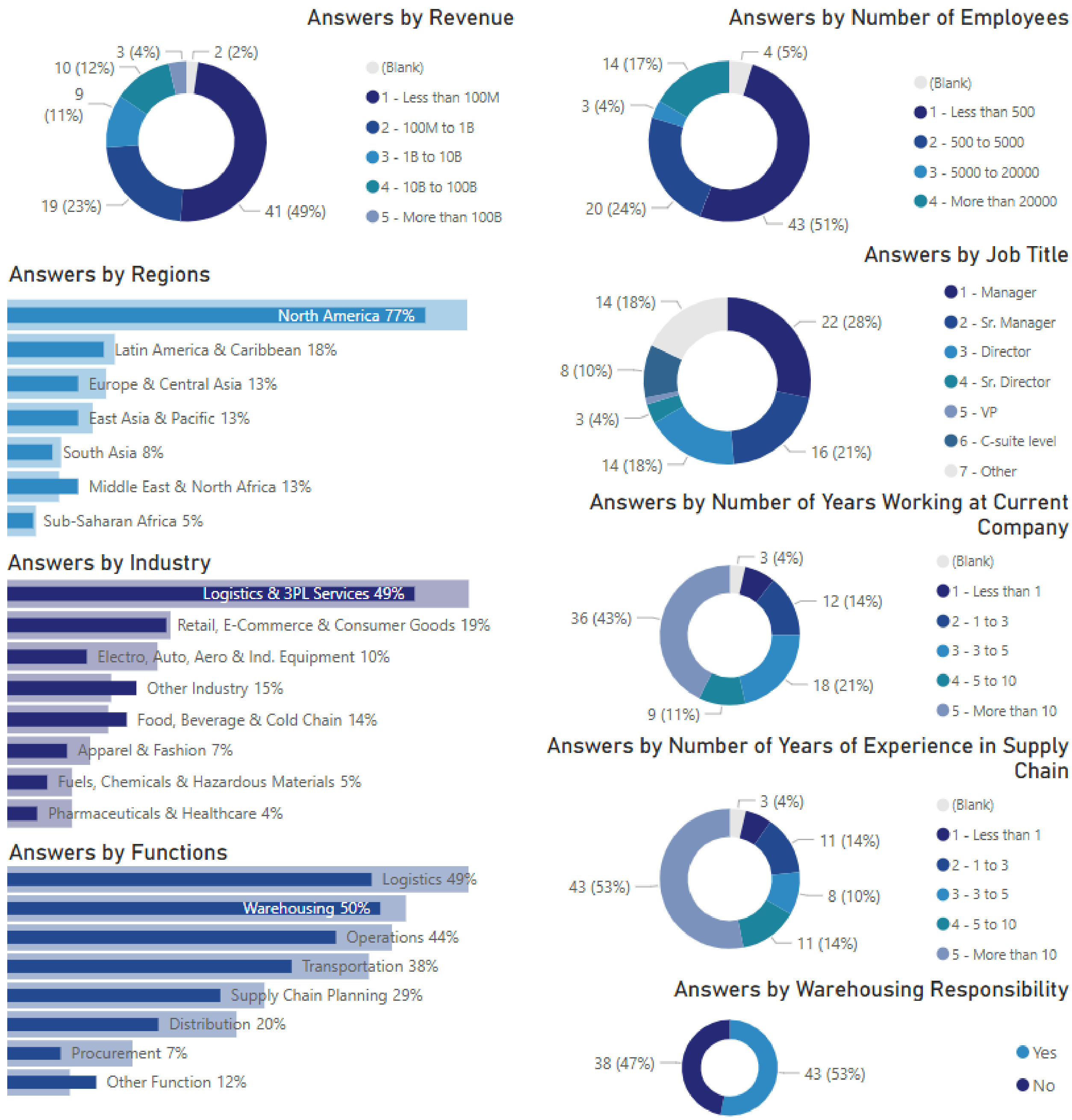


Figure E3. Cluster 2 demographics (N=134; revenue in US dollars)

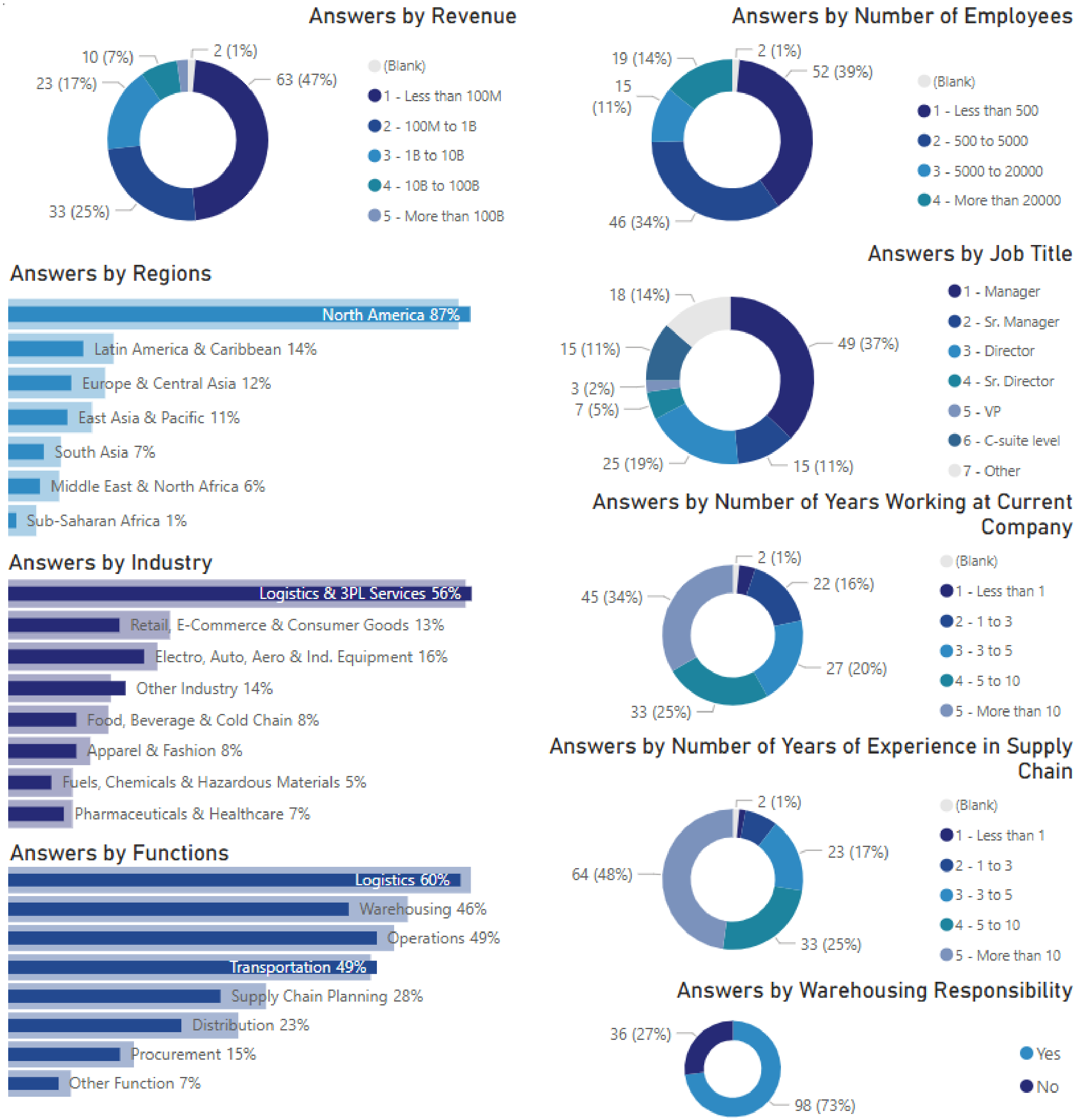


Figure E4. Workforce-related challenges by cluster

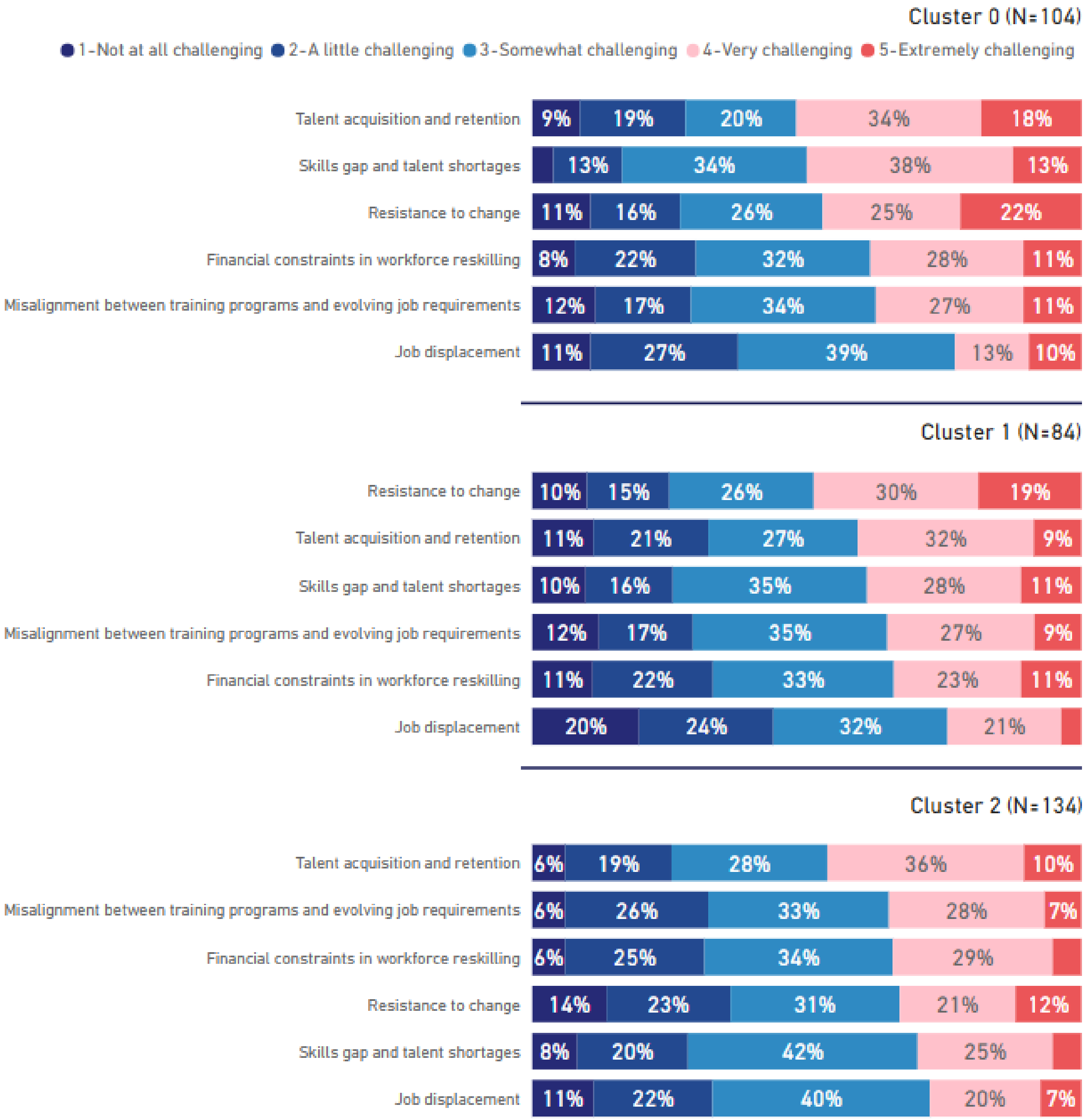


Figure E5. Technology used or planned to use in the next five years by cluster (Cluster 0, N=104, Cluster 1, N=84; Cluster 2, N=134)

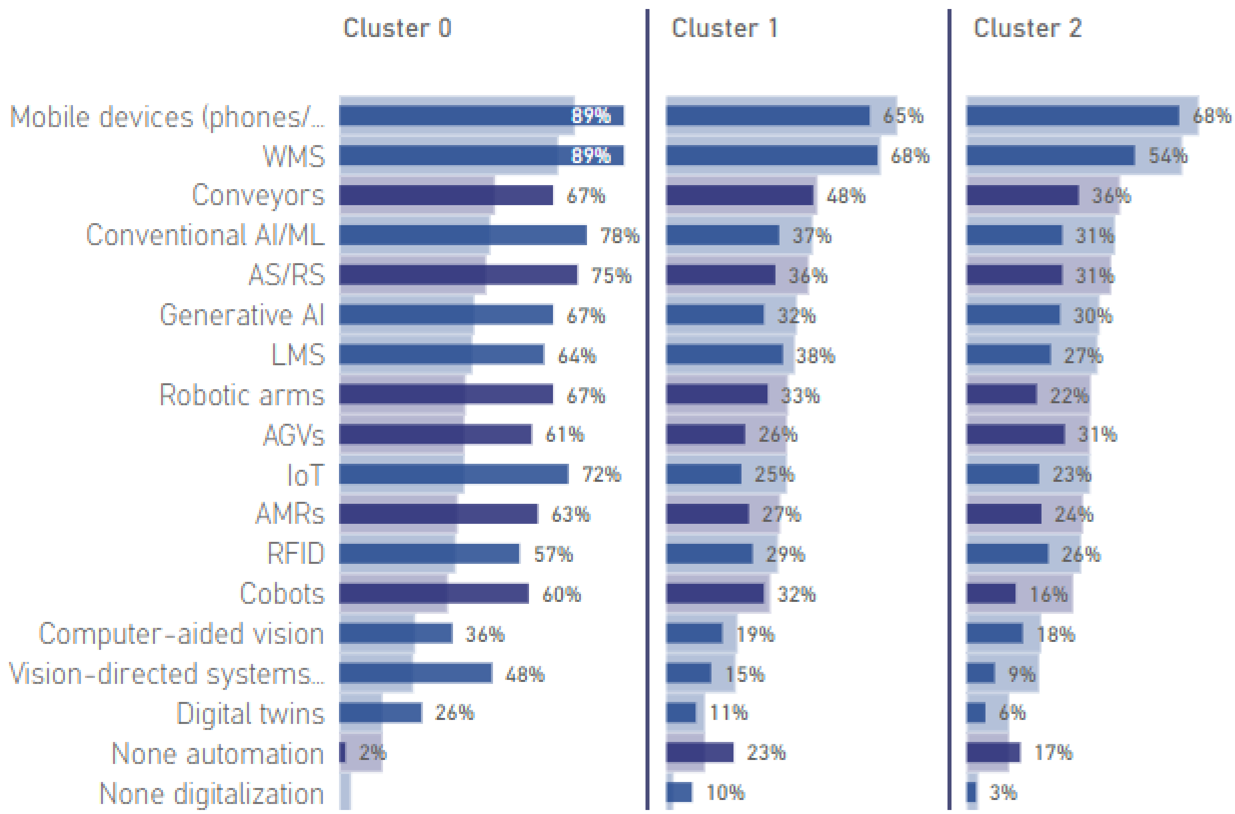


Figure E6. Warehouse frontline workers skills' readiness and relevance by cluster (Cluster 0, N=104, Cluster 1, N=84; Cluster 2, N=134)

Figure E7. Warehouse managers skills' readiness and relevance by cluster (Cluster 0, N=104, Cluster 1, N=84; Cluster 2, N=134)

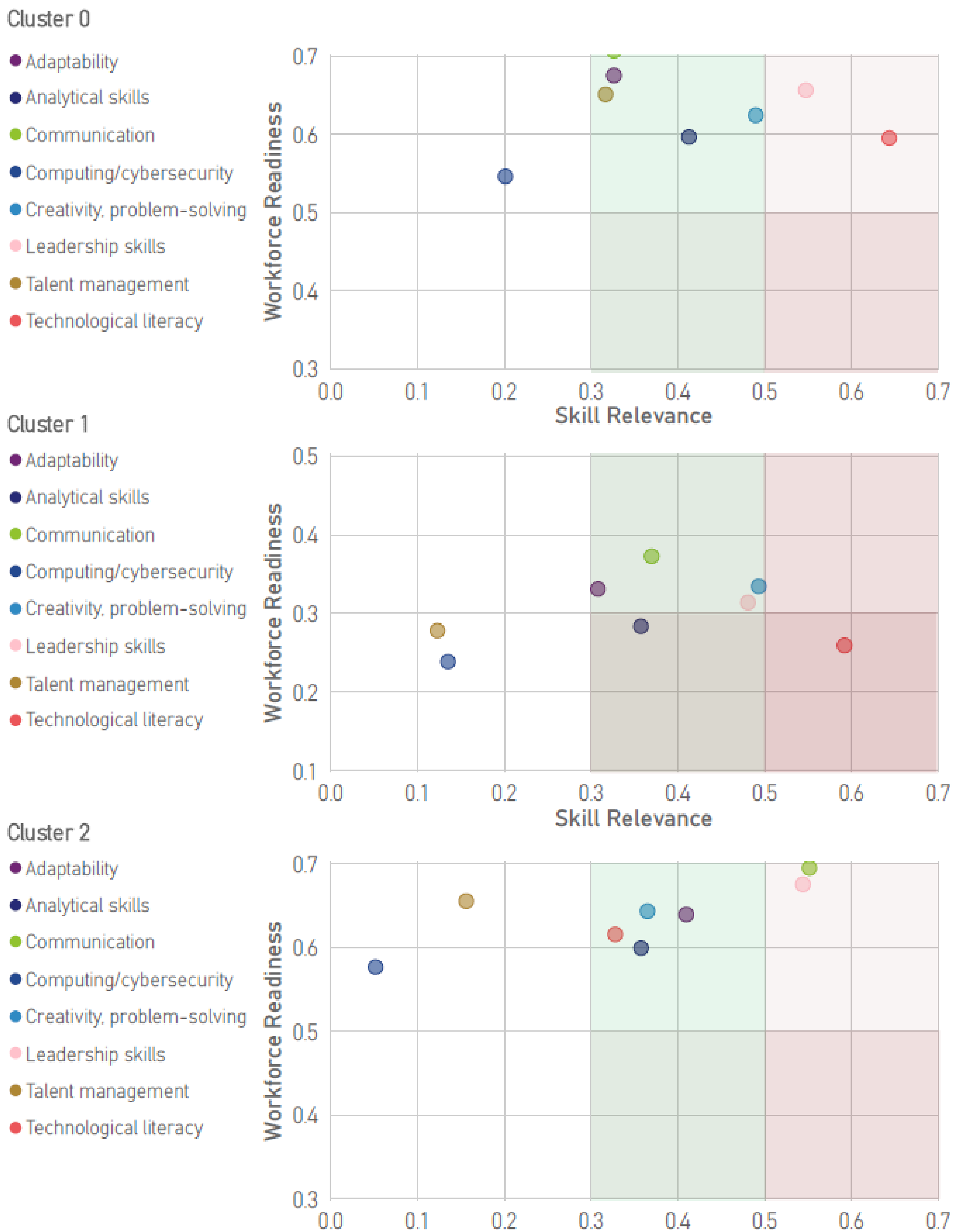


Figure E8. Training strategies' adoption and effectiveness by cluster (Cluster 0, N=104, Cluster 1, N=84; Cluster 2, N=134)

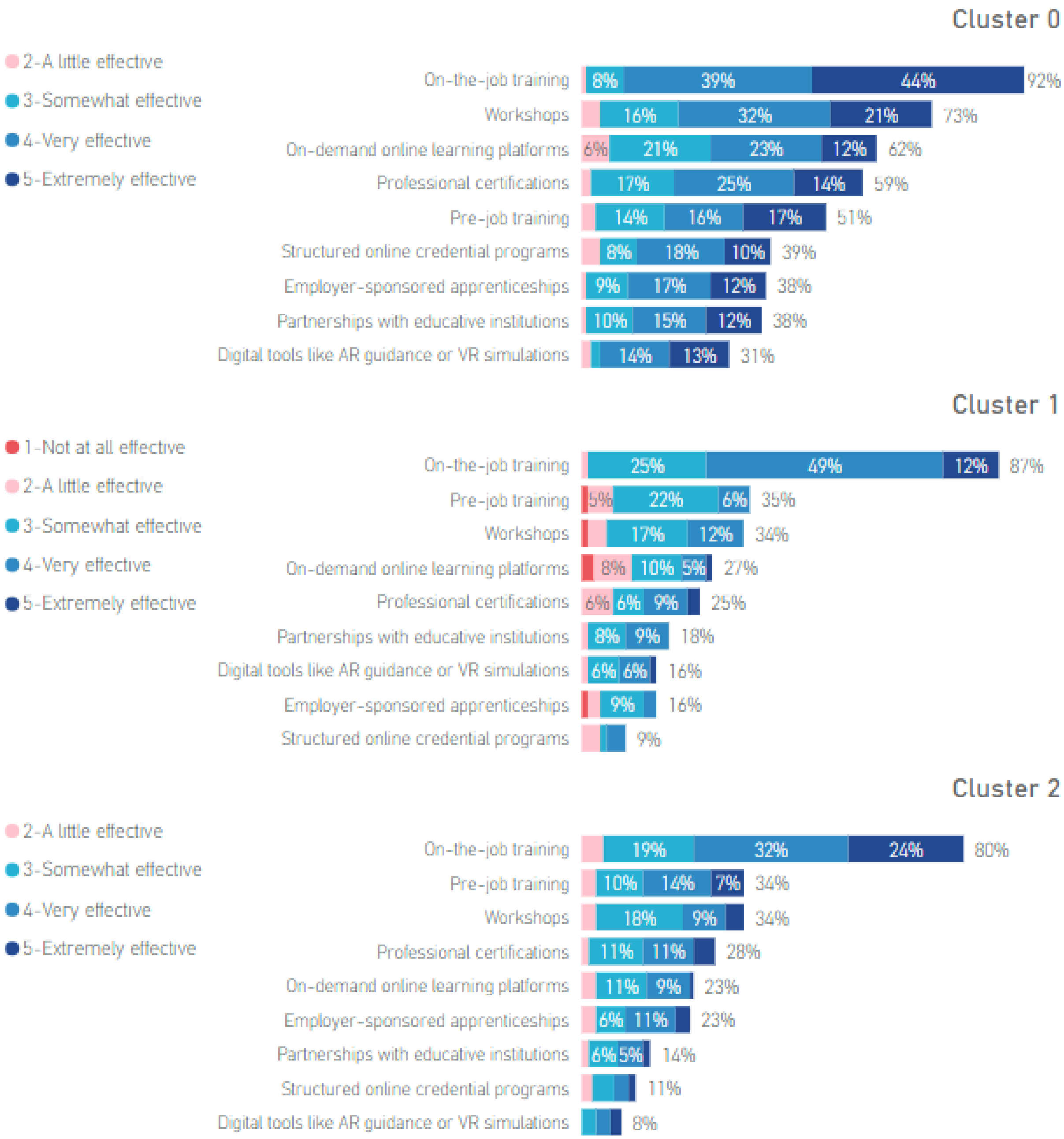


Figure 30. Relevant roles for warehousing and their use by cluster (Cluster 0, N=104, Cluster 1, N=84; Cluster 2, N=134)