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Strategic Human Capital Development in Logistics: A Competency-Based Training Framework Using Fuzzy Best-Worst Method for Evidence-Based Workforce Planning

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Abstract: Addressing persistent gaps in Human Resources Development (HRD) practice, this study presents a systematic framework for competency-based training needs analysis (TNA) that links strategic workforce development to business performance in logistics. Using the Fuzzy Best-Worst Method (F-BWM) with 21 expert judges, we develop an MCDM model that identifies both the strategic importance of technical and behavioral competencies and their current performance gaps. A two-level hierarchy of three dimensions and ten sub-competencies is introduced. Simulation results show that negotiation/conflict resolution skills represent the greatest training need (weighted priority: 6.20), followed by market analysis capacity (2.74) and resilience (2.71)—despite higher strategic weights for technical competencies (e.g., sales, operational knowledge). This divergence between importance and need provides a critical insight: strategic training investments must target performance gaps, not merely important competencies. The framework offers a reproducible, analytically grounded decision-support mechanism for human resources (HR) leaders and logistics businesses to align training with strategy and build organizational capability. The study contributes to HRD theory by demonstrating how MCDM enables rational, defensible resource allocation in complex, multi-stakeholder environments.

Keywords: human resource development, human capital development, talent development, workforce planning, strategic workforce development, evidence-based HR, strategic human resource management, competency-based training, training needs analysis, F-BWM, MCDM, emerging markets, logistics industry

1. Introduction

The logistics industry is a critical enabler of global trade and economic competitiveness (Christopher, 2016). As the World Bank highlights, logistics performance indices are strongly associated with national economic health, as efficient logistics systems lower transaction costs and increase resilience (Arvis et al., 2018). This macro-level performance ultimately depends on the knowledge, skills, and competencies of logistics professionals – a relationship elaborated in the literature review.

Historically focused on physical movement and warehousing, logistics now encompasses strategic planning, integrated supply chain management, and global network orchestration (Rushton, Croucher, & Baker, 2017). Professionals in logistics must manage cross-border transportation, navigate complex regulatory environments,

and mitigate risks arising from geopolitical instability and natural disasters, as global supply chains have become increasingly interconnected and vulnerable (Christopher, 2016; Christopher & Peck, 2004; Ivanov et al., 2019). Consequently, modern logistics managers require not only technical competencies related to systems such as transportation and warehouse management, but also advanced problem-solving capabilities, cross-cultural communication skills, and digital literacy to operate in complex and technology-driven supply chain environments effectively (Sharma et al., 2020; World Economic Forum, 2020; Ivanov & Dolgui, 2020; Nalbantoğlu, 2025).

Given this dynamic and demanding environment, identifying and remediating skill deficits through systematic Training Needs Analysis (TNA) is paramount. Competency-based training needs analysis (CbTNA) provides a systematic approach to identifying gaps between employees' current competencies and the skills required for effective job performance and organizational objectives, by integrating competency mapping with training needs assessment processes (Priyadarshini & Dave, 2012; Goldstein & Ford, 2002). Frameworks such as the Supply Chain Operations Reference (SCOR) model provide a comprehensive basis for evaluating supply chain performance and identifying key competencies required for effective logistics management (APICS, 2017). Similarly, the European Logistics Association (ELA) has developed standardized competency frameworks for logistics professionals, structured across different managerial levels—operational, senior (tactical), and strategic—reflecting the progression of responsibilities and decision-making scope in logistics roles (ELA, 2014; McKinnon et al., 2017). However, despite the acknowledged importance of such analysis, a significant lacuna persists in both academic inquiry and practical application within the field of management. While TNA is widely recognized as a critical prerequisite for effective training interventions, existing research indicates that it is often conducted in a non-systematic manner, with a predominant focus on individual-level skill gaps and limited alignment with organizational strategy and objectives (Nunes et al., 2025). Furthermore, a recent systematic literature review highlights that the field of management exhibits comparatively low academic output on TNA methodologies compared with more established domains such as healthcare and education (Nunes et al., 2025). This scholarly deficit is particularly acute in logistics operations in emerging markets, where human resources professionals must navigate the delicate balance between global best practices and local contextual constraints.

Addressing the prioritization of training interventions in such a complex, multifaceted environment necessitates a departure from heuristic or purely intuitive decision-making. The process of evaluating and ranking training needs inherently involves reconciling multiple, often conflicting, criteria under conditions of subjective uncertainty. Decision-making in this sphere is a construct of reliability and satisfaction derived from a bounded set of alternatives (Janis & Mann, 1979; Plous, 1993). To navigate this complexity, MCDM methods provide a robust analytical apparatus for structuring evaluation processes and deriving rational rankings from diverse inputs (Rezaei, 2015). By integrating fuzzy set theory with MCDM, it becomes possible to model the ambiguity and imprecision inherent in expert human judgment, thereby yielding more realistic and flexible outcomes in complex modeling scenarios (Triantaphyllou, 2000). This study, therefore, addresses the identified gap by developing a fundamental yet analytically rigorous CbTNA framework tailored to a logistics enterprise operating in a growing market. The relative importance of a defined set of competencies is derived through a multi-expert decision-making process incorporating analyses from 21 industry experts.

From an HRD perspective, this endeavor transcends mere identification of skills gaps; it is a strategic imperative for workforce development and organizational capability building. Contemporary HRD theory emphasizes that training and development investments should be aligned with organizational strategy and contribute to performance at individual and organizational levels. In this context, HR practices are increasingly expected to create value by linking human capital development with strategic capabilities and organizational objectives (Swanson & Holton, 2009; Ulrich & Dulebohn, 2015). The framework proposed herein is designed to assist logistics businesses in achieving critical human resources objectives, including the systematic quantification of competency gaps that impede supply chain effectiveness, the strategic allocation of finite training budgets toward high-impact developmental interventions, and the creation of transparent, defensible linkages between human capital investments and measurable business outcomes. By integrating competency prioritization with individual performance metrics, this model transforms the training function from a reactive, compliance-driven obligation into a proactive, strategic instrument for fostering organizational resilience and adaptive capacity.

The novelty of this study lies in its simultaneous, integrated focus on both technical and behavioral competencies within the specific, under-researched context of logistics operations in Türkiye. In this environment, localized literature on systematic TNA remains scarce. Methodologically, the application of a two-level hierarchical F-BWM in a multi-expert environment allows for a structured and reproducible assessment framework. By aggregating the evaluations of 21 experts to determine global competency weightings, the model enhances decision quality while explicitly accounting for the inherent uncertainty in subjective judgments. This approach ultimately yields a scalable decision-support mechanism, enabling businesses to prioritize training needs based on anticipated added value while accounting for real-world budgetary and temporal constraints. The subsequent sections of this paper will delineate the methodological application of this framework and demonstrate its modifiability through a sample departmental simulation.

2. Literature Review

2.1. Competencies in the Logistics Industry: Definitions, Dimensions, and Contextual Relevance

The dynamic nature of the modern logistics industry creates a continuous demand for workforce development and organizational learning, as supply chains are increasingly shaped by technological change and environmental uncertainty. In this context, competencies cannot be viewed as static assets but must continuously evolve in response to shifting strategies, emerging technologies, and changing market conditions. This necessitates a proactive approach to human resource development, in which training is systematically aligned with organizational strategy rather than implemented reactively. Accordingly, HRD professionals are expected to move beyond traditional training roles and act as strategic partners contributing to organizational development and competitive advantage (Garavan et al., 1995; Swanson & Holton, 2009; Ulrich & Dulebohn, 2015).

Although various definitions of the construct exist within the scholarly literature (see Gammelgaard & Larson, 2001; Kessler, 2008; Kotonen et al., 2011; Su et al., 2014), competency can broadly be defined as the combination of attitudes, abilities, skills, knowledge, and motivation required for sustainable and efficient performance

within a specific organizational or professional context (Mulder, 2001; Su et al., 2014, p.64; Sandberg, 2000; Fastré et al., 2014; Boyatzis, 2008; McClelland, 1973; Le Deist & Winterton, 2005). From this perspective, logistics competencies can be considered a blend of these elements typical to logistics specialists, aimed at achieving organizational goals, meeting task standards, and ensuring sustainable and efficient performance (Kotonen et al., 2011; Mulder, 2011; Vilkaite-Vaitone, 2021; Flint et al., 2005; Murphy & Poist, 2007; Prajogo & Sohal, 2013). Competencies are underlying characteristics related to effective performance that align with the broad definition posited by Spencer and Spencer (1993).

As defined above, a competency-based approach to selecting candidates for expert logistics roles extends beyond traditional knowledge, skills, and abilities (KSAs) to encompass broader individual characteristics, such as cognitive abilities and personality traits (Schmitt et al., 1998; Robertson & Smith, 2001; Hollenbeck et al., 1995). Competency modeling approaches emphasize the importance of identifying both technical and behavioral competencies to ensure effective job performance and organizational fit (Schippmann et al., 2000; Ryan & Tippins, 2004). Empirical research further demonstrates the strong and consistent relationship between personality traits—particularly conscientiousness and emotional stability—and job performance (Barrick & Mount, 1991; Salgado, 1997; Hurtz & Donovan, 2000; Barrick et al., 2001). In logistics contexts, behavioral competencies such as leadership, teamwork, and communication are widely recognized as critical determinants of performance (Spencer & Spencer, 1993; Mangan & Christopher, 2005; Derwik et al., 2016).

Reviewing the broader literature reveals that logistics professionals are expected to be both generalists and specialists, possessing a wide range of in-depth skills and knowledge in logistics, business, and management at various hierarchical levels (Vilela, Martins, & Siegler, 2018). They need to possess a broad and diverse set of competencies that reflect the multidimensional nature of logistics roles, spanning technical, managerial, cognitive, and behavioral domains (Kotzab et al., 2018; Murphy & Poist, 1991a; 1991b; 2007). The increasing globalization of supply chains and the widespread adoption of lean practices have further reinforced the need for integrated competency development and cross-functional capability building in logistics management (Christopher, 2016; Hines et al., 2004).

Additionally, education and experience—precursors to the development of individual skills and competencies—have been identified as critical factors influencing performance and value creation in logistics roles (Derwik et al., 2016; Myers et al., 2004). This relationship is further supported by Kolb's (1984) experiential learning theory, which emphasizes that knowledge and competencies are strengthened through concrete experience, reflective observation, and active experimentation.

Further studies highlight personality traits (Periatt, Chakrabarty, & Lemay, 2007), skills, competencies, and knowledge required for logistics roles and training across hierarchical levels (Gammelgaard & Larson, 2001; Thai et al., 2011; McKinnon et al., 2017; Özer Çaylan & Özkan Yıldız, 2016). The significance of personality traits in predicting job performance, particularly in logistics and related service contexts, aligns with McCrae and Costa's (1997) Five-Factor Model of personality, which identifies key traits that influence workplace behavior and performance outcomes.

Regardless of whether competencies are conceptualized at the individual or organizational level (Derwik et al., 2016; Winterton et al., 2006), the literature

converges on the view that logistics and supply chain competencies are inherently multidimensional and cannot be reduced to purely technical capabilities. Prior research classifies these competencies across a broad spectrum, including functional, social/behavioral, relational, managerial, cognitive, and business-oriented domains, as well as higher-order meta-competencies that enable adaptability and strategic alignment (Prajogo & Sohal, 2013; Derwik et al., 2016; Murphy & Poist, 2007). This multidimensional perspective reflects the increasing complexity of supply chain environments, where professionals are expected to integrate analytical thinking with interpersonal, managerial, and strategic skills.

Furthermore, empirical evidence suggests that while the core set of required competencies remains largely consistent across emerging and developed markets, their relative importance is context-dependent and shaped by regional, institutional, and market-specific dynamics (Shou & Wang, 2015). The role of cultural context in shaping the interpretation and application of competencies is supported by Hofstede's (1980) cultural dimensions theory, which explains how cultural differences influence managerial behavior and organizational practices across regions.

This study examines the competencies required of logistics professionals, considering regional and national differences as well as industry-specific dynamics faced by logistics businesses operating in Türkiye. Unlike traditional approaches, it evaluates behavioral and technical competencies in an integrated manner rather than focusing solely on technical skills. This approach aligns with the view that competencies should be understood within their regional, institutional, and cultural contexts, as managerial practices and human resource systems are not universally transferable across countries (Hofstede, 2001; Brewster, 2007; Paauwe & Boselie, 2005).

Structured for the specific conditions of Türkiye's logistics ecosystem, this framework enables evaluation of competencies not only against universal standards but also in light of local realities. In this way, the study contributes to logistics businesses by offering a more contextual, systematic, and applicable human resource approach. For businesses in emerging markets like Türkiye, competency-based training needs analysis (CbTNA) supported by rigorous analytical frameworks offers distinct competitive advantages: it enables strategic allocation of limited training budgets, builds local expertise aligned with global standards, creates transparent career development pathways that support talent retention, and generates measurable evidence of training effectiveness that supports ongoing HR investment justification.

2.2. The Strategic Role of Human Resource Development in Building Competitive Advantage

Within the logistics industry, the strategic alignment of HRD with organizational objectives is widely recognized as a critical factor for improving workforce capability and performance. The competency assessment framework presented in this study supports this strategic HRD function by enabling structured prioritization of competencies based on both their strategic relevance and current performance gaps. This approach is consistent with competency-based HRD and strategic training literature, which emphasizes the importance of aligning human capital development with organizational strategy and job performance requirements (Swanson & Holton, 2009; Garavan et al., 1995; Schippmann et al., 2000). When training and development initiatives are systematically aligned with organizational needs and competency requirements, they contribute to improved individual performance and broader organizational effectiveness.

2.3. CbTNA: Theoretical Foundations and Analytical Prioritization

2.3.1. Foundational Concepts and Organizational Imperatives

Competency-based Training Needs Analysis (CbTNA) is grounded in human resource development and competency modeling literature and represents a systematic approach for identifying gaps between current employee competencies and those required for effective job performance. This perspective emphasizes aligning training and development activities with organizational objectives and workforce capability requirements, particularly in dynamic business environments. Competency-based approaches highlight that competencies are not only relevant for development purposes but are also frequently embedded in selection and recruitment systems (Boyatzis, 1982; Spencer & Spencer, 1993; Campion et al., 2011). By focusing on competencies as observable, measurable constructs linked to performance, organizations can design more targeted development interventions that enhance employee effectiveness and contribute to overall organizational outcomes. This alignment between competency identification and development supports more efficient utilization of training investments and improved workforce capability.

Competency-based needs assessment approaches are widely used in management and human resource development to identify existing job requirements and systematically evaluate training needs and performance gaps. However, implementing CbTNA in the logistics industry presents several challenges due to the industry's dynamic, rapidly evolving nature, in which technological advancements and changing market conditions continuously reshape required skill sets (Goldstein & Ford, 2002; Campion et al., 2011). Accurately assessing current competency levels and identifying performance gaps, therefore, requires robust and structured assessment methodologies grounded in competency modeling and training needs analysis literature. In such dynamic and resource-constrained environments, reliance on subjective or purely qualitative judgments in competency prioritization may lead to inconsistent and suboptimal training decisions, undermining the effectiveness of human resource development interventions.

From an HRD perspective, CbTNA involves several interconnected steps, including defining competencies aligned with organizational strategy, assessing current competency levels through multiple evaluation methods, identifying performance gaps, and designing targeted training interventions. This systematic approach is grounded in competency-based HRD and training needs analysis literature, which emphasizes the integration of individual capabilities with organizational performance requirements (Goldstein & Ford, 2002; Campion et al., 2011). Competency is commonly conceptualized as a combination of knowledge, skills, abilities, attitudes, and other characteristics that contribute to effective job performance (Spencer & Spencer, 1993; Boyatzis, 1982; Campion et al., 2011). In addition, competency-based approaches support broader human resource functions such as recruitment, selection, succession planning, and career development, thereby contributing to an integrated human capital management system. The following key steps outline the procedural logic of CbTNA, emphasizing their strategic importance for HRD:

- **Defining Competencies:** The first step in CbTNA is to define the competencies required for specific roles within the business. These competencies should be clearly linked to job tasks and organizational objectives. In logistics contexts, key competencies often include strategic planning, problem-solving, and communication skills, which are critical for operational efficiency and performance

(Murphy & Poist, 2007; Kotzab et al., 2018).

- **Assessing Current Competency Levels:** After defining competencies, the next step involves evaluating employees' current competency levels using structured methods such as performance appraisals, self-assessment, and multi-source feedback systems. A widely used approach is 360-degree feedback, which integrates evaluations from multiple stakeholders to provide a comprehensive assessment of individual competencies (London & Smither, 1995; Bracken & Church, 2013; Fleenor et al., 2020).

- **Identifying Competency Gaps:** Competency gaps are identified by comparing current competency levels with required competency standards for effective job performance. This gap analysis is a core component of training needs assessment and provides the basis for targeted HRD interventions (Goldstein & Ford, 2002; Campion et al., 2011). In logistics contexts, such gaps may emerge in areas such as supply chain knowledge or technological proficiency (Christopher, 2016).

- **Designing Targeted Training Programs:** Based on identified gaps, training programs are designed using multiple learning approaches, including classroom instruction, on-the-job training, e-learning, workshops, and experiential learning techniques (Kolb, 1984). These programs should be aligned with both organizational objectives and individual learning needs. Experiential learning is particularly relevant in logistics, where practical application of knowledge is critical (Derwik et al., 2016; Gammelgaard & Larson, 2001).

- **Implementation and Evaluation:** The final step involves implementing and evaluating training programs through structured processes. Implementation includes scheduling training activities, assigning qualified trainers, and ensuring the availability of resources (Myers et al., 2004). Training effectiveness should be evaluated using pre- and post-assessment methods, feedback surveys, and performance indicators. The Kirkpatrick model and related evaluation frameworks provide structured approaches for measuring training outcomes at multiple levels (Kirkpatrick, 1994; Kraiger et al., 1993).

2.3.2. The Role of Analytical Prioritization in TNA

While the procedural framework for TNA is well established, a critical gap remains in the literature regarding the prioritization of competencies within resource-constrained environments. While maintaining the logical flow of the literature reviewed, this study does not aim to design, implement, or evaluate specific training programs in their entirety. Instead, it focuses on the analytical prioritization of competencies, emphasizing the importance of structured decision-making approaches. In this context, MCDM methods are used to determine the relative importance of each competency and to rank competency-based training needs in a real organizational setting. In this way, the study supports evidence-based and strategically aligned training decisions. Traditional talent needs analysis approaches often rely on descriptive gap analysis without systematically weighing the relative importance of competencies. However, in resource-limited business contexts—particularly those in emerging markets—not all competency gaps can be addressed simultaneously. Therefore, the inclusion of structured decision-making approaches to prioritize competencies based on their strategic contribution and operational impact is essential. The present study addresses this precise methodological lacuna by integrating competency assessment with robust analytical weighting to optimize HRD investment decisions. In this section, authors are required to provide a detailed account of the procedure that was followed while conducting the research described in the report.

This will help the readers to obtain a clear understanding of the research and allow them to replicate the study in the future.

3. Methodology

This study is designed to determine the relative importance of competency criteria, as assessed by experts, to provide a foundation for CbTNA in logistics. The research aims to systematically identify competency areas to prioritize in training planning, based on expert evaluations of the logistics industry. The competency structure is organized within a two-level hierarchical model comprising three main criteria and ten sub-criteria linked to them. To model uncertainty in expert judgments and differences in subjective evaluations, the F-BWM is used within a two-level hierarchical structure. This method is preferred because it allows decision-maker uncertainty to be represented through triangular fuzzy numbers (TFN). Expert evaluations are initially collected using the classical 1-9 scale, and the resulting values are then converted into triangular fuzzy numbers for fuzzy analysis. Thus, both expert opinions are preserved, and the model integrates decision uncertainty. As a result of the analysis, the main-criteria weights, the local sub-criteria weights, and the global weights obtained through hierarchical integration are calculated. Thus, a quantitative decision-support framework is developed to prioritize logistics training programs. Pairwise comparison data obtained from experts are compiled in Microsoft Excel and transferred to the R environment via the 'readxl' package. Data processing, fuzzy transformation, and weight calculation steps are algorithmically coded, and all calculations are performed programmatically. The entire analysis process is coded reproducibly, eliminating manual calculations.

3.1. F-BWM Method and Application Steps

F-BWM is a relatively new MCDM method and a suitable decision-making tool for deriving criterion weights under uncertainty. It uses subjective data that characterize people's judgments and behaviors (Ecer & Pamucar, 2020). Since the AHP method is proposed in the early 1980s, pairwise comparisons of criteria have played a significant role in the MCDM process (Ecer et al., 2018). However, the main disadvantage of AHP is decision-makers' inconsistency in pairwise comparisons, which can lead to erroneous conclusions. To overcome this problem and make pairwise comparisons rationally, Rezaei (2015) proposed the BWM method. The method aims to reduce inconsistency by reducing the number of pairwise comparisons, thereby maintaining consistency among opinions. Furthermore, it derives relative weights from pairwise comparisons by solving a nonlinear model (Hashemkhani Zolfani et al., 2020). BWM compares the degree of preference of the best criterion over all other criteria and the degree of preference of all criteria over the worst criterion by only performing reference comparisons. This type of procedure is much easier, more accurate, and less time-consuming because it does not require secondary comparisons, which are actually unnecessary (Rezaei, 2015). However, human judgments often contain uncertainty and ambiguity. Therefore, in this paper, a F-BWM proposed by Guo & Zhao (2017) is preferred for deriving the weights of the criteria. Finally, F-BWM can obtain more consistent results with fewer comparisons and can derive precise weights through fuzzy pairwise comparisons.

The application steps and basic equations used in F-BWM are presented. The method models decision-makers' evaluations as triangular fuzzy numbers (TFNs). The membership function of the triangular fuzzy numbers is defined by a two-part function with linearly increasing and linearly decreasing parts. The triangular fuzzy

numbers consist of a lower bound (l), a most likely value (l), and an upper bound (u), as shown in the figure below:

$$\tilde{a} = (l, m, u), 0 < l \leq m \leq u \quad (1)$$

The membership function increases linearly between l and m , and decreases linearly between m and u .

• **Step 1.** Determining the criteria set

Let $C = \{C_1, C_2, C_3\}$ denote the set of main criteria. Each main criterion C_i is associated with a subset of sub-criteria S_i . Thus, the hierarchical structure can be expressed as a two-level decision framework composed of main and sub-criterion sets. The hierarchical structure ensures that local weights of sub-criteria can later be integrated with main criteria weights to obtain global priority values.

The main set of criteria:

$$(C = \{C_1, C_2, C_3\} \quad (2)$$

Sub-criteria sets:

$$S_1 = \{S_{11}, S_{12}, S_{13}, S_{14}\} \quad (3)$$

$$S_2 = \{S_{21}, S_{22}, S_{23}\} \quad (4)$$

$$S_3 = \{S_{31}, S_{32}, S_{33}\} \quad (5)$$

Total set of criteria:

$$K = \bigcup_{i=1}^3 \{C_i\} \cup \bigcup_{i=1}^3 \{S_i\} \quad (6)$$

• **Step 2.** Determining the "best" and "worst" criteria

Each expert $d(d = 1, 2, \dots, 21)$ selects the most important criterion as best and the least important criterion as worst from a set of criteria $C = \{C_1, \dots, C_n\}$:

$$B^{(d)} \in C, W^{(d)} \in C \quad (7)$$

Here, $B^{(d)}$ and $W^{(d)}$ represent the best and worst criteria chosen by the d th expert, respectively. This selection is made both at the main-criteria level and for each sub-criterion group. Thus, the method is applied independently at two levels. The F-BWM procedure is first applied to determine the weights of the main criteria. Subsequently, the same procedure is independently conducted for each sub-criterion set under its corresponding main criterion. This two-level implementation ensures that local weights of sub-criteria are derived within their respective groups. Finally, global weights of sub-criteria are obtained by multiplying their local weights by the corresponding main criterion weight.

• **Step 3.** Creating the best-to-others (BO) vector

The relative importance ratios of the selected best criterion to other criteria (BO vector) and the relative importance ratios of other criteria to the worst criterion (OW vector) are obtained:

d -th expert evaluates the relative importance of the selected best criterion $B^{(d)}$ to all other criteria as TFN. Thus, the fuzzy BO vector is obtained:

$$\tilde{A}_B^{(d)} = (\tilde{a}_{B_1}^{(d)}, \tilde{a}_{B_2}^{(d)}, \dots, \tilde{a}_{B_n}^{(d)}) \quad (8)$$

Initially, values obtained on a crisp (1–9) scale are converted into triangular fuzzy numbers. For multiple experts, fuzzy evaluations are combined using the geometric mean. Each element is a triangular fuzzy number:

$$\tilde{a}_{B_j}^{(d)} = (l_{B_j}^{(d)}, m_{B_j}^{(k)}, u_{B_j}^{(k)}), j = 1, \dots, n \quad (9)$$

Furthermore, satisfies the following condition:

$$\tilde{a}_{BB}^{(d)} = (1, 1, 1) \quad (10)$$

Thus, the best score, relative to the criterion, is 1. As the value of $\tilde{a}_{Bj}^{(d)}$ increases, it is stated that $B^{(d)}$ becomes more important than C_j .

• **Step 4.** Combining 21 expert opinions

This study uses the evaluations from a total of $D = 21$ experts. The fuzzy Best-to-Others (BO) and Others-to-Worst (OW) comparison vectors generated by each expert are combined using the geometric mean method at the triangular fuzzy numbers (TFN) level to obtain the group decision. The fuzzy BO value at the group level for a criterion is calculated as follows:

$$\tilde{a}_{Bj}^{(d)} = \left(\left(\prod_{d=1}^{21} l_{Bj}^{(d)} \right)^{\frac{1}{21}}, \left(\prod_{d=1}^{21} m_{Bj}^{(d)} \right)^{\frac{1}{21}}, \left(\prod_{d=1}^{21} u_{Bj}^{(d)} \right)^{\frac{1}{21}} \right) \quad (11)$$

Similarly for OW values:

$$\tilde{a}_{jW}^{(G)} = \left(\left(\prod_{d=1}^{21} l_{jW}^{(d)} \right)^{\frac{1}{21}}, \left(\prod_{d=1}^{21} m_{jW}^{(d)} \right)^{\frac{1}{21}}, \left(\prod_{d=1}^{21} u_{jW}^{(d)} \right)^{\frac{1}{21}} \right) \quad (12)$$

Here, $d = 1, 2, \dots, D$ represents the expert index; l, m, u represent the lower, middle, and upper TFN components, respectively; and G represents the group-level value. This approach is based on the fuzzy geometric mean method, which is widely used in the literature for multi-decision-maker settings. All experts are considered to have equal weight.

• **Step 5.** Defining the OW vector

Each expert has assessed the relative importance of the j -th criterion to the worst criterion (W). Thus, the fuzzy OW vector is expressed as follows:

$$\tilde{A}_W^{(d)} = (\tilde{a}_{1W}^{(d)}, \tilde{a}_{2W}^{(d)}, \dots, \tilde{a}_{nW}^{(d)}) \quad (13)$$

here,

$$\tilde{a}_{jW}^{(d)} = (l_{jW}^{(d)}, m_{jW}^{(d)}, \dots, u_{jW}^{(d)}), j = 1, \dots, n \quad (14)$$

Expression shows the fuzzy relative importance of criterion j to the worst criterion (W). The worst criterion, when compared to itself, is:

$$\tilde{a}_{WW}^{(d)} = (1, 1, 1) \quad (15)$$

is the form.

• **Step 6.** Defuzzification

The fuzzy BO and OW values obtained at the group level are converted to sharp values using the centroid method:

$$a^c = \frac{l + m + u}{3} \quad (16)$$

As a result of this process, unique BO and OW ratios are obtained for each criterion.

• **Step 7.** Calculation of criterion weights

In this study, the classical F-BWM linear optimization model is not solved directly. Instead, a ratio-based approximate BWM formulation is used after defuzzification. The criterion weights are calculated as follows:

$$w_j \propto \frac{1}{\sqrt{a_{Bj} \times a_{jW}}} \quad (17)$$

Here,

a_{Bj}^c : defuzzified BO ratio

a_{jW}^c : defuzzified OW ratio

The obtained values are normalized, and the final criterion weights are calculated:

$$w_j = \frac{w_j}{\sum_{j=1}^n w_j} \quad (18)$$

This approach simplifies the computational process by maintaining the geometric balance of the BO and OW ratios, thereby enabling the acquisition of consistent weights without solving the optimization model.

• **Step 8. Hierarchical Integration**

The method is applied at two levels: (i) F-BWM for the main criteria, (ii) separate F-BWM for the sub-criteria under each main criterion. The global weights of the sub-criteria are calculated as follows:

$$w_{ij}^{global} = w_i^{main} \times w_{ij}^{local} \quad (19)$$

Thus, all sub-criteria have been made comparable on a single common scale.

3.1.1. The Theoretical Foundation of the Closed-Form Approach and Its Relationship with the LP Solution

In this study, instead of the classical linear programming (LP) based F-BWM model, a closed-form approximate solution based on the geometric balance of best-to-others (BO) and others-to-worst (OW) ratios after defuzzification is preferred. Although the closed-form approach does not directly minimize the consistency index (ζ), our analysis of the aggregated data (Tables 8-11) shows that the main criteria combination yields $\zeta = 0.158$, which falls within the acceptable range ($\zeta < 0.20$). The slightly higher consistency indices for sub-criteria dimensions ($\zeta \approx 0.21$ -0.24) are mitigated by the robust averaging of 21 expert opinions, which effectively dampens individual inconsistencies through geometric mean aggregation. This methodological choice prioritizes computational efficiency and practical reproducibility while maintaining statistical validity. This approach preserves the basic ratio logic of BWM. In the classical BWM model, the aim is to find the weight vector that simultaneously satisfies the conditions $\frac{w_B}{w_j} \approx a_{Bj}$ and $\frac{w_j}{w_W} \approx a_{jW}$ and to minimize the maximum deviation (ζ) (Rezaei, 2015). In the closed-form approach, the weights are calculated as in Equation 17.

Here, a_{Bj} represents the relative importance ratio of the best criterion to the j -th criterion, and a_{jW} represents the relative importance ratio of the j -th criterion to the worst criterion. The final weights are normalized to sum to 1. This approach reduces computational complexity while allowing the modeling of uncertainty in expert evaluations using fuzzy numbers and systematically reflecting subjective differences among decision-makers in the model. This expression is based on the geometric mean of the BO and OW ratios and treats both ratios symmetrically. Theoretically, it provides a balanced representation of the ratio conditions desired in the LP model. Especially when decision-maker evaluations are highly consistent, large differences in rankings between the closed-form and LP solutions are not expected. Indeed, the literature reports that the analytical and approximate solutions of BWM yield similar ranking results (Mi et al., 2019; Liang et al., 2020). However, the closed-form approach does not directly guarantee the minimization of the maximum deviation (ζ) in the LP model. Therefore, this method relies on structural ratio consistency rather

than strict mathematical optimality, and this limitation is explicitly acknowledged in the study.

Despite acknowledged limitations, it is essential to recognize that for decision problems with highly consistent expert judgments—such as those in our study—the closed-form approximation yields results closely aligned with the optimal solution derived from the linear programming model. The literature supports this perspective: Mi et al. (2019) demonstrate in their state-of-the-art survey that analytical approximations of BWM yield rankings comparable to those of the LP solution under consistent evaluation conditions. Similarly, Liang et al. (2020) establish that when the consistency thresholds are met, the differences between closed-form and optimization-based weights are negligible for practical prioritization. Consequently, the ratio-based approach employed in this study offers a computationally efficient and reproducible alternative without compromising the validity of the resulting competency rankings.

In addition, the robustness of the closed-form solution is assessed by examining whether the ranking structure remained stable across alternative normalization procedures. The results indicate that the relative ranking of criteria does not materially change, supporting the stability of the proposed approach.

3.1.2. Justification for Method Selection

In this study, a ratio-based approximation formulation is preferred over the classical F-BWM linear optimization model. This choice is justified by three main reasons: (i) the study involves the evaluation of 21 experts and a two-level hierarchical structure. Solving the linear fuzzy optimization model separately for each set of criteria significantly increases computational complexity. The ratio-based approach offers a simpler solution process by maintaining the geometric balance of BO and OW ratios; (ii) the ratios obtained after defuzzification are already reduced to a singular and consistent scale. In this context, the approximate formulation produces results close to the solution of the classical model and provides sufficient accuracy in terms of decision prioritization; (iii) the main objective of the study is to obtain the relative priority ranking of the criteria, and the calculation of the consistency index based on optimization is not the main focus of the research. Therefore, the method is chosen in accordance with the principles of practicality and reproducibility.

Table 1. Comparative analysis of existing BWM variants and the proposed F-BWM framework

Criterion	LP-Based BWM	LP-Based F-BWM	F-AHP	F-BWM (in this study)
Uncertainty Modeling	No	Yes (TFN)	Yes (TFN)	Yes (TFN)
Optimization Model	LP	F-LP	No	No
Consistency Indicator	Yes	Yes	CR	Not calculated directly
Computational Complexity	Medium	High	High	Low
Multi-Expert Integration	Geometric Mean	Geometric Mean	Geometric Mean	Geometric Mean
Hierarchical Application	Possible	Possible	Natural Structure	Possible
Practical Application	Medium	Low	Medium	High
Codability and Reproducibility	Medium	Hard	Medium	High
Suitability for Large Expert Groups	Limited	Complex	Hard	Suitable

Table 1 presents a structural comparison of the classical BWM, linear programming (LP)-based F-BWM, F-AHP, and the ratio-based F-BWM approach adopted in this study. The comparison reveals the balance between theoretical rigor, computational complexity, and applicability in multi-expert hierarchical decision environments. The classical BWM proposed by Rezaei (2015) offers a clear consistency metric, thanks to its linear programming formulation that minimizes the maximum absolute deviation (ζ), thereby enabling the mathematical derivation of optimal weights. Later-developed F-BWM approaches integrate decision uncertainty into the model using triangular fuzzy numbers (TFNs) and preserve the optimization structure (Guo & Zhao, 2017). These LP-based formulations offer a theoretically robust and methodologically consistent framework. The multi-expert approach helps improve the quality of the decision outcome, a key element in MCDM (Mi et al., 2019). However, in applications with multiple experts and two-level hierarchical structures, solving the linear (or fuzzy linear) optimization model separately for each set of criteria increases the computational load and complicates implementation. This can reduce operational efficiency, especially when many expert opinions are integrated. The Fuzzy AHP approach, developed by Saaty (1980) as a fuzzy extension of AHP, is a strong alternative for modeling uncertainty (Peykani et al., 2026). However, the large number of pairwise comparisons and the need to check the consistency ratio (CR) separately for each matrix increase the decision-maker's burden, especially in multi-expert and hierarchical models. The ratio-based F-BWM approach adopted in this study reduces computational complexity by maintaining the geometric balance between best-to-others (BO) and others-to-worst (OW) ratios. Although the classical linear programming model is not solved, and the ζ -based consistency index is not directly calculated, normalized weights are derived from the ratios obtained after defuzzification. This approach simplifies the computational process while maintaining structural consistency. In particular, this study, which integrates 21 expert opinions and features a two-level hierarchical structure, offers a balanced solution between theoretical rigor and practical application. Furthermore, conducting the entire analysis process in a code-based, reproducible manner is consistent with the principles of transparency and repeatability, which are gaining importance in the current multi-criteria decision-making literature.

3.2. Participants and Demographic Characteristics

The research is based on evaluations from 21 professionals actively engaged in decision-making across various industries. Participants are selected through purposive sampling, a strategy intentionally designed to recruit individuals with relevant logistics experience and direct involvement in organizational decision-making. This non-probability approach ensures that the data reflect informed, practice-based perspectives rather than generalizable population estimates, which is appropriate given the exploratory and context-specific nature of the research.

Table 2 summarizes the socio-demographic and occupational characteristics of the sample. As the table illustrates, the participant group is heterogeneous in terms of age, professional background, managerial level, and educational attainment. This diversity supports a multi-perspective evaluation of the decision-making criteria under investigation.

Table 2. Socio-demographic and occupational characteristics of participants

No	Gender	Age	Education Level	Department	Grade	Professional Experience	Total Experience
1	Male	33	Bachelor's	Supply Chain	Mid-Level Manager	14	14
2	Male	48	Bachelor's	Senior Management	Senior-Level Manager	22	30
3	Female	41	Bachelor's	Sales and Marketing	Not a Manager	15	14
4	Male	26	Bachelor's	Air Cargo	First-Level Manager	2	2
5	Male	31	Bachelor's	Import	First-Level Manager	4	4
6	Female	40	Bachelor's	Export	Specialist	12	13
7	Female	34	Bachelor's	Sea Freight & Project Export	First-Level Manager	5	5
8	Female	28	Bachelor's	Sea Freight	First-Level Manager	6	6
9	Male	45	Bachelor's	Sea & Air Freight	Senior-Level Manager	13	13
10	Female	29	Bachelor's	Import Operations	First-Level Manager	9	9
11	Female	25	Associate	Sea Freight & Project Cargo	First-Level Manager	3,3	3,3
12	Male	29	Bachelor's	Air Cargo	First-Level Manager	5	5
13	Male	44	Bachelor's	Management	Senior-Level Manager	16	16
14	Male	61	Bachelor's	Business Owner	Senior-Level Manager	30	30
15	Male	48	Associate	General Operations	Mid-Level Manager	32	32
16	Male	34	Graduate	Foreign Trade	Mid-Level Manager	9	9
17	Male	27	Bachelor's	Logistics	Specialist	6	6
18	Female	24	Bachelor's	Sales and Marketing	Specialist	2	2,5
19	Male	34	Bachelor's	Sea Freight Procurement	Mid-Level Manager	12	12
20	Female	30	Bachelor's	Procurement	Mid-Level Manager	8	8
21	Female	34	Graduate	Sales Manager	First-Level Manager	10	10

Examining the distribution of participants by hierarchical position concerning managerial levels reveals that first-level managers constitute the largest subgroup (8 participants, 38.1%), followed by middle-level managers (5 participants, 23.8%). Senior managers and specialists without managerial responsibilities each account for 4 participants (19.0%). This composition is methodologically significant: the overrepresentation of first-level managers offers strong insights into operational implementation, while the combined proportion of senior and middle-level managers (42.8%) ensures the integration of strategic perspectives within the model. As a result, the evaluation framework comprehensively incorporates both tactical execution and strategic oversight.

Regarding gender, the sample comprises 12 male participants (57.1%) and 9 female participants (42.9%). Although males constitute a slight majority, the nearly balanced distribution—exceeding 40% female representation—enhances the inclusion of diverse perspectives in the decision-making process. This equilibrium is particularly significant in a study focusing on communication and interpersonal

competencies, where a single-gender sample could introduce systematic bias.

Concerning age distribution, participants' ages range from 24 to 61 years, with a mean of 36.8 years. This broad span encompasses multiple career stages: younger participants provide recent operational familiarity, while older participants draw on extensive strategic and managerial experience. By including both early-career and seasoned professionals, the model avoids generational myopia and supports a multidimensional assessment framework.

Regarding professional and total experience, this study encompasses 2 to 32 years of experience in logistics and related industries, with an average of 11.3 years. Total professional experience, which may include roles outside the current industry, ranges from 2 to 30 years, with an average of 12.1 years. A significant proportion of participants possesses double-digit years of experience, indicating that evaluations are based on sustained practical engagement. The presence of individuals with 20 or more years of experience further highlights the strategic depth of the sample, suggesting that criterion weightings derive not solely from theoretical considerations but also from long-term, applied expertise.

Regarding educational attainment, the majority of participants hold a bachelor's degree (17, 81.0%), while 2 each hold an associate's degree (9.5%) and a postgraduate degree (9.5%). The predominance of bachelor's level or higher education indicates that the sample possesses adequate analytical capability to engage in structured, criterion-based evaluations. The inclusion of participants with postgraduate training further enhances the methodological and strategic rigor of the decision-making process. Overall, the educational profile supports the premise that the evaluation process is grounded in cognitive competence.

In terms of industrial diversity, participants operate across a wide range of functional areas, including supply chain management, business management, sales and marketing, air cargo, sea freight, import and export operations, logistics, foreign trade, procurement, and general operations. This cross-industry variation prevents the decision model from being narrowly confined to a single industry. Instead, it enhances the transferability of findings, indicating that the resulting framework may apply to various business contexts.

In summary, the demographic and occupational profiles of the 21 participants reflect a balanced, experienced, and academically capable cohort. The integration of diverse managerial levels, genders, age groups, experience durations, and industry backgrounds positions the study to capture both strategic and operational insights, thereby enhancing the credibility and relevance of subsequent analyses. The demographic composition indicates a heterogeneous sample, with varying experience levels represented in the model.

4. Results

The analysis findings are reported in three stages: (i) main criterion weights, (ii) local weights of sub-criteria, and (iii) global weights of sub-criteria. First, the weights of the main criteria are compared, then the local priorities of the sub-criteria under each main criterion are calculated. Finally, the local weights are combined with the main-criterion weights to obtain the global weights for the sub-criteria, and all sub-criteria are ranked on a common scale. The findings are presented in detail in the tables; in particular, the global weight ranking shows which sub-criteria are more decisive in the decision problem.

4.1. Main Criteria Weights

It is noteworthy that the first two main criteria (Interpersonal Competencies and Communication Skills Dimension and Business and Market Knowledge) received exactly equal weights (0.4136). This is not coincidental but stems from the symmetrical structure of best-to-others (BO) and others-to-worst (OW) ratios in expert evaluations. The ratio-based closed-form solution approach used in this study computes the criterion weights using the following relationship. Therefore, when the geometric products of the defuzzied BO and OW ratios for the two criteria are equal, the normalized weights are also equal. The combined structure of expert opinions shows that these two main criteria are perceived as equally dominant in the decision problem.

- Interpersonal Competencies and Communication Skills Dimension: 0.4136
- Job and Market Knowledge: 0.4136
- Work and Task Management Skills: 0.1727

Table 3. Weights of main competencies

Main Criterion	Weights
Interpersonal Competencies and Communication Skills	0,413636024
Work and Task Management Skills	0,172727951
Job and Market Knowledge	0,413636024

Global weights for the core competency clusters are presented in **Table 3**. This finding reveals that both interpersonal/communication skills and market knowledge dimensions are equally strategically important in logistics TNA. On the other hand, the lower weighting of the “Job and Task Management Skills” dimension suggests that experts view this competency as complementary.

4.1.1. Interpersonal Competencies Dimension

Within the interpersonal competencies dimension, the criteria “Effective Communication” (0.3427) and “Negotiation/Conflict Resolution Skills” (0.3427) have the highest local weights. This finding indicates that in the context of logistics, communicative competencies are not only supportive but also central to decision-making processes. In particular, the fact that negotiation skills are evaluated on the same level as communication aligns with the multi-stakeholder and coordination-intensive nature of logistics activities.

Table 4. Local weights of interpersonal competencies and communication sub-competencies

Sub-criterion (Interpersonal Competencies and Communication Skills)	Local Weights
Effective Communication	0,342739637
Collaboration and Coordination	0,153009486
Resilience	0,16151124
Negotiation / Conflict Resolution Skills	0,342739637

The relatively lower weightings of “Resilience” (0.1615) and “Collaboration

and Coordination” (0.1530) suggest that, while these elements are critical, they are perceived as complementary rather than distinctive. This indicates that experts position communication and consensus as a more strategic competency than operational resilience.

4.1.2. Business and Task Management Dimension

The fact that “Work/Process Management” (0.4069) and “Cost and Profit Sensitivity” (0.4069) criteria have equal local weights reveals that technical operational competence and financial awareness are evaluated together. This result shows that logistics performance is assessed holistically, not only from the perspective of operational flow efficiency but also from the perspectives of cost control and profitability.

Table 5. Local weights of work and task management skills sub-competencies

Sub-criterion (Work and Task Management Skills)	Local Weights
Work/Process Management	0,406939431
Work Ethics/Reliability/Consistency	0,186121138
Cost and Profit Sensitivity	0,406939431

In contrast, the lower weighting of the “Work Ethics/Reliability/Consistency” (0.1861) criterion suggests that this element may have been perceived as a "basic expectation" (hygiene factor) rather than a differentiating performance variable. In other words, experts may not have considered this competency as a necessary but competitive advantage-creating element.

4.1.3. Job and Market Knowledge Dimension

In the “Job and Market Knowledge” dimension, the equal, high weights of “Sales and Customer Acquisition Skills” (0.4024) and “Basic Operational Knowledge” (0.4024) indicate that market adaptation and operational application knowledge are considered equally important. This result reveals that in logistics, having only technical process knowledge is insufficient; customer acquisition and market expansion competencies are equally decisive.

Table 6. Local weights of job and market knowledge sub-competencies

Sub-criterion (Job and Market Knowledge)	Local Weights
Sales and Customer Acquisition Skills	0,40237718
Industry/Market/Competitor Analysis	0,195245641
Basic Operational Knowledge	0,40237718

The relatively low score for the “Industry/Market/Competitor Analysis” criterion (0.1952) indicates that analytical market knowledge is not prioritized as highly as direct sales and application skills. This suggests that experts place greater emphasis on "application-oriented" competencies.

4.2. Local Sub-Criteria Weights

The global ranking obtained by integrating local weights with the main criterion weights clearly reveals the effect of the hierarchical structure.

Table 7. Global weights and final ranking of sub-competencies

Sub-criterion	Global Weights	Rank
Sales and Customer Acquisition Skills	0,1664376970	1
Basic Operational Knowledge	0,1664376970	2
Effective Communication	0,1417694608	3
Negotiation / Conflict Resolution Skills	0,1417694608	4
Industry / Market / Competitor Analysis	0,0807606305	5
Work/Process Management	0,0702898141	6
Cost and Profit Sensitivity	0,0702898141	7
Resilience	0,0668068671	8
Collaboration and Coordination	0,0632902357	9
Work Ethics/Reliability/Consistency	0,0321483229	10

The criteria with the highest global weighting are:

- Sales and Customer Acquisition Skills (0.1664)
- Basic Operational Knowledge (0.1664)

The fact that these two criteria are ranked equally at the top indicates that training needs in logistics should be shaped primarily by market-oriented, application-based competencies. In particular, the fact that customer acquisition capacity is at the top, along with operational knowledge, suggests that both external markets and internal processes drive value creation in the industry. Following this:

- Effective Communication (0.1418)
- Negotiation / Conflict Resolution Skills (0.1418)

These criteria show that logistics performance depends on social and relational capital as much as technical knowledge. This finding supports the decisive role of coordination, contract management, and multi-actor collaboration processes in the modern logistics structure. The criterion with the lowest global weighting is:

- Work Ethics / Reliability / Consistency (0.0321)

However, this does not mean that this competency is unimportant. Conversely, it could be argued that this criterion is viewed as a default expectation for all candidates rather than a differentiating factor. Such criteria are generally considered threshold conditions rather than selection or educational prioritization criteria.

5. The Case Study

This study simulates a hypothetical department of four employees to demonstrate the applicability of the proposed CbTNA model. The participants are employees with varying levels of seniority and experience working in air import pricing and operations. The department structure includes two areas of expertise (pricing and operations), each with one specialist and one assistant specialist. Participants include employees at the beginning of their careers with limited experience, as well as those with extensive industry experience and expert-level responsibilities. This diversification is designed to show how the model performs at different seniority levels and job scopes. In the simulation, each participant's current competency level, required competency level, frequency of use, and difficulty level are evaluated. The resulting gap values are integrated with previously calculated competency weights to

prioritize training at the department level. This simulation is developed to demonstrate how the proposed decision model can be used in a real corporate context and does not represent any real institution.

- **Step 1.** Definition of the competency framework for the department

The department created within the scope of the simulation is determined by considering the general requirements of the logistics industry and the operational needs at the department level. In creating the competency set, detailed job descriptions for the relevant positions are examined, job postings for similar positions are analyzed, industrial reference documents and academic literature are utilized, and face-to-face interviews are conducted to verify the set.

Furthermore, to ensure the practical applicability of the competencies, expert opinions representing human resources management, operations management, and senior management perspectives are considered. As a result of this process, supported by academic contributions, competency groups encompassing technical and behavioral dimensions are created to evaluate the TNA of the job title holders. The determined competencies are presented below, along with their definitions:

Interpersonal Competencies and Communication Skills: These skills involve interacting with others effectively and conveying information.

a) Effective Communication: This assessment criterion refers to the ability to convey information clearly and efficiently through various channels, such as verbal, written, and non-verbal (body language), including skills in representing oneself or the business effectively.

b) Collaboration and Coordination: This assessment criterion denotes working effectively with others to achieve common goals, including the ability to coordinate activities and resources across different teams or departments.

c) Resilience: This assessment criterion is defined as the capacity to cope with and adapt to pressures, stress, anxiety, conflicts, and anger, maintaining effective performance and interpersonal relationships under challenging circumstances.

d) Negotiation / Conflict Resolution Skills: This assessment criterion denotes the ability to engage in discussions aimed at reaching mutually beneficial agreements, involving compromise, and negotiating terms or conditions successfully.

Work and Task Management Skills: These skills involve planning, organizing, and efficiently executing tasks.

a) Work/Process Management: This assessment criterion is regarded as the skills and abilities required to plan, execute, monitor, and complete tasks or projects, ensuring continuity and achieving desired outcomes.

b) Work Ethics/Reliability/Consistency: This assessment criterion infers the adherence to ethical principles and standards, demonstrating reliability and consistency in performance, behavior, and decision-making.

c) Cost and Profit Sensitivity: This assessment criterion is described as awareness and consideration of financial implications in decision-making, including the ability to manage costs effectively and maximize profitability.

Job and Market Knowledge: These skills involve understanding the business environment and market dynamics.

a) Sales and Customer Acquisition Skills: This assessment criterion refers to the competencies in identifying potential customers, presenting products or services persuasively, and closing sales effectively.

b) Industry / Market / Competitor Analysis: This assessment criterion is regarded as the knowledge and skills in gathering, analyzing, and interpreting

information about industry, markets, and competitors to support strategic decision-making and competitive advantage.

c) Basic Operational Knowledge: This assessment criterion represents the fundamental understanding of operational aspects such as documentation procedures, industry-specific terminology, routes or logistics paths, delivery and payment methods like INCOTERMS, and mechanisms.

As stated previously, the first step in the F-BWM is to clearly define the decision problem and determine the analysis's objective. The objective of this study is to prioritize the competencies required in a logistics context by evaluating their relative importance under a multi-expert environment.

To achieve this objective, a two-level hierarchical structure is established:

a) The overall objective at the top level (i.e., determining training priorities based on competency importance).

b) Main competency clusters and their corresponding sub-competencies at the second level.

Unlike full pairwise comparison approaches, F-BWM does not require evaluating alternatives. Instead, it focuses on determining the relative weights of predefined criteria through Best-Others and Others-Worst comparisons. Accordingly, once the main competency sets and sub-competencies are identified, the decision structure is completed and shown in **Figure 1**.

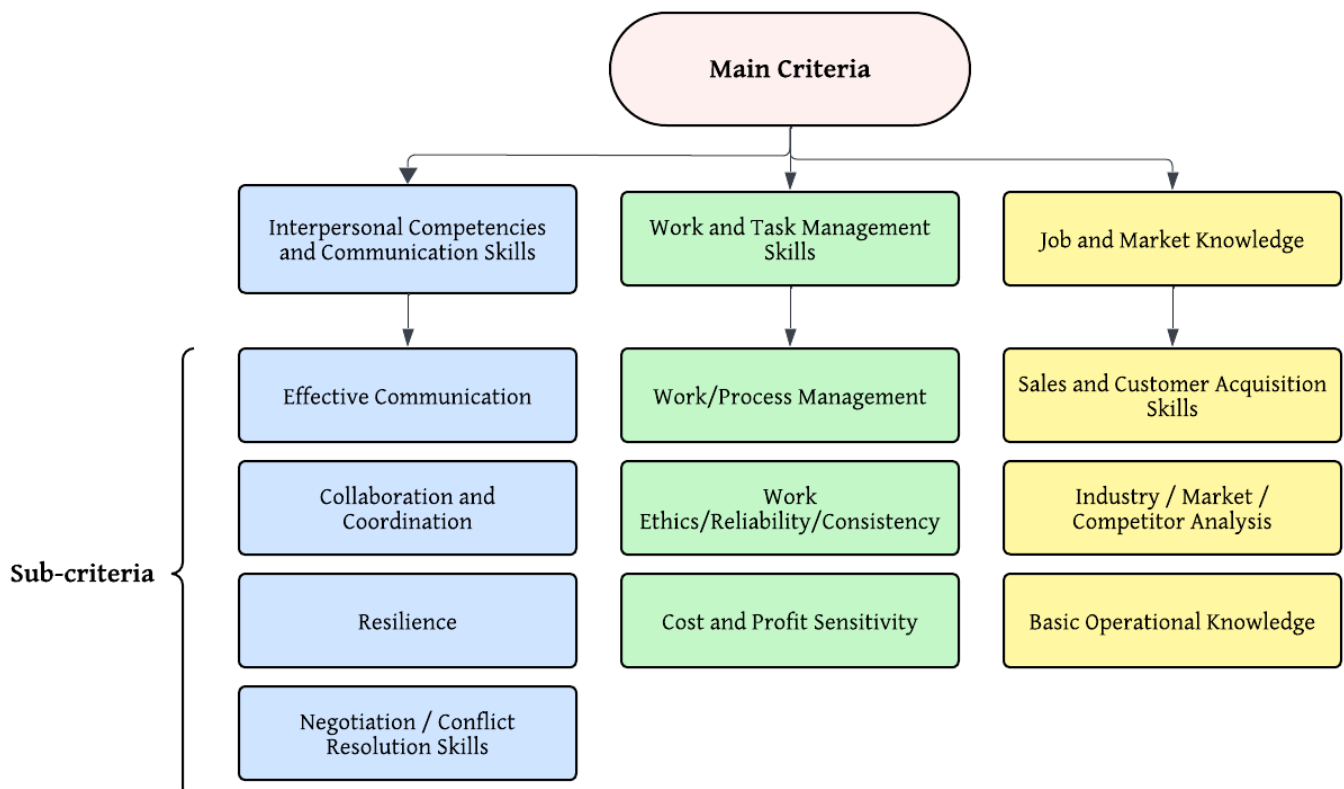


Figure 1. The hierarchical model of competencies

In line with the two-level hierarchical structure created (three main criteria and ten sub-criteria linked to them), the relative importance weights of the criteria are determined in the previous stage using the F-BWM. Within this scope, best-to-others (BO) and others-to-worst (OW) vectors are created for each set of criteria based on the opinions of 21 logistics experts. Evaluations are made using the 1-9 Saaty scale

and modeled using triangular fuzzy numbers (TFN). Expert opinions are combined using the geometric mean method, and the weights obtained from the F-BWM solution are defuzzified to calculate the final (crisp) criterion weights. In the case study, these final criterion weights are treated as fixed and used in performance evaluations conducted by four experts. Thus, the criterion importance levels are based on a broad expert group, and evaluations in the application phase are conducted within the context of the case. The global weights obtained from the previous F-BWM analysis are treated as fixed importance coefficients and used in the subsequent training need calculations.

Table 8. Aggregated F-BWM comparison vectors for main criteria

	Best	A1	A2	A3
Panel A. Best-to-Others (BO) Vector	TFN (l,m,u)	(1,1,1)	(4.87, 6.02, 7.41)	(5.92, 7.38, 8.96)
	Worst	A1	A2	A3
Panel B. Others-to-Worst (OW) Vector	TFN (l,m,u)	(5.92, 7.38, 8.96)	(2.31, 3.74, 5.28)	(1,1,1)

Expert judgments are aggregated using the geometric mean of triangular fuzzy numbers before solving the FBWM model.

Table 8 shows the aggregated fuzzy best-to-others (BO) and others-to-worst (OW) comparison vectors obtained by combining the evaluations of 21 experts for the main criteria using the geometric mean method. In accordance with the BO vector presented in Panel A, criterion A1 is identified as the best, as it takes the value (1, 1, 1). The superiority of A1 over A2 and A3 is expressed by triangular fuzzy numbers (4.87, 6.02, 7.41) and (5.92, 7.38, 8.96), respectively. These values indicate that the best criterion is perceived as superior, especially over A3. The width between the lower, middle, and upper limits of the fuzzy numbers reflects the level of uncertainty among expert opinions. The OW vector in Panel B shows the superiority of other criteria over the “worst” criterion. The value for A1 (5.92, 7.38, 8.96) indicates that this criterion is considered to have significantly greater superiority than the criterion with the least importance. The values obtained for A2 (2.31, 3.74, 5.28) indicate a relatively more moderate perception of superiority. For the “worst” criterion, the value (1,1,1) satisfies the identity condition.

Table 9. Aggregated F-BWM comparison vectors for interpersonal competencies and communication sub-criteria

	Best	B1	B2	B3	B4
Panel A. Best-to-Others (BO) Vector	TFN (l,m,u)	(1.0000, 1.0000, 1.0000)	(3.3767, 4.2777, 5.0725)	(2.9878, 3.8009, 4.5074)	(3.1029, 3.9088, 4.6388)
	Worst	B1	B2	B3	B4
Panel B. Others-to-Worst (OW) Vector	TFN (l,m,u)	(3.1029, 3.9088, 4.6388)	(3.4908, 4.6264, 5.6625)	(3.6904, 4.6737, 5.5695)	(1.0000, 1.0000, 1.0000)

Table 9 shows the aggregated fuzzy BO and OW vectors for the sub-criteria of interpersonal competencies. Considering the BO vector results, the most important selected sub-criterion shows a significant but not extreme superiority over B2, B3, and B4. The relatively higher fuzzy values for B2, in particular, indicate that the

relative importance of this sub-criterion is perceived more strongly. The presence of the value (1,1,1) for B4 in the OW vector reveals that this sub-criterion is identified as having the lowest importance.

Table 10. Aggregated F-BWM comparison vectors work and task management skills sub-criteria

	Best	C1	C2	C3
Panel A. Best-to- Others (BO) Vector	TFN (l,m,u)	(1.0000, 1.0000, 1.0000)	(5.1109, 5.8946, 6.6107)	(3.1464, 4.1602, 5.1079)
	Worst	C1	C2	C3
Panel B. Others-to- Worst (OW) Vector	TFN (l,m,u)	(3.1464, 4.1602, 5.1079)	(2.4885, 3.3964, 4.2217)	(1.0000, 1.0000, 1.0000)

Table 10 presents the aggregated fuzzy BO and OW vectors for the sub-criteria of Work and Task Management Skills. In the BO vector, C2 exhibits higher fuzzy superiority values than the other sub-criteria, indicating that it is perceived as the most important criterion in this dimension. In the OW vector, C3, identified as the worst criterion, takes the value (1, 1, 1), satisfying the identity condition. The superiority values of C1 and C2 with respect to the worst criterion differ: C1 exhibits a higher degree of superiority than C2. This indicates a differentiated but consistent priority structure within the sub-criteria group rather than a perfectly homogeneous distribution.

Table 11. Aggregated F-BWM comparison vectors for job and market knowledge sub-criteria

	Best	D1	D2	D3
Panel A. Best-to- Others (BO) Vector	TFN (l,m,u)	(1.0000, 1.0000, 1.0000)	(3.8260, 4.5458, 5.1974)	(3.8401, 4.8672, 5.7797)
	Worst	D1	D2	D3
Panel B. Others-to- Worst (OW) Vector	TFN (l,m,u)	(3.8401, 4.8672, 5.7797)	(3.5171, 4.6622, 5.7053)	(1.0000, 1.0000, 1.0000)

Table 11 presents the aggregated fuzzy BO and OW vectors for the Job and Market Knowledge sub-criteria. In the BO vector, D1 is identified as the best criterion and therefore takes the value (1,1,1), whereas D2 and D3 have higher fuzzy ratios, indicating lower priority relative to D1. In the OW vector, D3, identified as the worst criterion, takes the value (1, 1, 1), satisfying the identity condition. The OW ratios of D1 and D2 with respect to the worst criterion are close but not identical, suggesting a relatively balanced yet differentiated priority structure within this dimension.

Table 12 shows the final criterion weights obtained from the F-Best-Worst Method (FBWM). At the main criterion level, “Interpersonal Competencies and Communication Skills” and “Job and Market Knowledge” have the highest weights (0.41), while “Work and Task Management Skills” has a relatively lower weight (0.17). When the sub-criteria are examined, it is evident that the highest global weights are concentrated in “Sales and Customer Acquisition Skills” and “Basic Operational Knowledge”, followed by “Effective Communication” and “Negotiation / Conflict Skills”. In contrast, the sub-criterion “Work Ethics / Reliability / Consistency” has the lowest global weight. These results reveal that communication-based and market-

oriented competencies are perceived as more strategically decisive in a business context.

Table 12. The final global fuzzy weights for both primary and subcompetencies

Competency	Weights	Sub Competency	Local Weights	Global Weights	Rank
Interpersonal Competencies and Communication Skills	0,41	Effective Communication	0,342739637	0,1417694608	3
		Collaboration and Coordination	0,153009486	0,0632902357	9
		Resilience	0,16151124	0,0668068671	8
		Negotiation / Conflict Skills	0,342739637	0,1417694608	4
Work and Task Management Skills	0,17	Work/Process Management	0,406939431	0,0702898141	6
		Work Ethics / Reliability / Consistency	0,186121138	0,0321483229	10
		Cost and Profit Sensitivity	0,406939431	0,0702898141	7
		Sales and Customer Acquisition Skills	0,40237718	0,1664376970	1
Job and Market Knowledge	0,41	Industry / Market / Competitor Analysis	0,195245641	0,0807606305	5
		Basic Operational Knowledge	0,40237718	0,1664376970	2

• **Step 2.** Before assessing the current level of competency-based training needs, some explanations are required. To measure the gap between the required and current level of each competency, the titleholder is expected to have, and to evaluate each titleholder more objectively, a behavioral observation scale has been developed to use with a sample item presented in **Table 13**:

Table 13. A sample of behavioral observation scale with levels for competency

Competency : Cost and Profit Sensitivity (C6)	
Level 0	: S/he cannot conduct any cost/benefit analysis or financial feasibility studies.
Level 1	: With the guidance and/or assistance of someone else, s/he carries out the work required by her/his job, task, and/or project by the strategic goals of the institution, at low cost and high benefit.
Level 2	: While making decisions on her/his job, the tasks that s/he perform and/or the project that s/he is a part of, s/he tries to find solutions that will reduce costs in the way s/he does business and in the use of resources.
Level 3	: S/He makes a benefit/cost analysis when making decisions on her/his job, the task that s/he performs, and/or the project that s/he is a part of. In a situation where s/he thinks the return will be high, s/he considers the benefits in addition to the costs. Even though s/he cannot find a solution to reduce costs, s/he tries to produce solutions to increase the benefits her/his customers will receive.
Level 4	: When making decisions on her/his job, the task that s/he performs and/or the project that s/he is a part of, s/he considers budget targets and search for methods and solutions to ensure profitability above the targets.
Level 5	: S/he can predict the impact of her/his job, task, and/or project on the financial statements of the business. S/he can optimize positive/adverse effects. S/he can suggest and implement remedial/enhancing methods and educate the parties.

However, since each competency, although required, is not used daily for

each position, a frequency scale is created with the question “How often is this competency used in fulfilling the requirements of your job?” on a continuum starting from “0: Not executed at all”, followed by “1: Every few months throughout the year”, “3: Every few weeks throughout every month”, “3: Every few days throughout every week”, and “4: Every few hours throughout every day”, to end with “5: Many times throughout every hour). It has been adapted from the established job and work analysis methodologies (e.g., Brannick, Levine, & Morgeson, 2007). The use of such absolute-anchored frequency scales is further supported by research demonstrating their superior statistical properties, including greater between-task variability and higher interrater agreement compared to other scale types (Babcock, 2020).

Besides, the last scale is created to evaluate the difficulty level of each competency when the title holder uses it with the question ‘How much difficulty do you have in using this competency while fulfilling the requirements of the task?’ to be answered on a continuum ranging from the starting point of ‘1: Not forced to use’, followed by ‘2: Less difficult to use’, and ‘3: Having difficulty to use’ with the of ‘4: Very difficult to use’. It has been developed and validated through a pilot panel of logistics professionals (n = 5) prior to the main data collection to ensure content relevance and clarity for the specific operational context. Considering what has been discussed so far, **Table 14** below represents one of the completed samples for a TNA title holder in the position ‘Air Import Pricing Assistant Specialist’ under the competency ‘Resilience (C3)’.

Table 14. A filled sample of the CbTNA form

Competency	Required Level ^(a)	Current Level ^(b)	Frequency ^(c)	Difficulty Level ^(d)
Resilience	3	2	3	1

^(a) The score comes from the behavioral observation scale.

^(b) The score comes from the behavioral observation scale.

^(c) The score comes from a frequency scale.

^(d) The score comes from the importance level scale.

However, it should be noted that this form is completed by two people: the titleholder, who evaluates herself/himself, and her/his immediate manager, who assesses her/his quality in the relevant competency, with equal weights of 50% each. This process is regarded as an assessment of the required and current competency levels within the business. If it is repeated for each position in all departments, it should follow the step one mentioned above.

• **Step 3.** Having defined the competencies and assessed their current levels, the next step is to identify gaps by calculating the mean score for each competency across both scales to determine whether each titleholder needs training in the relevant competency. **Table 15** provides an example of how the training needs are calculated:

Table 15. A calculated sample for an Air Import Pricing Assistant Specialist of CbTNA form

Competency	Required Level	Current Level	Frequency	Difficulty Level
Resilience (Self-assessment)	2	2	5	2
Resilience (Immediate Managers' Assessment)	4	2	5	1
Arithmetic Mean	3	2	5	1,5

While there appears to be no requirement for the title holder (at least given that the required and current competency levels are considered equal in his/her self-assessment), a requirement exists because the arithmetic mean of the required level is greater than the arithmetic mean of the current level. However, some additional steps are necessary to prioritize the ranking of all departmental competencies. First, each title holder is assessed for any training needs. Second, each title holder who needs training is scored by multiplying the arithmetic mean of the points they received for each competency by the frequency and difficulty level, based on the gap between the required and current levels of that competency. Regarding **Table 15**, for instance, the gap is calculated by the difference between the required (3) and current level (2), which means there is a training need for resilience for the person working as an Air Import Pricing Assistant Specialist, and then the gap is multiplied by frequency (5) and difficulty levels (1,5) to calculate its overall importance of that need for the position. In this step, if there is more than one person with the same title, the multiplication is repeated for each person to calculate the total score for each competency under that title. Third, after the total scores for each competency are calculated, the sum of each competency for all titleholders is obtained. Fourth, the sum of each competency is multiplied by the relevant competency weight calculated through F-BWM. The last step requires ranking weighted totals from highest to lowest; the higher the total score, the greater the need for training in that competency, as shown in **Table 16**.

Table 16. TNA results

Competencies	Competency Sum	Competency Weighting	Weighted Total
Sales and Customer Acquisition Skills	11	0,166	1,83
Basic Operational Knowledge	10	0,166	1,66
Effective Communication	7,50	0,141	1,06
Negotiation / Conflict Resolution Skills	43,75	0,141	6,20
Industry / Market / Competitor Analysis	34	0,081	2,74
Work/Process Management	10	0,070	0,70
Cost and Profit Sensitivity	36	0,070	2,53
Resilience	40,50	0,067	2,71
Collaboration and Coordination	16,25	0,063	1,03
Work Ethics/Reliability/Consistency	0	0,032	0

The results presented in **Table 16** show that competency-based training needs cannot be explained solely by the strategic importance weights of the criteria; the performance gap (OGD-MD), along with frequency of use and difficulty level, significantly shapes training priority. Examining the weighted total scores reveals that the highest training priority is “Negotiation / Conflict Resolution Skills” (6.20). This finding suggests that this competency is both related to critical business outcomes and, in the context of the case, the current level of employees is below the expected level, and this gap is growing because it is a frequently used, relatively difficult competency to develop in daily workflows. The fact that negotiation skills take center

stage in training investment in logistics, where operational efficiency, stakeholder management, internal coordination, and customer/supplier interactions are intense, strongly indicates the need to directly improve the quality of decision-making and communication in the field.

This ranking reveals a critical insight that distinguishes strategic importance from training priority. If only the strategic weights derived from expert judgments had been considered, competencies such as Sales and Customer Acquisition Skills and Basic Operational Knowledge would have ranked first (global weights of 0.166 each). However, when performance gaps are incorporated—specifically the discrepancy between required and current competency levels—the training priority shifts. Negotiation and Conflict Resolution Skills, despite having a moderate global weight (0.142), emerges as the highest training need (weighted total: 6.20). This finding demonstrates that our model enables multi-dimensional, need-based planning rather than prioritizing competencies solely based on their perceived strategic importance. In other words, training investments should target areas where both strategic relevance and measurable performance gaps converge.

The second- and third-highest scores for "Industry/Market/Competitor Analysis" (2.74) and "Resilience" (2.71) indicate that the need for departmental-level training extends beyond technical operations to include the capacity to cope with uncertainty and to understand the external environment. The high score for "Industry/Market/Competitor Analysis" indicates a greater need for data-driven thinking and competitive positioning, particularly in processes such as pricing decisions, capacity planning, and customer acquisition. The high ranking of "Resilience" reveals that individual/organizational flexibility is a critical area for development in situations where logistics operations are inherently conducted under intense stress, time pressure, and the risk of disruption. The high combined scores for both competencies suggest that the department needs a stronger ability to adapt to both external environmental variables (market conditions) and internal process pressures (crises/disruptions).

Ranked fourth, "Cost and Profit Sensitivity" (2.53) indicates that financial awareness and cost-oriented decision-making capacity are in need of improvement. Given the relatively low margins in the logistics industry and the high sensitivity of cost items (fuel, warehousing, labor, delay penalties, etc.) to decision quality, the need for training in this competency is directly linked to profitability and resource-allocation efficiency. In contrast, the fact that "Sales and Customer Acquisition Skills" (1.83) and "Basic Operational Knowledge" (1.66), which have high global weightings in the F-BWM model, lag behind the top four offers a significant managerial insight: even though these competencies are considered strategically important, their training priority is lower in the context of the case because current levels are relatively sufficient or the development gap is more limited. In other words, the model differentiates between the concepts of "importance" and "need," suggesting that the training budget should be directed not only to high-weighting areas but also to those areas that generate the largest performance gaps.

The results in the lower-middle group can be interpreted similarly. The scores for "Effective Communication" (1.06) and "Collaboration and Coordination" (1.03) indicate a need for training in these competencies. However, the need is not as critical as negotiation, resilience, and analytical market knowledge. Completely neglecting these two areas may be incorrect, as interpersonal competencies often indirectly affect performance and create a "multiplier effect" in business processes. Therefore,

supporting communication and coordination in a modular way (e.g., stakeholder management, negotiation, and an effective communication package), especially in conjunction with negotiation skills, could enable a more efficient training design. The low score for “Work/Process Management” (0.70) suggests that a basic understanding of the process management approach is established within the department, or that the gap measured in this competency is limited within the current division of labor. Nevertheless, if process standardization and a culture of continuous improvement are targeted, this area can be supported with periodic refresher training.

Finally, the weighted total score of zero for Work Ethics/Reliability/Consistency should not be misinterpreted as evidence that this competency lacks strategic importance. This result simply indicates that, within the specific assessment period and for the employees evaluated, the current levels of these normative competencies meet the required expectations. In other words, no *immediate* training gap exists. However, competencies such as ethics and reliability often remain latent until critical incidents—misconduct, non-compliance, customer complaints, or data breaches—reveal hidden deficiencies. Therefore, the zero score does not diminish the strategic significance of this competency; it merely indicates that it is not an immediate training priority. Organizations are advised to maintain ongoing monitoring and supplement with periodic refresher modules (e.g., mandatory orientation, compliance updates) rather than intensive training investments.

Overall, the ranking presented in **Table 16** indicates that the department's training strategy should be shaped more around "relationship management, decision-making under uncertainty, and market literacy" rather than "technical knowledge transfer." One of the model's most significant contributions is its ability to numerically identify which competencies are both important and open to development by combining strategic weights (F-BWM) with field-level performance gaps. This allows training planning to move beyond intuitive preferences and adopt a measurable and justifiable prioritization logic.

6. Conclusion

6.1. Strategic Insights for Human Capital Development and Organizational Effectiveness

The training needs analysis findings derived from this study reveal critical insights for strategic human resource development and talent management within the logistics industry. These insights underscore a necessary evolution in HR practice, moving from generalized, compliance-driven training toward targeted, evidence-based capability building.

6.1.1. Relationship Management and Interpersonal Competencies as Organizational Imperative

The high priority assigned to “Negotiation and Conflict Resolution Skills” reflects the growing importance of interpersonal and relational competencies in complex logistics and supply chain environments. Organizational effectiveness in such multi-actor systems relies heavily on the ability to manage interactions, build trust, and resolve conflicts constructively under conditions of interdependence and time pressure. Research on emotional intelligence indicates that individuals with higher levels of emotional intelligence are more effective in negotiation contexts because they can perceive, regulate, and use emotions strategically in interpersonal interactions (Ogilvie & Carsky, 2002). Emotional intelligence is also associated with improved relationship management and communication effectiveness, which are

essential for reducing the intensity of conflict and fostering collaborative outcomes (Goleman, 1998; Goleman et al., 2002). In addition, leadership studies suggest that emotional intelligence contributes to effective interpersonal functioning and team coordination, indirectly supporting conflict resolution processes in organizational settings (Palmer et al., 2001). Accordingly, in logistics environments characterized by high complexity and stakeholder interdependence, negotiation and conflict-resolution competencies are critical operational capabilities rather than optional soft skills.

Implications for Human Resource Development Strategy: Businesses should invest substantially in scenario-based training, experiential learning programs, and mentoring systems to develop these critical soft skills. This includes comprehensive programs on cross-cultural communication, stakeholder engagement, and principled negotiation—particularly relevant for emerging-market logistics businesses operating in global, multicultural supply chain networks. HR leaders should also examine organizational systems and practices that either enable or hinder effective communication, including meeting structures, decision-making processes, and feedback mechanisms.

6.1.2. Analytical Capability and Data Literacy as Strategic Competitive Advantage

The high priority for "Industry/Market/Competitor Analysis" (2.74) indicates a significant need for employees to transcend tactical execution and develop strategic thinking capabilities. This competency gap signals an organizational imperative for employees to move beyond "doing the work" to "understanding the business environment." Such development directly supports organizational agility, informed decision-making, and adaptation to market changes.

Implications for Human Resource Development Strategy: Businesses should develop comprehensive training on business acumen, competitive analysis, data interpretation, and strategic thinking. This represents a fundamental shift toward developing "business-conscious" logistics professionals who can integrate operational excellence with a strategic business perspective. Training design should include real business scenarios, competitive case analyses, and decision-making simulations. Additionally, HR should identify high-potential employees for accelerated development programs to prepare them for strategic logistics leadership roles.

6.1.3. Resilience and Organizational Learning in Uncertain Environments

The significant emphasis on resilience (2.71) reflects the inherently unpredictable, high-pressure nature of modern supply chain operations and the substantial psychological demands on logistics professionals. Supply chain disruptions, demand volatility, geopolitical uncertainty, and operational crises are not exceptional events but regular features of the contemporary logistics landscape. Building individual and organizational resilience is, therefore, a strategic imperative.

Implications for Human Resource Development and Organizational Policy: Beyond formal training interventions, businesses must examine broader HR policies and organizational systems that support employee resilience. This includes flexible work arrangements that reduce burnout, stress management and mental health support programs, crisis management training, decision-making under time pressure, and career development opportunities that allow professionals to grow during organizational change. Additionally, leadership development programs should emphasize creating psychological safety and adaptive team dynamics—preconditions for organizational resilience.

6.1.4. Financial Acumen and Business Orientation for Operational Decision-Making

The identified need for training in "Cost and Profit Sensitivity" (2.53) indicates that modern logistics professionals must understand the business and financial implications of operational decisions. In an industry characterized by thin margins and high cost sensitivity—including fuel, warehousing, labor, and penalties for delays—financially literate operational staff make superior decisions that directly impact profitability and resource efficiency.

Implications for Human Resource Development and Organizational Practice: Businesses should develop integrated training combining financial concepts with operational scenarios relevant to participants' roles. This might include financial simulations, case-based learning using real business scenarios, and "business literacy" modules. Such training represents a strategic shift toward creating "business-conscious operational teams" rather than purely tactical specialists. HR should also facilitate cross-functional learning in which operations personnel understand financial perspectives and finance personnel understand operational realities, thereby breaking down organizational silos.

6.2. Managerial and Practical Implications

6.2.1. Strategic Workforce Development and Human Capital Planning

Based on the findings, strategic training planning in logistics businesses should be structured around prioritized, measurable performance gaps rather than standard, equally distributed programs that fail to address the most critical development needs. This represents a fundamental shift in HR practice from "training for everyone in everything" to "targeted development for maximum impact."

Key Strategic HR Recommendations:

a) Link Training to Strategic Supply Chain Objectives: Position training investment as a strategic supply chain capability-building initiative rather than a compliance or employee benefit function. HR leaders should partner with supply chain executives to ensure training addresses critical competitive requirements.

b) Establish Career Pathways and Talent Development Programs: Use competency assessment to create transparent career development pathways. Identify high-potential employees for accelerated development programs to prepare them for supply chain leadership. Support succession planning by understanding competency strengths and development needs across the business.

c) Implement Systematic, Recurring Competency Assessment: CbTNA should not be a one-off assessment but an ongoing process. Annual or biennial reassessment enables tracking of training effectiveness, identification of emerging competency needs, and adjustment to changing business requirements. Department-level comparisons reveal organizational strengths and capability gaps requiring strategic attention.

d) Integrate HR Practices Around Competency Framework: Extend competency assessment beyond training to inform recruitment and selection, performance management, compensation, promotion decisions, and organizational restructuring. This integration creates aligned human resource systems with a consistent focus on building required capabilities.

e) Support Training Transfer and Sustainability: Research demonstrates that training effectiveness depends heavily on organizational support for applying new competencies on the job. HR should work with managers to create conditions

enabling training transfer, including clear expectations for competency application, performance monitoring, peer learning communities, and ongoing coaching.

The high priority given to "Negotiation/Conflict Resolution Skills" necessitates the development of applied, scenario-based, and feedback-oriented training programs in this area. Similarly, the competency gap in "Industry/Market/Competitor Analysis" indicates that employees need not only operational application skills but also analytical thinking and data interpretation capabilities. Therefore, it is recommended to integrate data literacy and competitive analysis modules into training content. The need in the area of "Resilience" necessitates the inclusion of programs on crisis scenarios, decision-making under time pressure, and stress management in the corporate training plan. The training requirement on "Cost and Profit Sensitivity" should be supported by practical financial simulations that provide operational personnel with a fundamental understanding of profitability. Furthermore, it is important that the TNA process does not remain a one-off application but is repeated periodically, department-based comparisons are made, and it is integrated with career planning processes.

To operationalize these findings, logistics businesses can adopt the following concrete action plan: First, for negotiation and conflict resolution, a two-day, scenario-based workshop (16 hours) should be conducted every six months for all customer-facing and coordination roles, with a success criterion of at least one-level improvement in simulation performance for 80% of participants. Second, to build market analysis capability, monthly two-hour data literacy sessions, combined with quarterly strategic case analyses, should be implemented, aiming for a 30% reduction in competitor response time. Third, a low-cost alternative for resilience training includes monthly peer-led crisis case discussions (one hour) instead of expensive external programs. Fourth, any organization wishing to replicate this model must prepare three documents: a competency dictionary (10–12 items with behavioral anchors), an assessment form (current, required, frequency, difficulty), and an expert elicitation guide (best-worst comparisons). Finally, a yearly measurement loop (pre- and post-tests, manager reassessments) must be established to reallocate training budgets based on demonstrated competency gains.

To protect the investments made through this TNA framework, businesses must also prioritize stability in personnel contracts. High turnover and low job security—particularly in emerging markets—can lead to ineffective partnerships and the loss of critical expertise developed through these systematic training interventions (Nembaware et al., 2022). Regular application of the model will ensure that the competency structure remains up to date amid changing market conditions and organizational transformations. Furthermore, consistent with contemporary HRD scholarship (Nunes et al., 2025), modern TNA should serve as a proactive tool for diagnosing and anticipating future competency requirements arising from organizational strategy changes, technological advancement, and market evolution. Rather than responding to current skill deficits after they impact performance, forward-looking HR leaders use competency frameworks to anticipate future capability requirements and proactively develop talent.

6.2.2. Implications for Organizations in Emerging Markets

For businesses in emerging markets such as Türkiye, where developing logistics competency is hampered by resource constraints and rapid business change, this CbTNA framework offers distinctive value. In emerging economies, logistics businesses often operate with limited training budgets, constrained access to

specialized expertise, and rapid changes in business requirements. This framework addresses these constraints by enabling businesses to concentrate limited training resources on the highest-impact interventions, develop local expertise aligned with global best practices, and build organizational capability systematically despite resource limitations.

The framework demonstrates how businesses can balance adaptation to local contexts with alignment to global standards. Unlike one-size-fits-all frameworks developed in and for developed-market contexts, this approach accommodates regional economic realities, cultural factors, and local business practices while maintaining alignment with international logistics standards and practices. Such dual alignment is increasingly critical as emerging-market logistics businesses integrate into global supply chain networks. The framework acknowledges Hofstede's (1980) theory of cultural dimensions, recognizing that competency requirements may vary across contexts. While core logistics competencies may be universal, their relative importance and the behaviors through which they are demonstrated vary by culture. The F-BWM approach accommodates these differences through local expert judgment while maintaining methodological rigor.

In emerging markets characterized by greater business uncertainty, economic volatility, and supply chain disruptions, the identified emphasis on resilience, analytical capability, and relationship management becomes especially strategic. Building these "meta-competencies"—capabilities that support adaptation to change—creates organizational agility essential for success in volatile environments. Compared to frameworks widely used in developed markets, such as the ELA standards, this approach demonstrates adaptability by addressing region-specific constraints while maintaining alignment with international best practices.

6.2.3. Theoretical Contributions to Human Resource Development

This study makes three significant contributions to human resource development theory and practice. First, it advances competency-based HRD practice through analytical rigor. While competency-based approaches dominate contemporary HRD practice, most CbTNA relies heavily on qualitative judgment. This study demonstrates how Multi-Criteria Decision-Making methods can substantially improve decision quality by reducing bias, systematically integrating multiple expert perspectives, and creating transparent, defensible prioritization logic.

Second, it distinguishes between the importance of a competency and its need. A critical contribution is demonstrating that "importance" (strategic value) and "need" (current performance gap) are distinct dimensions requiring separate analysis. Many businesses mistake strategic importance for training priority, resulting in misallocated training budgets. This framework clarifies that optimal training investment targets competencies that are both strategically important and have measurable performance gaps.

Third, it supports analytics-driven HRD as a discipline. This study contributes to the emerging field of "analytics-driven HRD"—the application of data-driven decision-making to human resource development. As organizations increasingly expect HR to demonstrate business impact and financial return on investment, frameworks supporting evidence-based training decisions become strategically essential. The findings are consistent with previous research emphasizing the integration of technical and behavioral skills for effective logistics management (Christopher, 2016; Rushton, Croucher, & Baker, 2017). However, this study advances HRD scholarship by demonstrating that effective training prioritization

requires distinguishing between competency "importance" and "need"—a distinction often blurred in traditional needs assessment approaches.

6.3. Limitations and Future Research Directions

The F-BWM approach applied in this study has some methodological limitations. First, expert evaluations are initially collected on a classical 1–9 scale and then converted to triangular fuzzy numbers. While this conversion process allows for modeling expert uncertainty, it does not eliminate the structural assumptions of the initial scale. Second, multiple expert opinions are combined using the geometric mean, with all experts treated equally. Although there are differences between expert experience levels, the weighted expert model is not used. Third, the classical F-BWM linear optimization model is not solved in this study; instead, a ratio-based approximation formulation is preferred. This approach simplifies the computational process and facilitates application; however, it does not allow for the direct calculation of the linear-programming-based consistency indicator (ζ). Fourth, the method uses deterministic defuzzification (centroid method). Alternative defuzzification methods (e.g., α -cut-based approaches) may produce different results. Finally, the criterion structure is limited to a two-level hierarchical model. Inter-criterion feedback or network-type dependencies are not considered. Despite these limitations, the implemented method offers a computationally efficient and reproducible decision framework that integrates expert uncertainty into the model.

Beyond these methodological considerations, several contextual and design related limitations should be acknowledged. First, this study focuses exclusively on the logistics industry and is situated within a single country (Türkiye). While the proposed framework is theoretically transferable, the relative importance of specific competencies may vary across different industries (e.g., healthcare, finance, manufacturing) and cultural or institutional contexts. Therefore, the generalizability of the findings to other industries or countries requires empirical validation. Future research should replicate the framework in multiple industries and cross national settings to assess the stability of competency weightings and training priorities.

Second, the case study presented in this paper is based on a simulated departmental scenario rather than real world data. Although the simulation demonstrates the model's operational logic and step by step applicability, it does not capture the full complexity of actual workforce dynamics, such as political considerations, budget constraints, or varying employee motivation levels. Future studies should apply the framework to real world logistics businesses, using authentic employee assessment data, to validate its practical utility and measure the return on investment of training interventions.

Third, this study employs a cross sectional design, assessing competency gaps and training needs at a single point in time. However, competency requirements are not static; they evolve with technological advancements, market shifts, and changes in organizational strategy (e.g., digitalization, automation, new regulatory frameworks). A cross sectional snapshot may miss emerging needs or overemphasize temporary deficits. Longitudinal research is needed to track how competency gaps change over time, to evaluate the durability of training effects, and to enable dynamic, adaptive workforce planning. Future work should implement repeated assessments (e.g., annually or biennially) within the same organization to capture these temporal dynamics and refine the model accordingly.

While this study demonstrates the framework's effectiveness in a single logistics business in an emerging market context, broader applications across industries and

geographic regions remain unexplored. Given the framework's theoretical grounding in HRD principles and MCDM methodology, we anticipate strong applicability across knowledge-intensive industries, including healthcare, information technology, financial services, and government organizations. Future research should test the framework's effectiveness across these diverse contexts.

Future research could integrate machine learning techniques to refine competency assessment processes further. Techniques such as natural language processing (NLP) can be used to analyze job descriptions and competency frameworks to more accurately identify skill requirements. Additionally, clustering algorithms such as k-means can classify employees by their competency profiles, while predictive models, including neural networks, can predict future competency needs based on industry trends. These approaches can complement F-BWM by automating data-driven decision-making processes and increasing the scalability of competency assessments. Furthermore, longitudinal studies evaluating the long-term impact of F-BWM-based training interventions on organizational performance will provide deeper insights into the sustained value of this analytical prioritization methodology.

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The authors declare that this study has been conducted in full compliance with internationally recognized ethical standards for research involving human participants. All participants are notified about the purpose, scope, and procedures of the study prior to their involvement. They are clearly informed that participation is entirely voluntary and that they may withdraw from the study at any stage without negative consequences.

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