SCIENTIFIC OASIS

Journal of Intelligent Decision Making and Granular Computing

Journal homepage: www. jidmag.org
ISSN: 3042-3759

An Integrated CRITIC–TOPSIS Framework for Warehouse Personnel Performance Evaluation: Evidence from an Electronics Manufacturing Enterprise

Yu-Hsiang Chiu[1], Huai-Wei Lo[1], Sheng-Wei Lin[2*]

[1] Department of Industrial Engineering and Management, National Yunlin University of Science and Technology, Yunlin 640, Taiwan
[2] Department of Financial Management, National Defense University, Taipei, Taiwan

ARTICLE INFO

Article history:
Received 28 December 2025
Received in revised form 29 January 2026
Accepted 2 March 2026
Available online 15 March 2026

Keywords:
Multi-criteria decision making; CRITIC; TOPSIS; Warehouse management; Human resource management; Electronics manufacturing

ABSTRACT

Employee performance evaluation is a cornerstone of strategic human resource management, enabling organisations to align individual contributions with corporate objectives and sustain competitive advantage. In many manufacturing enterprises, appraisal systems remain generic in design, rely on simple additive scoring, and lack longitudinal tracking, thereby failing to capture the nuanced dynamics of specialised functional units. This study proposes an objective, department-specific evaluation framework integrating the Criteria Importance Through Intercriteria Correlation (CRITIC) weighting method with the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) ranking approach. The framework was developed for the warehouse management division of a large electronics contract manufacturer and applied across twelve consecutive monthly evaluation cycles. A panel of eleven senior managers defined a performance instrument comprising ten criteria and thirty-one sub-criteria. CRITIC objectively assigned criterion weights from the statistical variability and intercorrelation of scores, eliminating subjective bias. TOPSIS produced defensible employee performance rankings by measuring proximity to the ideal solution. Professional skills and leadership consistently received the two highest weights, jointly accounting for approximately 35% of the total weighting. Longitudinal tracking revealed meaningful performance trajectories supporting targeted talent development and intervention decisions. The framework has been formally adopted by the case company as its instrument for operational performance evaluation.

1. Introduction

The electronics contract manufacturing industry occupies a strategically critical position in global supply chains, providing full-service design, assembly, and logistics solutions to original equipment

* *Corresponding author.*
E-mail address: author.mail@gmail.com

https://doi.org/10.31181/jidmgc21202633

manufacturers worldwide. Enterprises in this sector face relentless pressure to reduce unit costs, accelerate product cycles, and maintain exacting quality standards, rendering human capital management an increasingly decisive source of competitive differentiation. As Kazlauskaite and Buciuniene [1] observed, human resources constitute the primary vehicle through which organisations develop core competencies and sustain long-term growth. Samson and Bhanugopan [2] corroborated this view by demonstrating that strategic human capital analytics substantially improve managerial decision-making and overall organisational performance.

Within human resource management, employee performance evaluation is widely regarded as the institutional mechanism through which organisations assess individual contributions, calibrate reward and development initiatives, and ensure that workforce capabilities remain aligned with strategic imperatives. Rusu *et al.,* [3] characterised performance appraisal as an indispensable management tool that not only verifies whether organisational goals are being pursued effectively but also releases latent organisational potential. Selvarajan *et al.,* [4] demonstrated that fair and transparent performance evaluations strengthen employees' intrinsic motivation and, ultimately, their performance. Despite this well-established importance, performance evaluation systems in practice continue to exhibit significant shortcomings.

Three recurring deficiencies are especially prevalent. First, most enterprise-wide instruments employ uniform criteria across all functional units, disregarding substantive differences in work content and skill requirements between departments. Second, performance scoring typically relies on simple weighted averages, presupposing linear independence among criteria. Bol [5] noted that when key performance indicators cannot be rigorously quantified, the evaluation system loses internal consistency. Third, most systems evaluate performance at a single point in time rather than tracking it longitudinally, thereby precluding trend analysis and early detection of talent development trajectories. Douthit *et al.,* [6] further observed that even the framing of performance information affects employees' perceptions of compensation fairness.

Company X, the subject of this empirical study, is a Taiwan-based electronics contract manufacturer with more than 4,000 employees across 30 production and service locations spanning four continents. Specialising in System-in-Package (SiP) module technologies and comprehensive micro-miniaturisation solutions, Company X provides global clients with integrated design, manufacturing, materials procurement, supply chain logistics, and after-sales services. The materials department, which encompasses the warehouse management function examined here, employs approximately 140 personnel. As the company has transitioned toward a high-mix, low-volume flexible manufacturing model, the demands for warehouse personnel have intensified considerably. Yet the existing performance appraisal system, designed as a universal instrument applicable to all departments, had not been updated to reflect these requirements. Evaluations were conducted on an impressionistic, single-period basis with no statistical weighting mechanism.

This study was motivated by the need to rectify those deficiencies. Its primary objectives are threefold: to construct a department-specific evaluation framework tailored to warehouse management in electronics manufacturing; to apply CRITIC to determine objective, data-driven criterion weights; and to implement TOPSIS to derive defensible employee performance rankings supported by 12 months of continuous data. The resulting system has been formally adopted by Company X as its official performance management instrument for the materials department. The remainder of this paper is organised as follows. Section 2 reviews the literature. Section 3 details the methodology. Section 4 presents the empirical application. Section 5 discusses the results and managerial implications. Section 6 concludes.

2. Literature Review

2.1 Employee Performance Evaluation

Performance evaluation is broadly understood as a systematic management process that uses scientific methods to assess the extent to which employees fulfil their designated responsibilities [7]. Contemporary organisations regard effective performance management as a determinant of organisational effectiveness, innovative capacity, and competitive standing [8]. The primary institutional goals of performance appraisal are to identify and cultivate employee potential and to provide equitable assessments that inform compensation, promotion, and disciplinary decisions [9,10].

Graen and Scandura [11] established the theoretical importance of leader-member exchange (LMX) dynamics, demonstrating that the quality of dyadic relationships between supervisors and subordinates substantially influences subsequent job performance outcomes. Fedor *et al.,* [12] showed that a supervisor's perceived sincerity and supportiveness moderate employees' receptiveness to feedback, while Liden *et al.,* [13] confirmed, through a longitudinal investigation, that early-stage LMX quality predicts future performance. Colquitt *et al.,* [10] conducted a landmark meta-analysis concluding that procedural, distributive, and interactional fairness dimensions are each significantly associated with employee performance, commitment, and satisfaction.

More recent scholarship has explored the roles of emotional intelligence, digital technology, and personality in shaping employee performance. Vidyarthi *et al.,* [14] demonstrated that emotionally perceptive leaders more effectively motivate employee performance under conditions of high task interdependence. Pitafi *et al.,* [15] found that enterprise social media platforms enhance employee performance through collaborative knowledge exchange. Buil *et al.,* [16] established that transformational leadership positively affects employee performance through the sequential mediation of organisational identification, engagement, and the expression of proactive personality [17]. In the warehouse and logistics context, Nong *et al.,* [18] demonstrated that employee competence and its alignment with job requirements exert direct effects on business performance, while Floyd *et al.,* [19] emphasised the valorisation of human resources as an enabling factor of competitiveness and sustainability.

2.2 Multi-Criteria Decision Making in Human Resource Management

Multi-criteria decision making (MCDM) methods provide a structured analytical foundation for problems that require the simultaneous evaluation of alternatives across multiple, potentially conflicting criteria [20]. Their application in human resource management has grown substantially, driven by recognition that personnel decisions are inherently multi-dimensional. Luo and Xing [21] proposed a hybrid framework integrating BWM, MABAC, and PROMETHEE for personnel selection, demonstrating that multi-method integration produces more robust outcomes. Chuang *et al.,* [22] developed a data-driven MCDM model for personnel selection and improvement, validated in a Taiwanese organisational context. Da Silva *et al.,* [23] reviewed the intersection of HRM and Industry 4.0, identifying MCDM-based assessment tools as a key methodological trend in HRM 4.0.

2.3 The CRITIC Weighting Method

CRITIC (Criteria Importance Through Intercriteria Correlation) is an objective weighting technique originally proposed by Diakoulaki *et al.,* and subsequently refined by Krishnan *et al.,* [24]. Its fundamental insight is that a criterion carries greater informational weight to the extent that (a) it exhibits high variability across alternatives, indicating discriminating power, and (b) it exhibits low correlation with other criteria, indicating that it captures unique information. By incorporating both the standard deviation of criterion scores and the inter-criterion correlation matrix, CRITIC produces weights that are sensitive to distributional variation and resistant to double-counting redundant information. Sharkasi and Rezakhah [25] proposed a fuzzy extension based on the Hamming distance, while Pala [26] introduced the ROCOSD method as a robustness-enhanced variant.

2.4 The TOPSIS Ranking Method

TOPSIS (Technique for Order Preference by Similarity to an Ideal Solution), reviewed comprehensively by Celikbilek and Tuysuz [27], is a distance-based MCDM technique that ranks alternatives based on their relative proximity to an ideal solution. The method constructs a positive ideal solution (PIS) composed of the best attainable values on each criterion and a negative ideal solution (NIS) composed of the worst attainable values. Each alternative's closeness coefficient is computed as a function of its Euclidean distances to both solutions. TOPSIS offers computational transparency, simultaneous reference to both ideal and anti-ideal solutions, and a clear ordering of alternatives. The present study adopts the modified closeness coefficient proposed by Kuo [28], which addresses limitations of the classical formulation and yields more reliable ranking outcomes.

2.5 Research Gap

A review of the existing literature reveals three substantive gaps that the present study addresses. First, while MCDM-based evaluation frameworks have been applied in several HRM contexts, their application to warehouse management personnel within the electronics manufacturing sector remains underexplored. Second, prior studies have predominantly employed subjective weighting methods such as AHP or BWM, which embed evaluator biases into the weight structure; the use of CRITIC for objective weighting in personnel evaluation represents a comparatively underexplored methodological contribution. Third, virtually no prior study in this domain has conducted a longitudinal performance evaluation over 12 consecutive monthly cycles, enabling systematic analysis of individual performance trajectories. The present study addresses all three gaps simultaneously.

3. Methodology

3.1 Overview of the Research Framework

The research methodology proceeds through three sequential phases. In the first phase, a performance evaluation framework is constructed through a structured combination of literature synthesis and expert consultation, yielding a hierarchical system of ten criteria and thirty-one sub-criteria. In the second phase, performance data collected from monthly evaluations are processed by the CRITIC algorithm to generate objective criterion weights that reflect the data's statistical properties. In the third phase, the weighted performance scores are fed into TOPSIS to produce ranked employee orderings within each evaluation period. The outputs from twelve evaluation cycles are then aggregated to generate cumulative rankings that reveal longitudinal performance trends.

Figure 1 presents the integrated research methodology framework governing the CRITIC–TOPSIS evaluation system developed in this study. The framework is organized into three sequential phases, each addressing a distinct methodological challenge inherent in personnel performance assessment.

Phase 1 establishes the analytical foundation through a dual-track knowledge construction process. A systematic literature review identifies theoretically grounded performance dimensions relevant to warehouse management, while parallel expert consultations with eleven senior managers from Company X's materials department validate and refine those dimensions against operational realities. The convergence of these two knowledge streams produces a hierarchical evaluation instrument comprising ten criteria and thirty-one sub-criteria, assessed on a five-level aspiration scale. This hybrid approach ensures that the resulting framework carries both theoretical legitimacy and contextual validity, addressing the criticism that generic appraisal instruments fail to capture the specific competency requirements of specialized functional roles.

Phase 2 operationalizes objective-criterion weighting using the CRITIC algorithm. Raw evaluation data are normalized using an aspiration-level transformation to ensure cross-period comparability, after which the standard deviation of each criterion and the full intercriteria correlation matrix are computed. The CRITIC information measure synthesizes these two statistical properties, rewarding criteria that exhibit high discriminating power while penalizing those that contribute redundant information already captured by correlated dimensions. The resulting weights are derived entirely from observed data, eliminating the subjective biases that typically arise in AHP- or BWM-based weighting procedures.

Phase 3 applies TOPSIS to translate the objectively weighted performance scores into a defensible employee ranking. By simultaneously measuring each employee's Euclidean distance from both the positive and negative ideal solutions and computing the modified closeness coefficient proposed by Kuo [28], TOPSIS produces rankings that reward balanced excellence rather than strength on isolated criteria. The dashed feedback loop connecting the output layer to Phase 2 emphasizes the longitudinal character of the study: the entire weighting and ranking procedure is repeated independently across twelve monthly cycles, generating the cumulative trajectory data that constitute the study's primary empirical contribution.

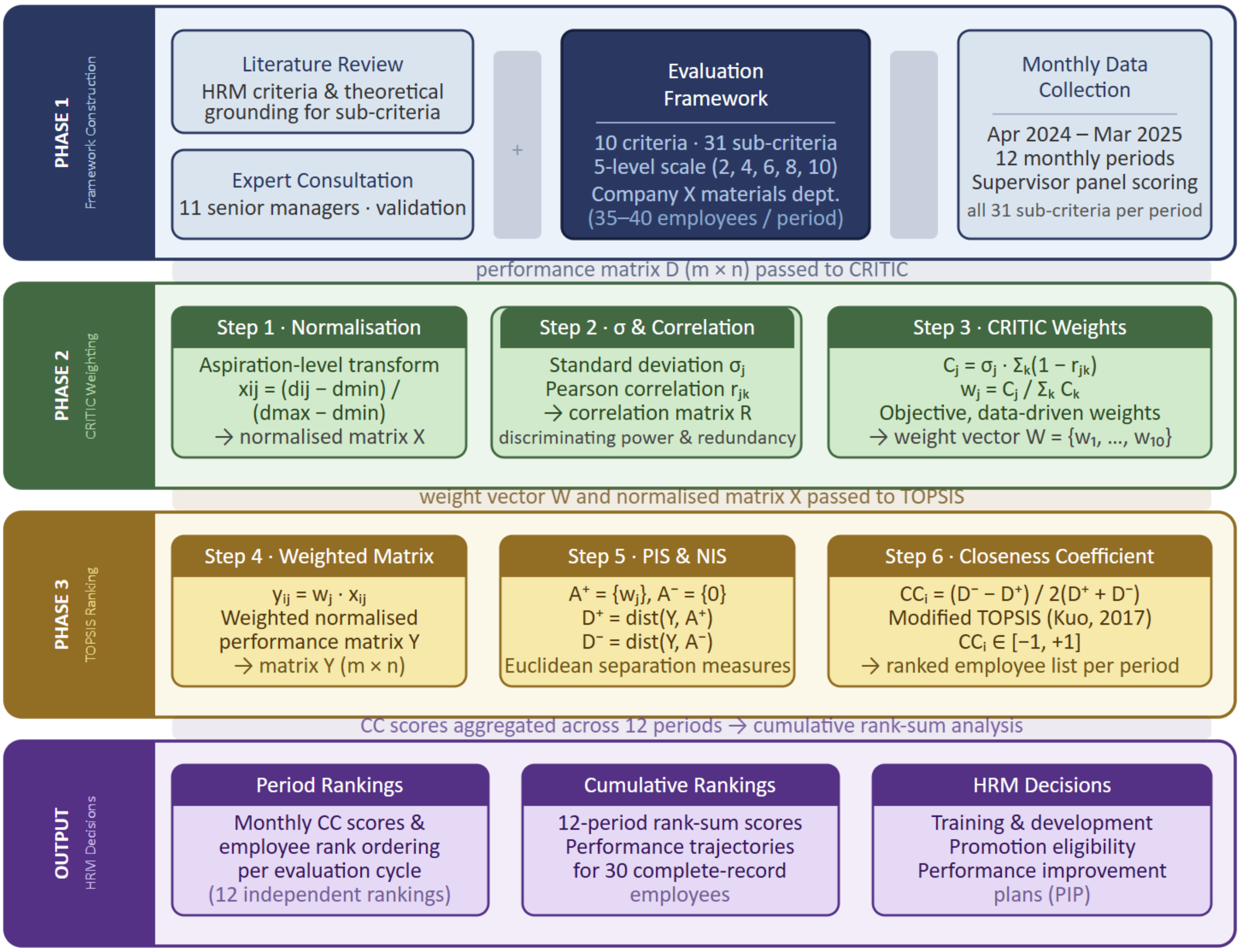

Fig. 1. Research Methodology Framework of the Integrated CRITIC–TOPSIS Evaluation System

3.2 CRITIC Criterion Weighting

Let D denote the initial performance matrix of dimensions m × n, where m is the number of employees and n is the number of criteria. The element d_{ij} represents employee i's aggregated score on criterion j, computed by applying the sub-criterion weights to the corresponding sub-criterion scores.

Step 1.1 (Normalisation). The performance matrix is normalised to the unit interval using the aspiration-level approach. Given a maximum achievable score of 10 and minimum of 2, the normalised value is computed as

$$x_{ij} = \frac{d_{ij}-2}{10-2} \quad (1)$$

The use of a fixed aspiration-level range rather than the observed range ensures scale consistency across evaluation periods.

Step 1.2 (Standard Deviation and Intercriteria Correlation). The standard deviation σ_j of criterion j across all employees is computed from the normalised matrix X. The Pearson correlation coefficient r_{jk} between criteria j and k is computed and assembled into the correlation matrix R.

Step 1.3 (Objective Weights). The information measure

$$C_j = \sigma_j \cdot \sum_{k\neq j}\left(1 - r_{jk}\right) \quad (2)$$

reflects both the criterion's standalone variability and its independence from the remaining criteria. The objective weight is obtained by normalisation:

$$w_j = \frac{C_j}{\sum_k C_k} \quad (3)$$

Criteria with high standard deviations and low intercorrelations receive higher weights; criteria highly correlated with others receive lower weights.

3.3 TOPSIS Employee Ranking

Step 2.1 (Weighted Normalised Matrix). The weighted normalised matrix Y is obtained as

$$y_{ij} = w_j \cdot x_{ij} \quad (4)$$

Step 2.2 (Ideal Solutions). The positive ideal solution $A^+ = \{w_j\}$ comprises the maximum weighted normalised value for each criterion. The negative ideal solution $A^- = \{0\}$ comprises the minimum value of zero for each criterion.

Step 2.3 (Separation Distances). Euclidean distances from the positive and negative ideal solutions are computed as

$$D_i^+ = \sqrt{\sum_j \left(y_{ij} - w_j\right)^2}, \quad D_i^- = \sqrt{\sum_j y_{ij}^2} \quad (5)$$

Step 2.4 (Closeness Coefficient and Ranking). Following Kuo [28], the closeness coefficient is defined as

$$CC_i = \frac{D_i^- - D_i^+}{2\left(D_i^+ + D_i^-\right)} \quad (6)$$

This formulation assigns equal weights of 0.5 to proximity to the positive ideal solution and distance from the negative ideal solution. CC_i values range from −1 (worst) to +1 (best). Employees are ranked in descending order of CC_i.

4. Empirical Application

4.1 Company Profile and Problem Description

Company X is a leading global electronics design and manufacturing service provider headquartered in Taiwan, with a workforce exceeding 4,000 employees distributed across 30 production and service facilities in Asia, Europe, the Americas, and Africa. Specialising in System-in-Package (SiP) module technology, Company X provides clients with comprehensive micro-miniaturisation solutions encompassing electronic product design, manufacturing, materials procurement, supply chain logistics, and after-sales repair services.

The materials department employs approximately 140 personnel. The warehouse management sub-unit examined here comprises 35 to 40 staff whose headcount fluctuates across evaluation periods due to turnover, maternity leave, mid-cycle transfers, and new hires. Prior to this study, the department used a company-wide generic appraisal instrument that relied primarily on impressionistic assessments and simple additive scoring across criteria not calibrated to warehouse management roles.

4.2 Evaluation Criteria Framework

The evaluation framework was developed through a systematic literature review followed by structured consultations with eleven senior managers from the materials department. The framework comprises ten main criteria (C1-C10) and thirty-one sub-criteria. Table 1 presents the complete framework, including sub-criterion descriptions, intra-criterion weights, and supporting references.

Table 1
Performance evaluation framework: criteria, sub-criteria, and intra-criterion weights

Criterion	Sub-Criteria (Weight)	Description	Ref.
C1: Responsibility	C11: Work Efficiency (40%) C12: Attendance (30%) C13: Special Task Completion (30%)	Achievement of operational standards; attendance; collaborative completion of project-based tasks	[37,38]
C2: Teamwork	C21: Policy Compliance (60%) C22: Cross-Unit Support (20%) C23: Collaborative Problem-Solving (20%)	Alignment with corporate strategy; cross-unit support; effective collaborative task completion	[32,33,19]
C3: Professional Skills	C31: Technical Knowledge (40%) C32: Spreadsheet Skills (20%) C33: Forklift Licence (20%) C34: TOEIC 350+ (20%)	Job-specific expertise; software proficiency; certified forklift operation; English language competency	[21,22,34]
C4: Work Experience	C41: Multi-Role Experience (40%) C42: Error Reduction (30%) C43: Process Improvement (30%)	Cross-functional experience breadth; error minimisation; workflow improvement proposals	[21,31]
C5: Ethical Conduct	C51: Respect for Others (40%) C52: Rule Compliance (30%) C53: Non-Harmful Behaviour (30%)	Respect for colleagues' rights; regulatory adherence; avoidance of harmful actions	[22,31,19]
C6: Personal Traits	C61: Proactiveness (40%) C62: Helpfulness (30%) C63: Stress Tolerance (30%)	Initiative beyond assigned duties; willingness to assist; capacity to overcome obstacles	[29,30]

Table 1
Continued

Criterion	Sub-Criteria (Weight)	Description	Ref.
C7: Logical Thinking	C71: Multi-Perspective Analysis (40%) C72: Sound Judgement (30%) C73: Problem-Solving (30%)	Capacity to examine issues from multiple angles; clear judgement; effective solution formulation	[31,39]
C8: Communication Skills	C81: Active Listening (40%) C82: Clarity of Expression (30%) C83: Consensus Building (30%)	Skill in listening; clarity in conveying ideas; effectiveness in reaching mutual agreement	[21,22,39]
C9: Continuous Learning	C91: Professional Training (50%) C92: English Improvement (30%) C93: In-Service Education (20%)	Participation in professional development; internal/external English learning; higher qualifications	[22,19,39]
C10: Leadership	C101: Role-Model Behaviour (50%) C102: Motivating Others (30%) C103: Mentorship (20%)	Setting a positive example; inspiring colleagues; providing guidance and developmental coaching	[35,36]

Supervisors evaluated each employee on each sub-criterion using a five-level scale with scores of 2, 4, 6, 8, and 10, corresponding to significantly below expectations, below expectations, meets expectations with room for improvement, outstanding with notable strengths, and fully meets supervisory expectations, respectively. Sub-criterion weights were determined by expert consensus through iterative consultation rounds.

4.3 Data Collection and Evaluation Cycles

Performance data were collected across twelve monthly evaluation cycles, designated Period 1 (April 2024) through Period 12 (March 2025). In each cycle, the eleven-member management panel collectively assessed each employee's performance on all thirty-one sub-criteria, drawing on direct supervisory observation accumulated over the preceding month. The number of employees evaluated varied from 35 to 40 per period due to personnel changes. Over the full twelve-month window, 44 unique employees appeared in at least one cycle, of whom 30 completed all twelve cycles without interruption.

4.4 CRITIC Weight Computation

The CRITIC weighting procedure was applied independently within each of the twelve evaluation periods, yielding period-specific objective weights. Table 2 reports the CRITIC-derived weights for each criterion across all periods, including the twelve-period average.

To illustrate the computational procedure, Table 3 reports the standard deviations of normalised criterion scores for Period 12 (March 2025). Criterion C9 exhibits a standard deviation of zero in this period, reflecting the absence of measurable variation among employees, as all received uniform scores on all three sub-criteria. This outcome is attributable to the binary and infrequent nature of C9 activities. Table 4 presents the intercriteria correlation matrix for the same period.

Several notable correlation patterns merit discussion. The correlation between C7 (Logical Thinking) and C8 (Communication Skills) is 0.900, indicating a strong tendency for employees who perform well on analytical reasoning to also exhibit strong interpersonal communication skills. Similarly, C6 (Personal Traits) and C8 are correlated at 0.840. These high intercorrelations are precisely the patterns that CRITIC penalises, resulting in lower weights for these criteria than a purely variance-based scheme would produce. Conversely, C3 (Professional Skills) exhibits relatively low correlations with most criteria (notably -0.071 with C1), reflecting the independence of technical proficiency from interpersonal dimensions. This independence, combined with C3's high standard deviation, contributes to its consistently high weight.

Table 2
CRITIC-derived objective criterion weights across twelve evaluation periods

Period	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
24-Apr	10%	10%	18%	3%	10%	12%	12%	11%	0%	15%
24-May	7%	7%	22%	4%	9%	13%	11%	10%	0%	16%
24-Jun	9%	7%	24%	5%	7%	12%	10%	10%	0%	16%
24-Jul	9%	3%	28%	4%	6%	10%	12%	11%	0%	17%
24-Aug	10%	4%	26%	7%	2%	11%	11%	12%	0%	17%
24-Sep	20%	3%	18%	8%	6%	10%	11%	10%	0%	14%
24-Oct	21%	4%	16%	10%	10%	10%	11%	6%	0%	13%
24-Nov	17%	4%	18%	6%	10%	10%	13%	8%	0%	14%
24-Dec	11%	10%	17%	11%	8%	9%	12%	8%	0%	13%
25-Jan	9%	1%	16%	6%	6%	12%	14%	10%	10%	16%
25-Feb	15%	4%	17%	10%	6%	11%	13%	11%	0%	13%
25-Mar	12%	6%	18%	9%	6%	11%	14%	11%	0%	13%
Average	13%	5%	20%	7%	7%	11%	12%	10%	1%	15%

Table 3
Standard deviations of normalised criterion scores, Period 12

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
0.081	0.064	0.14	0.073	0.059	0.138	0.168	0.147	0	0.166

Table 4
Intercriteria correlation matrix, Period 12

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	1	0.247	-0.071	0.027	0.372	0.298	0.065	0.22	0	0.198
C2	0.247	1	0.206	0.497	0.641	0.834	0.632	0.702	0	0.664
C3	-0.071	0.206	1	0.213	0.118	0.254	0.656	0.552	0	0.545
C4	0.027	0.497	0.213	1	0.207	0.512	0.536	0.495	0	0.622
C5	0.372	0.641	0.118	0.207	1	0.781	0.415	0.661	0	0.632
C6	0.298	0.834	0.254	0.512	0.781	1	0.638	0.84	0	0.762
C7	0.065	0.632	0.656	0.536	0.415	0.638	1	0.9	0	0.798
C8	0.22	0.702	0.552	0.495	0.661	0.84	0.9	1	0	0.863
C9	0	0	0	0	0	0	0	0	1	0
C10	0.198	0.664	0.545	0.622	0.632	0.762	0.798	0.863	0	1

4.5 TOPSIS Performance Ranking

TOPSIS was applied in each evaluation period using the corresponding CRITIC weights. Table 5 presents the TOPSIS results for Period 12, including the distance from the positive ideal solution (D+), the distance from the negative ideal solution (D-), and the closeness coefficient (CC) for selected employees. Employee identifiers have been anonymised in accordance with research ethics commitments.

Table 5
TOPSIS results for Period 12: selected employees ranked by closeness coefficient

Rank	Employee ID	D+	D-	CC
1	E31	0.108	0.273	0.008
2	E22	0.11	0.272	0.008
3	E05	0.118	0.278	0.008
4	E18	0.13	0.25	0.005
5	E25	0.14	0.261	0.005
...	...	...	...	...
33	E16	0.211	0.179	-0.005
34	E19	0.205	0.168	-0.005
35	E34	0.221	0.2	-0.005
36	E20	0.229	0.144	-0.008
37	E02	0.236	0.138	-0.009

Table 6 aggregates the results across all twelve periods by summing each employee's monthly rank, then ordering employees by their cumulative rank sum. A lower cumulative rank sum indicates more consistently high performance across the full study window. Only the 30 employees who completed all twelve periods without interruption are included in this cumulative ranking.

Table 6
Cumulative twelve-period performance rankings and key performance characteristics

12-Period Rank	Employee ID	Cumulative Rank Sum	Key Characteristic
1	E_Top1	19	Consistent top-three placement across all 12 periods
2	E_Top2	47	Strong improvement trajectory; moved from mid-tier to top-three from Period 5 onward
3	E_Top3	57	Particularly strong on professional skills and ethical conduct
4	E_Top4	69	Outstanding logical thinking and communication scores
5	E_Top5	74	Consistent performance across all criteria with no notable weaknesses
...	...	...	...
24	E_Bot2	339	Low professional skills and leadership; targeted training recommended
25	E_Bot1	342	Weakest cumulative performance: formal intervention plan warranted

5. Results and Discussion

5.1 Criterion Importance: Findings from CRITIC

The average CRITIC weights reported in Table 2 reveal a clear hierarchy of criterion importance across the twelve evaluation periods. Professional Skills (C3) received the highest average weight of 20%, followed by Leadership (C10) at 15%, Responsibility (C1) at 13%, Logical Thinking (C7) at 12%, and Personal Traits (C6) at 11%. Together, these five criteria account for approximately 71% of the total weighting. This distribution reflects the operational reality of warehouse management in electronics manufacturing, where technical proficiency and leadership capacity are the primary differentiators of employee effectiveness.

The high weight assigned to Professional Skills (C3) is particularly instructive. In this context, technical competencies encompass not only operational skills in materials handling and inventory management but also software proficiency for electronic documentation and certified skills in safe materials handling. As the company transitioned toward more complex, multi-variant production schedules, proficient use of spreadsheet software for inventory tracking and reporting has become increasingly central to effective job performance [38,39].

The relatively low average weights of Teamwork (C2) at 5% and Continuous Learning (C9) at 1% reflect not a low importance of these dimensions in principle but rather their limited discriminative power in the empirical data. On Teamwork, employees generally scored consistently high, reflecting the strongly collaborative culture within the materials department; the resulting low standard deviation translates into a low CRITIC weight. For Continuous Learning, the zero-variation problem in most periods is directly responsible for the near-zero weight. C9 received a non-negligible weight of 10% in January 2025 (Period 10), the only period when a subset of employees completed qualifying training programs. The temporal stability of the top-five criteria across twelve periods provides empirical support for the construct validity of the evaluation framework.

Figure 2 synthesizes the CRITIC-derived criterion weight evidence through two complementary visualizations that together illuminate both the cross-sectional and longitudinal dimensions of criterion importance in the warehouse personnel evaluation system.

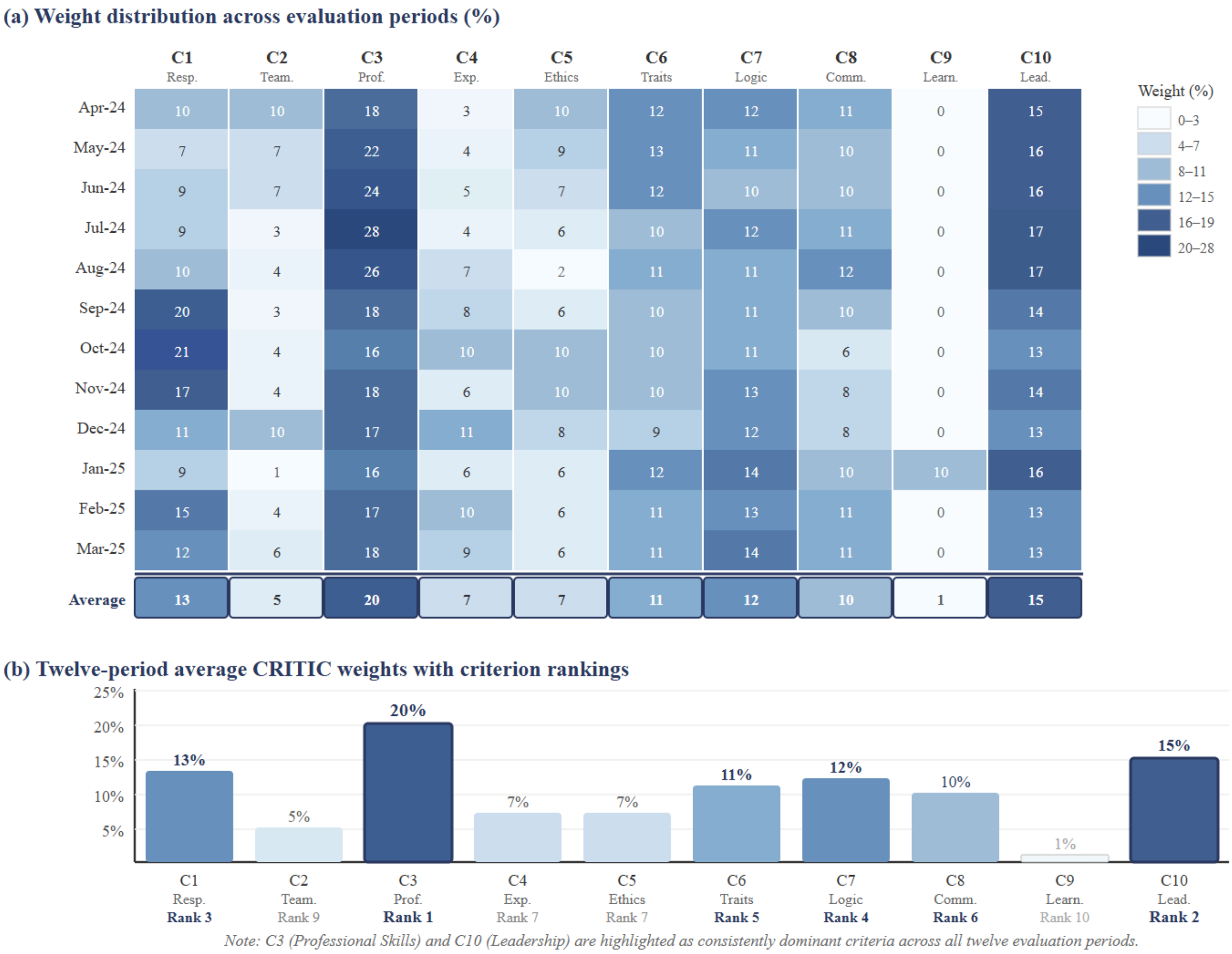

Fig. 2. CRITIC-Derived Criterion Weights Across Twelve Evaluation Periods and Twelve-Period Averages

Panel (a) presents a heatmap of CRITIC weights across all twelve evaluation periods. The color intensity, calibrated on a sequential blue scale from near-zero (white) to high-weight (dark navy), reveals two immediately striking patterns. First, C3 (Professional Skills) consistently occupies the darkest cells in virtually every period, confirming that technical proficiency constitutes the single most discriminating dimension of performance throughout the entire study window. This stability is attributable to C3's persistent combination of high standard deviation and low intercorrelations with behavioral criteria such as C1 and C5, precisely the data properties that the CRITIC algorithm rewards. Second, C9 (Continuous Learning) remains conspicuously white across eleven of twelve periods, reflecting the near-zero variance produced when no employees participate in qualifying training programs within a given month. The single exception in January 2025 (Period 10), where C9 rises to 10%, captures the effect of a cohort completing professional development activities, demonstrating that CRITIC weights are genuinely responsive to distributional changes in the underlying data rather than being anchored to static expert judgements.

Panel (b) complements the temporal heatmap with a bar chart of twelve-period average weights, annotated with criterion rankings. The clear height hierarchy confirms that C3 (20%, Rank 1) and C10 (Leadership, 15%, Rank 2) jointly dominate the weight distribution, accounting together for 35% of the total criterion importance. The next tier, comprising C1 (Responsibility, 13%), C7 (Logical Thinking, 12%), and C6 (Personal Traits, 11%), reflects the operational realities of warehouse coordination roles, where analytical problem-solving and proactive behavioral dispositions meaningfully differentiate higher performers. The pronounced underweighting of C2 (Teamwork, 5%) and C9 (Continuous Learning, 1%) does not imply managerial irrelevance; rather, it reflects the restricted variance in these dimensions within the studied workforce, an empirical signal that management interventions should prioritize the high-weight, high-variance dimensions where developmental investment yields the greatest differentiation in evaluated outcomes.

5.2 Employee Performance Rankings and Trajectories

The twelve-period cumulative rankings reveal clear groupings of consistently high-, mid-, and low-performing employees. The five employees with the lowest cumulative rank sums maintained top-tier positions across most evaluation periods, demonstrating sustained excellence. Their score profiles reveal two common characteristics: consistently strong ratings on C3 (Professional Skills) and C10 (Leadership), and uniformly high ratings on C5 (Ethical Conduct).

Trajectory analysis reveals heterogeneous patterns with meaningful managerial implications. One high-performing employee exhibited a strong upward trajectory, moving from a mid-tier position in the first three periods to a top-three position in all subsequent periods. This pattern is consistent with that of a new or recently transferred employee who required an initial familiarization period before demonstrating full competence. The multi-period framework makes such trajectories visible to management, enabling timely, evidence-based talent acceleration decisions.

Conversely, employees with the highest cumulative rank sums consistently exhibited low scores in professional skills and leadership, with some also showing deteriorating trends in logical thinking and communication. These employees are candidates for structured performance improvement plans (PIPs), with interventions targeted at specific competency deficiencies identified through sub-criterion level data. It bears noting that 14 of the 44 unique employees were excluded from the cumulative ranking due to incomplete participation, attributable to resignation, maternity leave, mid-cycle transfer, and compulsory military service.

5.3 Managerial Implications

The CRITIC-TOPSIS framework carries several substantive implications for HRM in warehouse operations of electronics manufacturing enterprises. First, the identification of Professional Skills and Leadership as the two dominant criteria provides a clear strategic signal for investment in training and development. The framework's sub-criterion data enables highly targeted development planning: a manager can identify that a specific employee has high scores on C31 (technical knowledge) but low scores on C33 (forklift certification), and accordingly direct that employee toward certification acquisition rather than general technical training [22].

Second, the multi-period longitudinal dimension enables a more sophisticated approach to performance management than is possible with single-period systems. Managers can observe whether an employee's performance is improving, stable, or declining over time. An employee who performs poorly initially but shows consistent improvement may merit retention and investment; an employee who is stable but below threshold over multiple periods may be better served by a structured PIP with clear milestones.

Third, the objective CRITIC weighting methodology explicitly removes the potential for evaluator bias in the criterion weighting process. By deriving weights from the distributional properties of actual performance data, CRITIC ensures that high-weight criteria are precisely those that genuinely differentiate employees, independent of supervisory preferences [24,25]. This property is particularly important for organisational fairness, supporting the legitimacy and acceptance of evaluation outcomes [3,4,10].

Fourth, the formal adoption of this system by Company X as its official evaluation instrument for the materials department represents practice-based validation extending beyond the academic research context. The system's continuous deployment across 12 evaluation cycles, without any requests to modify the framework, provides evidence of practical utility and managerial acceptance.

6. Conclusions

This study has developed and empirically validated an integrated CRITIC-TOPSIS framework for the objective, multi-period evaluation of warehouse personnel performance in an electronics manufacturing enterprise. The framework addresses three documented deficiencies in conventional performance appraisal practice: the use of generic, department-agnostic criteria; the use of simple, subjectively weighted additive scoring; and the absence of longitudinal performance tracking to enable trend analysis and trajectory-based human resource decisions.

The empirical analysis, conducted over 12 consecutive monthly evaluation cycles, covering 35 to 40 warehouse management personnel, yielded several substantive findings. Professional Skills and Leadership consistently emerged as the two highest-weighted criteria, jointly accounting for approximately 35% of the total CRITIC weight across all periods. The TOPSIS rankings effectively differentiated employees across the full performance spectrum. Longitudinal tracking revealed heterogeneous performance trajectories carrying meaningful implications for talent development, retention, and succession planning.

The theoretical contributions of this study are threefold. First, it extends the MCDM literature into the domain of warehouse personnel evaluation within electronics manufacturing. Second, it demonstrates the practical advantages of CRITIC over subjective weighting methods, particularly in reducing evaluator bias and enhancing the legitimacy of appraisals. Third, it establishes the methodological value of multi-period, longitudinal evaluation frameworks as a template for trend-based HRM analytics.

Several limitations warrant acknowledgement. The framework was developed for a single functional unit within a single enterprise, and its direct transferability to other departments or industries has not been empirically tested. The study does not include psychometric validation (e.g., Cronbach's alpha) of the evaluation instrument. Future research directions include extending to other functional departments, incorporating psychometric validation, and comparative evaluation of alternative MCDM methods, such as VIKOR, AHP-TOPSIS, and fuzzy TOPSIS, to assess the robustness of rankings to methodological choice.

Funding
This research received no external funding.

Data Availability Statement
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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

References
[1] Kazlauskaite, R., & Buciuniene, I. (2008). The role of human resources and their management in the establishment of sustainable competitive advantage. *Engineering Economics, 5*(60), 78-84.
[2] Samson, K., & Bhanugopan, R. (2022). Strategic human capital analytics and organisation performance: The mediating effects of managerial decision-making. *Journal of Business Research, 144*, 637-649. https://doi.org/10.1016/j.jbusres.2022.01.044
[3] Rusu, G., Avasilcai, S., & Hutu, C. A. (2016). Organizational context factors influencing employee performance appraisal: A research framework. *Procedia - Social and Behavioral Sciences, 221*, 57-65. https://doi.org/10.1016/j.sbspro.2016.05.090
[4] Selvarajan, T. T., Singh, B., & Solansky, S. (2018). Performance appraisal fairness, leader member exchange and motivation to improve performance: A study of US and Mexican employees. *Journal of Business Research, 85*, 142-154. https://doi.org/10.1016/j.jbusres.2017.11.043
[5] Bol, J. C. (2008). Subjectivity in compensation contracting. *Journal of Accounting Literature, 27*, 1-32.
[6] Douthit, J., Majerczyk, M., Shi, B., & Thomas, T. (2025). How the realized measure of a worker's performance affects their perception of their compensation. *Management Accounting Research, 66*, Article 100927. https://doi.org/10.1016/j.mar.2025.100927
[7] Audenaert, M., Decramer, A., & George, B. (2021). How to foster employee quality of life: The role of employee performance management and authentic leadership. *Evaluation and Program Planning, 85*, Article 101909. https://doi.org/10.1016/j.evalprogplan.2021.101909
[8] Altindag, E., & Kosedagi, Y. (2015). The relationship between emotional intelligence of managers, innovative corporate culture and employee performance. *Procedia - Social and Behavioral Sciences, 210*, 270-282. https://doi.org/10.1016/j.sbspro.2015.11.367
[9] Diamantidis, A. D., & Chatzoglou, P. (2019). Factors affecting employee performance: An empirical approach. *International Journal of Productivity and Performance Management, 68*(1), 171-193. https://doi.org/10.1108/IJPPM-01-2018-0012
[10] Colquitt, J. A., Conlon, D. E., Wesson, M. J., Porter, C. O., & Ng, K. Y. (2001). Justice at the millennium: A meta-analytic review of 25 years of organizational justice research. *Journal of Applied Psychology, 86*(3), 425-445. https://doi.org/10.1037/0021-9010.86.3.425
[11] Graen, G. B., & Scandura, T. A. (1987). Toward a psychology of dyadic organizing. *Research in Organizational Behavior, 9*, 175-208.
[12] Fedor, D. B., Eder, R. W., & Buckley, M. R. (1989). The contributory effects of supervisor intentions on subordinate feedback responses. *Organizational Behavior and Human Decision Processes, 44*(3), 396-414. https://doi.org/10.1016/0749-5978(89)90016-2
[13] Liden, R. C., Wayne, S. J., & Stilwell, D. (1993). A longitudinal study on the early development of leader-member exchanges. *Journal of Applied Psychology, 78*(4), 662-674. https://doi.org/10.1037/0021-9010.78.4.662
[14] Vidyarthi, P. R., Anand, S., & Liden, R. C. (2014). Do emotionally perceptive leaders motivate higher employee performance? *The Leadership Quarterly, 25*(2), 232-244. https://doi.org/10.1016/j.leaqua.2013.08.003

[15] Pitafi, A. H., Kanwal, S., Ali, A., Khan, A. N., & Ameen, M. W. (2018). Moderating roles of IT competency and work cooperation on employee work performance in an ESM environment. *Technology in Society, 55*, 199-208. https://doi.org/10.1016/j.techsoc.2018.08.002

[16] Buil, I., Martinez, E., & Matute, J. (2019). Transformational leadership and employee performance: The role of identification, engagement and proactive personality. *International Journal of Hospitality Management, 77*, 64-75. https://doi.org/10.1016/j.ijhm.2018.06.014

[17] Tisu, L., Lupsa, D., Virga, D., & Rusu, A. (2020). Personality characteristics, job performance and mental health: The mediating role of work engagement. *Personality and Individual Differences, 153*, Article 109644. https://doi.org/10.1016/j.paid.2019.109644

[18] Nong, N. M. T., Phuong, N. Q., & Duc-Son, H. (2024). The effect of employee competence and competence-job-fit on business performance through moderating role of social exchange. *The Asian Journal of Shipping and Logistics, 40*(4), 187-197. https://doi.org/10.1016/j.ajsl.2024.10.001

[19] Floyd, J. A., D'Adamo, I., Wamba, S. F., & Gastaldi, M. (2024). Competitiveness and sustainability in the paper industry: The valorisation of human resources as an enabling factor. *Computers and Industrial Engineering, 190*, Article 110035. https://doi.org/10.1016/j.cie.2024.110035

[20] Pamucar, D. S., & Savin, L. M. (2020). Multiple-criteria model for optimal off-road vehicle selection for passenger transportation: BWM-COPRAS model. *Vojnotehnicki glasnik, 68*(1), 28-64. https://doi.org/10.5937/vojtehg68-22916

[21] Luo, S. Z., & Xing, L. N. (2019). A hybrid decision making framework for personnel selection using BWM, MABAC and PROMETHEE. *International Journal of Fuzzy Systems, 21*(8), 2421-2434. https://doi.org/10.1007/s40815-019-00745-4

[22] Chuang, Y. C., Hu, S. K., Liou, J. J., & Tzeng, G. H. (2020). A data-driven MADM model for personnel selection and improvement. *Technological and Economic Development of Economy, 26*(4), 751-784. https://doi.org/10.3846/tede.2020.12366

[23] da Silva, L. B. P., Soltovski, R., Pontes, J., Treinta, F. T., Leitão, P., Mosconi, E., ... & Yoshino, R. T. (2022). Human resources management 4.0: Literature review and trends. *Computers & Industrial Engineering*, *168*, 108111.. https://doi.org/10.1016/j.cie.2022.108111

[24] Krishnan, A. R., Kasim, M. M., Hamid, R., & Ghazali, M. F. (2021). A modified CRITIC method to estimate the objective weights of decision criteria. *Symmetry, 13*(6), Article 973. https://doi.org/10.3390/sym13060973

[25] Sharkasi, N., & Rezakhah, S. (2022). A modified CRITIC with a reference point based on fuzzy logic and Hamming distance. *Knowledge-Based Systems, 255*, Article 109768. https://doi.org/10.1016/j.knosys.2022.109768

[26] Pala, O. (2023). A new objective weighting method based on robustness of ranking with standard deviation and correlation: The ROCOSD method. *Information Sciences, 636*, Article 118930. https://doi.org/10.1016/j.ins.2023.04.009

[27] Celikbilek, Y., & Tuysuz, F. (2020). An in-depth review of theory of the TOPSIS method: An experimental analysis. *Journal of Management Analytics, 7*(2), 281-300. https://doi.org/10.1080/23270012.2020.1748528

[28] Kuo, T. (2017). A modified TOPSIS with a different ranking index. *European Journal of Operational Research, 260*(1), 152-160. https://doi.org/10.1016/j.ejor.2016.11.052

[29] Ali, I. (2019). Personality traits, individual innovativeness and satisfaction with life. *Journal of Innovation & Knowledge, 4*(1), 38-46. https://doi.org/10.1016/j.jik.2017.11.002

[30] Abid, G., Arya, B., Arshad, A., Ahmed, S., & Farooqi, S. (2021). Positive personality traits and self-leadership in sustainable organizations: Mediating influence of thriving and moderating role of proactive personality. *Sustainable Production and Consumption*, *25*, 299-311.. https://doi.org/10.1016/j.spc.2020.09.005

[31] Sarkar, A., & Goswami, S. S. (2026). A Review of the Application of MCDM Methods in Business Analytics. *Applied Decision Analytics* , *2*(1), 150-180

[32] Wang, W., Atingabili, S., Mensah, I. A., Jiang, H., Zhang, H., Omari-Sasu, A. Y., & Tackie, E. A. (2022). Teamwork quality and health workers burnout nexus: a new insight from canonical correlation analysis. *Human resources for health*, *20*(1), 52.. https://doi.org/10.1186/s12960-022-00734-z

[33] Strode, D., Dingsoyr, T., & Lindsjorn, Y. (2022). A teamwork effectiveness model for agile software development. *Empirical Software Engineering, 27*(2), Article 56. https://doi.org/10.1007/s10664-021-10115-0

[34] Litvinenko, V., Bowbrick, I., Naumov, I., & Zaitseva, Z. (2022). Global guidelines and requirements for professional competencies of natural resource extraction engineers: Implications for ESG principles and sustainable development goals. *Journal of Cleaner Production*, *338*, 130530.. https://doi.org/10.1016/j.jclepro.2022.130530

[35] Cortellazzo, L., Bruni, E., & Zampieri, R. (2019). The role of leadership in a digitalized world: A review. *Frontiers in Psychology, 10*, Article 1938. https://doi.org/10.3389/fpsyg.2019.01938

[36] Piwowar-Sulej, K., & Iqbal, Q. (2023). Leadership styles and sustainable performance: A systematic literature review. *Journal of Cleaner Production, 382*, Article 134600. https://doi.org/10.1016/j.jclepro.2022.134600

[37] Cuadrado, E., Macias-Zambrano, L., Guzman, I., Carpio, A. J., & Tabernero, C. (2023). The role of implicit theories about climate change malleability in the prediction of pro-environmental behavioral intentions. *Environment, Development and Sustainability*, *25*(10), 11241-11261.. https://doi.org/10.1007/s10668-022-02525-x

[38] Wei, Y., Zhu, M., Lam, H. K., Liu, F., Yeung, A. C., Cheng, T. C. E., & Zhou, H. (2024). Protagonists in digital transformation: The impact of chief digital officers on firms' financial performance. *Journal of Industrial Information Integration*, *41*, 100678.. https://doi.org/10.1016/j.jii.2024.100678

[39] Xie, W., Zheng, D., Li, Z., Wang, Y., & Wang, L. (2024). Digital technology and manufacturing industrial change: Evidence from the Chinese manufacturing industry. *Computers & Industrial Engineering*, *187*, 109825.. https://doi.org/10.1016/j.cie.2023.109825