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Designing a Conceptual Model for Human Resource Performance Evaluation Indicators in the Banking Industry with Emphasis on the Fourth Industrial Revolution

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A B S T R A C T

The Fourth Industrial Revolution has not only introduced profound technological transformations but also brought about significant changes in business models and customer demands. In this context, human resources, as the most critical asset of organizations, play a key role in achieving these new objectives. Consequently, evaluating human resource performance has become one of the most crucial areas of organizational focus. This study aimed to design a conceptual model of human resource performance evaluation indicators in the banking industry, with a specific emphasis on the Fourth Industrial Revolution. The statistical population of this research was divided into two groups: fifteen subject-matter experts familiar with the research topic, and all senior, middle, and junior managers at various management levels within Bank Melli Iran. A sample of 335 individuals was selected from this population. Data were collected using three separate questionnaires. To analyze the data, fuzzy screening methods, exploratory factor analysis, and Interpretive Structural Modeling (ISM) were employed. The results of the fuzzy screening indicated that out of a total of 49 human resource performance evaluation indicators, 8 were eliminated, and 41 were confirmed by the experts. Moreover, the findings from the exploratory factor analysis showed that the 41 confirmed indicators could be categorized into seven main components. Finally, the results of the ISM phase revealed that flexibility and continuous learning constitute the foundation of the human resource performance evaluation model with an emphasis on the Fourth Industrial Revolution and are considered the most influential components within the model. In contrast, the component of quantitative and qualitative performance was identified as the most affected component in the structure of the proposed model.

Keywords: *Performance evaluation; Human resources; Fourth Industrial Revolution; Banking industry*

1. Introduction

In today's world, the banking industry, as one of the core pillars of every country's economic system, is facing new challenges that necessitate innovation and a transformation in managerial strategies (Challoumis & Eriotis, 2024). A prominent feature of these transformations is the emergence of the Fourth Industrial Revolution, which, by integrating advanced technologies such as artificial intelligence, the Internet of Things, big data, and advanced analytics, has opened new pathways for optimizing processes and organizational performance—especially within the banking industry (Ghandour, 2021). In this context, the importance of performance evaluation models for human resources in the banking sector becomes increasingly evident (Salampasis et al., 2015).

The Fourth Industrial Revolution has not only brought about technological changes but has also introduced significant shifts in business models, organizational culture, and customer expectations. For instance, in this era, customers seek personalized experiences and rapid services more than ever before, which demands specific capabilities from bank employees (Parida et al., 2019). Accordingly, human resources, as the most critical asset of organizations, play a pivotal role in achieving these objectives. This has transformed performance evaluation into one of the most important domains in human resource management—one that must be designed and implemented with sensitivity to new conditions and transformations (Ochieng, 2023).

In the context of Industry 4.0, employee performance evaluation should not be limited to merely measuring outcomes and individual achievements but must also give special attention to aspects such as perfectionism, innovation, and creativity (Kamble et al., 2020). With increasing competition and the commitment to continuous improvement, banks require a performance evaluation model that can accurately identify employee competencies and capacities in dealing with environmental and market challenges (Pahuja et al., 2024). Particularly, the use of emerging technologies such as machine learning systems in performance evaluation enables more precise data analysis and the discovery of hidden patterns. Moreover, the utilization of big data helps banks gain deeper insights into customer behavior and needs, thereby empowering employees to respond more effectively. This not only leads to increased customer satisfaction but also enhances organizational efficiency and productivity (Paramesha et al., 2024).

In addition, the rapid changes in the business environment and intensifying competition in the banking sector highlight the necessity of establishing unique performance evaluation mechanisms. These mechanisms must be designed in a way that allows adaptability to dynamic market conditions while simultaneously managing the risks and opportunities arising from technological transformations (Nasiri et al., 2020). Today, many banks aim to create a culture of continuous learning that not only promotes the knowledge and skills of employees but also fosters a spirit of collaboration and innovation among them (Amos & Natamba, 2015). In this regard, human resource performance evaluation systems should be structured to reward and recognize group-based and innovative efforts, rather than focusing solely on individual achievements.

Human resource performance evaluation refers to the systematic process of assessing and analyzing employee performance within organizations (Tahiri et al., 2020). It aims to determine the extent to which individual and organizational goals are achieved, identify strengths and weaknesses, and support planning for continuous improvement. The primary goal of performance evaluation is to deliver ongoing feedback that helps enhance employee skills and optimize efficiency (Cardy & Leonard, 2014). Effective evaluation not only identifies top talent and high performers, enabling organizations to retain and promote them, but also offers constructive feedback that guides individuals in overcoming weaknesses (Aguinis, 2009). Furthermore, when coupled with training and development programs, performance evaluation enhances skill-building and aligns personal objectives with organizational goals—boosting motivation and organizational commitment. Importantly, it also forms the basis for rewards, incentives, and promotions, fostering healthy internal competition and strategic alignment (Kamble et al., 2020). Performance appraisal is thus regarded as a vital tool that advances both individual progress and overarching organizational objectives (Ayers, 2015). Over the years, various models—such as 360-degree feedback, management by objectives (MBO), criteria-based evaluations, and data-driven systems—have been developed to ensure effective assessments (Tubré et al., 2014). In the banking sector, where rapid innovation is reshaping operations, having a flexible and effective performance evaluation framework is essential for improving service quality, enhancing efficiency, and meeting the evolving expectations of clients in the Industry 4.0 context.

Industry 4.0, also known as the Fourth Industrial Revolution, is driven by digital, communication, and automation technologies and aims to enhance responsiveness and productivity in dynamic markets. Key technologies include artificial intelligence, the Internet of Things (IoT), big data, and additive manufacturing (Rüßmann et al., 2015). These advances have significantly transformed human resource functions across multiple dimensions. First, employees' roles are shifting from routine tasks to more analytical and creative responsibilities, necessitating advanced digital skills (Bayraktar & Ataç, 2018). Second, there is a rising demand for new competencies in data analytics, programming, and interpersonal communication (Murugesan et al., 2023; Srinivasan et al., 2020). Third, the cultural foundation of organizations is changing to emphasize flexibility, innovation, collaboration, and team-based learning. Fourth, recruitment and evaluation processes are increasingly reliant on AI and digital tools, making selection and performance monitoring more efficient. Fifth, productivity gains and cost reductions are achieved through smart systems and automation, resulting in better service quality and customer satisfaction (Bayraktar & Ataç, 2018). Sixth, as digital work environments grow, employee well-being and mental health become crucial, requiring smart workplaces and employee experience feedback systems (Srinivasan et al., 2020). Seventh, the global nature of digital communications fosters greater diversity and inclusion, allowing organizations to access talent worldwide and benefit from varied perspectives (Vrchota, Maříková, et al., 2019; Vrchota, Volek, et al., 2019). Collectively, these changes call for continuous learning, adaptability, and a redefinition of performance indicators aligned with the demands of Industry 4.0.

As noted earlier, Industry 4.0 encompasses a set of technological shifts—including automation, IoT, AI, and big data analytics—that deeply impact performance evaluation systems, especially in banking. With automation replacing many repetitive banking tasks, employee responsibilities are becoming more analytical and strategic, requiring performance appraisals to emphasize creativity, problem-solving, and innovation (Reznik, 2021). Consequently, performance models must be updated to reflect this reality. Digital platforms and performance management software now enable real-time feedback and facilitate adaptive evaluation mechanisms (Lertpiromsuk et al., 2021; Sujatha et al., 2022). Moreover, lifelong learning is a foundational principle of Industry 4.0 (Prashar et al., 2023), and banks must prioritize continuous skill development to ensure employees can respond effectively to technological and market shifts. This commitment to training stimulates innovation and improves results. Alongside these demands, performance evaluations must also promote a culture rooted in flexibility, creativity, and growth (Hernandez-de-Menendez et al., 2020). Evaluations should go beyond operational and financial metrics to include the social impact and corporate responsibility of employees. While direct studies on HR performance evaluation in Industry 4.0 are limited, there is a growing body of research on required competencies in this era. Scholars (Kamble et al., 2020; Lertpiromsuk et al., 2021) argue that evaluation frameworks should reflect both emerging digital needs and enduring traditional indicators like career advancement and individual effectiveness. Thus, although the literature on direct performance measurement in Industry 4.0 is still emerging, competency-based models aligned with technological change are becoming increasingly prevalent in scholarly discourse.

Considering the above, the core research question is: How can a comprehensive and effective conceptual model for human resource performance evaluation be designed for Bank Melli Iran, which aligns with the developments of the Fourth Industrial Revolution and effectively assesses employee performance in an increasingly digital and automated environment? This model must be capable of identifying key performance indicators that not only measure employee efficiency and effectiveness but also account for their adaptability to new technologies, creativity, innovation, and continuous learning. Therefore, the development of a conceptual model for human resource performance evaluation indicators in Bank Melli Iran, with an emphasis on Industry 4.0, will not only contribute to enhancing employee performance and increasing organizational productivity but will also enable Bank Melli to compete effectively in the digital era and Industry 4.0, maintaining its position as one of the leading institutions in the banking sector. Accordingly, the objective of this study is to design a conceptual model for human resource performance evaluation indicators in the banking industry with an emphasis on the Fourth Industrial Revolution.

2. Methods and Materials

This study is applied in terms of its objective and descriptive in terms of its methodological approach. The research was conducted in three stages. The first stage involved fuzzy screening. In this stage, the importance of indicators identified from the literature was determined using the fuzzy screening method, and the significant indicators proceeded to the second stage of analysis. The statistical population in this phase consisted of experts. The experts in this study included human resource managers from banks with over 20 years of management experience and university professors with academic publications and teaching experience in the field of human resource performance. For data collection at this stage, a questionnaire specifically designed for the fuzzy screening method was used to assess the importance of each criterion based on expert opinion. The fuzzy screening method was also applied to analyze the collected data.

The fuzzy screening process is a two-step procedure consisting of three components: the first component includes the decision-making options from which a subset is to be selected for further analysis. The second component is a set of criteria on which the evaluation is based. The third component is a panel of experts whose opinions are utilized in the screening process. Each expert must indicate the extent to which each option satisfies the various criteria. This evaluation is performed using the elements of the scale presented in Table 1.

Table 1

Extracted Dimensions and Secondary Codes

Table 1. Scoring Scale in the Fuzzy Screening Method

Verbal Variable	Element	Verbal Variable Symbol
Very High	S_7	Very High (VH)
High	S_6	High (H)
Fairly High	S_5	Fairly High (FH)
Medium	S_4	Medium (M)
Fairly Low	S_3	Fairly Low (FL)
Low	S_2	Low (L)
Very Low	S_1	Very Low (VL)

The use of such a scale allows for a natural combination of the S_i elements, such that for any $i < j$, we have $S_i < S_j$. The maximum and minimum of any two elements are determined as follows:

$$\mathrm{Max}(S_i, S_j) = S_i \quad \text{if} \quad S_i \geq S_j \tag{1}$$

$$\mathrm{Max}(S_i, S_j) = S_j \quad \text{if} \quad S_i < S_j \tag{2}$$

Based on the above scale, each expert provides a set of *n* values (corresponding to the number of criteria) for each option. These values indicate the degree to which the given option satisfies criterion *j*:

$$\{\pi_1, \pi_2, \ldots, \pi_n\} \tag{3}$$

The next step in this process is to determine the overall evaluation of each option by each expert. For this purpose, the negative importance measure is determined as follows:

$$\mathrm{Neg}(S_i) = S_{q - i + 1} \tag{4}$$

Then, the single score of each option by each expert (U) is calculated using the following formula:

$$U_{ik} = \min\{ \mathrm{Neg}(I_{kj}) \vee \pi_{ijk} \} \tag{5}$$

$$i = 1, 2, \ldots, m$$

$$k = 1, 2, \ldots, r$$

Where U_{ik} is the single score of expert *k* for option *i*, I_{kj} represents the importance degree of criterion *j* from the perspective of expert *k*, and π_{ijk} indicates the possibility that option *i* satisfies criterion *j* according to expert *k*. The result of the first screening phase is the set of single scores of the experts for various options:

$$\{U_{ik}\} = \{U_{i1}, U_{i2}, \ldots, U_{ir}\} \tag{6}$$

In the second phase of the fuzzy screening process, these individual evaluations by experts are aggregated to derive a collective assessment for each option. The first step in this phase is to define a consensus function (Q) for the decision-making body. This function determines how many expert agreements are required for an option to pass the screening process. Accordingly, for each *i* (k = 1, 2, ..., r), the decision-making body provides a value Q(K), which specifies how the acceptance of an option depends on agreement from *K* experts. If *q* is the number of scale points and *r* is the number of participating experts, then the consensus function is defined as:

$$Q_a(K) = S_{b(K)} \quad (7)$$
$$b(K) = Int[1 + (K(q - 1) / r)]$$
$$K = 1, 2, ..., r$$

Where *Int* denotes the integer part. It is evident that regardless of the values of *q* and *r*, the following holds:

$$Q_a(0) = S_1 \quad (8)$$
$$Q_a(r) = S_q \quad (9)$$

Once the appropriate consensus function is chosen, the Ordered Weighted Averaging (OWA) operator can be used to aggregate expert opinions. For each of the *m* options, a single score has been provided by expert *k* (k = 1, 2, ..., r). For each option, the individual expert evaluations are sorted in descending order. B_{ij} represents the *j*-th highest score for option *i*, and the overall evaluation of option *i* is computed as follows:

$$u_i = \max\{ Q(j) \wedge B_{ij} \} \quad (10)$$
$$i = 1, 2, ..., m$$

In this equation, B_{ij} represents the *j*-th best score for option *i*. Q(j) indicates the degree to which the decision-maker believes that the support of at least *j* experts is necessary. $Q(j) \wedge B_{ij}$ is considered the weighted score for the *j*-th best value of option *i* based on the decision-maker's preference (which requires support from *j* experts). The *max* operator functions analogously to summation in traditional arithmetic averaging.

In the second stage, after fuzzy screening, exploratory factor analysis (EFA) was employed to identify the main components. The statistical population in this section consisted of all senior, middle, and junior managers at various levels within Bank Melli Iran. According to internal records, there were 2,408 managers nationwide. To determine the sample size, the Krejcie and Morgan table was used, resulting in a sample size of 335 individuals. The main data collection instrument was a questionnaire developed based on the results from the fuzzy screening phase. The questionnaire's validity was assessed via face validity, and its reliability, determined using Cronbach's alpha, was 0.810, indicating acceptable reliability for this section.

In the third phase, Interpretive Structural Modeling (ISM) was applied to determine the relationships among the main components of human resource performance evaluation indicators in the banking industry with emphasis on the Fourth Industrial Revolution. A paired comparison questionnaire based on the ISM methodology was used for data collection. Since the ISM method relies on expert judgment, the questionnaire was administered to the same panel of experts from the fuzzy screening phase. They were asked to assess the influence of each main component on the others through pairwise comparisons.

The ISM process involved the following steps:

Step 1 – Identifying the dimensions of the problem for modeling, which in this study are the main components identified through EFA for human resource performance evaluation in the banking industry.

Step 2 – Developing the initial reachability matrix based on expert judgment.

Step 3 – Computing the final reachability matrix.

Step 4 – Partitioning the final reachability matrix into hierarchical levels.

Step 5 – Drawing a hierarchical structural diagram based on the elimination of indirect relationships and variable levels, thereby illustrating the causal relationships among the variables.

3. Findings and Results

A total of 49 factors identified from the literature review, as shown in Table (1), were subjected to the fuzzy screening process. In this phase, a group of 15 experts responded to the fuzzy screening questionnaires. After organizing the responses, the consensus function for each criterion was calculated using Equation (7).

Given that in Equation (7), the value of *q* is determined by the number of scale levels—and considering the use of a seven-point scale for screening—the value of *q* was set at 7. The number of experts *r* in this study is 15. Accordingly, we obtain:

$$b(k) = Int[1 + (3/5) * k]$$

Thus, the consensus function results in:

$k = 1 \rightarrow b(1) = Int[1.6] = 1 \rightarrow Q\_A(1) = S_1 \approx$ Very Low (VL)

$k = 2 \rightarrow b(2) = Int[2.2] = 1 \rightarrow Q\_A(2) = S_2 \approx$ Very Low (VL)

$k = 3 \rightarrow b(3) = Int[2.8] = 2 \rightarrow Q\_A(3) = S_3 \approx$ Low (L)

$k = 4 \rightarrow b(4) = Int[3.4] = 2 \rightarrow Q\_A(4) = S_4 \approx$ Low (L)

k = 5 → b(5) = Int[4] = 3 → Q_A(5) = S_5 ≈ Fairly Low (FL)

k = 6 → b(6) = Int[4.6] = 3 → Q_A(6) = S_6 ≈ Fairly Low (FL)

k = 7 → b(7) = Int[5.2] = 3 → Q_A(7) = S_7 ≈ Fairly Low (FL)

k = 8 → b(8) = Int[5.8] = 4 → Q_A(8) = S_8 ≈ Medium (M)

k = 9 → b(9) = Int[6.4] = 4 → Q_A(9) = S_9 ≈ Medium (M)

k = 10 → b(10) = Int[7] = 5 → Q_A(10) = S_{10} ≈ Fairly High (FH)

k = 11 → b(11) = Int[7.6] = 5 → Q_A(11) = S_{10} ≈ Fairly High (FH)

k = 12 → b(12) = Int[8.2] = 5 → Q_A(12) = S_{10} ≈ Fairly High (FH)

k = 13 → b(13) = Int[8.8] = 6 → Q_A(13) = S_{10} ≈ High (H)

k = 14 → b(14) = Int[9.4] = 6 → Q_A(14) = S_{10} ≈ High (H)

k = 15 → b(15) = Int[10] = 7 → Q_A(15) = S_{10} ≈ Very High (VH)

Ultimately, the evaluations derived from the questionnaires are shown as follows, with sample results for the first and twelfth indicators:

U_1 = max { VL∧VH, VL∧VH, L∧VH, L∧VH, FL∧VH, FL∧H, FL∧H, M∧H, M∧H, FH∧H, FH∧H, FH∧FH, H∧FH, H∧FH, VH∧M } = FH

U_{12} = max { VL∧VH, VL∧H, L∧H, L∧H, FL∧H, FL∧H, FL∧H, M∧FH, M∧FH, FH∧M, FH∧M, FH∧M, H∧FL, H∧L, VH∧L } = M

The overall results of the data analysis are presented in Table 2:

Table 2

Importance of 49 Criteria Based on Fuzzy Screening

Index	Result	Index	Result	Index	Result	Index	Result
1	FH	14	H	27	FH	40	FH
2	H	15	M	28	M	41	H
3	H	16	VH	29	FH	42	VH
4	FH	17	M	30	VH	43	FH
5	VH	18	FH	31	FH	44	H
6	FH	19	VH	32	H	45	H
7	FH	20	VH	33	VH	46	FH
8	FH	21	M	34	H	47	M
9	H	22	H	35	H	48	H
10	VH	23	H	36	FH	49	FH
11	H	24	FH	37	FH	-	-
12	M	25	M	38	FH	-	-
13	FH	26	VH	39	M	-	-

Based on the obtained results, indicators that received a "Medium" importance rating were excluded from the total pool. Consequently, out of the 49 indicators originally identified from the literature, 8 were eliminated, and 41 were approved by experts and advanced to the next stage of analysis.

To identify the main components of human resource performance evaluation indicators in the banking industry with an emphasis on the Fourth Industrial Revolution, exploratory factor analysis was employed. In this process, the Kaiser-Meyer-Olkin (KMO) measure was used to assess sampling adequacy, and Bartlett's test was used to verify the null hypothesis that the correlation matrix is an identity matrix. The KMO value should be at least 0.5, and the significance level for Bartlett's test should be less than 0.05. The results of the KMO and Bartlett's tests are presented in Table 3:

Table 3

KMO and Bartlett's Test Results for Identifying Main Indicator Components

Indicator	Value

KMO Measure	0.892
Chi-square Value	9069.382
Degrees of Freedom	820
Significance Level (sig)	0.000

The data in Table 3 show the KMO value, Bartlett's test statistic, degrees of freedom, and significance level. Since the KMO value was calculated at 0.859 (greater than 0.5), the sample size was deemed adequate for factor analysis. Additionally, the significance level of Bartlett's test is less than 5%, confirming the suitability of factor analysis for identifying the underlying factor structure and rejecting the null hypothesis of an identity correlation matrix.

Table 4 presents the confirmed components and the total explained variance.

Table 4

Number of Confirmed Components and Total Variance Explained

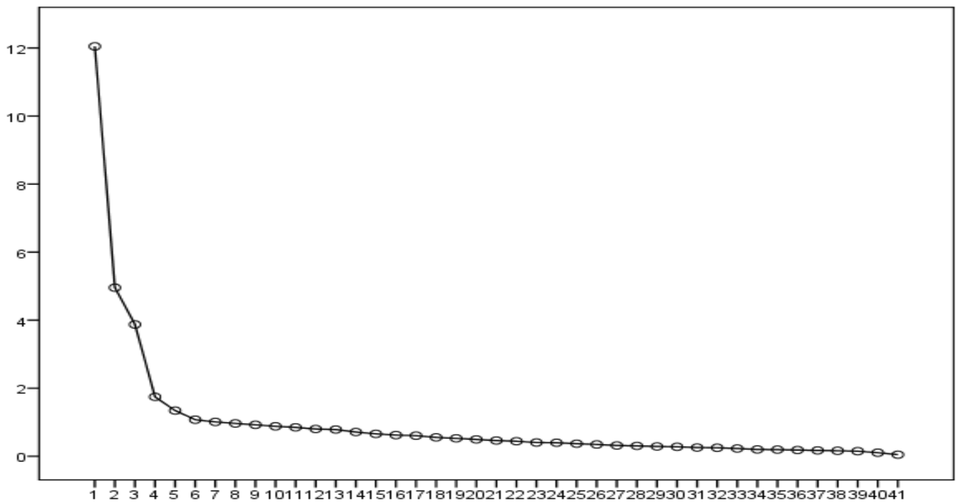
Component	Initial Eigenvalues			Unrotated Components			Rotated Components		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	12.046	29.381	29.381	12.046	29.381	29.381	9.444	23.035	23.035
2	4.955	12.086	41.467	4.955	12.086	41.467	4.962	12.102	35.137
3	3.873	9.446	50.913	3.873	9.446	50.913	3.889	9.486	44.623
4	1.746	4.258	55.171	1.746	4.258	55.171	3.038	7.410	52.033
5	1.343	3.275	58.446	1.343	3.275	58.446	1.611	3.928	55.961
6	1.074	2.620	61.066	1.074	2.620	61.066	1.592	3.883	59.844
7	1.010	2.464	63.530	1.010	2.464	63.530	1.511	3.686	63.530

Table 4 shows that seven main components were extracted from the total set of human resource performance evaluation indicators in the banking industry. These seven components explain a total of 63.530% of the variance in the human resource performance evaluation indicators within the studied population.

Figure 1 presents the Cattell Scree Plot, which illustrates the eigenvalues for identifying the main components with eigenvalues greater than 1.

Figure 1

Cattell Scree Plot for Identifying the Number of Main Components



Finally, the rotated component matrix, which displays the factor loadings of each indicator on the identified principal components, is presented. The results are shown in Table 5.

Table 5

Categorization of Indicators According to Principal Components Based on Factor Loadings

Principal Component	Indicator	Factor Loading	Code
Digital and Technology-Oriented Skills (DST)	Ability to work with smart systems and automation	0.520	DST1
	Data literacy	0.509	DST2
	Cybersecurity	0.734	DST3
	Programming and software development	0.759	DST4
	Cloud systems management	0.659	DST5
Flexibility and Continuous Learning (FCL)	Ability to adapt to change	0.662	FCL1
	Development of multiple skills	0.589	FCL2
	Acceptance of emerging technologies	0.603	FCL3
	Lifelong learning	0.519	FCL4
	Process analysis	0.899	FCL5
	Leadership skill development	0.850	FCL6
Creativity and Innovation (CAI)	Problem-solving	0.712	CAI1
	Process improvement	0.610	CAI2
	New product development	0.675	CAI3
	Learning from experience	0.582	CAI4
	Presenting new ideas	0.703	CAI5
Customer Engagement and Service Orientation (CES)	Omnichannel communication	0.574	CES1
	Communication skills	0.643	CES2
	Service personalization	0.693	CES3
	Rapid problem-solving	0.776	CES4
	Service quality	0.779	CES5
Teamwork and Collaboration (TWC)	Collaboration in cross-functional teams	0.571	TWC1
	Project leadership and management	0.641	TWC2
	Participation in decision-making	0.659	TWC3
	Task delegation	0.702	TWC4
	Internal communication	0.773	TWC5
	Accountability for performance	0.808	TWC6
Quantitative and Qualitative Performance (QQP)	Error rate	0.590	QQP1
	Accuracy and speed of task completion	0.756	QQP2
	Achievement of organizational goals	0.708	QQP3
	Operational efficiency	0.849	QQP4
	Organizational commitment	0.812	QQP5
	Participation in organizational activities	0.832	QQP6
	Career development	0.730	QQP7
Responsibility and Training (RAT)	Participation in educational projects	0.673	RAT1
	Knowledge transfer	0.758	RAT2
	Professional ethics	0.705	RAT3
	Conflict resolution	0.692	RAT4
	Responsiveness to feedback	0.862	RAT5
	Implementation of changes	0.888	RAT6
	Personal development	0.836	RAT7

Based on the factor analysis conducted and the results shown in Table 6 on the remaining 41 influential factors, seven main components were ultimately identified. These components were labeled in accordance with the nature of the indicators and the literature review as: Digital and Technology-Oriented Skills, Flexibility and Continuous Learning, Creativity and Innovation, Customer Engagement and Service Orientation, Teamwork and Collaboration, Quantitative and Qualitative Performance, and Responsibility and Training. Collectively, these principal components explain 63.530% of the variance in the human resource performance evaluation indicators in the banking industry within the context of the Fourth Industrial

Revolution. Based on these results, it is possible to determine the relationships among these main components.

In this section, the experts were asked to identify the presence or absence of a relationship between any two variables using the Interpretive Structural Modeling (ISM) method. In ISM, the first step involves creating an initial reachability matrix. In this step, experts were requested to indicate the influence of one component on another using "1" for presence of influence and "0" for absence (i.e., no relationship between the two variables). The results of this matrix are presented in Table 6.

Table 6

Initial Reachability Matrix

	DST	FCL	CAI	CES	TWC	QQP	RAT
DST	0	0	1	0	0	1	0
FCL	1	0	0	0	0	0	1
CAI	0	0	0	1	1	0	0
CES	0	0	0	0	0	1	0
TWC	0	0	0	0	0	1	0
QQP	0	0	0	0	0	0	0
RAT	0	0	1	0	1	0	0

In the next step, the final reachability matrix is calculated. At this stage, transitive relationships among elements are considered. Transitivity is a key assumption in Interpretive Structural Modeling (ISM), asserting that if element A influences B, and B influences C, then A also influences C. For this, the initial reachability matrix is exponentiated, and by the 4th power, the matrix reaches convergence. Based on this convergence, transitive relations among the main components are determined.

Table 7

Final Reachability Matrix

	DST	FCL	CAI	CES	TWC	QQP	RAT
DST	1	0	1	1*	1*	1	0
FCL	1	1	1*	1*	1*	1*	1
CAI	0	0	1	1	1	1*	0
CES	0	0	0	1	0	1	0
TWC	0	0	0	0	1	1	0
QQP	0	0	0	0	0	1	0
RAT	0	0	1	1*	1	1*	1

Next, the final reachability matrix is partitioned into levels. At this stage, variables (main components) are divided into two sets: reachability and antecedent. The reachability set includes the variable itself and those it affects. The antecedent set includes the variable itself and those that influence it. If the intersection of both sets is equal to the reachability set, that variable is positioned at the current level.

Table 8

First Level Partitioning of Main Human Resource Performance Indicators in Banking

Symbol	Main Component	Reachability	Antecedent	Intersection	Output
DST	Digital and Technology-Oriented Skills	DST, CAI, CES, TWC, QQP	DST, FCL	DST	-
FCL	Flexibility and Continuous Learning	DST, FCL, CAI, CES, TWC, QQP, RAT	FCL	FCL	-
CAI	Creativity and Innovation	CAI, CES, TWC, QQP	DST, FCL, CAI, RAT	CAI	-
CES	Customer Engagement and Services	CES, QQP	DST, FCL, CAI, CES, RAT	CES	-
TWC	Teamwork and Collaboration	TWC, QQP	DST, FCL, CAI, TWC, RAT	TWC	-

QQP	Quantitative and Qualitative Performance	QQP	DST, FCL, CAI, CES, TWC, QQP, RAT	QQP	QQP
RAT	Responsibility and Training	CAI, CES, TWC, QQP, RAT	FCL, RAT	RAT	-

As shown in Table 8, Quantitative and Qualitative Performance (QQP) is identified at the first level. After removing this variable, further partitioning continues until all variables are placed in levels. The summary of ISM results is provided below.

Table 9

Summary of ISM Modeling Results

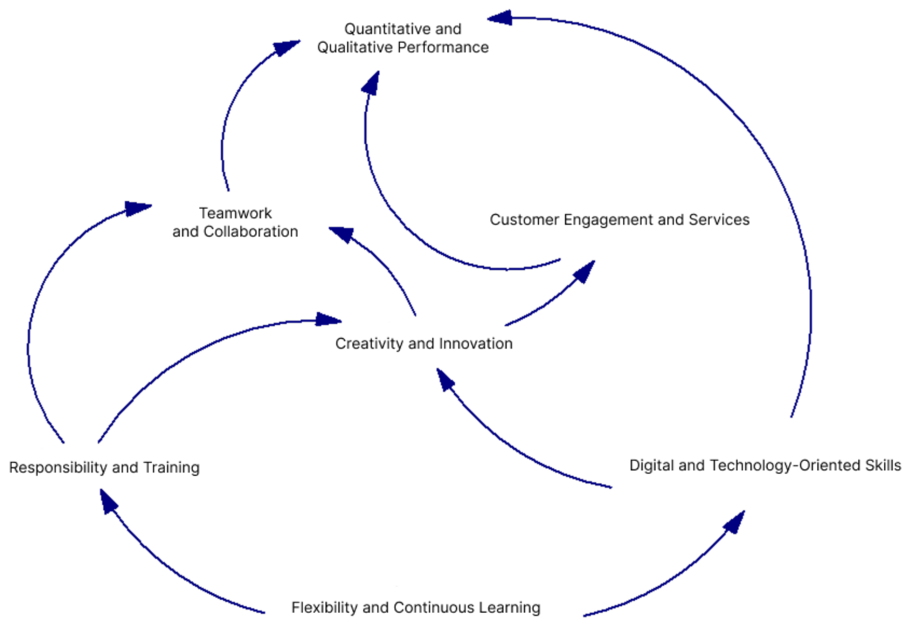
Step	Main Component	Reachability	Antecedent	Intersection	Output
First	Quantitative and Qualitative Performance (QQP)	QQP	DST, FCL, CAI, CES, TWC, QQP, RAT	QQP	QQP
Second	Customer Engagement and Services (CES)	CES	DST, FCL, CAI, CES, RAT	CES	CES
	Teamwork and Collaboration (TWC)	TWC	DST, FCL, CAI, TWC, RAT	TWC	TWC
Third	Creativity and Innovation (CAI)	CAI	DST, FCL, CAI, RAT	CAI	CAI
Fourth	Digital and Technology-Oriented Skills (DST)	DST	DST, FCL	DST	DST
	Responsibility and Training (RAT)	RAT	FCL, RAT	RAT	RAT
Fifth	Flexibility and Continuous Learning (FCL)	FCL	FCL	FCL	FCL

According to Table 9, the Quantitative and Qualitative Performance (QQP) component is at the first level, Customer Engagement and Services (CES) and Teamwork and Collaboration (TWC) are at the second level, Creativity and Innovation (CAI) is at the third level, Digital and Technology-Oriented Skills (DST) and Responsibility and Training (RAT) are at the fourth level, and Flexibility and Continuous Learning (FCL) occupies the fifth and top level.

After partitioning, the final step involves drawing a hierarchical conceptual model by removing indirect relationships and incorporating component levels. This model, representing the causal structure of human resource performance evaluation indicators in banking, is shown in Figure 2.

Figure 2

Conceptual Research Model



The results of Figure 2 reveal that Flexibility and Continuous Learning serves as the foundational and most influential component in the human resource performance evaluation model aligned with Industry 4.0. This component acts as a driver for two fourth-level components: Digital and Technology-Oriented Skills and Responsibility and Training. The Digital and Technology-Oriented Skills component subsequently enhances Creativity and Innovation at the third level, which ultimately improves Quantitative and Qualitative Performance at the first level. Simultaneously, Responsibility and Training, alongside technology skills, supports the development of Creativity and Innovation, and also serves as a stimulus for Teamwork and Collaboration at the second level. Moreover, Creativity and Innovation directly impacts Customer Engagement and Services and Teamwork and Collaboration, both situated at the second level. In turn, Customer Engagement and Teamwork directly lead to improvements in Quantitative and Qualitative Performance, making it the most influenced component in the human resource performance evaluation model within the framework of the Fourth Industrial Revolution.

4. Discussion and Conclusion

This study examined the design of a conceptual model for human resource performance evaluation indicators in the banking industry with an emphasis on the Fourth Industrial Revolution. Given the rapid pace of technological advancements and profound changes in the business environment, the need to update and adapt human resource performance indicators is more urgent than ever. The Fourth Industrial Revolution, driven by advanced technologies such as the Internet of Things, artificial intelligence, big data, and robotics, has introduced both challenges and opportunities to the banking sector. This paper employed Interpretive Structural Modeling (ISM) and fuzzy screening to analyze the causal relationships among key human resource performance evaluation components in banking under the influence of Industry 4.0. The results identified flexibility and continuous learning as the most influential core component in the proposed conceptual model.

Flexibility, defined as the organization's and employees' ability to rapidly adapt to environmental and technological changes, plays a critical role in organizational success in the era of Industry 4.0. According to (Cirillo et al., 2023; Hernandez-de-Menendez et al., 2020), human resource flexibility has become a key performance criterion for adapting to fourth-generation industrial technologies. These scholars identify adaptability, multi-skilling, and openness to emerging technologies as core indicators of flexibility. This component enables banks to respond promptly and effectively to rapid technological shifts and market changes. Moreover, continuous learning, as a process of ongoing skills and knowledge development, enhances an organization's capacity to utilize advanced technologies and foster innovation. In a context where technologies evolve rapidly, continuous learning is not just a need, but a strategic necessity for maintaining competitiveness. Researchers (Lertpiromsuk et al., 2021; Miah et al., 2024; Prashar et al., 2023; Reznik, 2021) have both implicitly and explicitly emphasized the importance of flexibility and lifelong learning in the context of Industry 4.0. Each of these researchers describes the fourth industrial environment as highly dynamic and competitive for businesses.

The study findings demonstrate that flexibility and continuous learning serve as catalysts for the two components: digital and technology-oriented skills and responsibility and training. These relationships have been supported by previous works (Hecklau et al., 2016; Lertpiromsuk et al., 2021; Miah et al., 2024; Moallem, 2021). In other words, flexibility and continuous learning—through the development of multi-skills, technological acceptance, and lifelong learning—lead to enhanced digital and technological skills as well as increased responsibility and improved training capabilities.

The digital and technology-oriented skills component directly stimulates both human resource creativity and innovation and quantitative and qualitative performance. Researchers (Moallem, 2021; Reznik, 2021) concur that these skills enhance creativity and innovation at both individual and organizational levels. Likewise, the responsibility and training component contributes to the development of human resource creativity and innovation and serves as a driver for teamwork and collaboration, which stems from organizational accountability. Creativity and innovation, by fostering new and inventive approaches, enable human resources to engage more effectively in customer-centric service. This has been reinforced in the prior works (Arromba et al., 2021; Hecklau et al., 2016; Lertpiromsuk et al., 2021; Miah et al., 2024; Vrchota, Maříková, et al., 2019; Vrchota, Volek, et al., 2019).

The conceptual model presented in this paper aims to align performance evaluation indicators with the needs and demands of the fourth industrial era. Designed through a review of the literature and analysis of the banking sector's requirements, the model includes indicators such as digital skills, technological adaptability, creativity and innovation, teamwork, and flexibility and lifelong learning. Furthermore, traditional indicators like career development, organizational commitment, and operational efficiency have been redefined with a modern perspective to better suit current conditions. The results of this study indicate that achieving optimal performance in banking requires treating human resource performance indicators as strategic tools—tools that not only measure individual and organizational outcomes but also serve as drivers of continuous improvement and development.

In the era of Industry 4.0, human capital must be viewed as an organization's most valuable asset—capable of leveraging advanced technologies and generating added value. Ultimately, this study suggests that banks and financial institutions, in order to remain competitive and responsive to customer needs, must continually review and update their performance evaluation models and indicators. This endeavor necessitates close collaboration among HR departments, IT divisions, and senior management to ensure that the developed indicators address both current organizational needs and future adaptability. In doing so, the banking industry will be able to demonstrate a distinctive and sustainable performance in the face of Industry 4.0 challenges.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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