

Research Article

Employee Performance Aware Intrapreneurial Behavior in Organizational Culture with Analytic Hierarchy Process and Graph based Deep Reinforcement Learning

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Abstract: The Analytical Hierarchy Model (AHM) organizes factors influencing Employee Performance in Organizational Culture into a hierarchical framework through two-level comparison on a nine-point scale, creating a standardized assessment matrix with weighted values. To address these difficulties, a novel paradigm called Intrapreneurial Behavior with Analytic Hierarchy and Graph based Deep Reinforcement Learning (IBAHGD) was developed. This system assesses employee performance through intrapreneurial behavior analysis, an analytic hierarchy model, and a graph-based reinforcement learning algorithm to identify proactive, creative employees who enhance organizational performance. The Credamo platform gathered 218 responses from employees and management, resulting in 163 valid replies and a 74.8% response rate, which were statistically validated using SPSS. The AHM organized the factors influencing Employee Intrapreneurial Behavior Analysis into a hierarchical structure with nine-level pair wise comparisons for evaluation. Ranking uses the eigenvalue method to derive the main eigenvector and maximum eigenvalue, with consistency accessed via the Consistency Index (CI) and Consistency Ratio (CR). The methodology, Graph-based Deep Reinforcement Learning (GDRL), combines deep reinforcement learning and Q-learning for improved decision-making based on total rewards and state-action interactions. The performance analysis is minimum weight based total earliness, IBAHGD C-Metric value analysis, IBAHGD IGD value analysis, IBAHGD S-Metric value analysis.

Keywords: Employee Performance in Organizational Culture, Analytical Hierarchy Model (AHM), Graph-based Deep Reinforcement Learning (GDRL), Consistency Index (CI) and Consistency Ratio (CR)

1. Introduction

Employee Performance in Organizational Culture intrapreneurship is increasingly recognized for enhancing innovation, engagement, competitiveness, and sustainability [1]. Literature indicates that intrapreneurs drive organizational growth through creativity, initiative, and opportunity recognition [2]. Previous studies link intrapreneurship with factors like loyalty, pay, and culture, yet current research methods inadequately address the complex relationship between organizational and individual characteristics [3]. Previous studies have only partially addressed how an employee's intrapreneurial mindset leads to both positive and negative outcomes. Research indicates that various internal and external factors, such as organizational support, workplace environment, leadership, and market shifts, influence intrapreneurial behavior [4]. Thus, measuring outcomes based on individual attributes may overlook the complexities of intrapreneurial behavior, and typical methodologies do not effectively rank the most significant factors or guide decision-making strategies [5]. Limited resources necessitate a systematic approach through configuration, performance measurement, and decision analysis.



The proposed IBAHGD method integrates Performance Analysis, Graph-Based Deep Reinforcement Learning, Analytic Hierarchy Model, and Employee Intrapreneurial Behavior Analysis, emphasizing creativity, initiative, and risk-taking. The major contribution of the paper is discussed below. This report analyzes employee intrapreneurial behavior, considering creativity, initiative, risk-taking, self-renewal, opportunity recognition, and entrepreneurial conduct. A robust data collection process targeted middle-level managers and employees, alongside assessments for validity, reliability, sampling, and factorability. The use of fsQCA3.0 enhances the research by providing a comprehensive analysis of the causes and their relations to outcomes. They ranked factors influencing employee intrapreneurial behaviors via the AHM and proposed GDRL to enhance performance analysis, addressing conventional limitations with Q-learning and DDQN architectures.

2. Related Works

In [6], the objective of this study had two parts: to generate a systemic concept related to academic Intrapreneurship and to evaluate graduate's employability and welfare. The analysis was used data from 141 UK higher education institutions, and obtained various research findings. The study highlighted that the intrapreneurial ecosystem focused on improving graduate's employment quality, skills and overall outcomes. In [7], this study suggested that the activities of universities and HEIs may be categorized as intrapreneurship instead of entrepreneurship. It used a specialized dataset obtained from five HEIs in five different countries to examine intrapreneurial activities. The results provided three main contributions: improving the understanding of the nature and scope of HEIs' activities, presenting an analytical framework to reveal the intrapreneurial dimensions and providing directions for future research related to intrapreneurship and entrepreneurial universities. In [8], this study examines the factors affecting the utilization of AI technologies in Thai e-government services using the SEM method. For this purpose, collected data through questionnaire from 400 400 e-government service users and 400 Thai civil servants who use AI technologies through questionnaire. It also explores the relationship between PU, PEOU, ATU and ASU by using TAM and DOI theory. The results showed that several features increase the use of AI in Thai e-government services, such as enhancing trust in government, overcoming privacy issues, increasing awareness of AI and improving the quality of e-government services.

In [9], the study had two major aims: (1) proposing a machine learning-based surrogate model developed to estimate simulation outputs, thereby, reducing computational overhead and maintaining accuracy, (2) comparing the capability of supervised learning algorithms to create a surrogate model. The main contribution of this study is the benchmarking and fine-tuning of ten supervised learning algorithms. The results showed that random forests achieved $R^2 = 0.91$ value, making it useful tool for surrogate modeling. In [10], this study addressed the FJSP by proposing a hybrid multi-agent DRL method called PRISMA, which uses CP solutions. The method combines supervised learning and reinforcement learning within a multi-agent framework. The results showed that PRISMA improved convergence speed and provided high solution compared with current DRL methods. In [11], the author explored the DFJSP-PT and considered random job arrivals and urgent order insertions. The study also introduced a hybrid model using GNN and DRL. The results showed that the proposed model provided better convergence performance and improved solution quality, therefore, making it a useful technical method for intelligent job shop scheduling. In [12], this paper proposed a new PFJSP-AW-MR that reduces total weighted tardiness and performance deviation. An INSGN- II_NS method was proposed to overcome the

NP-hard issue, which uses three-layer encoding. Experimental results showed that the INSGN-II_NS achieved better performance compared with existing methods, thereby, providing effective balance between production performance and efficiency.

In [13], the author investigated the impact of sense of ownership on intrapreneurial behavior and how it improves task performance. For this, 523 responses were collected and tested form full-time works through online questionnaire. The results confirmed that intrapreneurial behavior serves as a full mediator between tack performance and psychological ownership. In [14], this paper, the association between potential entrepreneurial behavior and preferred culture type was examined. It conducted PCA on sample data obtained form 1056 university students, thereby identifying four main principles of enterprising behavior. Additionally, the study carried out a linear regression analysis to examine the relationship among cultural type and behavior using OCAI tool. In [15], this study used the AHP to detect the factors that affect ESIB in Albania's manufacturing sector. It identified that strong supervisor relationship quality and expected image gains were the main factors affecting ESIB. It also suggested implementing monthly workshops to enhance workers behavior. In [16], this paper investigated six factors: entrepreneurial self-confidence and competence, task skill stage, perceived value, reward method and managements contribution. Workers entrepreneurial behavior was analyzed using fsQCA based on 163 sample data. The results showed that these factors had asymmetric causal relationship related to entrepreneurial behavior. In [17], this study hypothesizes that intrapreneurial behavior provides advantages to workers, organizations, and society. It tested the hypotheses using Hayes' PROCESS macro through regression analyses, and data obtained from 617 workers from different organizations regression analyses in Israel. The study showed that organizational setting and individual changes play a main role in fostering intrapreneurial behavior and improving workers performance. The existing research summary is explained in the table 1.

Table 1: Existing Research Summary

Ref.	Dataset / Method	Major Contribution
[6]	141 UK HEIs	Academic intrapreneurship ecosystem improves graduate employability, skills, and welfare.
[7]	Five HEIs (5 countries)	Proposed an intrapreneurship framework and identified future research directions for HEIs.
[8]	SEM, TAM, DOI; 400 users + 400 civil servants	AI adoption in e-government is driven by trust, privacy, awareness, and service quality.
[9]	ML surrogate model; 10 supervised algorithms	Random Forest achieved $R^2 = 0.91$, reducing simulation cost while maintaining accuracy.
[10]	PRISMA (Multi-agent DRL + CP + SL)	Improved convergence speed and solution quality for FJSP.
[11]	GNN + DRL for DFJSP-PT	Enhanced convergence and scheduling solution quality under dynamic conditions.
[12]	PFJSP-AW-MR; INSGN-II_NS	Reduced weighted tardiness and improved production efficiency for NP-hard scheduling.
[13]	523 employees; questionnaire	Psychological ownership enhances task performance through intrapreneurial behavior.
[14]	PCA, OCAI; 1056 students	Identified four entrepreneurial behavior dimensions and their cultural associations.
[15]	AHP; Albania manufacturing	Supervisor relationship and image gains are key ESIB drivers.

Ref.	Dataset / Method	Major Contribution
[16]	fsQCA; 163 workers	Entrepreneurial behavior is influenced by asymmetric causal factors.
[17]	PROCESS regression; 617 workers	Organizational and individual factors promote intrapreneurial behavior and performance.

3. Proposed IBAHGD Model

The proposed model is mainly developed to provide effective employee performance analysis with the presence of deep learning techniques where its workflow is shown in figure 1. The core modules of this model are Employee Intrapreneurial Behavior Analysis, Analytic Hierarchy Model (AHM), Graph based Deep Reinforcement Learning (GDRL) and Performance Analysis.

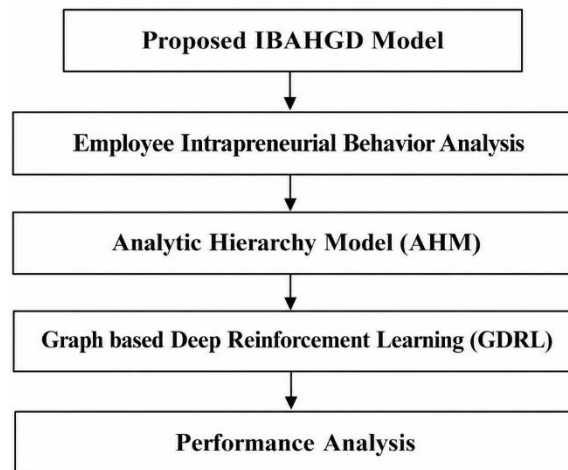


Figure 1:Structure of IBAHGD Model

Employee Intrapreneurial Behavior Analysis

According to the definition of intrapreneurial behavior, it is clear that workers recognize and take advantage of opportunities through creativity, initiative, and risk-taking to help companies develop new goods, services, and processes as well as improve their performance and competitiveness through self-renewal or entrepreneurship. Instead of top-level management, employees or middle-level managers are mostly in charge of this process, which is an example of a bottom-up approach to innovation. In order to guarantee sample representativeness and to make data collecting and analysis easier, the survey mainly targets middle-level managers and regular employees inside the company. Surveys will be carried out via the Credamo specialized data platform to guarantee the samples' universality and make data gathering and management easier. Following the creation, distribution, and collection of the questionnaire, 218 were returned, 163 of these were found to be legitimate, yielding a valid response rate of 74.8%. In table 2, the data based statistical analysis is explained with the presence of the collected sample data of the participants.

Table 2: Statistical Analysis

Characteristic	Category	n	%
Sex	Male	85	52.1
	Female	78	47.9
Age (Years)	20–30	73	44.8
	31–40	74	45.4

Characteristic	Category	n	%
	Other age groups	16	9.8
Education	Bachelor's degree or above	137	84.1
	Below bachelor's degree	26	15.9
Job Position	Middle-level manager	70	42.9
	Regular employee	~70	~42.9
	Other positions	~23	~14.2
Total Participants	-	163	100.0

In table 3, the data validation process and testing analysis are explained which is performed in the SPSS which is utilized to measure the coefficient values.

Table 3: Data Validation Process and Testing analysis

Analysis	Indicator	Result	Criterion
Reliability	Overall Cronbach's α	0.924	> 0.70
Reliability	Subscale Cronbach's α	0.754–0.884	> 0.70
Internal Consistency	Composite Reliability (CR)	> 0.60	> 0.60
Convergent Validity	Average Variance Extracted (AVE)	> 0.50	> 0.50
Sampling Adequacy	KMO (Influencing Factors Questionnaire)	0.893	> 0.60
Sampling Adequacy	KMO (Intrapreneurial Behavior Questionnaire)	0.849	> 0.60
Factorability	Bartlett's Test of Sphericity	Significant ($p < 0.05$)	Significant
Construct Validity	Standardized Factor Loadings	0.60–0.90	≥ 0.60
Discriminant Validity	Cross-loadings	None	No cross-loadings
Overall Assessment	Reliability & Validity	Satisfied	Meets all criteria

Using fsQCA3.0, this study performed a necessity analysis of the six prerequisites for employees' intrapreneurial activity. The findings show that there are no preconditions with consistency coefficients greater than 0.9, indicating that there are no prerequisite causal conditions for the two outcomes to occur. These results cannot be explained by a single prerequisite. As a result, all preconditions were taken into account in the analysis that followed, and no causal circumstances were disregarded in this study. This study creates and examines the configuration of these intrapreneurial behaviors in order to investigate the factors influencing employees' intrapreneurial behavior. A particular investigation of the configuration of intrapreneurial behavior among a group of high-performing and non-high-performing personnel was carried out using the previously indicated data processing.

Analytic Hierarchy Model (AHM)

A multi-criteria approach is necessary for the qualitative part of assessing ESIB variables. The Analytic Hierarchy Method (AHM) is a commonly used approach in these situations. In order to identify the optimum option, the AHM arranges decision-making elements into a hierarchical hierarchy that permits a combination of subjective assessments and objective

evaluations. By methodically combining qualitative and quantitative analysis, it improves the decision-making process's dependability. Comparing the criteria and the options pairwise is the next stage. Prioritization establishes the relative significance of each level's criteria and their alternatives. A nine-level standardized measure served as the foundation for the pairwise comparisons. A $n \times n$ pairwise assessment matrix summarizes the pairwise comparison of n criteria. The decision-making process known as the Thomas Saati scale AHM was first created by Thomas Saaty. As a set of ESIB factor criteria, let us define $C = C_j \ j = 1; 2; \dots; n$. The $n \times n$ assessment matrix includes a comparison of the criteria from the set C . The matrix A is given by equation (1):

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \quad (1)$$

In this case, a_{ij} represents the numerical evaluation of the pairwise comparison of criteria i and j according to the AHM hierarchy. For instance, $a_{ij} = 7$ if the requirement i takes precedence over the criterion j ; otherwise, $a_{ij} = 1/7$. The following guidelines define matrix A 's entries:

$$a_{ij} \neq 0, a_{ij} = 1, a_{ij} = \frac{1}{a_{ji}} \quad (2)$$

The AHM method's next step involves normalizing and calculating the weight of matrix A . The items in each column of matrix A are divided by the appropriate column sums to achieve this. The major eigenvector w , which correlates to matrix A 's maximum eigenvalue, $\lambda_{\max}$, then establishes the elements' priority or precedence:

$$Aw = \lambda_{\max} w \quad (3)$$

Because the congruity of the pairwise comparison assessments greatly influence the prominence of the AHM results, the last stage in the process is to do a consistency analysis. There are two sections to the consistency analysis. The CI is first computed as follows:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (4)$$

Next, the following formula is used to determine the final CR:

$$CR = \frac{CI}{RI} \quad (5)$$

Because it shows the consistency of the paired assessments, the use of CR is crucial. The literature currently in publication recognizes 0.1 as the maximum value of CR.

Graph based Deep Reinforcement Learning (GDRL)

By updating present action values based on future action values, Q-learning, a temporal difference reinforcement learning technique, approximates the optimal policy. It is a model-free technique based on MDP that allows agents to continuously interact with their environment to learn the best choice strategies. The structural diagram of the Q-learning model is illustrated in the figure 2

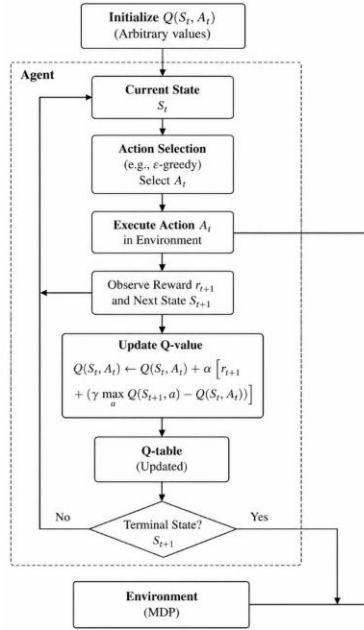


Figure 2: Q-learning model

The Q-value function, the algorithm's central component, aims to maximize long-term cumulative rewards. This function calculates the anticipated long-term return of carrying out a particular activity in a particular state. The equation (6) mathematically defines its update rule.

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[r_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t) \right] \quad (6)$$

where r_{t+1} is the immediate reward, α is the learning rate, and γ is the discount factor. The quality of the activity is directly reflected in the Q-value's magnitude: a high Q-value denotes an action with a larger long-term payout, whereas a low Q-value indicates worse projected results. Q-learning is a table-based reinforcement learning technique that tackles the problem of high-dimensional state-action spaces by storing Q-values for every state-action combination in a tabular manner. The program uses a greedy methodology to strike a balance between exploration and exploitation. The equation (7) displays the ideal Q-value function.

$$Q^*(S, A) = E \left[r_{t+1} + \gamma \max_a Q^*(S_{t+1}, a') \mid S_t = S, A_t = A \right] \quad (7)$$

Q-learning derives the optimal policy π^* by iteratively updating the Q-value function to converge toward the optimal policy Q^* . as demonstrated in its equation (8).

$$\pi^*(S) = \operatorname{argmax}_a Q^*(S, a) \quad (8)$$

Constructing Q-value tables for high-dimensional state spaces is a major hurdle for traditional Q-learning, which restricts its application to complex decision-making tasks. DQN was suggested as a creative way to get around this restriction. DQN uses value function approximation to handle high-dimensional states and substitutes neural networks for the traditional tabular representation. The algorithm's performance and stability are significantly enhanced by the combination of the experience replay mechanism and target network. Traditional DQN still has overestimation bias despite these developments. The employment of a single network for both action selection and value estimate gives rise to this issue. Because of this, the algorithm frequently performs less than optimally, with real rewards falling short of

expectations. By separating the action selection and value evaluation procedures, GDRL resolves this problem. GDRL uses two separate networks: the target network Q' for value estimate and the Q network for action selection. In particular, the target network Q' assesses the Q-value of the chosen action, whereas the Q network determines which action maximizes the expected reward. The overestimation bias present in conventional DQN is successfully reduced by this decoupling technique. The equation (9) presents the mathematical expression for DDQN which is given below.

$$Q(S_t, A_t) \leftrightarrow R_t + Q' \left(S_{t+1}, \underset{a}{\operatorname{argmax}} Q(S_{t+1}, a) \right) \quad (9)$$

The permanent solution for the GDRL learning process is discussed in the table 4 with the presence of these theoretical considerations.

Table 4: GDRL Learning Process

Feature	Advantage
Discrete action space	Optimizes composite dispatching rules for JSP
DDQN architecture	Reduces overestimation and improves learning stability
Experience replay	Enhances sample efficiency using historical experiences
PER mechanism	Prioritizes high TD-error samples for faster convergence
GDRL framework	Improves scheduling performance and policy quality

4. Simulation Environment

In this proposed IBAHGD research the performance of the employees in terms of their intrapreneurial behavior is analysed in an effective way with the presence of the GDRL model. The simulation of this model is performed in the python tool and the parameters which are measured for the analysis are minimum weight based total earliness, C-metric value, IGD value and S-metric value calculation. The final outcome of the proposed IBAHGD model is compared with the earlier methods such as ESIBA [15], UIBEC [16], EPSIA [17].

Minimum Weight based Total Earliness

A Minimum Weight Total Earliness of 3564 at epoch 0, reduced to 3122 at epoch 100. After 200 epochs, it reaches 2145, while competitors show 3561, 3418, and 3324. At 300 epochs, IBAHGD achieves 1168 compared to 2856, 2546, and 2275 for others. At 400 epochs, IBAHGD is at 685, lower than competitors at 1547, 1233, and 1142. At 500 epochs, it drops to 358, while others report 865, 768, and 698. The learning process in IBAHGD, reducing earliness from 5841 to 358 (93.87%), as represented in figure 3 and table 5. Other algorithms showed similar reductions: UIBEC from 5547 to 358 (93.54%) and EPSIA from 5317 to 358.

Table 5: Minimum Weight based Total Earliness Measure

Training Epochs	ESIBA	UIBEC	EPSIA	IBAHGD
0	5841	5547	5317	3564
100	4189	3946	3867	3122
200	3561	3418	3324	2145
300	2856	2546	2275	1168
400	1547	1233	1142	685
500	865	768	698	358

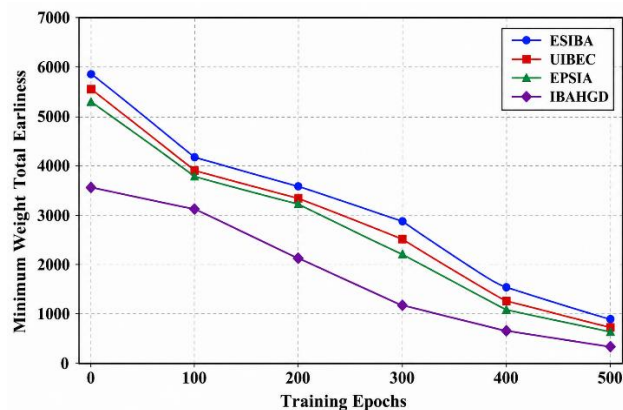


Figure 3: Minimum Weight Total Earliness Calculation

IBAHGD C-Metric Value Analysis

C-Metrics scores are 0.75, 0.56, 0.69, 0.96, 0.95, 0.58, and 0.81, with a mean of 0.76. The IBAHGD metric peaked at 0.96 at instance 8, declined to 0.95 at instance 10, dropped to 0.58 at instance 12, and rose to 0.81 at instance 14. Lower scores at instances 4 and 12 model performance varies with specific traits. A C-Metric above 0.50, with high values reflecting the model's ability to continuously find quality solutions across iterations, as shown in figure 4 and table 6.

Table 6: IBAHGD C-Metric Value Measure

Instance	2	4	6	8	10	12	14
Values	0.75	0.56	0.69	0.96	0.95	0.58	0.81

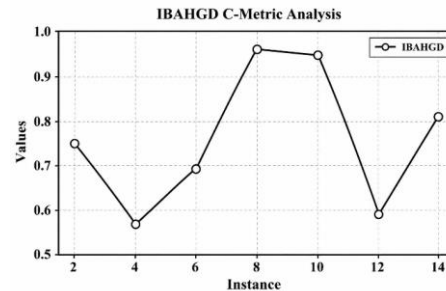


Figure 4: IBAHGD C-Metric Value Calculation

IBAHGD IGD Value Analysis

IBAHGD achieves an IGD of 0.15 at instance 2. It drops to 0.05 at instance 4. At instance 6, it rises to 0.58, the highest value. By instance 8, the IGD improves to 0.06 and stabilizes at 0.09 in instance 10, production of Pareto-optimal solutions. The score at instance 12 rises to 0.28. The IGD value is 0.34 at instance 14, below the peak of 0.58 at instance 6, as shown in figure 5 and table 7. Averaging 0.22, the seven IGD values show that IBAHGD generally converges, with low IGD values at instances 4, 8, and 10, while higher values at 6, 12, and 14 optimization scenarios.

Table 7: IBAHGD IGD Value Measure

Instance	2	4	6	8	10	12	14
Values	0.15	0.05	0.58	0.06	0.09	0.28	0.34

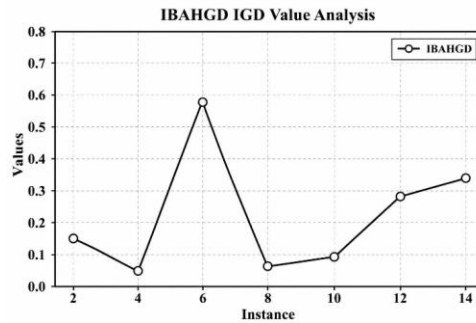


Figure 5: IBAHGD IGD Value Calculation

IBAHD S-Metric Value Analysis

IBAHD's S-Metric fluctuates 0.51 at instance 14 to a low of 0.43 at instance 8 to a high of 0.65 at instance 12, with an average value of 0.53. The high S-Metric in case 12 indicates a promising solution, while the low value in case 8 suggests a challenging optimization problem. The rise in the S-Metric from cases 2 to 4 and 6 IBAHD's optimization capability, and the recovery seen in cases 10 and 12 suggests resilience despite prior drops, as represented in figure 6 and table 8. However, comparisons to ESIBA, UIBEC, and EPSIA lack evidence for determining IBAHD's superiority.

Table 8: IBAHD S-Metric Value Measure

Instance	2	4	6	8	10	12	14
Values	0.45	0.57	0.59	0.43	0.53	0.65	0.51

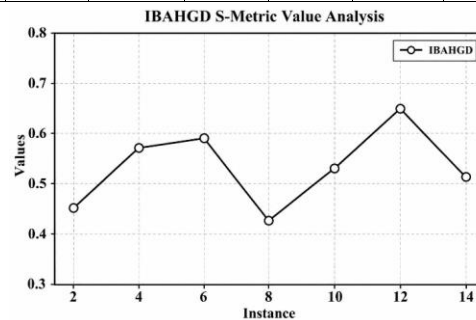


Figure 6: IBAHD S-Metric Value Calculation

5. Conclusion

The study on employee intrapreneurial behavior analyzes factors like creativity, proactivity, risk-taking, opportunity recognition, and entrepreneurial behaviors, based on 163 completed responses from 218 questionnaires using Credamo. Goodness of fit was confirmed through statistical validation, consistency, and reliability checks. fsQCA3.0 analyzes influences on intrapreneurial behavior, while the AHM hierarchically ranks ESIB elements by significance through pair comparisons. Agreement among judges is assessed using a CI and ratio. The GDRL component enhances decision-making by analyzing the impact of decisions and cumulative rewards. The DDQN model mitigates overestimation bias in deep Q-learning by separating decision-making from value estimation. Reusing past experiences accelerates an agent's learning and stabilizes results, serving as a method for studying employee behaviors and identifying performance variations. At epoch 0, Minimum Weight Total Earliness is 3564, reducing to 3122 at 100 epochs and 2145 at 200. At 300 epochs, IBAHD is 1168, lower than competitors; it drops to 685 at 400 epochs and 358 at 500. IBAHD C-Metrics average 0.76, peaking at 0.96 at instance 8, then falling to 0.58 at instance 12 before rising to 0.81 at instance 14. IGD peaks at

0.58 at instance 6, stabilizing around 0.09 by instance 10. S-Metric ranges from 0.43 at instance 8 to 0.65 at instance 12, averaging 0.53. Future research with larger, diverse data sets from various sectors may enhance the validity of this method and clarify intrapreneurial behavior fluctuations over time.

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