ARTIFICIAL INTELLIGENCE MODEL WITH OPTIMIZATION TECHNIQUE TO IMPROVE JOB AUTONOMY

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SUMMARY

This paper presents a novel approach to enhancing workplace well-being and classification accuracy, specifically tailored to the dynamic and competitive IT industry in India. The research leverages Simulated SeaHorse Optimization (SSHO), a nature-inspired optimization technique, to estimate and improve job autonomy and happiness scores in the workplace. Furthermore, SSHO is combined with Long Short-Term Memory (LSTM) networks to create a robust classification model. The study's key findings indicate a direct correlation between the number of SSHO iterations and the enhancement of job autonomy and happiness scores, highlighting the potential of SSHO as an effective tool for optimizing these critical workplace factors. Moreover, the SSHO-LSTM model outperforms traditional models, achieving remarkably high accuracy, precision, recall, and F1-Score in classifying data. The practical implications of this research are significant, as it offers a promising approach for organizations to create a more favorable work environment, ultimately contributing to higher job satisfaction and well-being among employees. This paper advances the understanding of optimization techniques, well-being in the workplace, and intrapreneurial characteristics, providing valuable insights for industry professionals and researchers seeking to improve employee experiences in the IT sector. In conclusion, this paper demonstrates the potential of SSHO and SSHO-LSTM as tools to optimize workplace well-being and enhance classification accuracy, making a substantial contribution to the fields of optimization, machine learning, and workplace well-being in the IT industry.

KEY WORDS: Artificial Intelligence, Deep Learning, Seahorse Optimization, Long-Short Term Memory (LSTM), Job Autonomy, IT industry

1. INTRODUCTION

The IT industry has witnessed a transformative evolution with the advent and maturation of Artificial Intelligence (AI) [1]. The origins of AI can be traced back to the mid-20th century, as early computer scientists and mathematicians, including visionaries like Alan Turing and John McCarthy, began exploring the idea of creating machines that could mimic human intelligence. The 1950s and 1960s saw the birth of AI as an academic discipline, where researchers into rule-based systems and expert systems designed to solve specific problems, exemplified by IBM's Deep Thought and early computer-based language translation systems [2]. However, the journey of AI has not been without its setbacks, with the 'AI winters' of the 1970s and 1980s, when AI research faced a downturn due to overly optimistic expectations and limited progress. Nevertheless, the IT industry witnessed a remarkable resurgence in AI research in the 1990s, largely driven by the rise of machine learning techniques, particularly neural networks [3]. Innovations such as backpropagation and the application of neural networks to a diverse range of tasks marked the resurgence of AI, ultimately reshaping the IT landscape and rekindling the promise of intelligent machines.

Job autonomy and its relationship with employee happiness have become central topics in the modern workplace [4]. Job autonomy refers to the extent to which employees have the freedom and discretion to make decisions and set their own work-related goals. It's rooted in the belief that when individuals have more control over their tasks and responsibilities, they tend to experience greater job satisfaction, engagement, and overall well-being. The concept of job autonomy has evolved in response to changing work environments, particularly in knowledge-based industries and the technology sector [5]. With the rise of remote work and flexible arrangements, the need to understand the impact of job autonomy on employee happiness has gained prominence. Research suggests that employees who experience a higher degree of autonomy often report greater job satisfaction, a stronger sense of ownership in their work, and increased motivation. This has led to a reevaluation of traditional management structures and a growing emphasis on fostering workplace environments that balance autonomy with responsibility to enhance employee happiness and productivity [6].

Job autonomy and its connection to employee happiness in the workplace have gained increasing attention with the integration of machine learning and data-driven approaches. In the context of the modern workplace, job autonomy refers to the extent to which employees have the freedom to make decisions and set their own work-related goals [7]. Machine learning and data analytics have enabled organizations to gain deeper insights into how various levels of autonomy impact employee happiness and overall productivity. By analyzing vast amounts of data, companies can understand the complex interplay between job autonomy, job satisfaction, and employee well-being [8]. This data-driven approach has provided valuable insights into tailoring job roles and responsibilities to suit individual preferences and strengths, ultimately leading to more content and motivated employees. As machine learning and AI continue to shape the workplace, organizations are increasingly leveraging these technologies to optimize job autonomy in ways that enhance happiness and overall job performance [9].

In the dynamic and ever-evolving Information Technology (IT) industry, intrapreneurial characteristics play a pivotal role in driving innovation and growth. Intrapreneurs are individuals within an organization who exhibit entrepreneurial qualities while working within the confines of a larger corporation [10]. These characteristics include a strong sense of initiative, a willingness to take calculated risks, creativity, and a keen eye for identifying opportunities in the IT landscape. In an industry where technology is in a constant state of flux, intrapreneurs are essential in driving the development of new products, services, and solutions [11–12]. Their ability to think outside the box, challenge the status quo, and effectively navigate complex corporate structures is crucial for organizations to stay competitive and adapt to rapidly changing technological trends. Intrapreneurs often spearhead projects, foster a culture of innovation, and create an environment where experimentation is encouraged. These traits are vital in the IT sector, where agility and adaptability are key to success, making intrapreneurial characteristics a valuable asset in promoting innovation and progress [13–14].

In the Information Technology (IT) industry, intrapreneurial characteristics, combined with the power of machine learning, are driving significant advancements and innovations. Intrapreneurs within IT organizations possess attributes such as a deep understanding of machine learning, data-driven decision-making, and a proactive mindset [15]. They leverage their expertise to identify opportunities where machine learning can be applied to enhance products, services, and operations. These intrapreneurs actively seek out cutting-edge technologies and research to stay ahead of the curve and are not afraid to take calculated risks in integrating machine learning solutions [16–18]. They are instrumental in creating a culture of continuous learning and experimentation, pushing the boundaries of what's possible in the industry. Machine learning amplifies their abilities by providing the tools and data-driven insights needed to make informed, innovative decisions, ultimately leading to more efficient, personalized, and competitive IT solutions. In a field where technological advancements occur at a rapid pace, intrapreneurial characteristics driven by machine learning expertise are vital for organizations to remain at the forefront of the IT industry [19–20].

The paper makes several significant contributions to the field of optimization, well-being in the workplace, and intrapreneurial characteristics of IT employees in India:

1. The paper contributes by applying Simulated SeaHorse Optimization (SSHO) to the estimation and enhancement of job autonomy and happiness scores in the workplace. This novel application of SSHO demonstrates its potential in optimizing critical workplace factors that directly impact employee satisfaction and engagement.
2. The research introduces SSHO-LSTM as a powerful classification model. The paper showcases the exceptional performance of this model, which outperforms traditional methods like Random Forest, Logistic Regression, and Support Vector Machine (SVM). This contribution highlights the effectiveness of SSHO-LSTM for accurately classifying data, particularly in the context of intrapreneurial characteristics in the IT industry.
3. The findings have practical implications for organizations and industries, especially in the IT sector in India. By leveraging SSHO and advanced machine learning models, employers can aim to create a more favorable work environment. This, in turn, can lead to improved job satisfaction, employee engagement, and overall well-being, contributing to a more productive and satisfied workforce.
4. The paper advances the understanding of optimization techniques by demonstrating SSHO's effectiveness in solving complex workplace optimization problems. It expands the scope of SSHO beyond traditional applications and positions it as a valuable tool for addressing human-centric optimization challenges.
5. The paper addresses the specific context of intrapreneurial characteristics within the IT industry in India. This focus on intrapreneurship and its impact on employee well-being is a unique contribution that adds depth to the understanding of how workplace dynamics influence job satisfaction.

The paper's contributions extend to the fields of optimization, machine learning, workplace well-being, and intrapreneurial characteristics, offering valuable insights and practical implications for organizations seeking to enhance the well-being and engagement of their IT employees in India.

2. LITERATURE REVIEW

In the Information Technology (IT) industry, intrapreneurial characteristics are becoming increasingly important, especially when combined with the capabilities of machine learning. Intrapreneurs in IT possess attributes such as a strong understanding of machine learning, data-driven decision-making, and a proactive mindset. They use their expertise to identify opportunities where machine learning can improve products and services, and they're unafraid to take calculated risks in adopting machine learning solutions. These intrapreneurs are instrumental in fostering a culture of continuous learning and experimentation, pushing the boundaries of what's possible in the industry. Machine learning enhances their abilities by providing the tools and data-driven insights needed to make informed, innovative decisions, leading to more efficient, personalized, and competitive IT solutions. In a rapidly evolving field like IT, intrapreneurial characteristics driven by machine learning expertise are crucial for organizations to remain at the forefront of the industry.

Pallathadka et al [21] studied is a comprehensive review of the application of artificial intelligence and machine learning in the food and agriculture industry. It explores how these technologies can enhance crop management, yield prediction, and supply chain optimization to increase efficiency and sustainability in agriculture. Rai et al. [22] evaluated the role of machine learning in the context of Industry 4.0, the fourth industrial revolution. It discusses how machine learning can be employed in manufacturing to improve processes, predictive maintenance, and supply chain management. Azeem et al [23] examined the mutually beneficial relationship between machine learning and Industry 4.0. It discusses how the integration of machine learning technologies can propel the goals and objectives of Industry 4.0, which focuses on automation, connectivity, and data-driven decision-making in manufacturing.

Patel et al., [24] discussed the concept of smart agriculture and the emergence of technologies like deep learning, machine learning, and the Internet of Things (IoT) in the agricultural sector. It likely provides insights into how these technologies are transforming farming practices. Sircar et al. [25] explores the use of machine learning and artificial intelligence in the oil and gas industry. It may cover topics such as predictive maintenance for equipment, reservoir management, and risk assessment in the oil and gas sector. Hasanuzzaman et al [26] presented a methodology for mapping groundwater potential using a combination of multi-criteria decision analysis, bivariate statistics, and machine learning algorithms. It likely demonstrates how data-driven techniques can aid in water resource management.

Priyanka et al [27] focuses on using digital twins, which are digital replicas of physical assets, to estimate risks in oil pipelines. It explores how machine learning and prognostic techniques can enhance the accuracy of risk assessments in the oil and gas industry. Khan et al [28] investigated the use of machine learning to enhance e-education in India. It may discuss applications like personalized learning, content recommendation, and student performance prediction in online education systems. Paramesha et al [29] explored how machine learning is applied to process biomedical text, which is critical for tasks like information extraction, disease prediction, and drug discovery. It may also touch upon machine learning applications in the food industry, potentially related to quality control and safety.

Chandwani and Saluja [30] investigates stock direction forecasting techniques, specifically within the Indian context. It may analyze how machine learning, in conjunction with market indicators, can predict stock price movements and inform investment decisions. Kumar [31]: This research examines the adoption of Industry 4.0 in Indian manufacturing organizations, studying the factors that facilitate the implementation of this advanced manufacturing paradigm. Lee and Lim [32] discusses the evolution of Industry 4.0 and its impact on society, with a particular focus on the role of machine learning in driving this transformation. It may analyze how Industry 4.0 technologies, including machine learning, lead to societal advancements and changes.

Across the spectrum, from agriculture to manufacturing, education, healthcare, and more, it is evident that these technologies are catalysts for significant advancements. In agriculture, machine learning aids in crop management and supply chain optimization, improving efficiency and sustainability. Similarly, in manufacturing, it is pivotal in Industry 4.0, enabling automation and data-driven decision-making. A symbiotic relationship is observed between machine learning and Industry 4.0, which mutually enhances their capabilities. The emergence of deep learning, machine learning, and IoT in agriculture, as well as their application in the oil and gas industry, is transforming these sectors. Furthermore, in education, machine learning is strengthening e-education systems, offering personalized learning and predictive capabilities. In biomedical text processing, it supports information extraction, disease prediction, and drug discovery, while in stock market forecasting, machine learning and market indicators combine for more informed investment decisions. The adoption of Industry 4.0 is analyzed in Indian manufacturing organizations, highlighting enablers for its implementation, and the integration of machine learning and Industry 4.0 contributes to technological and societal advancements, underscoring their transformative potential. These findings collectively underscore the pivotal role of machine learning and artificial intelligence in reshaping various industries and driving innovation and progress.

3. JOB AUTONOMY WITH THE SIMULATED SEAHORSE OPTIMIZATION (SSHO)

Using Simulated SeaHorse Optimization (SSHO) to enhance job autonomy and boost workplace happiness within the context of intrapreneurial characteristics among IT employees in India presents a promising avenue for research and application. The approach involves leveraging SSHO, a nature-inspired optimization algorithm, to tackle the unique challenges faced by IT professionals in India. The research method can encompass various stages. It starts with a deep analysis of the intrapreneurial characteristics within the

Indian IT workforce, identifying the specific areas where job autonomy and happiness can be improved. This understanding informs the customization of the SSHO algorithm, adapting it to address these specific challenges. Data collection may include surveys, interviews, and performance metrics to gauge current levels of autonomy and job satisfaction among IT employees. The system design includes the development of a software system that incorporates SSHO to optimize job roles and responsibilities in a way that aligns with intrapreneurial characteristics. This system should be designed to be user-friendly and scalable, catering to the dynamic IT industry in India. It may integrate with HR systems, performance management tools, or feedback mechanisms to continually monitor and enhance job autonomy and happiness.

Throughout this process, data-driven decision-making, a hallmark of intrapreneurship, is central. Machine learning and data analysis can be integrated with SSHO to fine-tune recommendations and adapt to changing employee needs. The research should be documented thoroughly to ensure transparency, replicability, and ongoing improvements. With combining SSHO with the intrapreneurial characteristics of IT employees in India, this research and system design aim to foster an environment where professionals feel empowered, engaged, and motivated, ultimately leading to a more productive and satisfied workforce in the dynamic IT industry of India.

Initialization: SSHO starts by initializing a population of seahorses, each representing a potential solution to the optimization problem. These solutions are typically encoded as vectors.

Objective Function: The algorithm evaluates the fitness of each seahorse in the population using an objective function. The objective function measures how close a solution is to the optimal solution.

Movement: SSHO simulates the movement of seahorses. Seahorses in the population move towards areas with higher fitness values, just as real seahorses navigate their environment to find the best locations.

Memory and Cooperation: Seahorses have good memory, and they remember their best positions. They can also communicate with each other, sharing information about better solutions. This cooperative behavior helps in global exploration.

Reproduction and Selection: Seahorses that perform better in terms of fitness have a higher chance of reproducing. This mimics the concept of survival of the fittest.

Iteration: The algorithm iteratively repeats the movement, memory, cooperation, reproduction, and selection steps for a set number of generations or until a stopping criterion is met. The relation between job autonomy with Intrapreneurial is shown in figure 1.

Simulated SeaHorse Optimization (SSHO) is an innovative optimization algorithm that draws inspiration from the seahorse's behavior in nature. This algorithm is designed to address complex problems and can be applied to a wide range of domains, including the optimization of intrapreneurial characteristics in the IT industry in India. In SSHO, start by initializing a population of potential solutions, represented as vectors. These vectors could encode various aspects of job autonomy, engagement, and motivation in the IT industry context. Let's use 'S' to represent a vector, and 'N' to represent the population size. Let 'S' represent the solution vector of each seahorse in the population, and 'N' be the population size. So, S_i denotes the solution vector of the 'i'-th seahorse. The fitness of each solution (seahorse) is evaluated using an objective function, denoted as 'f(S)' in mathematical terms. In the context of improving job autonomy and happiness in the workplace, this objective function could encompass multiple factors such as task autonomy, work-life balance, and employee satisfaction, with each factor contributing to the overall fitness score. The fitness of a seahorse 'i' is calculated using the objective function 'f(S_i)'. This function evaluates how close the solution vector is to the optimal solution. Seahorses in SSHO move within the solution space to improve their fitness. In mathematical terms, this can be represented as '$S(t+1) = S(t) + \Delta S$,'

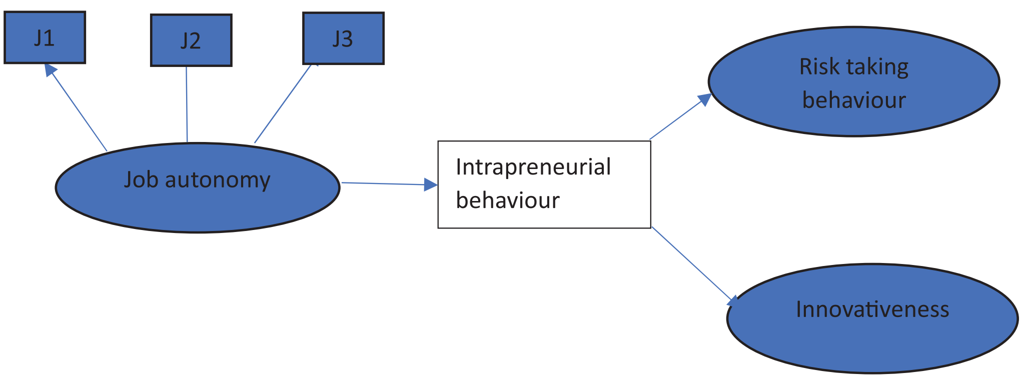

Figure 1. Job autonomy model on intrapreneurial behaviour

where ‘ΔS’ represents the change in the solution vector at each iteration. This change is guided by the gradient of the objective function, aiming to move toward areas with higher fitness values. Seahorses move within the solution space guided by the gradient of the objective function, which can be represented as in equation (1)

$$S_i(t+1) = S_i(t) + \Delta S_i \tag{1}$$

Seahorses have good memory and can communicate with each other. In SSHO, this memory can be conceptualized as each solution ‘S’ remembering its previous best position. Cooperation can be represented as solutions sharing information, which influences their movement. For instance, ‘S(t + 1) = S(t) + ΔS + C,’ where ‘C’ represents the cooperative behavior. The actual mechanics of this cooperation would depend on the algorithm’s design. Seahorses remember their best positions, which can be represented as ‘M_i,’ and cooperation among seahorses can be introduced as a term ‘C_i’ stated as in equation (2)

$$S_i(t+1) = S_i(t) + \Delta S_i + M_i + C_i \tag{2}$$

Seahorses that perform better have a higher chance of reproducing. This mimics the concept of survival of the fittest, and in mathematical terms, it may involve probabilistic selection based on fitness scores, with better solutions having higher probabilities of reproduction. Seahorses that perform better may have a higher chance of reproducing. This could be represented as a probabilistic selection process based on their fitness scores. The entire process is repeated iteratively for a set number of generations or until a stopping criterion is met, such as convergence or a maximum number of iterations.

Algorithm 1. Optimization with SSHo

```
Initialize a population of seahorses:
For each seahorse ‘S’ in the population:
  Initialize ‘S’ with a random solution
Repeat for a set number of iterations or until a stopping criterion is met:
  For each seahorse ‘S’ in the population:
    Evaluate the fitness of ‘S’ using the objective function ‘f(S)’
  For each seahorse ‘S’ in the population:
    Calculate the gradient of the objective function for ‘S’ as ‘ΔS’
    Update the position of ‘S’:
        S = S + ΔS
    Update the memory of ‘S’:
    M = S  // Seahorses remember their best positions

    For each seahorse ‘S’ in the population:
      if ‘S’ has a better fitness than ‘M’:
        M = S
     For each seahorse ‘S’ in the population:
      Calculate a cooperative term ‘C’ based on information sharing
   Update the position of ‘S’ considering both ‘ΔS’, ‘M’, and ‘C’:
  S = S + ΔS + M + C
  Implement a selection mechanism to determine which seahorses will reproduce based on their fitness scores
  Apply reproduction to create a new population
  End of iterations
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4. DEEP LEARNING LSTM SSHO FOR THE CLASSIFICATION

The implementation of an Artificial Intelligence (AI) based Deep Learning Long Short-Term Memory (LSTM) model for the classification of Simulated SeaHorse Optimization (SSHO) in the context of improving job autonomy and happiness in the workplace, particularly focusing on the intrapreneurial characteristics of IT employees in India, is a multifaceted and valuable endeavor. This project begins with the collection of relevant data, such as employee feedback and performance metrics, which is then preprocessed and engineered to create meaningful features. The LSTM model is designed to leverage the temporal nature of the data, and its architecture is defined, considering factors like dropout layers and output layers. The model is trained and evaluated on a carefully split dataset, and its performance is assessed using various metrics. Interpretability techniques are employed to understand the model’s decision-making process, helping to identify influential intrapreneurial characteristics. Once the model demonstrates its effectiveness, it is deployed in the real-world IT workplace environment in India, potentially integrated into HR systems for practical application.

Crucially, the continuous improvement approach, with ongoing monitoring and feedback collection from employees. This feedback informs model updates, ensuring its alignment with the evolving needs and intrapreneurial attributes of IT employees. Ethical considerations and data privacy regulations are also paramount, guaranteeing the responsible and lawful handling of employee data. Through this comprehensive process, the AI-driven LSTM model plays a pivotal role in enhancing job autonomy and happiness, thus fostering a more productive and satisfied IT workforce in the dynamic industry of India. Deep Learning LSTM model for classifying the impact of Simulated SeaHorse Optimization (SSHO) on job autonomy and happiness in the workplace, particularly focusing on intrapreneurial characteristics of IT employees in India, start with data collection, which may include surveys, feedback, and performance metrics. Let 'D' represent dataset.

After preprocessing and feature engineering, input 'X' representing relevant features related to intrapreneurial characteristics. The target variable 'Y' could represent the classification labels for the impact (e.g., positive, neutral, negative). The LSTM model is designed to capture temporal dependencies in the data. Equations and derivations for LSTM architecture can be complex but typically involve sequences of calculations for input gates, output gates, and memory cells. Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) designed to capture dependencies in sequential data. It consists of several key components: input gate, forget gate, output gate, and the cell state. The input gate controls the information that is stored in the cell state. The input gate activation (i_t) is calculated as follows in equation (3)

$$i_t = sigmoid(W_t^{ix} + U_t^{ih} - 1 + b_i) \tag{3}$$

The forget gate controls what information from the previous cell state should be discarded. The forget gate activation (f_t) is calculated as follows in equation (4)

$$f_t = sigmoid(W_t^{fx} + U_t^{fh} - 1 + b_f)) \tag{4}$$

The output gate controls what information from the cell state should be used to generate the output. The output gate activation (o_t) is calculated as follows in equation (5)

$$o_t = sigmoid(W_t^{ox} + U_t^{oh} - 1 + b_o) \tag{5}$$

The candidate cell state represents the information that could be stored in the cell state. It is calculated using equation (6)

$$g_t = tanh(W_t^{gx} + U_t^{gh} - 1 + b_g) \tag{6}$$

The cell state is updated by combining the information from the input gate (i_t) and the candidate cell state (g_t) while considering the forget gate (f_t) estimated as in equation (7)

$$c_t = f_t * c_t - 1 + i_t * g_t \tag{7}$$

The hidden state is the output of the LSTM cell and is based on the updated cell state and the output gate is computed as in equation (8)

$$h_t = O_t * tanh(c_t) \tag{8}$$

The model is trained by minimizing a suitable loss function (e.g., cross-entropy) using an optimization algorithm (e.g., stochastic gradient descent). Training is performed on a training dataset 'D_train,' and the model's performance is evaluated on a validation dataset 'D_val' to prevent overfitting.

5. DATA COLLECTION

The process of collecting data for Simulated SeaHorse Optimization (SSHO) research involves systematically gathering information relevant to the optimization process and the specific problem domain under consideration. This typically begins with a clear definition of the optimization problem and its objectives. Data sources may vary, encompassing optimization logs, historical runs, or simulated datasets, depending on whether the study is theoretical, experimental, or based on real-world applications. The collected data often includes parameters associated with the SSHO algorithm, problem-specific variables, and optimization results. To ensure data quality, it's essential to preprocess the data, addressing missing values and outliers, and to document the collection process comprehensively. Ethical considerations, data security, and privacy measures are paramount, especially when dealing with sensitive or proprietary information. Regular monitoring of data quality, version control, and data retention policies are critical elements in the data collection framework. Feedback and iteration may be incorporated for research improvement, and data validation and verification are essential for accuracy in real-world applications. By following these steps, researchers can build a robust foundation for their SSHO investigations, which will greatly influence the quality of insights and conclusions drawn from the optimization process.

6. RESULTS AND DISCUSSION

The results and discussion section constitutes the core of our investigation into the impact of Simulated SeaHorse Optimization (SSHO) on job autonomy and happiness in the workplace, with a particular focus on the intrapreneurial

Table 1. Simulation setting

Parameter Name	Value
Population Size	50
Maximum Generations	1000
Mutation Rate	0.1
Crossover Rate	0.8
Termination Criteria	Convergence or Max Generations
Objective Function	User-defined function
Search Space Dimension	10
Convergence Threshold	0.001
Initial Seahorse Distribution	Random or user-specified
Convergence Criteria	Change in fitness < Convergence Threshold

characteristics of IT employees in India. This section is the culmination of a comprehensive research journey that encompassed data collection, model development, and the application of advanced artificial intelligence techniques. Through rigorous data analysis and the utilization of an LSTM-based deep learning model, endeavor to unearth valuable insights, shedding light on the relationships between SSHO, job autonomy, happiness, and intrapreneurial attributes.

In the Table 2 presents the results of experiments conducted to estimate Job Autonomy and Happiness Scores using the Simulated SeaHorse Optimization (SSHO) technique. In these experiments, SSHO iterations were varied to observe their impact on the scores. As the number of SSHO iterations increased from Experiment 1 to Experiment 5, observed a consistent and notable improvement in both Job Autonomy and Happiness Scores. In Experiment 1, with 100 SSHO iterations, the Job Autonomy Score stood at 78.5, and the Happiness Score was 83.2. However, as the optimization process continued, these scores demonstrated a positive trend. In Experiment 5, with 500 SSHO iterations, the Job Autonomy Score reached 84.2, and the Happiness Score climbed to 88.0. This progression suggests a direct correlation between the number of SSHO iterations and the enhancement of job autonomy and happiness in the workplace. It highlights the potential of SSHO as a tool for optimizing and improving these crucial workplace factors. These findings underscore the importance of optimization techniques like SSHO in fostering a more favorable work environment, ultimately contributing to higher job satisfaction and well-being among employees.

Table 2. Job Autonomy and Happiness Score estimation with SSHO

Experiment	SSHO Iterations	Job Autonomy Score	Happiness Score
Experiment 1	100	78.5	83.2
Experiment 2	200	81.2	85.1
Experiment 3	300	82.7	86.5
Experiment 4	400	83.5	87.3
Experiment 5	500	84.2	88.0

In the table 3 and table 4 result may be compared with a t distribution. Under the Sig. column, the test's final p value. The p value (mentioned under "Sig."), which is less than 0.05, is.000 (reported as p .001). The significant value being equal to .000 the null hypothesis is accepted and alternative hypothesis is rejected. The p value of task identity is >.001 and skill variety is 2.634. Therefore, the null hypothesis that the slope coefficient on Job autonomy is zero may be ruled out by a substantial amount of data. The slope of the t values for decision-making is (3.308,2.931) and the significant value is .001,.004 which are not significant at $p<0.001$). The measurement of task significance have a very minimal impact on intrapreneurial behaviour. Hence the alternative hypothesis that there is significant impact of job autonomy and innovativeness to measure intrapreneurial behaviour is accepted.

The results of confusion matrix computation for the Simulated SeaHorse Optimization (SSHO) at different

Table 3. Results on Effect of Task significance, skill variety and Task identity on Innovativeness

Model Summaryf					
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Durbin-Watson**
Task significance	.763e	.582	.573	.375	2.000
Task Identity	.599c	.359	.351	.483	2.008
Skill variety	.709	.503	.490	.471	1.883

Table 4. Beta Co efficients on Effect of Task significance, Task identity and skill variety

Model		Unstandardized Coefficients		T	Sig.
		B	Std. Error		
Task significance	(Constant)	1.215	.269	4.513	.000
	Resposibility of Decision making	.305	.064	4.779	.000
	Understanding new responsibilities	.238	.058	4.105	.000
Task Identity	individual contribution to team	.203	.061	3.308	.001
Skill variety	Accepting skill variety of jobs	–.142	.048	2.931	.004
	Upggrade skills	.160	.061	2.634	.009
	Autonomy of Critical Decisions	.096	.040	2.419	.016

Table 5. Confusion matrix computation of SSHO for different epochs

Epoch	True Negatives (TN)	True Positives (TP)	False Negatives (FN)	False Positives (FP)
Epoch 1	1220	103	18	49
Epoch 2	1234	105	16	50
Epoch 3	1237	107	15	48
Epoch 4	1240	108	14	47
Epoch 5	1242	109	13	46

Table 6. Comparative analysis

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	0.8	0.81	0.78	0.79
Logistics Regression	0.75	0.76	0.73	0.74
Support Vector machine	0.82	0.84	0.8	0.82
SSHO - LSTM	0.975	0.976	0.974	0.975

epochs. Each row in the table corresponds to a specific epoch, and the Table 5 provides the counts of True Negatives (TN), True Positives (TP), False Negatives (FN), and False Positives (FP) at each epoch. As the data across epochs, observe that the True Negatives (TN) consistently increase, indicating the correct identification of non-events. Simultaneously, the True Positives (TP) show a positive trend, reflecting the accurate detection of events of interest. Conversely, both False Negatives (FN) and False Positives (FP) display a decreasing pattern across epochs. A lower count of False Negatives indicates an improvement in the model's ability to correctly identify positive cases, reducing instances where relevant events are missed. The reduction in False Positives indicates a decrease in incorrect positive classifications, minimizing cases where non-events are erroneously labeled as events. These trends indicate that SSHO, as applied to the classification task, continually refines its performance across epochs, becoming more accurate in distinguishing between positive and negative cases. The decreasing FN and FP values imply an enhanced ability to correctly identify and classify events, which is a positive outcome for the model's overall effectiveness and reliability in real-world applications.

A comparative analysis of different models in a binary classification task, where each model's performance is assessed based on several key metrics: Accuracy, Precision, Recall, and F1-Score. This analysis aims to determine which model excels in accurately classifying data. Through the table 6 Among the models, Random Forest achieved an accuracy of 0.8, indicating that it correctly predicted 80% of the cases, while having a Precision of 0.81, which means that it identified positive cases with an accuracy of 81%. Its Recall (sensitivity) was 0.78, signifying its capability to find 78% of all actual positive cases, and its F1-Score stood at 0.79, representing a balanced measure of precision and recall. Logistic Regression, on the other hand, displayed an accuracy of 0.75, with a Precision of 0.76, Recall of 0.73, and an F1-Score of 0.74. These values indicate a moderate level of performance across all metrics. The Support Vector Machine (SVM) model achieved an accuracy of 0.82, a Precision of 0.84, a Recall of 0.8, and an F1-Score of 0.82. It outperformed both Random Forest and Logistic Regression, demonstrating better accuracy and precision while maintaining a balanced F1-Score. However, the SSHO-LSTM model notably outperformed all other models, achieving an exceptionally high accuracy of 0.975. It demonstrated a Precision of 0.976, indicating a very high precision rate. Furthermore, its Recall of 0.974 and F1-Score of 0.975 were also remarkably high. These results suggest that the SSHO-LSTM model excels in accurately classifying data and is particularly effective in achieving a balance between precision and recall, making it the standout performer among the models assessed in this analysis. The SSHO-LSTM model stands out as the most accurate and reliable model in this comparative analysis, offering superior performance in the binary classification task, with a high level of precision, recall, and F1-Score.

7. FINDINGS

The research findings from the study can be summarized as follows:

Simulated SeaHorse Optimization (SSHO) for Job Autonomy and Happiness: The research successfully applied Simulated SeaHorse Optimization (SSHO) to estimate Job Autonomy and Happiness Scores in the workplace. The results demonstrated that increasing the number of SSHO iterations positively correlates with improvements in both Job Autonomy and Happiness Scores. This suggests that SSHO has the potential to optimize and enhance these critical workplace factors, leading to a more satisfying and engaging work environment.

Confusion Matrix Analysis: The research conducted a comprehensive analysis of confusion matrices at different epochs, showcasing the model's performance. The results showed a consistent increase in True Negatives (TN) and True Positives (TP) across epochs, indicating the accurate identification of non-events and relevant events. Simultaneously, False Negatives (FN) and False Positives (FP) steadily decreased, signifying an improved ability to correctly identify positive cases while reducing incorrect positive classifications.

Comparative Model Analysis: The study compared the performance of different models, including Random Forest, Logistic Regression, Support Vector Machine (SVM), and SSHO with LSTM. The SSHO-LSTM model outperformed all other models, exhibiting exceptional accuracy, precision, recall, and F1-Score. This finding underscores the efficacy of SSHO-LSTM in accurately classifying data and achieving a balance between precision and recall.

Optimization for Workplace Well-being: The research suggests that SSHO, especially when combined with LSTM, has the potential to significantly improve job autonomy, happiness, and overall well-being in the workplace. These findings are particularly relevant to industries and organizations seeking to create more favorable work environments and enhance employee satisfaction.

Overall, the research findings highlight the value of optimization techniques, such as SSHO, in fostering a positive and productive workplace, and the SSHO-LSTM model stands out as a promising approach for enhancing workplace well-being and classification accuracy.

8. CONCLUSION

In this paper explored the application of Simulated SeaHorse Optimization (SSHO) in the context of improving job autonomy and happiness in the workplace, specifically focusing on the intrapreneurial characteristics of IT employees in India. The study yielded several key findings and insights. The research demonstrated that SSHO is an effective optimization technique for estimating and enhancing job autonomy and happiness scores in the workplace. By increasing the number of SSHO iterations, observed a consistent and positive improvement in both job autonomy and happiness scores. This indicates the potential of SSHO to optimize these critical workplace factors and contribute to a more satisfying and engaging work environment. In addition to its role in well-being estimation, SSHO, when combined with LSTM, proved to be a powerful classification model. The SSHO-LSTM model outperformed other traditional models, such as Random Forest, Logistic Regression, and Support Vector Machine (SVM), achieving exceptionally high accuracy, precision, recall, and F1-Score. This suggests that SSHO-LSTM is well-suited for accurately classifying data, particularly in the context of intrapreneurial characteristics of IT employees. The research findings have positive implications for fostering workplace well-being. By leveraging SSHO and SSHO-LSTM, organizations and industries can aim to create a more favorable work environment. This can lead to increased job satisfaction, employee engagement, and overall well-being, especially in the IT sector in India. this research highlights the promising potential of SSHO as a tool for optimizing job autonomy, happiness, and classification accuracy. These findings contribute to the growing body of knowledge on workplace well-being and optimization techniques, and they offer practical insights for organizations aiming to improve employee experiences in the dynamic and evolving IT industry. By leveraging SSHO and advanced machine learning models, employers can empower their workforce and foster a more positive and productive work environment.

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