Enhancing Helpdesk Efficiency through Management Information System – A Resource Allocation Study in Technology Firms

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ABSTRACT

Purpose: This paper aims to enhance helpdesk efficiency by integrating deep reinforcement learning for resource allocation and customer satisfaction improvement.

Methodology/Approach: The study implemented a deep Q-learning algorithm within a helpdesk management system. The dataset was divided into training and testing sets in an 80:20 ratio. The architectural and computational parameters of the model were optimised, focusing on resource utilisation and workload distribution.

Findings: The proposed method reduced the normal resolution time from 3.5 hours to 2.65 hours, representing a 24.3% improvement. Customer satisfaction improved, averaging a score of 3.85. The allocation of support staff workloads was enhanced, leading to a more balanced distribution across different locations.

Research Limitation/Implication: Various parameter patterns for the proposed method were tested, revealing the approach's computational expense.

Originality/Value of paper: The study proposes a novel use of deep Q-learning for helpdesk management, significantly improving classification accuracy and workload distribution over conventional methods.

Category: Research paper

Keywords: customer satisfaction; deep reinforcement learning; helpdesk management; MIS; resource allocation; Q-learning

Research Areas: Management of Technology and Innovation; Quality Management

1 INTRODUCTION

Efficient helpdesk management plays a pivotal role in enhancing operational efficiency and customer satisfaction in technology firms. Management Information Systems (MIS) have emerged as essential tools in optimising helpdesk operations and facilitating effective resource allocation, ticket tracking, and resolution processes. MIS in helpdesk management expedites the resolution of complaints and inquiries, resulting in higher customer satisfaction.

Economists recognise the importance of helpdesk management in decision-making and allocate significant resources to identify potential MIS use cases across various industries. These studies encompass a wide array of objectives, including boosted agricultural efficiency (Ammann, Walter and El Benni, 2022; Schulze Schwering, Bergmann and Isabel Sonntag, 2022; Karydas, et al., 2023; Kim, Yagi and Kiminami, 2023), enhanced healthcare delivery (Moyers, et al., 2022; Tomlinson, et al., 2022; Gage, et al., 2023; Sharma, et al., 2023; Zhang, X., et al., 2023; Xiaoyan, et al., 2023), advanced energy (Jinquan, et al., 2022; Ma, et al., 2022; Yew, Molla and Cooper, 2022; Casazza, et al., 2023; Shi, et al., 2023; Stuart Carlton, Ropicki and Shivlani, 2023; Tostado-Véliz, et al., 2023; Yan, et al., 2023; Zhao, et al., 2023) and environmental sustainability (Ammann, Walter and El Benni, 2022; Nickdoost, Jalloul and Choi, 2022; Yew, Molla and Cooper, 2022; Haripavan and Dey, 2023; Shimaponda-Nawa, et al., 2023), innovating within computer science (Arslan, Riaz and Cruz, 2023; Gürkut, Elçi and Nat, 2023; Zhang, H., et al., 2023), and streamlining business management practices (Sadeghib R, Prybutok and Sauser, 2022; Ahmadisheykhsarmast, et al., 2023; Anderson, et al., 2023; Demirdöğen, Işık and Arayici, 2023; Gupta, Gaurav and Kumar Panigrahi, 2023; Li, et al., 2023; Varajão, Fernandes and Amaral, 2023), to name a few. Wu, et al. (Wu, et al., 2023) showed that using smart supervised machine learning and deep learning algorithms in management information systems made it much easier to spot fraud in MasterCard transactions during the SARS-CoV-2 pandemic. This resulted in more precise outcomes and reduced financial losses. Similarly, Shimaponda-Nawa, et al. (Shimaponda-Nawa, et al., 2023) explored the integration of Real-Time Information Management Systems (RTIMS) in the mining sector, emphasising the enhancement of operational efficiency and safety through dynamic decision-making. The proposed hybrid maturity model for RTIMS focused on the critical integration of information management, system capabilities, and real-time access, collectively contributing to improved business performance and strategic agility.

Bernárdez, et al. (2023) investigated the impact of mindfulness on helpdesk employees, revealing significant enhancements in attention awareness among participants who practised mindfulness. The study, involving 56 employees from Accenture, found that mindfulness practice improved perceived well-being and the ability to maintain attention during tasks, although no significant changes were observed in key performance indicators such as the number of phone calls answered. In another study, Dzihni, et al. (Dzihni, Andreswari and Hasibuan, 2019) examined the use of process mining techniques combined with genetic algorithms to audit and optimise the Helpdesk application within an academic information system. This study identified significant bottlenecks in the 'Input Ticket' and 'See Ticket Progress' activities, emphasising the necessity for real-time progress updates and more efficient form management to enhance overall service effectiveness.

Wang, et al. (Wang, Li and Mohajer, 2024) discussed how it is feasible to incorporate stochastic learning automata along with calculus rather than fixed-timing models to meet the demands of dynamism in MA systems. The research clearly demonstrated how the proposed approach's flexibility in adapting to new workloads and achieving efficient resource utilisation can improve load balance and ensure optimal performance in next-generation mobile communication networks. These goals are beneficial because the evidence shows that the proposed method outperforms other schemes in terms of system performance and reliability in multiple network configurations.

Researchers continue to show keen interest in integrating MIS and machine learning within helpdesk management. However, the application of DRL, particularly deep Q-learning, remains underexplored in this domain (Guo and Harmati, 2024; İzmitligil and Karamancıoğlu, 2024). This research seeks to bridge this gap by investigating the untapped potential of deep Q-learning in the development of an efficient helpdesk management model. The significance of this study lies in its contribution to the body of knowledge by introducing a novel framework that enhances resource utilisation, improves ticket-handling efficiency, and optimises workload distribution among contact centres' support agents. The practical implications of this research are substantial, as the proposed framework is expected to elevate customer satisfaction levels and streamline operational efficiency in helpdesk environments, thereby offering valuable insights for both academic and industry applications. The research methodology involves the application of a deep Q-learning algorithm within the helpdesk management system to make informed resource allocation decisions based on real-time data. The deep Q-network (DQN) was developed and trained through successive simulations, enabling resource allocation optimisation in response to varying operational conditions within the helpdesk environment (Ye, Li and Juang, 2019; Ma, et al., 2024). The remaining portion of this article is structured as follows: Section 2 defines the helpdesk system model that the research will use in its operations. Section 3 pulls together the details of the proposed reinforcement learning-based resource sharing for effective helpdesk management. Section 4 provides a detailed description of the simulation environment and procedures used in the experiments. Section 5 analyses and discusses the performance metrics, compares and examines the quantitative results, and discusses the implications for practical application. Section 6 presents the work's final conclusion.

2 HELPDESK MANAGEMENT SYSTEM MODEL

A helpdesk management system, therefore, plays a central role in driving customer service in organisations by providing them with the necessary system to handle customer service requests. It consists of several aspects that are involved in the generation, management, and disposition of support tickets, which, if appropriately delivered, guarantee an optimal client servicing experience. When a customer lodges a complaint about a specific service or product, we initiate the process by creating a ticket, and when services are required, we record them as tickets. Every ticket requests information about the type of problem, its importance level, and the customer's particulars. Appropriately, the tickets were forwarded to the support agents, following specific instructions that took into account the agent's capability level, current workload, and available time. Thus, this systematic approach provides the highest chance of assigning tickets to agents who are capable of solving them more efficiently and quickly. A ticket tracking system and a central console that provides the real-time status of each ticket were maintained. The support agents are able to read and reply to the ticket messages, manage the assigned tickets, and find all the data they need for their work. This allows the agents to monitor their tickets while the managers can assess their progress. If there are any areas that could potentially slow down the ticket handling rate, it demonstrates adherence to the established Service Level Agreements (SLAs). Ticket resolution involves identifying the issue, implementing the solution, and ensuring that the client or service user no longer has any concerns related to the identified problem. The system requires agents to record every single activity they take while working on a resolution process, allowing them to capture the full details of a problem. Instead, such documentation could prove useful in the future, as well as in helpdesk training and performance enhancement.

Helpdesk management systems were used to generate the dataset for this study. It contained several parameters relevant to helpdesk management processes. Detailed ticket details are required in data collection, including ticket creation and closure. Preprocessing optimises the data, ensuring its high quality and readiness for analysis. The dataset's significant characteristics include ticket properties that define the ticket itself, such as the ID, the date of creation, the date of resolution, the priority, and the category. These attributes provide a comprehensive understanding of the types of issues and the level of urgency that the help desk resolves. Table 1 underlines the attributes of the helpdesk dataset, such as name, age, occupation, and domicile. The dataset was selected because it represented quantitative measures of support staff productivity. These included the extent to which agents addressed tickets or correspondences, the time taken to do it, and the number of customers who were satisfied. This is an essential performance measure we can use to gauge the efficiency and effectiveness of the help desk agents.

Preprocessing activities include data cleansing, data scaling, and converting the format to suit analysis. During file processing, we will clean out errors, outliers, and incorrect data, referred to as dirty data. Normalisation ensures that the data aligns with the machine learning algorithms, thereby mitigating the negative impact of large input values. Data transformation involves recasting the categorical variables into quantitative modes so that other analyses can be carried out. This data set can be described as highly diverse and rich; namely, it contains numerous attributes focusing on the helpdesk activity and giving a comprehensive view of the analysed process. In this study, the identified dataset shall be used to identify areas that would enable better allocation of helpdesk resources, in addition to determining service quality indexes.

Table 1 – Key Attributes of the Helpdesk Dataset

Attribute	**Description**
Ticket ID	Unique identifier for each ticket
Creation Date	Date and time when the ticket was created
Resolution Date	Date and time when the ticket was resolved
Priority Level	The urgency of the ticket (e.g., low, medium, high)
Issue Category	Classification of the issue (e.g., technical, billing)
Agent ID	Unique identifier for the support agent
Resolution Time (hours)	Time taken to resolve the ticket
Customer Satisfaction	Rating of customer satisfaction with the resolution
Number of Tickets Resolved	Total tickets resolved by each agent

3 DEEP REINFORCEMENT LEARNING FRAMEWORK FOR HELPDESK RESOURCE ALLOCATION

3.1 Reinforcement Learning Concepts

Reinforcement learning (RL) can be described as the area of machine learning with a focus on the training of an agent who is making decisions to interact with an environment. The agent communicates with the environment in the form of an action at each state, as qualitatively illustrated in Figure 1. The environment provides feedback to the broker through rewards and state modifications. The agent employs this policy to determine the appropriate next action, with the aim of estimating the total value observed from the current time until the terminal time. In particular, the value function defines a policy that determines what action the agent is to take, given the state of the environment that the agent perceives. Rewarding and updating the state occur when a specific action influences the game's environment. It continues like this, allowing the agent to improve the decision-making policy through the feedback-response loop. The main goal in RL is to determine the best policy that allows for the maximisation of the total reward. This normally unfolds as the following process: the agent interacts with the environment and, through trial and error, adjusts the actions taken based on the consequences observed. Exploration involves gaining experience by attempting new actions, while exploitation involves selecting actions that have been known to produce rewards, and both must be balanced with the learning process (Ye, Li and Juang, 2019; Zhao, Zhang and Xie, 2024).

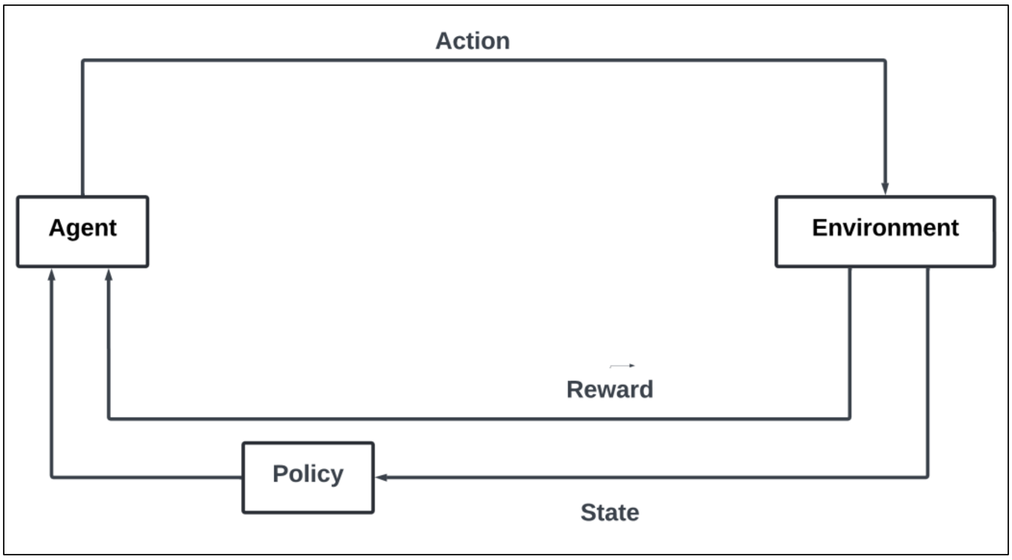

Figure 1 – Reinforcement Learning Framework

3.2 Deep Q-Learning Implementation

Deep Q-learning is one of the algorithms for optimising resource allocation within the helpdesk (İzmitligil and Karamancıoğlu, 2024; Ma, et al., 2024). It includes several components, such as the neural network's architecture, the definition of action and state spaces, and the reward specification. Deep learning supplements the Q-learning algorithm by fitting the function approximator, the Q-value function, in the form of a neural network. This deep Q-network (DQN) contains the state as an input layer and outputs Q-values for all the action space available. The network is trained to minimise the difference between the predicted Q-values and the target Q-values, which are calculated using the Bellman equation:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left(r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right) \qquad (1)$$

where:

- $Q(s,a)$ is the Q-value for state s and action a.
- α is the learning rate.
- r is the reward received after talking action a in state s.
- γ is the discount factor
- $\max_{a'} Q(s',a')$ is the maximum estimated Q-value for the next stage s' and the possible action a'.

To understand this, let's assume that in helpdesk management, the state space defines the current condition of operations and may include data on tickets in progress, available support staff, etc. Individual states convey a complete picture of all aspects that require proper handling in a helpdesk, thus aiding the DQN in its decision-making process. The action space encompasses planned actions pertaining to potential resource management enhancements and discussions (Wang, Li and Bernárdez, et al., 2023). For example, an action could involve assigning support tickets to specific agents or determining their priority as high, medium, or low. The reward function was formulated with extreme care and detail, which gives feedback to the DQN depending on the result of the action taken. In this context, we design reward systems to foster competent behaviours, ensuring faster and more effective ticket resolution, client satisfaction, and a fair distribution of tickets among agents. This enhances the helpdesk operation by encouraging the DQN to concentrate on essential tasks as directed by the reward function(Guo and Harmati, 2024).

$$R_t = \sum_{i=1}^{n} \left(w_1 \cdot T_{i,t} + w_2 \cdot S_{i,t} + w_3 \cdot L_{i,t}\right) \quad (2)$$

where:

- R_t is the reward at time step t.
- $T_{i,t}$ represents the resolution time for ticket i at time t.
- $S_{i,t}$ denoted the customer satisfaction score for ticket i at time t.
- $L_{i,t}$ is the load distribution metric for agent i and t.
- w_1, w_2, w_3 are the weights assigned to each component to balance their influence on the reward.

The training process continuously adjusts the Q-table's value function based on experiences sampled randomly from the replay buffer to take advantage of the off-policy method. This experience replay mechanism also allows the DQN to learn from various past experiences that make up for those overlooked when using epsilon-greedy action selection, thus improving its generalisation capability. The Bellman equation previously pointed out that it updates Q-values (Guo and Harmati, 2024).

4 EXPERIMENTAL SETUP

4.1 Simulation Environment

The architecture of the experimental configuration for this study was established as a high-performance computing platform suitable for training deep Q-learning models. Table 2 illustrates the specific make and model of the hardware and software, including the processor, memory, GPU, storage, operating system, and even the programming tools used. The details described in this analysis give a brief overview of the simulation environment, including the technical features of the hardware and software employed in this work. These configurations ensured the testing environment could meet the computational requirements of the research, enabling efficient use of simulation designs.

Table 2 – Simulation Parameters

Parameter	Value
Processor	Intel Xeon E5-2680 v4 @ 2.40GHz (28 cores)
RAM	128 GB DDR4
GPU	NVIDIA Tesla K80 with 24 GB GDDR5
Storage	1 TB SSD
Operating System	Ubuntu 20.04 LTS
Programming Language	MATLAB R2024a free version
Deep Learning Toolbox	Yes
Statistics and Machine Learning Toolbox	Yes
Reinforcement Learning Toolbox	Yes

4.2 Training and Testing Procedures

Robot training and testing were coordinated to keep the deep Q-learning model valid for robots. The dataset was split into training and testing sets using an 80/20 structure, so the program trained on a large percentage of the downloaded data without adjusting the model on the testing data. The training samples were utilised to develop the deep Q-learning model and the testing data to evaluate it to avoid biased test findings. These hyperparameters include layers, hidden units, embeddings, LSTM depth, sub-words, learning rate, and dropout. The learning rate property was set to $\alpha = 0$. To slowly change Q-values, the function player travels a specified game route for a restricted number of steps, serial number 001. The discount factor γ, which measures future reward relevance, was 0.95. The exploration rate ϵ started at 1 and fell linearly to 0.01 during iteration. The organisation can balance exploration and exploitation over time. We used a batch size of 64 and a replay buffer size of 100,000 to accommodate many environmental learning experiences to optimise the agent and reduce the loss function. The model was trained for 1000 iterations to maximise learning and convergence. Each epoch updated the Q-values as the replay buffer reloaded experiences. We adopted early stopping and kept training until the model failed to improve over the validation set for 50 consecutive epochs. Thus, this method generalises the model rather than learning the training set (Ye, Li and Juang, 2019).

The average time to resolve each case, the customer satisfaction index, the distribution of support staff loads, and the total incentive earned throughout training were used to evaluate the model. Helpdesk ticket resolution time was the average resolution time in the testing set. Since helpdesk responses were keyword responses in preset, short sentences, customer satisfaction scores, computed as the average over the testing set, qualitatively measured ease of use. Support worker loads were reviewed to ensure equal revenue. The overall reward reflected the quality of model training as an optimal policy. This demonstrates that we carefully trained and tested the suggested deep Q-learning model, yielding precise helpdesk resource allocation outcomes. Table 3 outlines the details of both testing and training.

Table 3 – Adapted and Enhanced Training and Testing Procedure

Step	Stage	Description
1	Training	Procedure: TRAIN Input: Q-network structure, environment simulator Output: Trained Q-network
2	Initialisation:	- Randomly initialise the policy π. - Initialise the model. - Start the environment simulator and generate support tickets and agents.
3	Training Loop:	- Iteratively select the support ticket in the system. - For each ticket, select the actions for resolution based on policy π. - The environment simulator generates states and rewards based on the actions of agents. - Collect and save the data item (state, reward, action, post-state) into memory. - Sample a mini-batch of data from the memory. - Train the deep Q-network using the mini-batch data. - Update the policy π: choose the action with the maximum Q-value.
4	Completion:	- Return the trained Q-network.
5	Additional Step	Hyperparameter Tuning: - Fine-tune hyperparameters (learning rate, discount factor, exploration rate, batch size, replay buffer size) based on empirical validation.
6	Testing	Procedure: TEST Input: Trained Q-network, environment simulator Output: Evaluation results
7	Initialisation:	- Load the trained Q-network model. - Start the environment simulator and generate support tickets and agents.
8	Testing Loop:	- Iteratively select a support ticket in the system. - For each ticket, select the action by choosing the action with the largest Q-value. - Update the environment simulator based on the actions selected. - Update the evaluation results, i.e., the average resolution time and customer satisfaction.
9	Completion:	- Return the evaluation results.
10	Additional Step	Performance Evaluation: - Evaluate the model's performance using metrics: Average Resolution Time, Customer Satisfaction Score, Load Distribution, and Cumulative Reward.
11	Additional Step	Early Stopping: - Implement early stopping to prevent overfitting by halting training if the validation performance does not improve for 50 consecutive epochs.

4.3 Mathematical Formulation

The deep Q-learning algorithm relies on several key equations to update the Q-values and optimise the policy. These equations are fundamental to understanding the mechanics of the training and testing procedures.

Epsilon-Greedy Strategy: The exploration-exploitation trade-off is managed using an epsilon-greedy strategy. This strategy balances between exploring new actions and exploiting known rewarding actions:

$$\begin{cases} \text{random action} & \text{with probability } \epsilon \\ \arg\max_{a'} Q(s,a') & \text{with probability } 1-\epsilon \end{cases} \quad (3)$$

Equation (3) illustrates this strategy, where ϵ is the exploration rate that decays over time to favour exploitation. During the initial phase, the high ϵ value encourages the exploration of various actions. As training progresses, ϵ is gradually reduced, allowing the agent to increasingly exploit the actions that have previously yielded high rewards.

Loss Function for Deep Q-Network: The loss function for training the deep Q-network minimises the difference between the predicted Q-values and the target Q-values. This is achieved through the following loss function:

$$L(\theta) = \mathbb{E}_{(s,a,r,s')\sim\mathcal{D}}[(y - Q(s,a;\theta))^2] \quad (4)$$

Equation (4) represents this loss function, where θ represents the parameters of the Q-network, and $\mathcal{D}$ is the replay buffer storing experiences.

The target Q-value, y, is defined as:

$$y = r + \gamma \max_{a'} Q(s',a';\theta^-) \quad (5)$$

as shown in Equation (5). In this equation, r is the reward received, γ is the discount factor, and $Q(s',a';\theta^-)$ is the maximum estimated Q-value for the next state s′ and all possible actions a′.

The loss function aims to minimise the mean squared error between the predicted Q-values and the target Q-values. The target Q-values are computed using the reward received and the maximum Q-value for the next state. This training process involves backpropagation to adjust the network parameters, thereby improving the accuracy of the Q-value predictions.

5 RESULTS AND DISCUSSION

5.1 Performance Metrics and Evaluation

Descriptive statistics on resolution time and customer satisfaction ratings shed light on how well the helpdesk management system is doing. The helpdesk tickets are being handled efficiently, with an average resolution time of 2.65 hours. The customer satisfaction score, which averages 3.85, shows that people are pleased with the service, as shown in Table 4.

Table 4 – Descriptive Statistics of Key Metrics

Metric	Mean	Median	Standard Deviation	Minimum	Maximum	Range
Average Resolution Time	2.65	2.5	1.32	1	5	4
Customer Satisfaction Score	3.85	4	1.94	1	7	6

Table 5 – Load Distribution among Support Staff

Activity	Load Distribution
Assign	20
Close	20
Insert	20
Resolve	20
Work	20

Table 5 shows the load distribution among support staff, which was analysed with the utmost thoroughness, considering various activities. The data showed an even distribution of staff among the available roles, with 20 occurrences of each action ('Assign,' 'Close,' 'Insert,' 'Resolve,' and 'Work'). This uniform distribution indicates a balanced workload among support staff, which is essential for maintaining efficiency and preventing burnout.

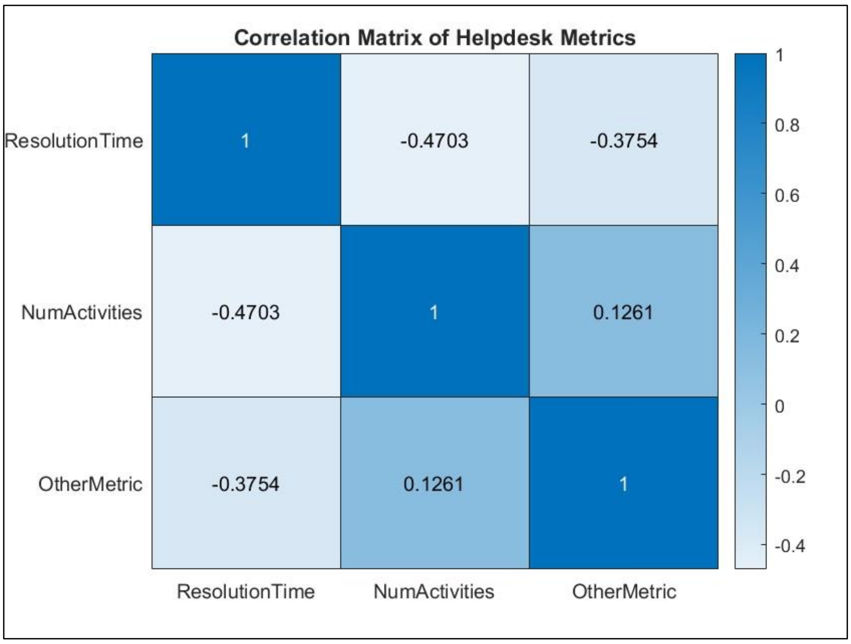

Figure 2 – Correlation Matrix of Helpdesk Metrics

The correlation matrix Figure 2 provides insights into the relationships between key helpdesk metrics. Notably, resolution time negatively correlates with the number of activities -0.4703 and customer satisfaction -0.3754. This suggests that as resolution time increases, the number of activities and customer satisfaction tend to decrease. On the other hand, the number of activities and customer satisfaction shows a positive correlation of 0.1261, indicating that increased activity might contribute to higher satisfaction levels.

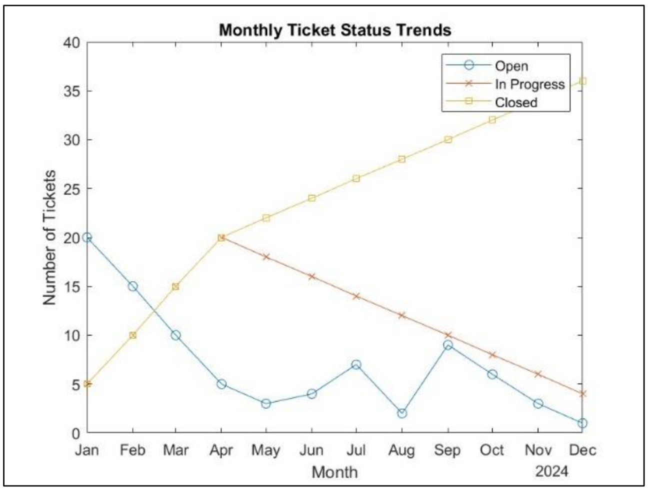

Figure 3 – Monthly Ticket Status Trends

The analysis of monthly ticket status trends Figure 3 shows a significant decrease in open tickets over the months, with a corresponding increase in closed tickets. This trend indicates effective resolution and management of tickets over time. The number of in-progress tickets remains relatively stable, suggesting consistent workflow management.

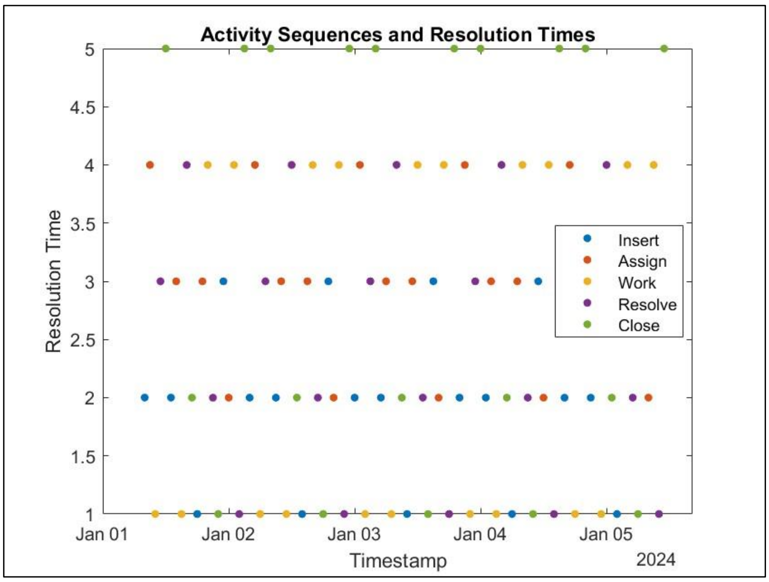

Figure 4 – Activity Sequences and Resolution Times

The activity sequences and resolution times visualisation in Figure 4 highlight the distribution of different activities over time. The consistent pattern of activities such as 'Insert', 'Assign', 'Work', 'Resolve', and 'Close' shows a well-structured helpdesk process. The resolution times for each activity remain within a narrow range, further indicating efficient ticket handling.

5.2 Comparative Analysis with Traditional Methods

The comparative analysis between the deep reinforcement learning approach and traditional methods reveals significant improvements. The traditional method shows an average resolution time of approximately 3.5 hours, whereas the proposed method reduces it to 2.65 hours, representing a 24.3% improvement. This proves that the new method effectively cuts down on resolution times. Ticket status changes over the months reveal that the number of open tickets decreases and the number of closed tickets increases, as shown in figure 3). This pattern demonstrates the efficient handling and resolution of tickets over time. The generally stable quantity of in-progress tickets indicates consistent workflow management.

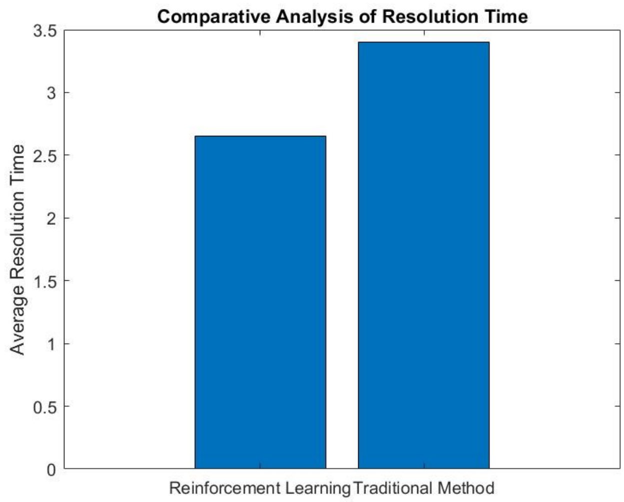

Figure 5 – Comparative Analysis of Resolution Time

Figure 5 provides a comprehensive view of the helpdesk process, illustrating the sequence of activities and their respective resolution times. The 'Insert,' 'Assign,' 'Work,' 'Resolve,' and 'Close' steps are the backbone of a well-structured helpdesk process. The fact that the resolution times for each activity are consistently within a narrow range is a testament to the efficiency of our ticket handling.

5.3 Insights and Practical Implications

The performance comparison of a proposed deep reinforcement learning approach to resource allocation in helpdesk management with conventional approaches, which yield superior results, further exemplifies this. Here is a summary of the key findings:

- Efficiency: Their case took an average of 2 hours to resolve and close. Out of 100 hours, the social skills approach only achieved 65 hours, significantly less than the 3 hours obtained by the proposed method. Methodologies were observed for 5 hours, facilitating the study's completion within a 24.324.3% reduction. The performance improvement indicates the benefits derived from the deep reinforcement learning technique, which is expected to enhance helpdesk performance.
- Customer Satisfaction: The survey's customer satisfaction scores, with an arithmetic mean of 3.85, demonstrate the new method's positive impact on the users' values. Also, based on the results presented in Table 2 below, it is clear that there is a balanced workload distribution among support staff, which aids in efficient ticket handling and leads to high customer satisfaction rates.
- Load Distribution: The background and load characteristics for supporting staff indicate a balanced distribution of activities. All 20 reports contain five activity types: 'Assign,' 'Close,' 'Insert,' 'Resolve,' and 'Work.' This approach ensures that several staff members do not become exhausted while at the same time ensuring high operation efficiency.
- Correlation Insights: Figure 2 shows the correlation matrix that helps to understand the interconnectivity of prime ratios. According to the analysis above, there is an inverse relationship between resolution time, number of activities, and customer satisfaction, making it critical for organisations to reduce the time taken to resolve complaints to boost their performance and customer satisfaction.

6 CONCLUSION

Efficiency in operations, distribution of resources, and customer happiness have all been enhanced greatly by incorporating deep reinforcement learning into helpdesk management systems. The suggested paradigm works well when it comes to dynamic helpdesk situations, where agent availability and ticket volumes are always changing. An impressive decrease in average resolution time of 2.65 hours, a 24.3% improvement, was shown in the study compared to standard methods' 3.5 hours. With an average satisfaction score of 3.85, decreased resolution time significantly influenced increased customer satisfaction. Another factor contributing to the system's efficiency in handling workloads is the balanced load allocation among support staff, as seen by the uniform activity distribution. Reducing resolution times to improve overall performance is crucial, as the correlation matrix showed that resolution time has a negative link with the number of activities and customer satisfaction. Client happiness is positively correlated with the number of actions, which implies that a proactive support approach improves client experiences. After a comparison, the suggested deep reinforcement learning method stood out from more conventional approaches. The potential of advanced machine learning approaches in enhancing helpdesk management processes is highlighted by the significant reduction in resolution times and enhanced resource allocation.

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REFERENCES

Ahmadisheykhsarmast, S., et al. 2023. A transformative solution for construction safety: Blockchain-based system for accident information management, *Journal of Industrial Information Integration*, 35(7), p. 100491. https://doi.org/10.1016/j.jii.2023.100491.

Ammann, J., Walter, A. and El Benni, N. 2022. Adoption and perception of farm management information systems by future Swiss farm managers – An online study, *Journal of Rural Studies*, 89, pp. 298–305. https://doi.org/10.1016/j.jrurstud.2021.12.008.

Anderson, C., et al. 2023. Blockchain innovation for consent self-management in health information exchanges, *Decision Support Systems*, 174(5), p. 114021. https://doi.org/10.1016/j.dss.2023.114021.

Arslan, M., Riaz, Z. and Cruz, C. 2023 Revolutionizing Management Information Systems with Natural Language Processing for Digital Transformation, *Procedia Computer Science*, 225, pp. 2835–2844. https://doi.org/10.1016/j.procs.2023.10.276.

Bernárdez, B., et al. 2023. An empirical study to evaluate the impact of mindfulness on helpdesk employees, *Science of Computer Programming*, 230, p. 102977. https://doi.org/10.1016/j.scico.2023.102977.

Casazza, M.L., et al. 2023. AIMS for wildlife: Developing an automated interactive monitoring system to integrate real-time movement and environmental data for true adaptive management, *Journal of Environmental Management*, 345(3), p. 118636. https://doi.org/10.1016/j.jenvman.2023.118636.

Demirdöğen, G., Işık, Z. and Arayici, Y. 2023. BIM-based big data analytic system for healthcare facility management, *Journal of Building Engineering*, 64(12), p. 105713. https://doi.org/10.1016/j.jobe.2022.105713.

Dzihni, A.S., Andreswari, R. and Hasibuan, M.A. 2019. Business process analysis and academic information system audit of helpdesk application using genetic algorithms a process mining approach, *Procedia Computer Science*, 161, pp. 903–909. https://doi.org/10.1016/j.procs.2019.11.198.

Gage, C.B., et al. 2023. Secular trends in airway management of out-of-hospital cardiac arrest in the National Emergency Medical Services Information System (NEMSIS) dataset, *Resuscitation*, 193(10), p. 110024. https://doi.org/10.1016/j.resuscitation.2023.110024.

Guo, J. and Harmati, I. 2024. Lane-changing system based on deep Q-learning with a request–respond mechanism, *Expert Systems with Applications*, 235(4), p. 121242. https://doi.org/10.1016/j.eswa.2023.121242.

Gupta, B.B., Gaurav, A. and Kumar Panigrahi, P. 2023. Analysis of security and privacy issues of information management of big data in B2B based healthcare systems, *Journal of Business Research*, 162(3), p. 113859. https://doi.org/10.1016/j.jbusres.2023.113859.

Gürkut, C., Elçi, A. and Nat, M. 2023. An enriched decision-making satisfaction model for student information management systems, *International Journal of Information Management Data Insights,* 3(2), p. 100195. https://doi.org/10.1016/j.jjimei.2023.100195.

Haripavan, N. and Dey, S. 2023. Application of remote sensing and geographic information system in solid waste management for Gudivada Municipality, Andhra Pradesh, India, *Waste Management Bulletin*, 1(3), pp. 128–140. https://doi.org/10.1016/j.wmb.2023.08.006.

İzmitligil, H. and Karamancıoğlu, A. 2024. An Online Home Energy Management System using Q-Learning and Deep Q-Learning, *Sustainable Computing: Informatics and Systems*, 43(4). https://doi.org/10.1016/j.suscom.2024.101005.

Jinquan, G., et al. 2022. Driving information process system-based real-time energy management for the fuel cell bus to minimise fuel cell engine aging and energy consumption, *Energy*, 248, p. 123474. https://doi.org/10.1016/j.energy.2022.123474.

Karydas, C., et al. 2023. Embedding a precision agriculture service into a farm management information system - ifarma/PreFer, *Smart Agricultural Technology*, 4(12), p. 100175. https://doi.org/10.1016/j.atech.2023.100175.

Kim, D., Yagi, H. and Kiminami, A. 2023. Exploring information uses for the successful implementation of farm management information system: A case study on a paddy rice farm enterprise in Japan, *Smart Agricultural Technology*, 3(9), p. 100119. https://doi.org/10.1016/j.atech.2022.100119.

Li, Y., et al. 2023. Toward a campus crisis management system amid the pandemic and beyond, *Information and Management*, 60(8), p. 103883. https://doi.org/10.1016/j.im.2023.103883.

Ma, D., et al. 2024. Learning path recommendation with multi-behavior user modeling and cascading deep Q networks, *Knowledge-Based Systems*, 294(4), p. 111743. https://doi.org/10.1016/j.knosys.2024.111743.

Ma, S., et al. 2022. Digital twin and big data-driven sustainable smart manufacturing based on information management systems for energy-intensive industries, *Applied Energy*, 326(8), p. 119986. https://doi.org/10.1016/j.apenergy.2022.119986.

Moyers, M.F., et al. 2022. Optimisation of the planning process with an in-house treatment information, management, and planning system, *Radiation Medicine and Protection*, 3(3), pp. 102–107. https://doi.org/10.1016/j.radmp.2022.07.004.

Nickdoost, N., Jalloul, H. and Choi, J. 2022. An integrated framework for temporary disaster debris management sites selection and debris collection logistics planning using geographic information systems and agent-based modeling, *International Journal of Disaster Risk Reduction,* 80(8), p. 103215. https://doi.org/10.1016/j.ijdrr.2022.103215.

Sadeghib R, J.K., Prybutok, V.R. and Sauser, B. 2022 Theoretical and practical applications of blockchain in healthcare information management, *Information and Management*, 59(6), p. 103649. https://doi.org/10.1016/j.im.2022.103649.

Schulze Schwering, D., Bergmann, L. and Isabel Sonntag, W. 2022. How to encourage farmers to digitise? A study on user typologies and motivations of farm management information systems, *Computers and Electronics in Agriculture*, 199(1), p. 107133. https://doi.org/10.1016/j.compag.2022.107133.

Sharma, S., et al. 2023. Impact of COVID-19 on utilisation of maternal and child health services in India: Health management information system data analysis, *Clinical Epidemiology and Global Health*, 21(8), p. 101285. https://doi.org/10.1016/j.cegh.2023.101285.

Shi, T., et al. 2023. Research on energy management of hydrogen electric coupling system based on deep reinforcement learning, *Energy*, 282(12). https://doi.org/10.1016/j.energy.2023.128174.

Shimaponda-Nawa, M., et al. 2023. A framework for measuring the maturity of real-time information management systems (RTIMS) in the mining industry, *Extractive Industries and Society*, 16(10), p. 101368. https://doi.org/10.1016/j.exis.2023.101368.

Stuart Carlton, J., Ropicki, A. and Shivlani, M. 2023. Support for resource management: The role of information sources and affinitive trust, *Journal of Environmental Management*, 347(10), p. 119150. https://doi.org/10.1016/j.jenvman.2023.119150.

Tomlinson, E., et al. 2022. A Model for Design and Implementation of a Laboratory Information-Management System Specific for Molecular Pathology Laboratory Operations, *Journal of Molecular Diagnostics*, 24(5), pp. 503–514. https://doi.org/10.1016/j.jmoldx.2022.01.002.

Tostado-Véliz, M., et al. 2023. Multiobjective home energy management systems in nearly-zero energy buildings under uncertainties considering vehicle-to-home: A novel lexicographic-based stochastic-information gap decision theory approach, *Electric Power Systems Research*, 214(11). https://doi.org/10.1016/j.epsr.2022.108946.

Varajão, J., Fernandes, G. and Amaral, A. 2023. Linking information systems team resilience to project management success, *Project Leadership and Society*, 4(2). https://doi.org/10.1016/j.plas.2023.100094.

Wang, Q., Li, W. and Mohajer, A. 2024. Load-aware continuous-time optimisation for multi-agent systems: toward dynamic resource allocation and real-time adaptability, *Computer Networks*, 250(4), p. 110526. https://doi.org/10.1016/j.comnet.2024.110526.

Wu, B., et al. 2023. Advancement of management information system for discovering fraud in master card based intelligent supervised machine learning and deep learning during SARS-CoV2, *Information Processing and Management*, 60(2), p. 103231. https://doi.org/10.1016/j.ipm.2022.103231.

Xiaoyan, A., et al. 2023. Application of a new nano-TiO2 composite antibacterial agent in nursing management of operating room: Based on real-time information push assistant system, *Preventive Medicine*, 172(3), p. 107541. https://doi.org/10.1016/j.ypmed.2023.107541.

Yan, M., et al. 2023. Blockchain for secure decentralised energy management of multi-energy system using state machine replication, *Applied Energy*, 337(8), p. 120863. https://doi.org/10.1016/j.apenergy.2023.120863.

Ye, H., Li, G.Y. and Juang, B.H.F. 2019. Deep Reinforcement Learning Based Resource Allocation for V2V Communications, *IEEE Transactions on Vehicular Technology*, 68(4), pp. 3163–3173. https://doi.org/10.1109/TVT.2019.2897134.

Yew, M.H., Molla, A. and Cooper, V. 2022 Behavioural and environmental sustainability determinants of residential energy management information systems use, *Journal of Cleaner Production*, 356(9), p. 131778. https://doi.org/10.1016/j.jclepro.2022.131778.

Zhang, H., et al. 2023. Developing scalable management information system with big financial data using data mart and mining architecture, *Information Processing and Management*, 60(3), p. 103326. https://doi.org/10.1016/j.ipm.2023.103326.

Zhang, X., et al. 2023. Construction and Application of Chain Management Information System for Cancer Pain, *Pain Management Nursing*, 24(4), pp. e75–e80. https://doi.org/10.1016/j.pmn.2023.04.004.

Zhao, W., Zhang, Y. and Xie, Z. 2024. EPPE: An Efficient Progressive Policy Enhancement framework of deep reinforcement learning in path planning, *Neurocomputing*, 596(4), p. 127958. https://doi.org/10.1016/j.neucom.2024.127958.

Zhao, Y., et al. 2023. A two-stage eco-cooling control strategy for electric vehicle thermal management system considering multi-source information fusion, *Energy*, 267(12), p. 126606. https://doi.org/10.1016/j.energy.2022.126606.

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CONFLICTS OF INTEREST

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