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Digital Transformation and Organizational Restructuring: Assessing the Impact of Artificial Intelligence on Organizational Innovation

Yiming Feng

Division of Business Administration, Seoul School of Integrated Sciences and Technologies, Seoul 03767, Korea

fengyiming@stud.assist.ac.kr

Abstract. The landscape of digital transformation is marked by profound shifts in organizational structures and operational models. Central to this transformation is the role of Artificial Intelligence (AI), presenting a myriad of challenges and opportunities, particularly in collaborative management and human resource allocation. This study delves into the application of AI technologies in fostering organizational innovation, with a focus on their impact on structural adjustments. It has been observed that, despite the implementation of such technologies, a comprehensive analysis and evaluation of their effectiveness and potential for optimization within organizations are notably absent in existing literature. This gap is addressed by employing the RoBERTa-Whole Word Masking (WWM) deep model for the rapid identification and integration of knowledge in collaborative management via project text similarity detection. Furthermore, multi-agent reinforcement learning is utilized to enhance the efficiency and responsiveness of human resource allocation in organizational structures. The research highlights the need for an in-depth discussion on the adaptability of these technologies across diverse organizational environments and a thorough assessment of their practical benefits. The study enriches existing research by providing a thorough theoretical and empirical analysis and introduces innovative approaches for intelligent restructuring within organizational frameworks. Empirical evidence substantiates the effectiveness of the proposed methods, offering substantial theoretical support and practical guidance for organizations in the midst of digital transformation.

Keywords: organizational restructuring, digital transformation, project text similarity, multi-agent reinforcement learning, collaborative management, human resource optimization, knowledge integration

1. Introduction

In the current wave of digital transformation, organizations are navigating a landscape filled with unparalleled challenges and opportunities (Glebova et al., 2023; Kumar et al., 2023; Madaio et al., 2022; Muafi et al., 2023; Nadeem et al., 2021; Paliwal et al., 2023; Senturk and Baghırov, 2023; Sun et al., 2021; Wang et al. 2022; Xie et al., 2023; Xu et al., 2023). The advancement of AI technologies necessitates a pivotal adjustment in organizational structures, aligning with the demands of this new era (Berbenni-Rehm, 2023; Dadhich et al., 2023). This is especially evident in the realms of organizational collaboration and human resource management, where the integration of intelligent technologies has not merely altered working methodologies but also infused a new vigor of innovation (Füller et al., 2022). Tools harnessing text similarity detection and human resource optimization are revolutionizing team collaboration, propelling the integration of knowledge, and augmenting the efficiency and effectiveness of organizational operations.

The primary focus of this study lies in the domain of organizational transformation and innovation. It explores the role of AI in refining organizational structures and pioneering innovative models of collaboration (Burri et al., 2023; Grabowski et al., 2023; Li et al., 2023; Lu and Gao, 2022; Mwange and Chansa, 2022; Öztürk and Kula, 2021; Potluri et al., 2023; Rakova, et al., 2021; Su et al., 2022). In the milieu of digital transformation, proficiency in these technologies emerges as a cornerstone for organizational sustainability and a catalyst for progression towards heightened efficiency and intelligence (Alomar, 2022; Iskanderov et al., 2021). A thorough analysis of the application of these technologies serves to better equip organizations in leveraging their intrinsic potential, boosting competitiveness, and fostering a more adaptable and productive work environment for employees.

While initial research on the integration of Artificial Intelligence in organizational collaboration and human resource optimization has demonstrated some effectiveness, prevailing gaps and deficiencies in this area of study are evident (Biliavska et al., 2022; de Oliveira et al., 2021; Jiang, 2023; Koumpan and Topol, 2023; Krasivskyy et al., 2023; Liu, 2021; Zhang, 2023). It is observed that the majority of existing literature primarily focuses on the functional aspects of AI technologies, lacking a comprehensive analysis of their practical implementation in real-world organizational settings (Nortje and Grobbelaar, 2020). Moreover, the complexity inherent in cross-departmental and cross-project collaboration, along with the challenges of real-time optimization in human resource allocation within dynamic environments, is often inadequately addressed (Gibson et al., 2023; Wijnhoven, 2022). These gaps have been found to constrain the theoretical guidance for practical application and limit the innovative and practical implications of the research findings.

This paper endeavors to bridge these identified gaps by proposing and empirically validating two novel methods of application. The first method involves the deployment of the RoBERTa-WWM deep model for project text similarity detection within the sphere of organizational collaborative management. By extracting and analyzing semantic features, this method is capable of accurately identifying and assimilating documents edited by disparate project teams, thereby fostering effective knowledge sharing and integration. The second method delves into the application of multi-agent reinforcement learning for human resource allocation, aiming to refine organizational structures through intelligent algorithms and enhance the adaptability and efficiency of resource distribution. The synergistic combination of these methods not only furnishes novel solutions for internal collaboration in organizations but also presents practical frameworks for the digital transformation of human resource management, contributing substantially to both theoretical understanding and practical application.

2. Organizational Collaborative Management Based on Project Text Similarity Detection

Within the digital transformation context, organizational innovation relies heavily on the rapid flow of information and effective integration of knowledge resources. The utilization of Artificial Intelligence tools for project text similarity detection plays a pivotal role in organizational collaborative management, enabling organizations to swiftly adapt and respond to the dynamic market environment. This approach, by harnessing intelligent knowledge management, substantially elevates the quality of decision-making, thereby conferring competitive advantages and bolstering innovation and leadership capabilities in the digital economy. Furthermore, it expedites the recognition and amalgamation of knowledge spread across various projects or teams, thereby overcoming knowledge silos and promoting cross-boundary collaboration and comprehensive knowledge management. Additionally, this method significantly streamlines work processes and enhances innovative capacities by minimizing redundant labor and optimizing information retrieval efficiency, leading to reduced operational costs. Figure 1 illustrates a standardized project document employing the project text similarity detection model.

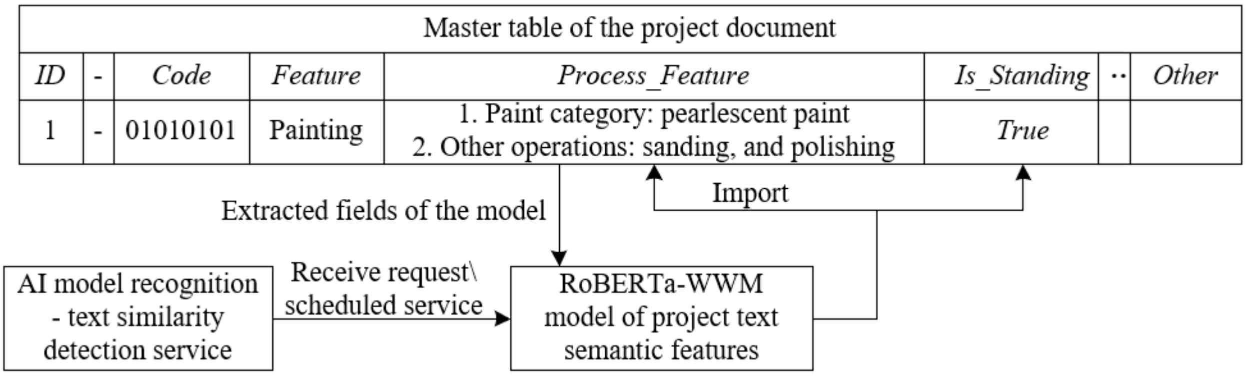


Fig. 1: Example of standardized project document using the project text similarity detection model

This methodology involves collecting diverse documents from various projects and teams, including reports, emails, meeting records, and design documents. The gathered data is subjected to preprocessing steps such as format removal, key information extraction, and word segmentation. These processes are crucial for standardizing the textual data, setting the stage for subsequent analyses. The RoBERTa-WWM model is employed for extracting semantic features from each sentence within the sections of the project text under review and the corresponding target project text. This process entails feeding natural language text into the pretrained RoBERTa-WWM model, which interprets the context embedded within the text and encodes sentences into vector representations in a high-dimensional space. These vectors encapsulate deep semantic information of sentences, encompassing aspects such as vocabulary usage, grammatical structure, and contextual implications. Subsequently, the similarity between texts from different documents is calculated to discern thematic or content-related links. Depending on the degree of similarity, texts are grouped into knowledge clusters. These clusters are then scrutinized to extract valuable insights, which are integrated into the organization's comprehensive knowledge base. This updated knowledge base, made accessible to all members of the organization, facilitates the sharing and dissemination of knowledge, with mechanisms in place to ensure its timeliness and accuracy. Figure 2 displays the implementation process of organizational collaborative management based on project text similarity detection.

In this research, the project text similarity detection process is stratified into three distinct levels. Initially, the detection of similarity between sentences is employed to uncover overlaps in knowledge and information at a granular level. This approach facilitates the identification and meticulous management of discrete knowledge fragments. Subsequently, the exploration of similarities between different sections and sentences within documents plays a crucial role in discerning the underlying connections within their internal structures. Such an analysis reveals common themes or concepts, thereby fostering macro-level knowledge integration. Finally, the detection of text similarity across diverse texts is instrumental in identifying both connections and variances on a more expansive scale among documents originating from various projects or teams. This level of analysis is pivotal in guiding strategies for cross-project knowledge transfer and integration, further enhancing the scope of collaborative management within the organization.

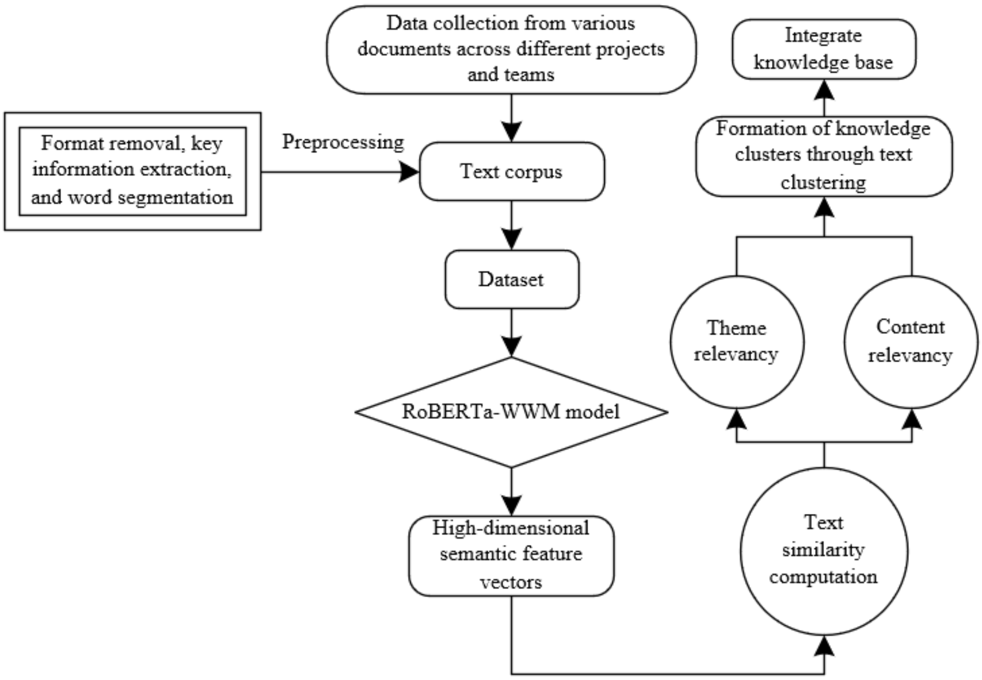


Fig. 2: Implementation process of organizational collaborative management utilizing project text similarity detection

(a) Definition of semantic similarity between sentences

In project texts, semantic similarity between sentences is quantified as the extent of similarity or relevance among meanings, concepts, or informational points articulated by various sentences within a single document. The calculation of semantic similarity between sentences is a process where Artificial Intelligence is utilized to detect redundancy in knowledge or to identify complementary information within the document. This process is pivotal for enhancing the refinement of knowledge and ensuring internal consistency, serving as a cornerstone for advanced information extraction and knowledge management efforts.

Considering two sentences, where the semantic feature vectors extracted are denoted as *i* and *n*, and the threshold is represented by η, the function $d_{SIM}(i,n,\eta)$ is defined to quantify the semantic similarity between *i* and *n*:

$$d_{SIM}\left(i,n,\eta\right)=\begin{cases}CSIM\left(i,n\right),CSIM\left(i,n\right)\geq\eta\\ \dfrac{CSIM\left(i,n\right)+ESIM\left(i,n\right)}{2},else\end{cases} \quad (1)$$

(b) Definition of semantic similarity between sections and sentences

Semantic similarity between sections and sentences encapsulates the associations across different textual levels, specifically the semantic connections between varying sections within a document or analogous sections across distinct documents, and individual sentences. This analytical approach is integral to comprehending the knowledge structure and conceptual framework within larger textual units. It plays a critical role in unveiling themes and the distribution of knowledge, which is essential for the integration of information across documents and the establishment of a coherent knowledge system. For instance, the maximal semantic similarity between the k-th sentence of section X_u in a project document and each sentence in section Y_u is defined as the similarity between the k-th sentence of X_u and Y_u. The semantic similarity calculation, $d_{SIM}(D_{Xuk},D_{Yu},\eta)$, is performed for the k-th row D_{Xuk} in the semantic feature matrix D_{Xu} of section X_u and each row in the semantic feature matrix D_{Yu} of section Y_u, yielding a set of V_{Yu} sentence similarities. The highest value among these similarities is selected as the semantic similarity between the k-th row vector of the semantic feature matrix D_{Xu} and the semantic feature matrix D_{Yu}, given $0<k<V_{Xu}$:

$$SIM\left(X_{uk},Y_u\right)=\underset{0<j\leq V_Y}{MAX}\, d_{SIM}\left(D_{X_{uk}},D_{Y_{uj}},\eta\right) \qquad (2)$$

Given the number of sentences in section X_u as V_{Xu}, a V_{Xu}-dimensional vector t is constructed, encapsulating the similarity of each sentence in X_u with Y_u:

$$t\left(X_u,Y_u\right)=\left[SIM\left(X_{u1},Y_u\right),SIM\left(X_{u2},Y_u\right),...,SIM\left(X_{uV_{Xu}},Y_u\right)\right] \qquad (3)$$

(c) Definition of text similarity

Textual semantic similarity across different documents is defined as the extent of meaningful association they share. This similarity primarily focuses on establishing knowledge linkages and ensuring content consistency across varied documents. It plays a crucial role in enabling organizations to identify knowledge connections between disparate projects or teams and assess the extent and depth of knowledge coverage. Such detection of similarity is instrumental in promoting knowledge sharing and fusion at an organizational level. By analyzing the overall text semantic similarity, organizations are empowered to comprehend knowledge assets at a macroscopic level, which is essential in supporting strategic decision-making and innovation activities. Specifically, weights assigned to different sections of a project document are denoted as x_u, with the sum of these weights from the first to the fifth section represented by $\Sigma^5_{u=1}\alpha x_u=\alpha$, where α signifies the smoothing coefficient. The following equation delineates the similarity between texts X and Y:

$$SIM\left(X,Y\right)=\sum_{u=1}^{5}\alpha x_u t\left(X_u,Y_u\right) \qquad (4)$$

A key strength of the RoBERTa-WWM model in aiding knowledge integration lies in its precision in identifying and amalgamating dispersed knowledge points. This necessitates that the model's loss function accurately reflects the semantic similarity between texts. Hence, the loss function is structured as a contrastive loss, a form that encourages semantic representations generated by the model in high-dimensional space to align more closely for related or similar texts, while ensuring that representations of unrelated texts are more distinct. The study amalgamates this loss function with cosine similarity, aimed at maximizing the cosine similarity between text fragments sharing the same theme or context, and minimizing it between text fragments of differing themes. Assuming the actual text similarity between documents u and k is represented by $RE(u,k)$, the loss function is defined by the following formula:

$$LOSS\left(\alpha,\eta\right)=\sum_{u=1}\left\{\sum_{k=1}\left[SIM\left(u,k\right)-RE\left(u,k\right)\right]^2\right\}^2 \qquad (5)$$

3. Organizational Composition Optimization Based on Human Resource Allocation

In addressing the optimization of organizational composition through human resource allocation, a multi-agent reinforcement learning algorithm is developed. The initial step involves modeling the internal work environment of the organization, where diverse work tasks, projects, or objectives are defined as environmental states. In this model, agents, representing teams or individuals tasked with executing specific duties, are capable of undertaking various actions, such as the allocation of distinct tasks or resources. A crucial aspect of this process is the design of a reward mechanism to train agents to make organization-beneficial decisions. Within the sphere of human resource allocation, rewards are generally linked to the efficiency and quality of task completion, as well as the extent of resource optimization. Strategies yielding effective allocation are rewarded positively, while those that are inefficient or consume excessive resources are subject to penalties. Agents are programmed to select and execute actions based on the prevailing environmental state. The environment, in turn, adapts its state in reaction to the agents' actions, exemplified by alterations in task progress due to human resource allocation. The interactions of agents with the environment, encapsulating states, actions, rewards, and subsequent states, are methodically recorded in a memory pool. This repository of experiences serves as a foundation for future learning, enabling agents to derive insights from their historical behaviors. The learning process involves training a deep neural network, integrating Double Deep Q-Network (DQN) and Dueling DQN structures, which utilizes the amassed experiences to predict the potential value of each action. This approach allows agents to evaluate the long-term implications of varying actions, thereby facilitating more informed decision-making. Based on the neural network's outputs, agents are programmed to refine their strategies for future action selection. This refinement typically incorporates a soft update mechanism, ensuring a gradual and stable evolution of policies and mitigating the risk of instability from rapid changes. Figure 3 delineates the algorithmic workflow for human resource allocation underpinned by the multi-agent reinforcement learning framework.

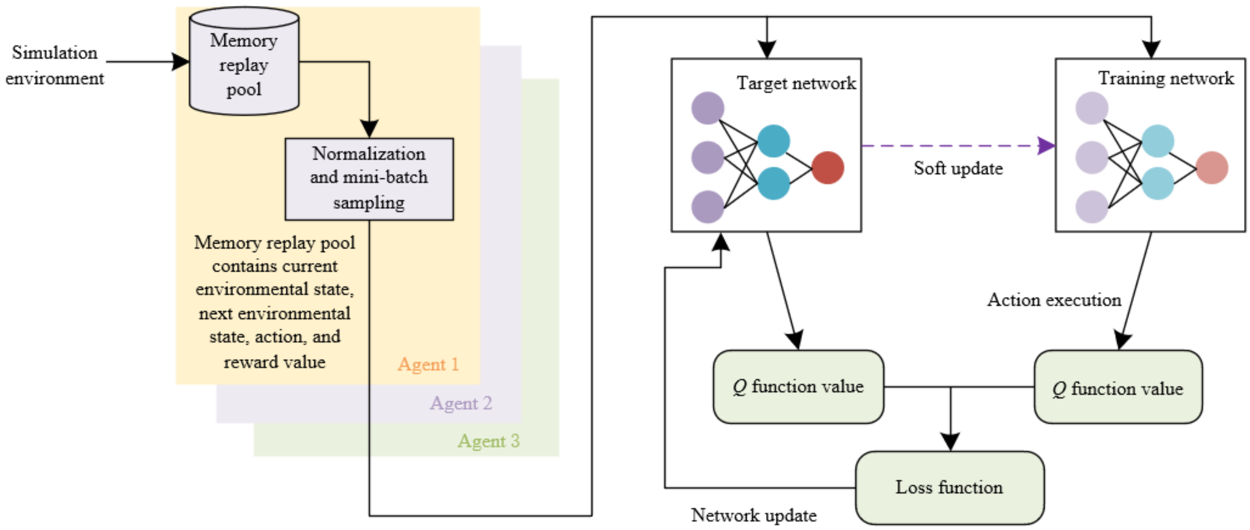


Fig. 3: Algorithmic workflow for human resource allocation in a multi-agent reinforcement learning framework

The methodology encompasses a cyclical process in which agents persistently interact with the environment, gather data, engage in training, and update the network, thus incrementally refining their strategies for human resource allocation. This cycle enables organizations to utilize artificial intelligence for continuous optimization of internal resource distribution, enhancing work efficiency, curtailing costs, and bolstering innovation. Multi-agent reinforcement learning algorithms are particularly apt for addressing such issues, given their capability to emulate the interactions and cooperative efforts of multiple decision-makers within an organizational context.

In the proposed approach to optimize organizational composition via human resource allocation, the training phase of the algorithm includes three primary components: the interaction between agents and the environment, the acquisition and processing of data within the memory pool, and the training and updating of the deep reinforcement learning network. The interaction between agents and the environment constitutes the bedrock of multi-agent reinforcement learning. During this phase, each agent operates based on the current strategy, exploring the environment and receiving feedback. This feedback encompasses immediate rewards related to human resource allocation and new environmental state information, which are instrumental in shaping the agents' future decisions. Actions undertaken in this phase may involve modifications to human resource configurations, the initiation of specific innovation projects, or the allocation of tasks to designated teams. The memory pool functions as a repository for agents' experiences, capturing state transitions, actions, and rewards from interactions with the environment. Sampling from the memory pool enhances learning stability and efficacy by disrupting the temporal correlation between data and augmenting sample utilization. In the context of human resource optimization, the memory pool facilitates learning from historical data, allowing the algorithm to discern patterns in effective and ineffective human resource configurations, thereby informing future decision-making. This aspect is crucial for ensuring optimal resource allocation within the organization to foster innovation.

The training and updating of the deep reinforcement learning network constitute pivotal stages for implementing intelligent decision-making in organizational contexts. This paper will provide a detailed exposition of this component of the methodology.

(a) Training network fundamental module

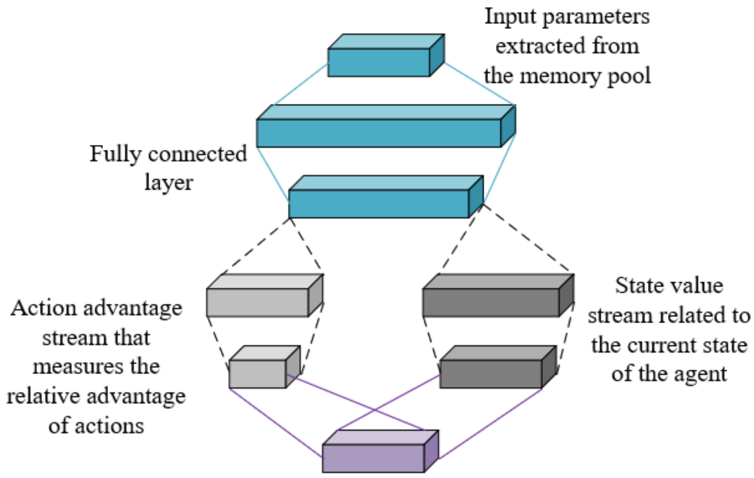


Fig. 4: Schematic diagram of the training network fundamental module structure

The training and updating phases of the deep reinforcement learning network are essential. The integration of Double DQN and Dueling DQN structures is designed to mitigate the limitations inherent in traditional DQN algorithms and to refine the quality of decision-making, as depicted in Figure 4. Double DQN, by dissociating the selection and evaluation of actions, mitigates the overestimation often observed in traditional models, thus enhancing policy evaluation accuracy. Dueling DQN, through its distinction between state values and action advantages, facilitates learning about the significance of states rather than merely the value of actions. This distinction is instrumental in acquiring a more nuanced understanding of environmental states and conducting more precise resource allocations. The amalgamation of these two structures enables the algorithm to strike a more effective balance between exploration and exploitation, particularly in the realm of human resource allocation within organizations. This synergy improves learning efficiency, thereby elevating the quality of organizational decision-making and innovation capacity. Assuming the output of one data stream is represented by $N(t;\phi,\alpha)$, and another by $X(t,x;\ \Phi,\beta)$, with Φ denoting the parameters of the fully connected layer and β and α representing the parameters of the two DQN module networks, the equation for the combined structure is as follows:

$$W\left(t,x;\Phi,\beta,\alpha\right)=N\left(t;\varphi,\alpha\right)+\left(X\left(t.x;\Phi,\beta\right)-\frac{1}{|X|}\sum_{x'}X\left(t,x';\Gamma,\beta\right)\right) \tag{6}$$

(b) Soft update module

In the multi-agent reinforcement learning network, the incorporation of a soft update module is essential for a gradual transition of the target network parameters, significantly enhancing the stability of the learning process. This mechanism, by progressively merging the weights from the main network into the target network, effectively mitigates the oscillations or instabilities associated with hard updates, thus ensuring the robustness of the algorithm in the pursuit of optimal human resource allocation strategies. Such a method is particularly effective in scenarios of organizational innovation, where policies must adapt to the continuously evolving demands of the organization and market conditions. The implementation of soft updates guarantees the gradual evolution of strategies, facilitating organizations to adeptly respond to dynamic environmental shifts and consistently refine their human resource configurations. The parameters of the evaluation network, denoted by ϕ, alongside those of the target network, indicated by ϕ^{-}, are transformed using the soft update weight factor ω, leading to updated network parameters as follows:

$$\varphi_{u+1}^{-}\leftarrow\left(1-\omega\right)\varphi_{u}^{-}+\omega\varphi_{u} \tag{7}$$

(c) Low-dimensional fingerprint module

To confront the challenge of non-stationarity arising from dynamic agent changes within a multi-agent environment, the methodology includes the introduction of a low-dimensional fingerprint module into the reinforcement learning algorithm. This module serves as a compact encoding mechanism, condensing information regarding other agents' strategies or environmental state alterations into succinct, low-dimensional features. These features are then employed as supplementary inputs in the deep reinforcement learning process. Such an approach enables agents to identify and adapt to the behavioral modifications of their counterparts, thus enhancing their coordination and optimizing decisions related to human resource allocation. In the sphere of organizational innovation, this translates to the algorithm's increased adaptability and flexibility in diverse and evolving environments, ensuring that human resource allocation strategies remain relevant amid internal and external organizational changes. This enhances the organization's capability to navigate market fluctuations, support continuous innovation, and maintain competitive advantages. The study integrates fingerprint features, such as agents' training iterations and exploration rates, into the memory replay pool, adopting a fingerprint feature-based training regime. Assuming the environmental observations for an agent at a given timestep are represented by N_{py}, and following the agent's action x leading to a new environmental state at the next timestep by N_{py}', with the action denoted by x_v, and the reward feedback post-interaction by RW, the current greed exploration rate and training iterations are represented by γ and m, respectively. The memory replay pool for each agent includes data as outlined in the following formula:

$$RP=\left\{N_{oy},N_{oy}',x_{v},RW,\gamma,m\right\} \tag{8}$$

(d) Reward function module

In addressing the problem of optimizing organizational composition, the construction of an apt reward function is integral for steering agents towards enhancing organizational efficiency and innovation capacity. The reward mechanism, designed to offer positive reinforcement for actions aligned with organizational objectives and to impose penalties on actions leading to resource wastage or inefficiency, equips agents to learn decision-making strategies that favor the broader interests of the organization in the complex arena of human resource allocation. This approach not only aids agents in balancing exploration with exploitation but also aligns the learning process with the organization's long-range goals of boosting innovation and competitive edge through optimized human resource configurations. To avert issues of blind exploration during initial training phases and unidirectional guidance in later stages, caused by focusing solely on the ultimate objective, the paper proposes a nuanced approach to sub-goal rewards based on their contribution magnitude. For instance, with the weight constant denoted as θ_1, the reward function for each task within the v-th team is formulated as follows:

$$E_v(s) = \frac{\sum_{t=1}^{T} \varsigma_v[t] Z_v^N[t,s]}{\theta_1}, Y_v > 0 \quad (9)$$

Moreover, the paper sets reward points relative to the volume of members requiring optimization in the organization and formulates the reward functions for all agents at each timestep, as elucidated in the subsequent formula:

$$E_l(s) = \sum_t Z_l^U[t,s] \quad (10)$$

In pursuit of the ultimate objectives of elevated employee performance and satisfaction, coupled with minimizing turnover rates, it becomes essential to amalgamate these two reward functions through a weighted scheme. The weight factor employed for balancing these distinct reward functions is symbolized by μ, with the constant factors represented by θ_2 and θ_3. The combined reward function is thus articulated as follows:

$$RW = \mu \frac{E_l(s)}{\theta_2} + (1-\mu)\frac{E_v(t)}{\theta_3} \quad (11)$$

4. Experimental Results and Analysis

Table 1: Comparative analysis of project text pair similarity calculation outcome

Model	(1) Identical	(2) Essentially identical	(3) Entirely different
Method based on string edit distance	0.5584	0.5213	0.2347
Method based on TF-IDF	0.6126	0.5897	0.2315
Method presented in this study	0.9875	0.9784	0.0645

The research introduced a method for detecting project text similarity utilizing the RoBERTa-WWM deep learning model. This approach harnesses deep learning's capability to discern and extract semantic features from texts, aiming to identify similarities in documents edited by disparate project team members, thereby facilitating knowledge sharing and integration in the domain of organizational collaborative management. To evaluate the effectiveness of this method, an experiment was conducted with three categories of text pairs, each representing varying levels of similarity: identical, essentially identical, and entirely different project contents. This experiment entailed the manual selection of text pairs fitting these categories, with each pair subsequently analyzed using three distinct methods for calculating similarity: a method based on string edit distance, a method based on term frequency–inverse document frequency (TF-IDF), and the method proposed in this study, employing the RoBERTa-WWM model.

Table 1 encapsulates the experimental results, delineating the performance of the three methods across the different similarity scenarios. The findings reveal that for text pairs that were completely identical, the method introduced in this study attained a high score of 0.9875. In the case of essentially identical text pairs, it achieved a score of 0.9784, while for entirely different texts, the score was markedly lower at 0.0645. These results underscore the presented method's high precision in differentiating between completely identical and entirely different text pairs, as well as its capacity to sustain high similarity scores for essentially identical text pairs. Consequently, the efficacy of the method in capturing profound semantic insights and enhancing the accuracy of text similarity detection in organizational collaborative management is affirmed.

Table 2: Evaluation of text processing performance

ID	Document type	Actual number of sentences or keywords	Total number of extracted semantic features	Correctly extracted count	Accuracy	Recall	F1-score
1	Chinese abstract	27	25	22	0.8148	0.9874	0.9236
2	English abstract	110	102	98	0.8909	0.9632	0.9687
3	Table of contents	75	75	74	0.9867	0.9784	0.9785
4	Project overview	126	116	106	0.8413	1	0.9421
5	Introduction	120	114	100	0.8333	1	0.9236
6	Background study	100	100	100	1.0000	1	1
7	Problem statement	7	5	5	0.7143	0.7215	0.8214
8	Project objectives	122	111	102	0.8361	11	0.9368
9	Research method	85	78	74.2654	0.8737	0.9852	0.9784
10	Empirical method	120	113	100	0.8333	1	0.9235
11	Material preparation	105	105	105	1.0000	1	1
12	Data analysis	165	154	94	0.5697	0.9852	0.7748
13	Result summary	74	71	62	0.8378	0.9687	0.9125
14	Discussion	27	23	22	0.8148	1	0.9632
15	Conclusions and recommendations	126	121	115	0.9127	0.9862	0.9784

This table delineates the statistical outcomes of text processing using the RoBERTa-WWM deep model, covering an array of document types, including Chinese and English abstracts, tables of contents, and more. For each document type, the table enumerates the actual number of sentences or keywords, the total number of semantic features extracted, the count of accurately extracted features, along with computed metrics like accuracy, recall, and F1-score. These metrics serve to evaluate the model's efficacy. The findings reveal that the RoBERTa-WWM-based text processing approach exhibits robust performance across diverse types of project documents. Notably, it reaches optimal accuracy and recall rates in categories such as "background study" and "material preparation," while achieving exceptionally high F1-score across most document types. This indicates the method's efficiency in effectively recognizing and amalgamating documents edited by various project team members, significantly enhancing knowledge sharing and integration within the scope of organizational collaborative management.

In investigating the applications of multi-agent reinforcement learning in human resource allocation, this study delves into the utilization of intelligent algorithms for the enhancement of organizational structure optimization. Specifically, the algorithms are analyzed for their capability to distribute tasks and roles within an organization effectively, aiming to elevate overall productivity and employee satisfaction. The effectiveness of various algorithms, including Local Q-Learning (LQL), Multi-Agent Deep Deterministic Policy Gradient (MADDPG), Value Decomposition Networks (VDN), Multi-Agent Actor-Critic (MAAC), and the algorithm proposed herein, is assessed through comparative analysis of their performance in human resource allocation tasks. Experimental results reveal a pattern of increasing cumulative rewards across all algorithms with the progression of training cycles, a characteristic trend in reinforcement learning where agents refine their strategies through iterative trial and error. This upward trajectory in cumulative rewards signifies the agents' growing proficiency in human resource allocation. Notably, the algorithm introduced in this research demonstrates rapid and stable convergence, maintaining robust performance in varied and complex environments. This indicates the algorithm's suitability for practical implementation, particularly in organizational frameworks requiring swift and effective human resource decision-making.

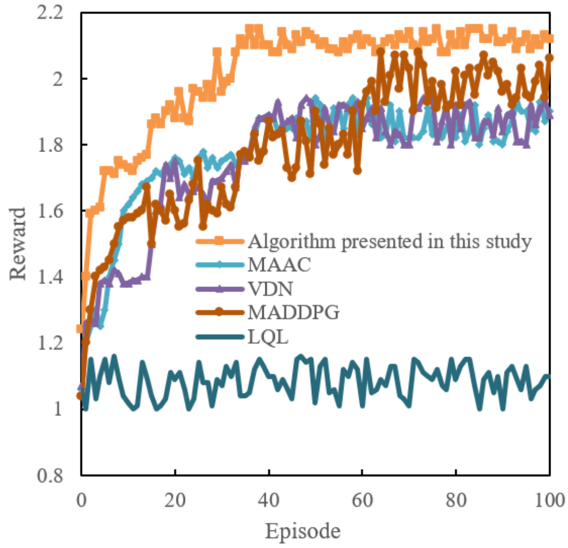
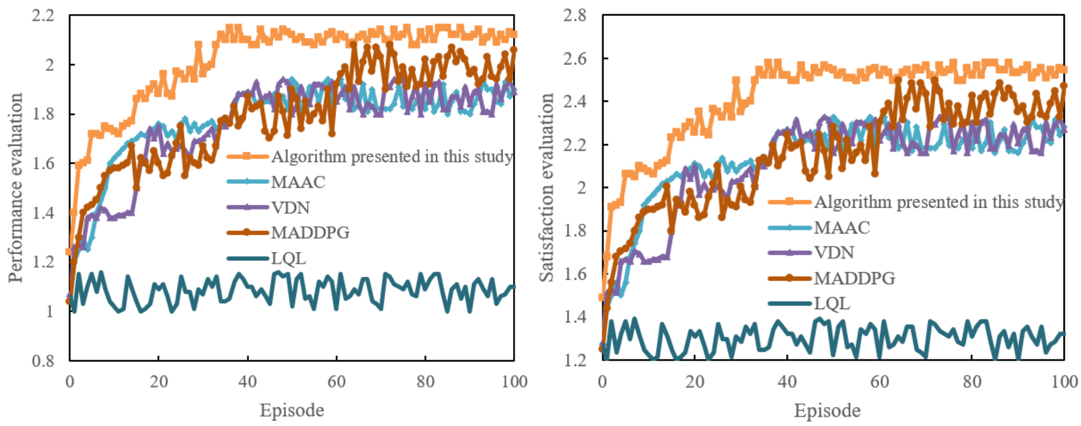


Fig. 6: Convergence comparison of different human resource allocation methods

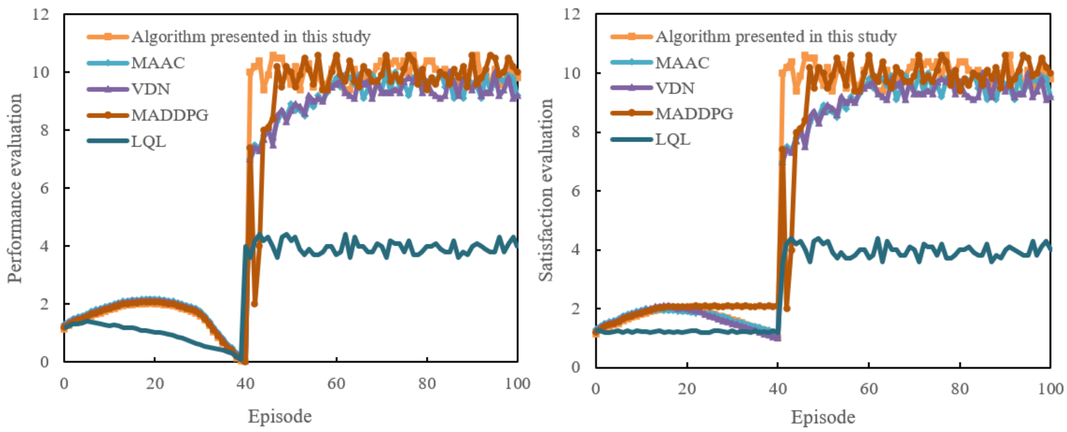
The study investigates the optimization of organizational composition through human resource allocation, applying this approach across diverse business scenarios. Two distinct application scenarios were employed to compare the effectiveness of different human resource allocation methods in optimizing organizational composition.

In the first scenario, focused on skill matching and team composition, the necessity of aligning specific skill sets with project or task requirements is highlighted. This scenario emphasizes the allocation of employees to teams or projects that align with their skills, experience, and career aspirations, underpinning the importance of strategic team formation in organizational efficacy.

The second scenario, centered on shift scheduling in service industries like healthcare, retail, and hospitality, addresses the challenge of adapting employee shift schedules to fluctuating demand. The optimization objective in this context is to ensure adequate staffing for each shift, while taking into account employee preferences and compliance with legal working hours.



1) Scenario 1



2) Scenario 2

Fig. 7: Comparison of organizational composition optimization effects of different human resource allocation methods in different scenarios

Experimental findings, as illustrated in Figure 7, offer insights into the performance and satisfaction evaluations of employees under different human resource allocation methods, encompassing LQL, MADDPG, VDN, MAAC, and the algorithm proposed in this study. The results demonstrate a trend of gradual improvement and stabilization in employee performance evaluations across all algorithms, as the number of training episodes increases. This pattern indicates the algorithms' growing competence in effective human resource allocation, contributing to enhanced work efficiency. Similarly, employee satisfaction evaluations also show a rising and stabilizing trend, suggesting that the algorithms successfully balance task efficiency with consideration of employee preferences and well-being. The study concludes that the algorithm introduced in this research surpasses other methods in boosting employee performance and satisfaction, signifying its superior accuracy, adaptability, and individual differentiation handling. While other algorithms like MADDPG, VDN, and MAAC show positive learning outcomes, they are outperformed by the proposed algorithm in these evaluative metrics.

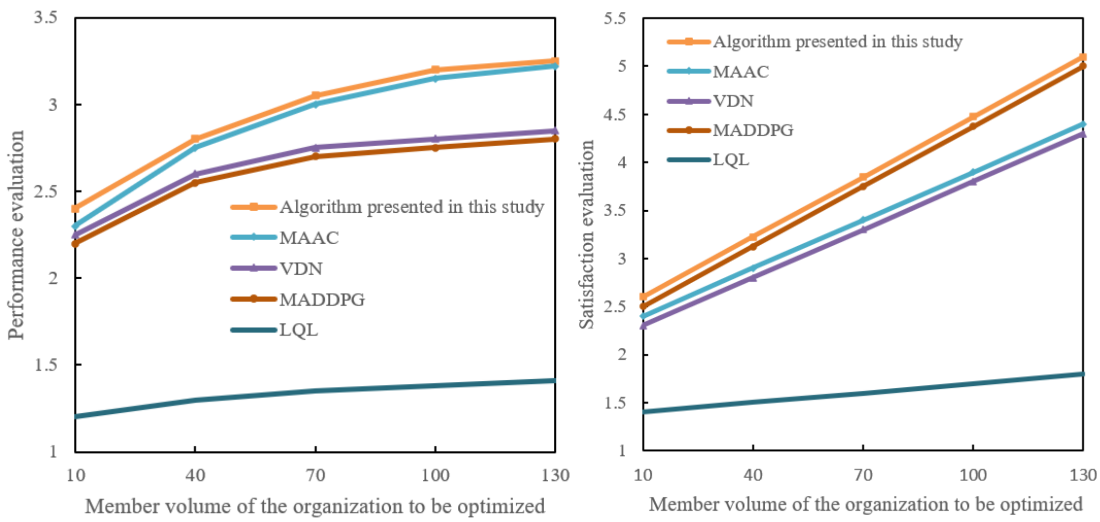


Fig. 8: Organizational composition optimization effect comparison of the organization to be optimized under varying member volumes

The effectiveness of the optimization of organizational composition under varying volumes of organizational members was further examined in this study. Analysis of the effects of different human resource allocation methods on employee performance and satisfaction, with respect to changing member volumes for optimization, is illustrated in Figure 8. The data reveal an upward trajectory in both employee performance and satisfaction evaluations across all algorithms as the number of members requiring optimization increases. This trend suggests enhanced efficiency of the algorithms in allocating human resources with an expanding member base, thereby boosting overall work performance and employee satisfaction. It is inferred that, across diverse scales of organizational member volumes, the algorithm introduced in this study consistently excels in augmenting employee work performance and satisfaction. This denotes the algorithm's aptitude in managing the complexities and dynamic nature of human resource allocation. Notably, the algorithm demonstrates sustained or even enhanced optimization efficacy as organizational member volumes escalate, underscoring its scalability and utility in larger organizations. In comparison to other algorithms, the algorithm from this study stands out in both crucial evaluative aspects. This not only attests to its efficiency in task allocation but also highlights its proficiency in accommodating employee preferences and elevating employee satisfaction levels.

5. Conclusion

The study delineated herein comprises two principal components. The first part introduces a method for detecting text similarity based on the RoBERTa-WWM deep model, applied within the realm of organizational collaborative management. This approach facilitates the identification and amalgamation of documents crafted by various project team members, aiming to refine the accuracy of knowledge sharing and integration, consequently fostering organizational efficiency and the capacity for innovation. The second facet of this research advocates the utilization of multi-agent reinforcement learning for optimizing human resource allocation, thereby augmenting organizational structures through intelligent algorithms. This enhances the flexibility and efficacy of resource distribution.

Experiments were conducted to compare the RoBERTa-WWM model's performance in calculating similarities between pairs of project texts against other models. The text processing outcomes demonstrate the RoBERTa-WWM model's superior accuracy. Further, the study encompasses a convergence analysis among various human resource allocation methods, including the algorithm introduced in this paper, alongside MAAC, VDN, MADDPG, and LQL. The research also includes a comparative assessment of human resource allocation methodologies' impact on organizational composition optimization across diverse scenarios. This comparison underscores the versatility and effectiveness of different algorithms under a range of conditions. An evaluation of the optimization effects brought about by different human resource allocation methods in response to fluctuating member volumes was undertaken. Findings indicate that the algorithm developed in this research surpasses others in enhancing employee work performance and satisfaction, maintaining its efficiency even as organizational scale varies. The successful deployment of these methodologies and algorithms carries profound implications for improving organizational efficiency and employee satisfaction, as well as for advancing knowledge management and human resource optimization practices.

References

Alomar, M. A. (2022). Performance Optimization of Industrial Supply Chain Using Artificial Intelligence. Computational Intelligence and Neuroscience, 2022, 9306265. https://doi.org/10.1155/2022/9306265

Berbenni-Rehm, C. (2023). Evidence-based AI, ethics and the circular economy of knowledge. *AI & SOCIETY,* 38(2), 889-895. https://doi.org/10.1007/s00146-022-01581-1

Biliavska, V., Castanho, R. A., & Vulevic, A. (2022). Analysis of the Impact of Artificial Intelligence in Enhancing the Human Resource Practices. *Journal of Intelligent Management and Decision*, 1(2), 128-136. https://doi.org/10.56578/jimd010206

Burri, S. R., Kumar, A., Baliyan, A., & Kumar, T. A. (2023). Predictive intelligence for healthcare outcomes: An AI architecture overview. *In 2023 2nd International Conference on Smart Technologies and Systems for Next Generation Computing (ICSTSN)*, Villupuram, India, (pp. 1-6). IEEE. https://doi.org/10.1109/ICSTSN57873.2023.10151477

Dadhich, M., Yadav, P., Saxena, A., Birda, R. K., Mathur, S., & Hiran, K. K. (2023). Dynamic determinants of AI-based innovation management practices and sustainable FinTech: Application preferences of AI-innovators. *In 2023 IEEE International Conference on Contemporary Computing and Communications (InC4)*, 1, (pp. 1-5). IEEE. https://doi.org/10.1109/InC457730.2023.10263140

de Oliveira, M. A., Dalla Valentina, L. V., Futami, A. H., Possamai, O., & Flesch, C. A. (2021). Project performance prediction model linking agility and flexibility demands to project type. *Expert Systems*, 38(4), e12675. https://doi.org/10.1111/exsy.12675

Füller, J., Hutter, K., Wahl, J., Bilgram, V., & Tekic, Z. (2022). How AI revolutionizes innovation management–Perceptions and implementation preferences of AI-based innovators. *Technological Forecasting and Social Change,* 178, 121598. https://doi.org/10.1016/j.techfore.2022.121598

Gibson, D., Kovanovic, V., Ifenthaler, D., Dexter, S., & Feng, S. (2023). Learning theories for artificial intelligence promoting learning processes. *British Journal of Educational Technology*, 54(5), 1125-1146. https://doi.org/10.1111/bjet.13341

Glebova, I., Berman, S., Khafizova, L., Biktimirova, A., & Alhasov, Z. (2023). Digital divide of regions: Possible growth points for their digital maturity. *International Journal of Sustainable Development and Planning*, 18(5), 1457-1465. https://doi.org/10.18280/ijsdp.180516

Grabowski, M., Martelli, P. F., & Roberts, K. H. (2023). Reliability-Seeking virtual organizations at the margins of systems, resources and capacity. *Safety Science*, 168, 106327. https://doi.org/10.1016/j.ssci.2023.106327

Iskanderov, Y., Svistunova, A., Khasanov, D., & Pautov, M. (2021). Using actor-network theory to understand intelligent systems: The case of intelligent IS for logistics. *In International Conference Cyber-Physical Systems and Control*, (pp. 381-391). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-20875-1_35

Jiang, W.J. (2023). Enhancing operational efficiency in e-commerce through artificial intelligence and information management integration. *Revue d'Intelligence Artificielle*, 37(6), 1545-1555. https://doi.org/10.18280/ria.370619

Koumpan, E., & Topol, A. W. (2023). Society 5.0 a vision for a privacy and AI-infused human-centric society driving a new era of innovation and value creation. *In International Congress on Information and Communication Technology*, London, (pp. 229-239). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-99-3243-6_19

Krasivskyy, O., Pirozhenko, N., Samborska, O., Harbusiuk, V., & Inozemtseva, O. (2023). A model for implementing digital personnel management in security and safety for engineering enterprises. *International Journal of Safety and Security Engineering*, 13(3), 519-526. https://doi.org/10.18280/ijsse.130314

Kumar, R., Kaur, S., Erceg, Ž., & Mirović, I. (2023). Industry 4.0 and Its Impact on Entrepreneurial Ecosystems: An Examination of Trends and Key Implications. *Journal of Organizations, Technology and Entrepreneurship*, 1(1), 12-34. https://doi.org/10.56578/jote010102

Li, C., Xu, Y., Zheng, H., Wang, Z., Han, H., & Zeng, L. (2023). Artificial intelligence, resource reallocation, and corporate innovation efficiency: Evidence from China's listed companies. *Resources Policy*, 81, 103324. https://doi.org/10.1016/j.resourpol.2023.103324

Liu, Z. (2021). Construction of computer mega data security technology platform based on machine learning. *In 2021 IEEE 4th International Conference on Information Systems and Computer Aided Education (ICISCAE)*, Dalian, China, (pp. 538-541). IEEE. https://doi.org/10.1109/ICISCAE52414.2021.9590732

Lu, Y., & Gao, X. (2022). The impact of artificial intelligence technology on market public administration in a complex market environment. *Wireless Communications and Mobile Computing*, 2022, 5646234. https://doi.org/10.1155/2022/5646234

Madaio, M., Egede, L., Subramonyam, H., Wortman Vaughan, J., & Wallach, H. (2022). Assessing the fairness of AI systems: AI practitioners' processes, challenges, and needs for support. *Proceedings of the ACM on Human-Computer Interaction*, 6(CSCW1), 1-26. https://doi.org/10.1145/3512899

Muafi, Sanusi, Z.M., & Roostika, R. (2023). Digital skills, digital entrepreneurship, job satisfaction, and sustainable performance of MSMEs: A survey on MSMEs in Indonesia. *International Journal of Sustainable Development and Planning*, 18(2), 465-473. https://doi.org/10.18280/ijsdp.180215

Mwange, A. & Chansa, M. (2022). Emerging Issues In Accounting: A Theoretical Review. *Journal of Accounting, Finance and Auditing Studies*, 8(4), 172-196. https://doi.org/10.32602/jafas.2022.032

Nadeem, A., Marjanovic, O., & Abedin, B. (2021). Gender bias in AI: Implications for managerial practices. *In Responsible AI and Analytics for an Ethical and Inclusive Digitized Society: 20th IFIP WG 6.11 Conference on e-Business, e-Services and e-Society, I3E 2021*, Galway, Ireland, (pp. 259-270). Springer International Publishing. https://doi.org/10.1007/978-3-030-85447-8_23

Nortje, M. A., & Grobbelaar, S. S. (2020). A framework for the implementation of artificial intelligence in business enterprises: a readiness model. *In 2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*, Cardiff, UK, (pp. 1-10). IEEE. https://doi.org/10.1109/ICE/ITMC49519.2020.9198436

Öztürk, R. & Kula, V. (2021). A General Profile of Artificial Intelligence Adoption in Banking Sector: A Survey of Banks in Afyonkarahisar Province of Turkey. *Journal of Corporate Governance, Insurance, and Risk Management*, 8(2), 146-157. https://doi.org/10.51410/jcgirm.8.2.10

Paliwal, M., Chatradhi, N., Tripathy, S., & Jha, S. (2023). Growth of digital entrepreneurship in academic literature: A bibliometric analysis. *International Journal of Sustainable Development and Planning*, 18(6), 1929-1942. https://doi.org/10.18280/ijsdp.180629

Potluri, J., Gummadi, H., Bhogi, M., Katta, Y. S., Ramesh, G., & Reddy, T. S. M. (2023). Unveiling covert conversational agents: Enhancing insight, archives, and dialog acts with ChatGPT. *In 2023 7th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)*, Kirtipur, Nepal, (pp. 766-772). IEEE. https://doi.org/10.1109/I-SMAC58438.2023.10290195

Rakova, B., Yang, J., Cramer, H., & Chowdhury, R. (2021). Where responsible AI meets reality: Practitioner perspectives on enablers for shifting organizational practices. *Proceedings of the ACM on Human-Computer Interaction,* 5(CSCW1), 1-23. https://doi.org/10.1145/3449081

Senturk, O. & Baghırov, A. (2023). Enhancing Sustainable Development Through Blockchain: A Study on Risk Management and Data Integrity. *Journal of Organizations, Technology and Entrepreneurship*, 1(2), 110-126. https://doi.org/10.56578/jote010204

Su, H., Qu, X., Tian, S., Ma, Q., Li, L., & Chen, Y. (2022). Artificial intelligence empowerment: The impact of research and development investment on green radical innovation in high-tech enterprises. *Systems Research and Behavioral Science*, 39(3), 489-502. https://doi.org/10.1002/sres.2853

Sun, K., Rayudu, H., & Pujara, J. (2021). A hybrid probabilistic approach for table understanding. In *Proceedings of the AAAI Conference on Artificial Intelligence,* 35(5), 4366-4374. https://doi.org/10.1609/aaai.v35i5.16562

Wang, D., Prabhat, S., & Sambasivan, N. (2022). Whose AI dream? In search of the aspiration in data annotation. *In Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems*, New Orleans LA USA, (pp. 1-16). Association for Computing Machinery https://doi.org/10.1145/3491102.3502121

Wijnhoven, F. (2022). Organizational learning for intelligence amplification adoption: Lessons from a clinical decision support system adoption project. *Information Systems Frontiers*, 24(3), 731-744. https://doi.org/10.1007/s10796-021-10206-9

Xie, J. L., Yang, Y. J., & Chen, J. L. (2023). Mechanisms of Digital Economy Empowering High-Quality Development in Manufacturing: A Case Study of Hebei Province, a Traditional Manufacturing Powerhouse in China. *Journal of Organizations, Technology and Entrepreneurship*, 1(1), 47-57. https://doi.org/10.56578/jote010104

Xu, G. W., Ali, D. A., Bhaumik, A., Yang, M. S., & Wang, N. (2023). The Influence of Digital Transformation in Enterprises on the Dynamics of Supply Chain Concentration: An Empirical Analysis of Chinese A-Share Listed Companies. *Journal of Organizations, Technology and Entrepreneurship*, 1(2), 88-97. https://doi.org/10.56578/jote010202

Zhang, J. (2022). Research on visualization management of human resources based on big data neural network technology. *Review of Computer Engineering Studies*, 9(2), 79-81. https://doi.org/10.18280/rces.090206