Journal of High Technology Management Research 34 (2023) 100471



Contents lists available at ScienceDirect

Journal of High Technology Management Research

journal homepage: www.elsevier.com/locate/hitech





Resource management projects in entrepreneurship and retain customer based on big data analysis and artificial intelligence

Pham Quang Huy [a], Shavkatov Navruzbek Shavkatovich [b], Zulkiflee Abdul-Samad [c], D.K. Agrawal [d], K.M. Ashifa [e], Mahendran Arumugam [f,*]

[a] University of Economics Ho Chi Minh City (UEH), Viet Nam
[b] Department of Corporate Finance and Securities, Tashkent Institute of Finance, Tashkent, Uzbekistan
[c] Department of Quantity Surveying, Faculty of Built Environment, University of Malaya, 50603 Kuala Lumpur, Malaysia
[d] Department of Innovation, Incubation and Entrepreneurship, Krishna Vishwa Vidya Peeth, Karad (MS), Agashivnagar, Malkapur, Maharashtra, India
[e] Asst. Professor in Social Work, Faculty of Health Science, Istanbul Gelisim University, Turkey
[f] Center for Transdisciplinary Research, Saveetha Dental College, Saveetha institute of Medical and Technical Science, Chennai, India

ARTICLE INFO

Keywords:
Human resource management
Business entrepreneurship
Customer retain
Machine learning techniques
Behavioral pattern analysis

ABSTRACT

Retaining clients is turning into an estimation center in an industry with expanding rivalry. Because it is difficult to keep customers and easy for them to switch brands, the idea of customer retention has become the subject of research in the sales industry. Traditional human resource management systems are unable to manage and analyze data because of the rapid growth of enterprise-generated data's processing capacity. This exploration proposes novel strategy in human asset the executives for little new company business with their client hold utilizing Artificial intelligence (AI) procedures. Behavioral pattern analysis based on reinforcement radial fuzzy decision with quadratic kernel vector machine is utilized here for human resource management and customer relationship retention. In terms of prediction accuracy, area under the curve (AUC), average precision, sensitivity, and quadratic normalized square error, various human resource datasets based on entrepreneurship are the subjects of the experimental analysis. The proposed technique attained prediction accuracy of 98%, AUC of 89%, average precision of 83%, sensitivity of 66%, quadratic normalized square error of 59%.

1. Introduction

An important enterprise management tool, human resource management system (HRMS) is crucial to the growth of businesses. HRMS has gone through three phases (Bhalerao, Kumar, Kumar, & Pujari, 2022) since its inception. In the 1960s, the first HRMS generation was released. At the time, HRMS's primary function was to use a computer system to automatically calculate employees' salaries, excluding salary data analysis as well as other financial data. Limited resources and technical requirements at the time were primarily to blame for these circumstances. e second era of HRMS began in the mid-1980s. 'Development of database technology as well as other needs that were absent from the first generation enabled the second generation to overcome the primary shortcomings of the first generation. Customers are the most important foundation for a company's success and revenue (Budhwar, Malik, De Silva, &

* Corresponding author.
E-mail address: mahendrana.sdc@saveetha.com (M. Arumugam).

https://doi.org/10.1016/j.hitech.2023.100471
Received 22 April 2023; Received in revised form 27 June 2023; Accepted 19 July 2023
Available online 18 August 2023
1047-8310/© 2023 Published by Elsevier Inc.

Thevisuthan, 2022). In recent years, businesses have increased their awareness of the crucial role that customers play in the pursuit of customer satisfaction. Customer relationship management (CRM) is becoming a competitive advantage and now essential to an organization's success. Because it helps unlock additional data that businesses collect on their customers, machine learning has become the mainstay feature of customer relationship management in recent years (Ahmad & Mustafa, 2022). Relationship management using AI techniques The board receives a mix of large and little perks from the organizations they oversee. Instance-based learning, ensemble learning, decision tree-based learning, regression analysis, and other machine methods are used to aid in and improve customer relationship management. In the dynamic business environment, satisfying and retaining customers relies heavily on providing them with a positive experience. However, customers may easily get overwhelmed by the seemingly endless online advertising and information resources. As a result, in order to provide current and potential customers with channels for direct communication and a positive experience, businesses need an all-encompassing strategy (Chowdhury et al., 2023). As a result, businesses must continue to focus on selling processes, developing new goods and services, and even communicating company messages. In the field of customer relationship management, it has been demonstrated that information technology provides businesses with a variety of advantages. A customer relationship management system can help businesses improve their customer experience by fostering and enhancing customer loyalty and satisfaction. A customer relationship management system also gives the company a competitive advantage and boosts sales and revenue (Ahmed, Agarwal, Kurniawan, Anantadjaya, & Krishnan, 2022). AI is the most common way of preparing the given information and anticipating the given information by taking care of them into the calculation and thusly they produce the new test information. Machine learning is broken down into three distinct subfields: supervised learning, unsupervised learning, and reinforcement learning. By providing labelled datasets as input to train algorithms, supervised machine learning is mostly used to train data and predict outcomes. This process of supervised learning primarily aids in numerous practical issues, such as separating spam mail from legitimate mail in our email account (Zhang, 2022).

The goal of this research is to encourage creative approaches among human resource managers who deal directly with clients by means of AI design predicated on a conduct inquiry based on a spiral fluffy choice supported by a quadratic bit vector machine. The innovative model of the renewal price adjustment problem presented in this study is its key contribution since it considers not only the specifics of each customer's situation but also the overall state of the business when making recommendations. Customers' reactions to the decision to charge their accounts are reflected in the global situation of the company and will affect future decisions. Furthermore, income and client retention are prioritized in every decision. Researchers have developed a number of methods for handling resources in network slicing situations. Management of resources, for instance, might be carried either by apportioning the available resource fairly among the individual slices, or by using some sort of meticulous prediction. In contrast to the first, which only provides a single viable option, the second drastically minimizes the amount of processing needed.

2. Related works

To solve this issue, a variety of statistical and machine-learning methods are utilized. There have been numerous attempts to compare as well as benchmark methods utilized for predicting churn. Decision trees, logistic regression, and NN methods were contrasted in (Chen, Jiang, Jia, & Liu, 2022; Dubey, Bryde, Dwivedi, Graham, & Foropon, 2022). Neural networks performed slightly better than the other two methods, according to the study. Another comparison between a group of methods and their boosted versions is covered in (Elfatih et al., 2022). In this study, a two-layer Back-Propagation neural network (BPN), Decision Trees, SVM, Logistic Regression, and Logistic Regression were all employed. Decision trees and BPN both scored 94% accuracy, SVM came in second with 93% accuracy, while logistic regression failed with 86% accuracy, according to the study. The study also discovered that the boosted copies outperformed the originals by 1–4%. Accuracy of various methods like multi-layer perceptron (MLP) and Decision Tree (C5) were examined in (Lazaroiu, Androniceanu, Grecu, Grecu, & Neguriță, 2022). The study demonstrated that MLP outperforms C5 decision trees by 89.63% with an accuracy of 95.51%. A little regrettable connection with a client, could imply that the client could beat (Vrontis et al., 2022). The company must have a solid understanding of its customers' requirements in order to analyze their patterns holistically. At the point when clients are happy with the assistance or items, client steadfastness increments (Da Silva et al., 2022). According to the authors (Cooke, Dickmann, & Parry, 2022), retaining existing customers will result in higher revenues and margins than acquiring new ones. The most ordinarily talked about authority style for development and learning is the groundbreaking administration style (Agarwal, Mathiyazhagan, Malhotra, & Saikouk, 2022). Beyond transformational leadership, Industry 4.0 requires something more specialized in learning and innovation. As the change authority is restricted to admire impact, helpful inspiration, scholarly excitement, and giving vision (Roundy & Burke-Smalley, 2022). As of late, with the headway of AI and normal language handling methods, canny resume proposal frameworks are being created to work with the enrollment cycle and further develop effectiveness by more precisely recognizing qualified resumes (Sharma, Luthra, Joshi, & Kumar, 2022). A resume classification model based on a word embedding model and a convolutional neural network was proposed by Work (Alshurideh et al., 2022). A resume recommendation method based on K-means as well as part-of-speech TF-IDF that performed better than word frequency vector was proposed by author (Michalikova, Suler, & Robinson, 2022). Creator (Jaiswal, Arun, & Varma, 2022) proposed a resume suggestion framework utilizing the Straight Help Vector Classifier, Content-based Proposal utilizing Cosine Similitude, and k-Closest Neighbors, with an exactness of 78.53% accomplished. A resume ranking system based on Cosine Similarity and k-Nearest Neighbors, as used in Content-Based Recommendation, was proposed by Author (Khan et al., 2022). However, the improved accuracy of 92% was attained by increasing text parsing accuracy.

3. System model

This section discusses a novel technique in customer retain analysis with human resource management using behavioral pattern analysis based on reinforcement radial fuzzy decision with quadratic kernel vector machine. The propose model is shown in Fig. 1.

In a true recruitment website, a candidate is initially required to provide some basic personal data. This information is usually formatted and comes with fixed options for selection. Likewise, the framework will likewise give more data to fill in sections, for example, self-presentation, instructive foundation, work insight, and self-assessment. These are just plain text records without any arbitrary formatting. In the expert application procedure, companies pay even more attention to the applicant's unique resume. However, in addition to the standard structured information such as pay ranges, working hours, and perks, companies may also offer textual supplements such as job descriptions and recruitment requirements when posting job openings on recruiting portals. The resume's written content is more succinct and expert than any customized template could ever be in the recruiting process. In addition, candidates and organizations have greater leeway and efficiency in describing their own content characteristics since text information is richer than structured information.

4. Behavioral pattern analysis based on reinforcement radial fuzzy decision with quadratic kernel vector machine

Network cloning and experience replay both encourage adopting off-policy Q-learning since the updating policy, which depends on the data from the new episodes, is independent of the sampling policy. In contrast, the sampling strategy simply relies on the Q-value NN that has already been trained. On the other hand, the DQL agent might gather the information (the state-action-reward pair) and train its policy covertly. Additionally, learned policy is stored in NNs, making it simple to switch between similar situations. In other words, as depicted in Fig. 2, the DQL was able to execute the resource allocation decision in a timely and effective manner.

Network cloning and experience replay both encourage adopting off-policy Q-learning since the updating policy, which depends on the data from the new episodes, is independent of the sampling policy. In contrast, the sampling strategy simply relies on the Q-value NN that has already been trained. On the other hand, the DQL agent might gather the information (the state-action-reward pair) and train its policy covertly. R(s, a) represents the immediate reward following the performance of action, and [0,1] represents a discount factor to account for the declining influence of the present reward on future rewards. To maximize the value function, which is commonly defined as the predicted discounted cumulative reward by the Bellman eq. (1), the objective of MDP is typically to identify a policy a = (s) that defines the chosen action an under state s.

$$V^{\pi}(\hat{s}) = E_{\pi}\left[\sum_{k=0}^{\infty}\gamma^{k}R\left(s^{(k)},\pi\left(s^{(k)}\right)\right)\middle|s^{(0)}=\hat{s}\right] = E_{\pi}[R(\hat{s},\pi(\hat{s}))) + \gamma\sum_{s\in\mathcal{S}}P(s'|\hat{s},\pi(\hat{s}))V^{\pi}(s') \tag{1}$$

The Bellman problem may be solved using dynamic programming if the state transition probability P(s 0 |s, a) is known a priori without the influence of random variables. But the goal of RL, which draws inspiration from both behaviorist psychology and control theory, is to arrive at the best course of action in situations with unpredictable and partially random dynamics. Since, RL lacks explicit

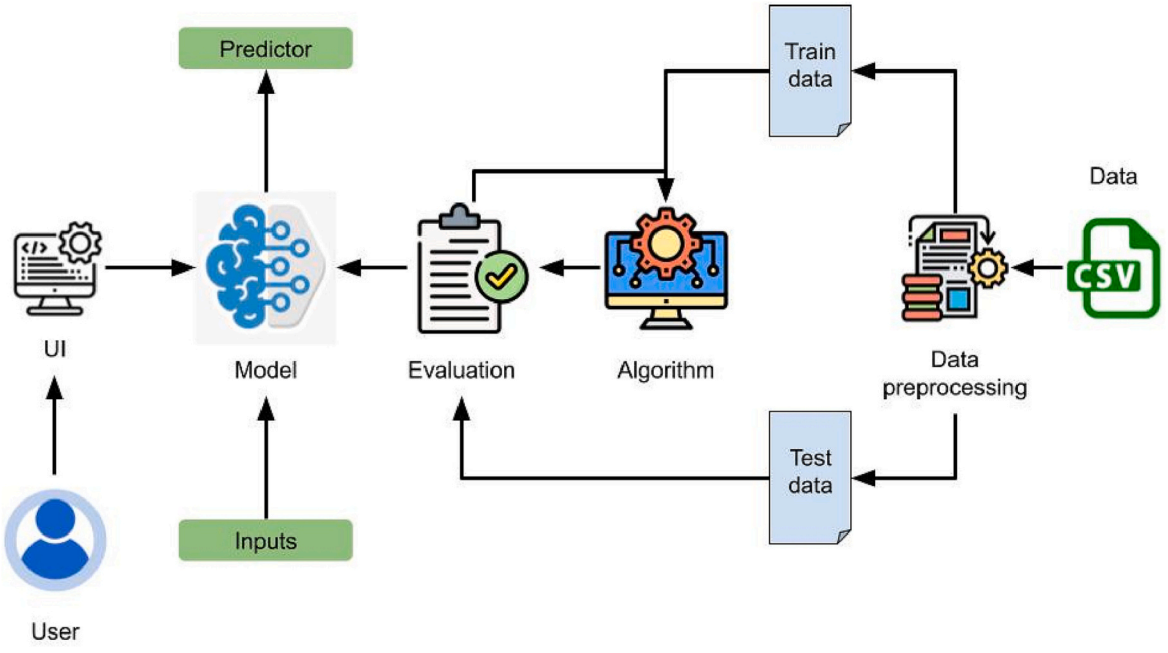


Fig. 1. Proposed data analysis using machine learning architecture.

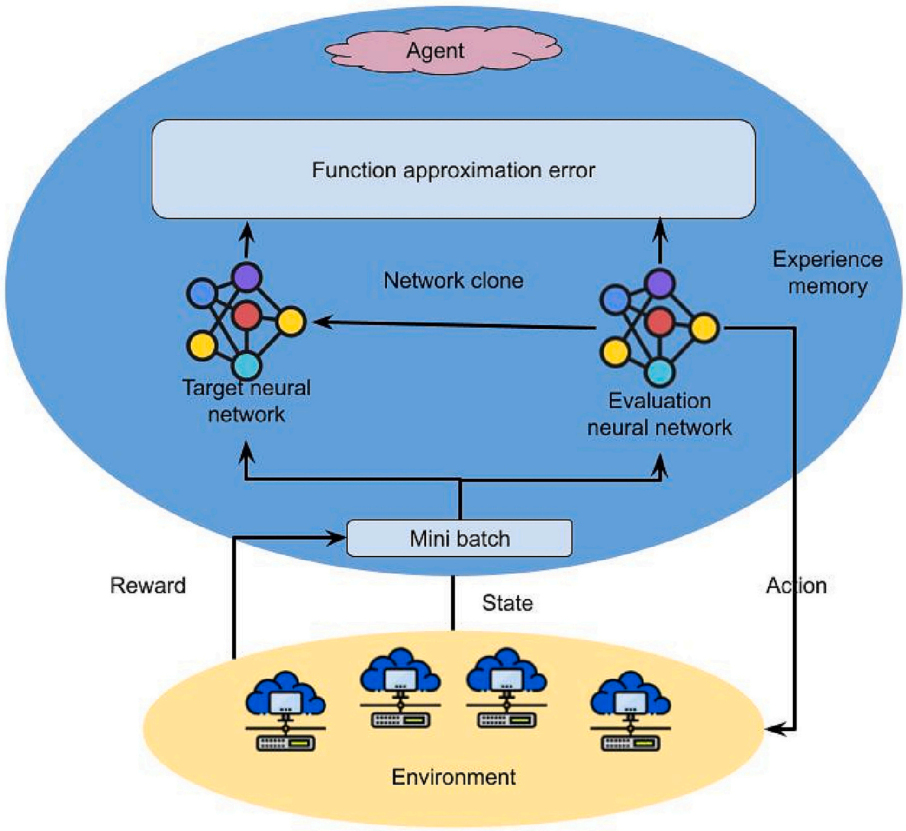


Fig. 2. Proposed behavioral pattern analysis using reinforcement training.

knowledge of its progress towards its objective, it must strike a balance between considering new alternative courses of action and making use of previously acquired knowledge. A few traditional RL algorithms have been used up to this point, including Q-learning, the actor-critic technique, SARSA, TD(*), etc.

HRMS's objective is to enhance candidates' user experience when searching for jobs on employment platform. Its most fundamental function is to recommend candidates for jobs that they might be interested in so that jobs it recommends have a high degree of compatibility with candidates, making it more likely that candidates will succeed in getting jobs. To accomplish this objective, the framework needs to give channels to contender to transfer and distribute their own data. It is a channel for organizations to post jobs and an entry for contender to land customized position proposals. In general, HRMS needs to meet the following requirements: 1) Candidates can sign up, upload, and post their own information about the job. 2) The system allows businesses to post new requirements for recruitment. It is able to provide basic information as well as a textual description of position. 3) Candidates have access to the system's personalized list of jobs that have been recommended to them. 4) Candidates can click on job records they are interested in to browse, save, and apply for them. 5) Applicants can oversee and follow-up on top picks and went after positions. The majority of the above-given prerequisites have a place with the fundamental business necessities of the framework. The ability to use the system to get personalized job recommendations is the most important requirement. Candidate's level of satisfaction with recommendation system is determined by the quality of the personalized recommendation list. The agent uses its policy to interact with the environment at every time—a mapping from state to action. Goal is to identify the best course of action that maximizes expected discounted long-term reward $\mathbb{E}\left[\sum_{t=0}^{\infty}\gamma^t r_t|\pi\right]$ a problem that is handled by evaluating value functions. $V^{\pi}(s)=\mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty}\gamma^t r_t|s_0=s\right]$ and $Q^{\pi}(s,a)=\mathbb{E}_{\pi}\left[\sum_{t=0}^{\infty}\gamma^t r_t|s_0=s,a_0=a\right]$. Optimal value functions are described as $V^{*}(s)=max_{\pi}V^{\pi}(s)$ and $Q^{*}(s,a)=max_{\pi}Q^{\pi}(s,a)$

Bellman equation, is stated recursively as in Eq, is satisfied by optimal value functions V* and Q*. Eqs. (2,3)

$$V^{*}(s)=max_{a\in A}Q^{*}(s,a) \tag{2}$$

$$Q^{*}(s,a)=r(s,a)+\gamma\sum_{s'\in S}p(s'|s,a)V^{*}(s') \tag{3}$$

The best value function V is determined by value iteration Bellman starting from any initial value function V0, based on iterative update Vk + 1 = T Vk, where T is Bellman operator denoted by eq. (4)

$$(\mathcal{T}V)(s) = max_{a\in A}\left[r(s,a) + \sum_{s'\in S} p(s'|s,a)\gamma V(s')\right] \tag{4}$$

Q-learning is a powerful method to learn by observing the environment while the model is unknown. Eq. (5) defines the value evaluation as well as update for a given trajectory (s, a, r, s0) for Q-learning.

$$Q(s,a) = (1-\alpha)Q(s,a) + \alpha(r + \gamma max_{a'} Q(s',a')) \tag{5}$$

where the learning rate is indicated by α. It should be noted that Q-learning changes value functions by eq. (6) using the hard max operator

$$max(\mathbf{X}) = max_i x_i \tag{6}$$

The log-sum-exp operator via eq. (7) is another often used operator

$$L_\beta(\mathbf{X}) = \frac{1}{\beta} log\left(\sum\nolimits_{i=1}^{n} e^{\beta x_i}\right) \tag{7}$$

Let, T_m be the function that uses the max operator to iterate any value function. The next is by eq. (8)

$$\left\|\left(\mathcal{T}_{\beta_t}V_1\right) - \left(\mathcal{T}_m V_2\right)\right\|_\infty \leq \underbrace{\left\|\left(\mathcal{T}_{\beta_t}V_1\right) - \left(\mathcal{T}_m V_1\right)\right\|_\infty}_{(I)} + \underbrace{\left\|\left(\mathcal{T}_m V_1\right) - \left(\mathcal{T}_m V_2\right)\right\|_\infty}_{(II)} \tag{8}$$

For term (I), we have by eq. (9)

$$\left\|\left(\mathcal{T}_{\mathcal{T}_t}V_1\right) - \left(\mathcal{T}_m V_1\right)\right\|_\infty \leq \frac{log(|A|)}{\beta_t} \tag{9}$$

For term (II), we have by eq. (10)

$$\left\|\left(\mathcal{T}_m V_1\right) - \left(\mathcal{T}_m V_2\right)\right\|_\infty \leq \gamma\|V_1 - V_2\| \tag{10}$$

Combining the eq. (7–10), we have by Eq. (11)

$$\left\|\left(\mathcal{T}_{\beta_t}V_1\right) - \left(\mathcal{T}_m V_2\right)\right\|_\infty \leq \gamma\|V_1 - V_2\|_\infty + \frac{log(|A|)}{\beta_t} \tag{11}$$

Max is a contraction mapping, hence $T_m V = V$ is the result of the Banach fixed point theorem. Based on the DBS value iteration specification in Eq. (12–14),

$$\|V_t - V^*\|_\infty = \left\|\left(\mathcal{T}_{\beta_t}\ldots\mathcal{T}_{\beta_1}\right)V_0 - \left(\mathcal{T}_m\ldots\mathcal{T}_m\right)V^*\right\|_\infty \tag{12}$$

$$\leq \gamma\left\|\left(\mathcal{T}_{\beta_{t-1}}\ldots\mathcal{T}_{\beta_1}\right)V_0 - \left(\mathcal{T}_m\ldots\mathcal{T}_m\right)V^*\right\|\infty + \frac{log(|A|)}{\beta_t} \tag{13}$$

$$\leq \gamma^t\|V_0 - V^*\|\gamma_\infty + log(|A|)\sum\nolimits_{k=1}^{t}\frac{\gamma^{t-k}}{\beta_k} \tag{14}$$

If $,\beta_t \to \infty$, then $lim_{t\to\infty}\sum_{k=1}^{t}\frac{\gamma^{t-k}}{\beta_k} = 0$ Taking limit of right-hand side of Eq. (13), we obtain $lim_{t\to\infty}\ \| V_{t+1} - V^*\Pi_\infty = 0$. Although non-expansion property may be broken during dynamic adjustment of βt for some specific values of β.

$$max\left\{O\left(\frac{log\left(\frac{1}{2}\right) + log\left(\frac{1}{1-2}\right) + log(R)}{log(1)}\right), O\left(\left(\frac{1}{(1-\gamma)_\varepsilon)}\right)^{\frac{1}{p}}\right)\right\} \text{ steps, error } \|V_t - v\|\infty \leq \epsilon \tag{15}$$

Reinforcement learning considers agents that may carry out a series of actions in an environment, denoted by E, across a number of discrete time steps, denoted by t 1, …, T. A new state, S (t + 1), and a scalar reward, R t, will then appear to the agent. The goal of agents is to devise a plan of action that maximizes the objective function, which is anticipated by eq. (16) to result in a cumulative return of form.

$$J(\pi) := \sum\nolimits_{t=0}^{T}\mathbb{E}_{(s_t,a_t)}[\gamma^t r(\boldsymbol{s}_t,\boldsymbol{a}_t)] \tag{16}$$

$$max_{\boldsymbol{\theta}\in\mathbb{R}^d} J(\boldsymbol{\theta}) \tag{17}$$

$$F(s,t,s,t) = \gamma\phi(s,t) - \phi(s,t) \tag{18}$$

$$F(s,a,t,s^{'},a^{'},t^{'}) = \gamma\phi(s^{'},a^{'},t^{'}) - \phi(s,a,t) \tag{19}$$

Assume, T is a different set for saving instances to satisfy constraints for all iterations and G denotes a collection of indices of selected blocks in sampling. Choose g, an index in MG, first. Entries of xg are based on probability density function (xg, u) to generate anxg given g. It is generated using the Bernoulli distribution of the parameter for all ul in xg. When xig = 1, indicator um for residual blocks in MG is adjusted based on xg, such that uim = 0 for mMG. If the implied cardinality of, |G|, is same as M, then useful sample is produced. Valuable samples are gathered in T, sampling is done according to T's cardinality, which is implied by the symbol |T|, and S is the result. It shows that the closer to (x) and (x) are, the smaller the minimum (q, p) is. It means that using Eq. (20),

$$minH(q,p) = max\sum \mid \mathscr{T} \mid q(x)lnp(x) \tag{20}$$

where(x)=1S, where S is cardinality of a set and 1/S is probability of an autonomous result in a group of samples. The aim is utilized to determine best optimal indicator u for lowering (q, p) based on the problems in (20). In the t^{th} iteration, a candidate is chosen from a S series of random examples and retrieved using the probability ψ(x, u). Adaptive sampling's potential sample is established. The aim (x_s) s = 1 S is determined to be calculated, and it is organized as $\psi(x[1]) \le \psi(x$ (Budhwar et al., 2022)) $\le \cdots \le \psi(x[S])$. Then, elite samples are chosen, such as x (Bhalerao et al., 2022; Budhwar et al., 2022), or [elite], which offers the lower target. The best indicator for strategy X is then determined by computing Eq. (21):

$$u^{*} = argmax_{\mathrm{u}} \frac{1}{S} \sum_{s=1}^{\bar{-}_{s_{elite}}} lnp\left(x^{[s]}, u\right) \tag{21}$$

By utilizing Eq. (20) and (21) and promoting $\frac{\partial H(q,p)}{S} = 0$, the saddle point c is obtained.

$$u_l^{*} = \frac{1}{S_{elite}} \sum_{s=1}^{s_{elite}} x_l^{[s]} \tag{22}$$

The CE-related measure from the model that is now being given is used to increase the probability. This is done by assuming that the sampling process is random and that the sample count is minimum. By eq. (23) it is applicable.

$$u^{(t+1)} = \alpha u^{*} + (1-\alpha)u^{(t)} \tag{23}$$

Moreover, the expansion of the likelihood of client acknowledgment changes the issue into a stochastic issue which makes it hard to take care of it as a direct issue. In addition, we assume that learning agent is completely unaware of the underlying model dynamics. Because of this, additional methods, such as those based on method-free RL, are required. Proposed method can learn to price from dynamic environment-generated data and go model-free in this paper. In point of fact, the approach that has been suggested is more in line with what actually takes place in the real world, where insurer offers renewal prices to a series of customers that visits one at a time. Last but not least, taking into account any price-related business constraints is an essential consideration. For our situation, we consider such requirements Ci are characterized for every client I in portfolio. These reaches can be changed by considering organization's targets, advertising efforts, changes in regulation or even the skill of other insurance agency. For instance, the lower furthest reaches of these reaches can be discounted to offer lower reestablishment costs in light of a market of forceful contest or showcasing efforts that expect to hold the largest number of clients.

5. Performance analysis

In this paper, trials and examination are completed utilizing genuine datasets., e informational index utilized in this paper is the information gathered from the HR work stage referenced previously. A human resources data warehouse that is suitable for recommendation is obtained through a series of data preprocessing tasks. Preparation of a Dataset: Real Data: The actual information we have from BBVA consists of 83,200 judgements with 11 features from a portfolio of home insurance. The Synthetic Dataset is this. It will let us validate the suggested RL use framework. However, we will use a fictitious dataset for the research phase that only takes into consideration the essential elements of the genuine dataset. Experts in insurance from BBVA have suggested selecting these features, removing those that were irrelevant to the analyzed task. Values for customer features in synthetic dataset are also produced using a method that has been customized to the real data. By doing this, the confidentiality of the original dataset is protected while ensuring that synthetic dataset as well as original dataset have same statistical characteristics. The resulting synthetic dataset's seven attributes are listed in Table 1. Table 1 lists names of features, their types, their mean values and standard deviations, as well as a brief description of each feature. Scale of experimental data is shown in Table 2. Dataset consists of 170,844 recordings of user behavior, 15,000 records

Table 1
Human resources dataset size.

Name	Number
Applicants	4692
Behavior record	170,844
Jobs	15,000

Table 2
Synthetic dataset.

Feature	Type	Mean	Description
price	Numeric	207.1 ± 89.1	Insurance price
$\rho(v)$	Numeric	0.7 ± 0.2	Probability of customer acceptance
v	Numeric	1.1 ± 0.1	Renewal ratio
tier	Nominal	–	Financial segment of customer
C	Numeric	$[0.9 \pm 0.1; 1.1 \pm 0.1]$	Range renewal ratio
class	Nominal	–	Price acceptance $\sim \mathscr{B}(\rho(v))$
gain	Numeric	224.7 ± 97.9	price $*v$

of jobs, and 4692 records of applicants. As a result, the dataset becomes sparse: Calculations for CDL and HDCF are performed utilizing MXNetDL architecture; architecture form is 0.8.0; working environment is Ubuntu Kylin 16.04 LTS; and Python version is 2.7.0. The SyriaTel dataset was utilized to explore its structure using the Spark engine; exploration phase and required pre-preparation have to be finished for dataset to be appropriate for classification algorithms. After analyzing data, we found that 15% of the numerical variables and 33% of the categorical variables only have one value, while approximately 50% of the numerical variables have one or two discrete values and almost 80% of the categorical variables have fewer than ten categories. The majority of a few characteristics are nothing. We found that 77% of numerical variables have more than 97% of their values set to 0 or null. These findings demonstrate that many variables are either fixed or very nearly constant, making their elimination possible.

As a result, we take into account five primary customer characteristics in this synthetic dataset: price, tier, and C. The price shown in Eq. 6, also known as the insurance price, is the feature price. In the insurance industry, tier is a well-known indicator of a customer's financial status. A clustering procedure that takes into account a number of customer characteristics (such as age and the number of claims in the previous year) is typically used to perform customer segmentation. This way, rather than analyzing each individual customer's characteristics individually, the business only looks at the market segment it falls into when making a decision about that customer. It is expected that all of a group's customers will react in same way to decisions made by the company. As a result, businesses can even customize decisions made for each segment.

In particular, we take into account four segments and, as a result, four values for this feature: tiers 1, 2, 3, and 4, where the customer runs a greater risk the higher the value of the tier. Include v is the restoration proportion proposed to the client for trial-and-error purposes. The third characteristic C is the business restrictions, or range in which renewal ratio v is selected for a specific customer. Gain as well as class is features that were derivate from prior features. Specifically, gain is new protection value proposed to client and class is recharging acknowledgment class inspected from.

6. Proposed analysis

The above Table 3 shows parametric analysis for proposed technique based on various human resource management dataset. Dataset analyzed are Synthetic, Human Resources, SyriaTel dataset in terms of prediction accuracy, AUC, average precision, sensitivity, quadratic normalized square error.

The above Fig. 3 shows parametric analysis based on proposed technique for various resource management dataset. The proposed technique attained prediction accuracy of 89%, AUC of 81%, average precision of 65%, sensitivity of 62%, quadratic normalized square error of 51% for Synthetic dataset; for Human Resources dataset prediction accuracy of 93%, AUC of 86%, average precision of 73%, sensitivity of 66%, quadratic normalized square error of 53%; the proposed technique attained prediction accuracy of 98%, AUC of 89%, average precision of 83%, sensitivity of 66%, quadratic normalized square error of 59% for Synthetic dataset.

7. Comparative analysis

Fig. 4 shows analysis in terms of prediction accuracy. For Synthetic dataset proposed technique attained prediction accuracy of 89%, existing SVM attained prediction accuracy of 85%, BPN attained prediction accuracy of 88%; proposed technique attained prediction accuracy of 93%, existing SVM attained prediction accuracy of 89%, BPN attained prediction accuracy of 91% for Human Resources dataset; For SyriaTel dataset proposed technique attained prediction accuracy of 98%, existing SVM attained prediction accuracy of 92%, BPN attained prediction accuracy of 96%.

Fig. 5 comparison for AUC is shown. For Synthetic dataset proposed technique attained AUC of 81%, existing SVM attained AUC of 77%, BPN attained AUC of 78%; proposed technique attained AUC of 86%, existing SVM attained AUC of 82%, BPN attained AUC of 84% for Human Resources dataset; For SyriaTel dataset proposed technique attained AUC of 89%, existing SVM attained AUC of 83%,

Table 3
parametric analysis based on various resource management dataset using proposed technique.

Dataset	Prediction Accuracy	AUC	Average Precision	Sensitivity	Quadratic Normalized Square Error
Synthetic	89	81	65	62	51
Human Resources	93	86	73	66	53
SyriaTel	98	89	83	66	59

Table 4
Analysis based on various HRM and customer dataset.

Dataset	Techniques	Prediction Accuracy	AUC	Average Precision	Sensitivity	Quadratic Normalized Square Error (QNSE)
Synthetic	SVM	85	77	56	55	46
	BPN	88	78	62	59	48
	RE_BDA_AI	89	81	65	62	51
Human Resources	SVM	89	82	68	58	49
	BPN	91	84	72	63	52
	RE_BDA_AI	93	86	73	66	53
SyriaTel	SVM	92	83	75	61	52
	BPN	96	86	79	65	55
	RE_BDA_AI	98	89	83	66	59

Table 4 shows analysis based on various human resource management and customer dataset. The dataset analyzed are Synthetic, Human Resources, SyriaTel dataset in terms of prediction accuracy, AUC, average precision, sensitivity, quadratic normalized square error.

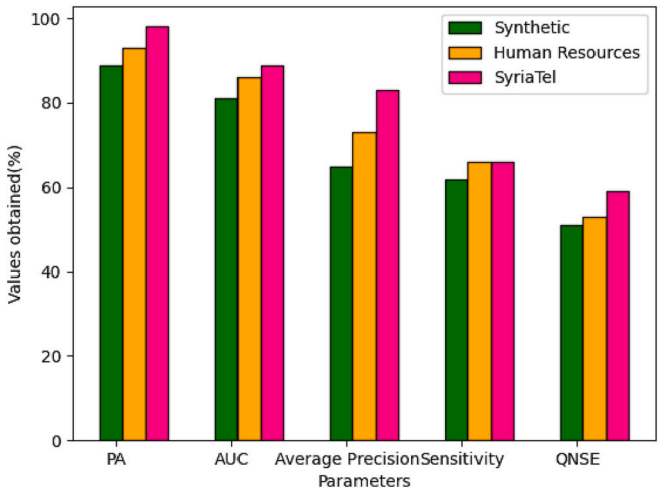


Fig. 3. Proposed model based parametric analysis for various human resource management dataset.

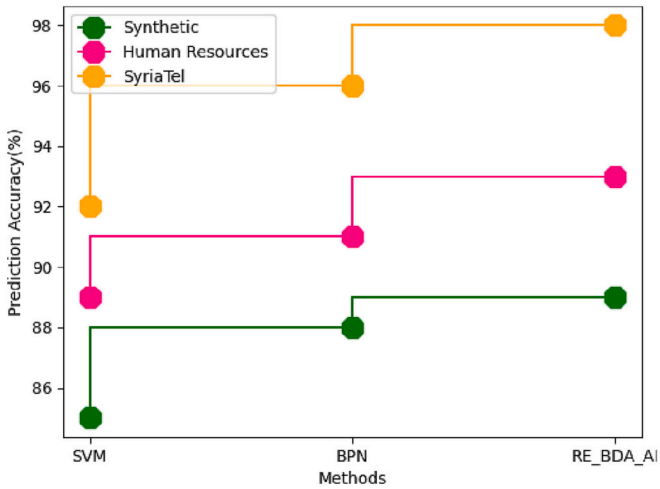


Fig. 4. Comparison of prediction accuracy.

BPN attained AUC of 86%.

Fig. 6 shows analysis in terms of Average Precision. For Synthetic dataset proposed technique attained Average Precision of 65%, existing SVM attained Average Precision of 56%, BPN attained Average Precision of 62%; the proposed technique attained Average Precision of 73%, existing SVM attained Average Precision of 68%, BPN attained Average Precision of 72% for Human Resources

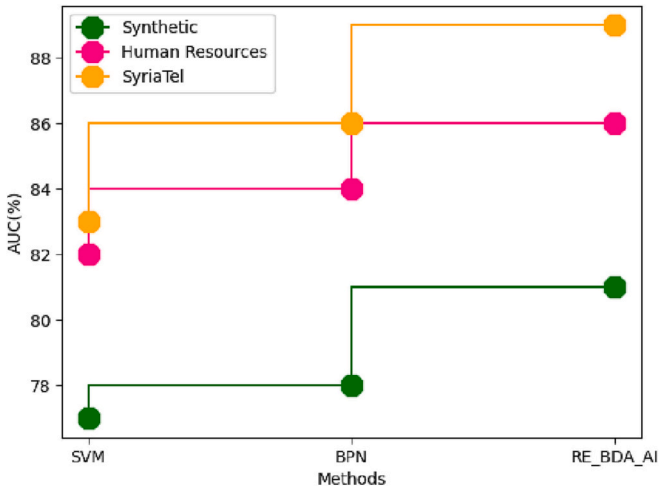


Fig. 5. Comparison of AUC.

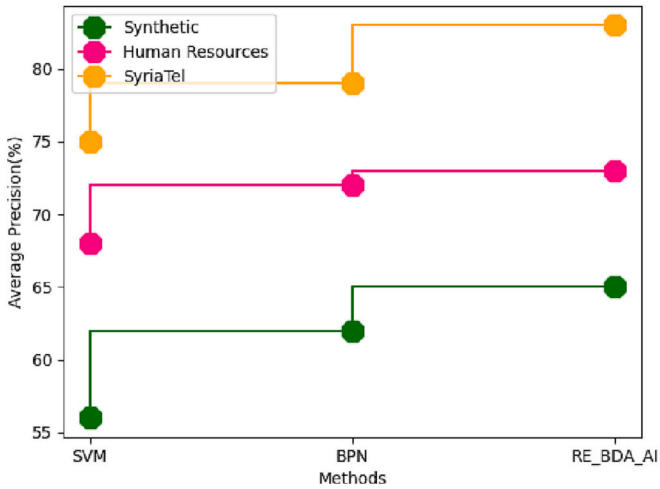


Fig. 6. Comparison of Average Precision.

dataset; For SyriaTel dataset the proposed technique attained Average Precision of 83%, existing SVM attained Average Precision of 75%, BPN attained Average Precision of 79%.

From above Fig. 7 the comparison for Sensitivity is shown. For Synthetic dataset proposed technique attained Sensitivity of 62%, existing SVM attained Sensitivity of 55%, BPN attained Sensitivity of 59%; the proposed technique attained Sensitivity of 66%, existing SVM attained Sensitivity of 58%, BPN attained Sensitivity of 63% for Human Resources dataset; For SyriaTel dataset proposed technique attained Sensitivity of 66%, existing SVM attained Sensitivity of 61%, BPN attained Sensitivity of 65%.

Fig. 8 shows analysis in terms of QNSE. For Synthetic dataset proposed technique attained QNSE of 51%, existing SVM attained QNSE of 46%, BPN attained QNSE of 48%; the proposed technique attained QNSE of 53%, existing SVM attained QNSE of 49%, BPN attained QNSE of 52% for Human Resources dataset; For SyriaTel dataset the proposed technique attained QNSE of 59%, existing SVM attained QNSE of 52%, BPN attained QNSE of 55%.

Behavior records of candidates are divided chronologically into two parts in this experiment: the training set, which accounts for approximately 90% of the data, and test set, which accounts for 10% of data. Because HDCF method uses different algorithms to process the two distinct parts of human resource data—cold start as well as noncold start. The experiment consists of four parts: the deep model's parameter tuning, the structure of the deep network's tuning, the algorithm's effectiveness verification, and algorithm effect comparison. The results of the experiment and the findings of the analysis will be discussed in this section. As such, DQL could uphold elective answers for exploit the processing assets and diminish holding up time by first serving clients with higher business esteem. In order to fulfill the requirement for salary calculation, information from attendance management system ought to be imported into salary management system; Customer relationship management (CRM) system's data ought to be consistent with that of the maintenance intelligent dispatching system as well as site quality verification system's follow-up data on task implementation.

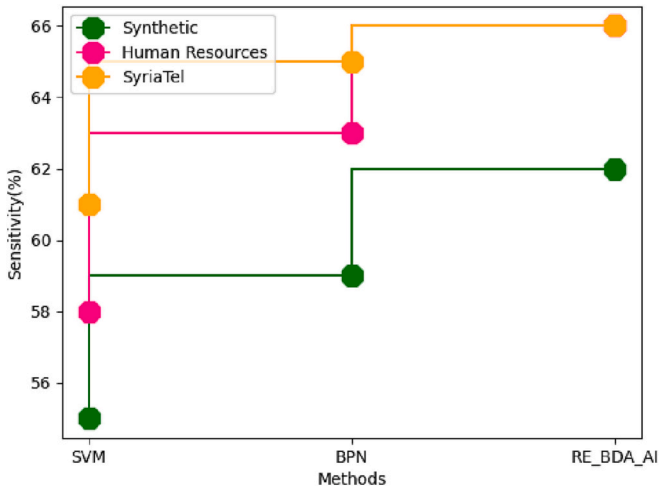


Fig. 7. Comparison of Sensitivity.

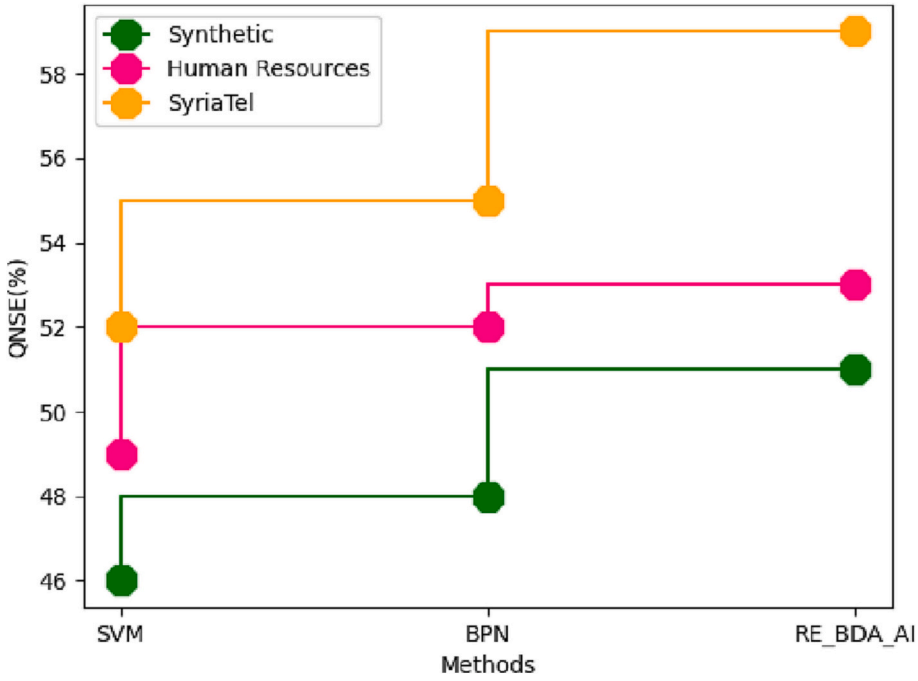


Fig. 8. Comparison of QNSE.

Eventually, the system should function as a closed-loop service and be consistent.

8. Conclusion

This study uses AI to improve human resource executives with client hold. Complete the personal conduct standard investigation-based support spiral fluffy choice using quadratic part vector machine. Different numbers of hidden layer neurons and iterations have been used to test the model's stability and effectiveness. This study uses gradient descent technique and its variations by doing several trials for each version. The insurer gives this tool a customer's current pricing and section. The tool incorporates insurance business income and retention. This pricing, segment, revenue, and retention describe the system. The proposed method has 98% prediction accuracy, 89% AUC, 83% average precision, 66% sensitivity, and 59% quadratic normalized square error. For this state, the tool's learned policy determines the insurer's renewal pricing. Additional work involves analyzing clients' market basket studies, where association rules describe goods usually bought together. This will help retailers improve their products. Each item acquired by a

customer will be characterized to show buying habits.

CRediT authorship contribution statement

Pham Quang Huy: Conceptualization, Methodology, Software. **Shavkatov Navruzbek Shavkatovich:** Data curation, Writing – original draft. **Zulkiflee Abdul-Samad:** Visualization, Investigation. **D.K. Agrawal:** Supervision. **K.M. Ashifa:** Software, Validation. **Mahendran Arumugam:** Writing – review & editing.

Data availability

The data that has been used is confidential.

References

Agarwal, V., Mathiyazhagan, K., Malhotra, S., & Saikouk, T. (2022). Analysis of challenges in sustainable human resource management due to disruptions by industry 4.0: An emerging economy perspective. *International Journal of Manpower, 43*(2), 513–541.

Ahmad, H., & Mustafa, H. (2022). The impact of artificial intelligence, big data analytics and business intelligence on transforming capability and digital transformation in Jordanian telecommunication firms. *International Journal of Data and Network Science, 6*(3), 727–732.

Ahmed, A. A. A., Agarwal, S., Kurniawan, I. G. A., Anantadjaya, S. P., & Krishnan, C. (2022). Business boosting through sentiment analysis using Artificial Intelligence approach. *International Journal of System Assurance Engineering and Management, 13*(Suppl. 1), 699–709.

Alshurideh, M. T., Al Kurdi, B., Alzoubi, H. M., Ghazal, T. M., Said, R. A., AlHamad, A. Q., … Al-kassem, A. H. (2022). Fuzzy assisted human resource management for supply chain management issues. *Annals of Operations Research*, 1–19.

Bhalerao, K., Kumar, A., Kumar, A., & Pujari, P. (2022). A study of barriers and benefits of artificial intelligence adoption in small and medium enterprise. *Academy of Marketing Studies Journal, 26*, 1–6.

Budhwar, P., Malik, A., De Silva, M. T., & Thevisuthan, P. (2022). Artificial intelligence–challenges and opportunities for international HRM: A review and research agenda. *The International Journal of Human Resource Management, 33*(6), 1065–1097.

Chen, L., Jiang, M., Jia, F., & Liu, G. (2022). Artificial intelligence adoption in business-to-business marketing: Toward a conceptual framework. *Journal of Business & Industrial Marketing, 37*(5), 1025–1044.

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review, 33*(1), Article 100899.

Cooke, F. L., Dickmann, M., & Parry, E. (2022). Building sustainable societies through human-centred human resource management: Emerging issues and research opportunities. *The International Journal of Human Resource Management, 33*(1), 1–15.

Da Silva, L. B. P., Soltovski, R., Pontes, J., Treinta, F. T., Leitão, P., Mosconi, E., … Yoshino, R. T. (2022). Human resources management 4.0: Literature review and trends. *Computers & Industrial Engineering, 108111*.

Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., & Foropon, C. (2022). Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view. *International Journal of Production Economics, 250*, Article 108618.

Elfatih, N. M., Hasan, M. K., Kamal, Z., Gupta, D., Saeed, R. A., Ali, E. S., & Hosain, M. S. (2022). Internet of vehicle's resource management in 5G networks using AI technologies: Current status and trends. *IET Communications, 16*(5), 400–420.

Jaiswal, A., Arun, C. J., & Varma, A. (2022). Rebooting employees: Upskilling for artificial intelligence in multinational corporations. *The International Journal of Human Resource Management, 33*(6), 1179–1208.

Khan, T., Tian, W., Zhou, G., Ilager, S., Gong, M., & Buyya, R. (2022). Machine learning (ML)–centric resource management in cloud computing: A review and future directions. *Journal of Network and Computer Applications, 103405*.

Lazaroiu, G., Androniceanu, A., Grecu, I., Grecu, G., & Neguriță, O. (2022). Artificial intelligence-based decision-making algorithms, internet of things sensing networks, and sustainable cyber-physical management systems in big data-driven cognitive manufacturing. *OeconomiaCopernicana, 13*(4), 1047–1080.

Michalikova, K. F., Suler, P., & Robinson, R. (2022). Virtual hiring and training processes in the Metaverse: Remote work apps, sensory algorithmic devices, and decision intelligence and modeling. *Psychosociological Issues in Human Resource Management, 10*(1), 50–63.

Roundy, P. T., & Burke-Smalley, L. (2022). Leveraging entrepreneurial ecosystems as human resource systems: A theory of meta-organizational human resource management. *Human Resource Management Review, 32*(4), Article 100863.

Sharma, M., Luthra, S., Joshi, S., & Kumar, A. (2022). Analysing the impact of sustainable human resource management practices and industry 4.0 technologies adoption on employability skills. *International Journal of Manpower* (ahead-of-print).

Vrontis, D., Christofi, M., Pereira, V., Tarba, S., Makrides, A., & Trichina, E. (2022). Artificial intelligence, robotics, advanced technologies and human resource management: A systematic review. *The International Journal of Human Resource Management, 33*(6), 1237–1266.

Zhang, Y. (2022). Development and application of artificial intelligence multimedia technology based on big data. *Mobile Information Systems, 2022*, 1–10.