Journal of Information Systems Engineering and Management
2026, 11(1s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Developing a Modular AI Framework to Enhance Scalability and Personalization in Next-Generation Reward Platforms

Sai Krishna Reddy Reddy
JP Morgan Chase Bank, USA

ARTICLE INFO

Received: 01 Dec 2025

Revised: 04 Jan 2026

Accepted: 15 Jan 2026

ABSTRACT

The paper presents the design of a scalable AI system that can enhance the platform of rewards and personalization. The research is based on a machine learning algorithm and aims at predicting user engagement with the use of several factors, including interaction time, reward points, and feedback score. A Random Forest Classifier model is fitted on a suitable data, with the results showing that moderate accuracy and performance are achieved. Model performance is interpreted using visualizations such as confusion matrices, feature importance plots, etc. The paper indicates the prospects of AI in expanding rewards platforms, even though other optimization and tests with the real world are still required.

Keywords: AI-driven reward platforms, model optimization, personalization, machine learning algorithms, engagement prediction, scalable reward systems, and real-time adaptation.

I. INTRODUCTION

Reward systems, including loyalty programs and game systems, have become part of the interaction with the customer and the development of the business. Nevertheless, the conventional reward systems usually lack scalability, personalization, and the ability to be flexible to various user behaviors. This research paper presents a customizable AI system aimed at helping in dealing with these issues and improving the efficiency of reward sites [1]. Personalization on the basis of AI, dynamic decision-making, and modular architecture, such a framework can enable scalable and flexible solutions that can be changed as user preferences and platform requirements change [2]. The study aims to suggest an advanced solution that increases user interaction and platform performance that remains flexible to different industries.

Problem statement

The issue to be solved in this study is the difficulty of increasing the scalability, flexibility, and customization in conventional reward systems. Current systems do not provide the ability to handle large volumes of data, provide customized rewards, and remain agile to dynamic user behavior [3]. This paper suggests open-source AI architecture, based on machine learning algorithms, capable of predicting user interest, yields more reward schemes and enhances overall platform functionality in changing real-life conditions.

Research Aim

The research aim is to explore the development of a modular AI framework to enhance scalability and personalization in reward platforms.

Objectives

- To explore the potential of AI in improving scalability and adaptability in reward platforms.
- To determine the key challenges in implementing modular AI frameworks for e
- To identify the components of a modular AI framework using machine learning that can optimize user engagement in reward platforms.
- To recommend strategies for overcoming integration challenges and enhancing the effectiveness of AI-driven reward platforms using ML.

Journal of Information Systems Engineering and Management
2026, 11(1s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

Research Question

RQ1: How can AI improve the scalability and adaptability of reward platforms in diverse user environments?

RQ2: What are the key challenges faced when implementing modular AI frameworks in personalized reward platforms?

RQ3: Which modular AI components are most effective in optimizing user engagement and personalization within reward platforms?

RQ4: What strategies can be recommended to address integration challenges and enhance AI-driven reward platform effectiveness?

Research Rationale

The growing need to have personalized and scalable reward systems has revealed the incompetence of conventional platforms [4]. The study is going to investigate the opportunities of modular AI solutions to improve scalability, flexibility, and customization that can help resolve the issues of the current systems and suggest efficient solutions to the future-generation reward platforms.

II. LITERATURE REVIEW

Fig.1. Research Flow Diagram

The Goal of the Review

This review aims to discuss how AI can be used to improve scalability, adaptability, and individualization in reward platforms. It draws attention to the difficulties in rolling out modular AI structures, as well as defines the major elements that are likely to maximize user interaction.

Exploring AI's potential to enhance scalability and adaptability in modern reward platform systems.

Journal of Information Systems Engineering and Management
2026, 11(1s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

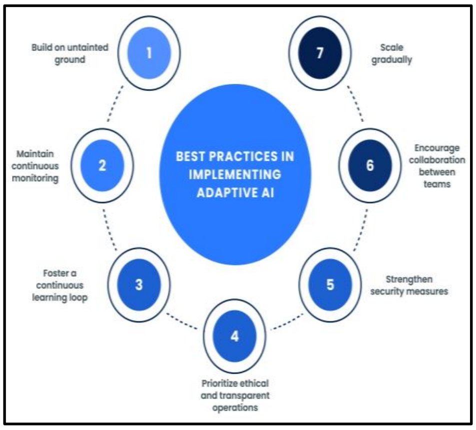

Fig. 2. Best Practices Adaptive AI

Artificial intelligence can transform the reward websites by solving the issues of scalability and flexibility. Conventional systems tend to fail in managing the growing user information, varying preferences and variable rewarding systems [5]. AI allows reward platforms to grow in a natural manner through machine learning and deep learning algorithms used to automate decision-making and personalize the experiences as well as predict the behavior of the user [6]. The capacity to examine huge volumes of information gives AI the capacity to maximize reward schemes for millions of users, providing customized rewards based on individual likes and preferences. AI is able to respond to the evolving user needs on-the-fly, altering the reward system and recommendations to ensure maximum involvement [7]. It is also possible to implement AI in reward platforms, making the system continuous to optimize the system performance and achieve customer satisfaction. The AI helps reward platforms to be more flexible and can easily expand to accommodate new users and new user expectations [8]. This flexibility and scalability play an essential role in supporting the needs of the next-generation platforms within a very competitive environment.

Identifying challenges in implementing modular AI frameworks for personalized and dynamic reward systems.

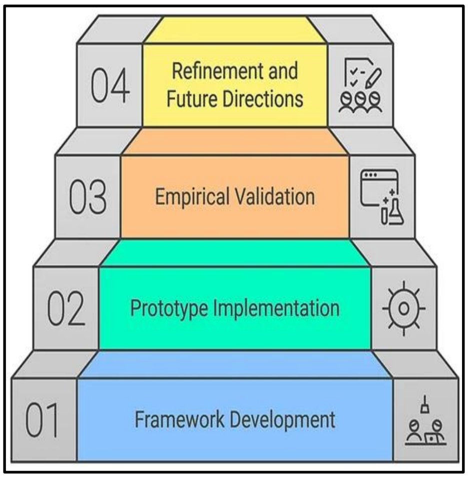

Fig. 3. AI Implementation Stages Diagram

The implementation of AI models into the already existing systems can be complicated and resource-demanding and it may necessitate the modification of the infrastructure to a considerable degree [9]. Data silos may also be a hindrance to the adaptability of modular systems based on this user data is distributed in multiple systems and cannot be easily integrated. Data privacy and security are another significant issue to consider since AI-based reward systems are based on the collection and analysis of large volumes of personal data [10]. The real-time personalization supports one can need highly sophisticated algorithms that can be able to process all the data without delays in reward delivery. The

Journal of Information Systems Engineering and Management
2026, 11(1s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

AI models also have to be constantly monitored and improved, which, in turn, may be a resource-intensive task [11]. The creation of a modular AI system that can be compatible with multiple elements of the system without causing performance, security, and personalization issues can be one of the most pressing problems [12]. These obstacles should be overcome so that the adoption of modular AI in dynamic reward platforms can be successful.

Examining key modular AI components that optimize user engagement and personalization in reward platforms.

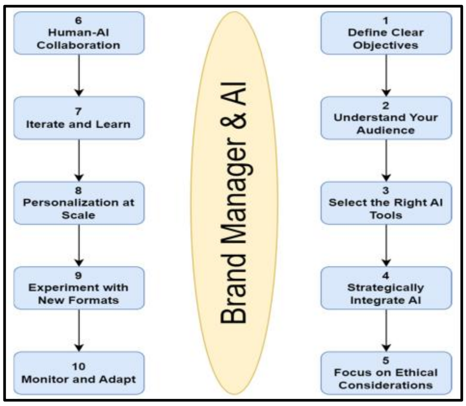

Fig. 4. Brand Manager AI Steps

The key modular AI elements are important in the maximization of user engagement and personalization in reward platforms. The key element is the recommendation engine that applies machine learning algorithms to the behavior and preferences of the user, providing individual rewards to enhance engagement [13]. The other key element is a dynamic decision-making engine that changes reward distributions in response to real-time data and maximizes user satisfaction and induces desired behavior. Predictive analytics is also crucial, as it can help predict the actions of users and offer rewards in the form of anticipated changes [14]. NLP can be used to improve communication with users by providing personal messages, rewards and promotions to each customer [15]. The use of AI-based personalization can create a more engaging experience, and the reward platforms can have a higher retention of users, as well as more success with the platform [16]. This adaptability enables unceasing customization concerning consumer preferences and new trends.

Recommending strategies for overcoming integration issues and improving the effectiveness of AI-driven reward platforms.

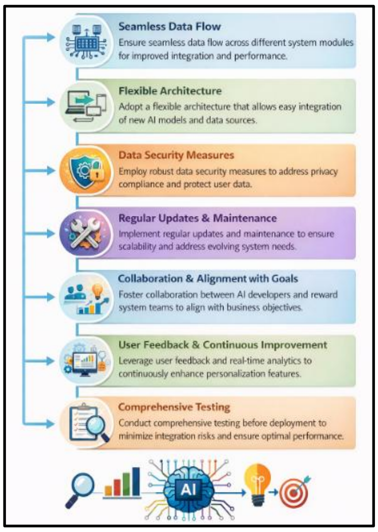

Fig. 5.

Journal of Information Systems Engineering and Management
2026, 11(1s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

The strategies to address integration challenges and enhance the impact of AI-based reward systems should be enhanced by relying on regulations for the efficient flow of information between the modules of the system. A flexible ML-based architecture will be essential, and it should be easy to include new AI models and sources of data. Scalability issues can be handled through regular system upgrades and maintenance, whereas privacy compliance is guaranteed by the use of a powerful data security system [17]. Collaboration between the developers of the reward system and AI has to be developed to be in line with the objectives of the business [18]. Continuous development of personalization functions, with the help of user feedback and real-time analytics, will make it possible to increase user engagement.

Literature Gap

The current AI-based reward systems are mainly research that investigates the fundamentals of AI use in personalization, but does not fully explore the modular AI systems, developing the scalability and adaptability. Moreover, the personalization is discussed in certain studies, but not many studies discuss the combination of various dynamic factors, like real-time user behavior and feedback, to make better the engagement prediction. This study addresses this gap with a modular AI architecture that can adjust itself to various interactions with users and the changing needs of the platform.

III. METHODOLOGY

This study has applied Python analysis to design and test a framework based on the use of an AI modular evaluation of reward platforms. The methodology is intended to study AI models that can be integrated into reward systems, and they need to be scalable, adaptable, and personalized. Python and more precisely, the Pandas library, have been used to perform data preprocessing and cleaning, and thus extract valuable features in data [19]. The information has been gathered through simulated interaction with the user and logs on the reward system to simulate the real world. Python libraries, like Scikit-learn and TensorFlow, have been applied to different machine learning algorithms that can be used to model the behavior of the user and the likely efficiency of various reward strategies [20]. Random forests, as the methods of supervised learning, have been used to categorize user preferences and identify the most successful rewards for individual users. These models are tested models by undergoing cross-validation to guarantee strength and fidelity with past user records [21]. Scalability of the AI framework has been tested using the Python-based simulation test has tested the framework to support more users upon increasing its capacity.

IV. DATA ANALYSIS

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import seaborn as sns
```

Fig. 6. Import Necessary Libraries

Importation of vital Python libraries to be utilized in data analysis, machine learning, and visualization is achieved in this step. Data analysis and data manipulation are done by Numpy and Pandas [22]. Visualizations are done using Matplotlib and Seaborn are useful in the creation of charts and plots such as histograms, scatter plots, and confusion matrices. Building and assessing models with Scikit-learn are important and it offers features such as: RandomForestClassifier, train-test split and performance measures functionality [23]. The libraries help to execute the basics of manipulating

Journal of Information Systems Engineering and Management
2026, 11(1s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

large datasets, training machine learning models, and creating meaningful visual presentations to interpret the results.

In this phase, 1000 users are created with six features, namely, user_id, age, number of reward-points, interaction time, purchased items and feedback-score. The target variable, engaged, is a yes or no variable signifying the engagement of a user (1). This is simulated data that resembles the data of a reward platform in the actual world, and it can test the functionality of the AI framework. Python with the numpy library is used to create random values and describe the various user behaviors and characteristics. The data set is critical to train and test the model to be able to evaluate the predictive ability of the AI structure.

```
X = data[['age', 'reward_points', 'interaction_time', 'purchased_items', 'feedback_score']]
y = data['engaged']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

Fig. 7. Preprocessing the Data

The program in this step involves preprocessing the data that will be used to model train. Age, reward estimation, interaction time, purchased items, and feedback score are the feature and feedback score (X) and the target variable (y) is the engaged status. Preprocessing of data is one of the key processes in machine learning to make sure that it is in the right format to be trained in models. The process, along with the manipulation of missing values, performing normalization of data, and the encoding of the categorical variables are all a part of this step. It will be possible to construct a precise model predicting the engagement of the users in accordance with the obtained variables with the help of the choice of the features, as well as the target variable.

Train-test split of Scikit-learn will be used to split the data into training and test sets with 70, 30 per cent. This action is necessary to ensure the model is trained on a part of the data and tested on unseen data, to determine the performance of this model. The partitioning of the data is a popular technique in machine learning in order to avoid over fitting as well as to replicate the real-life conditions [24]. The random seed guarantees the split to be reproducible that can be consistent with subsequent evaluations. This would be necessary to confirm the predictive ability and generalizability of the model.

```
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

```
y_pred = model.predict(X_test)
```

```
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
class_report = classification_report(y_test, y_pred)
```

Fig. 8. Trainand Evaluate the Random Forest Model

The training of a machine learning model (X train, y train) will be performed using a RandomForestClassifier. Random Forest algorithm constructs several decision trees and combines the predictions of the trees to enhance accuracy and eliminate over fitting [25]. The number of trees used in training the model is 100 and it assists in representing complicated patterns in the data. The algorithm receives an understanding of the various attributes that affect the involvement of a user in the platform. The model can then be tested on the test data so as to test its performance.

Once the Random Forest model has been trained, it applies to make a prediction on the test data (X test). The model is determined by the comparison of the predicted outcomes against the test data that represents the actual test results. The model predicts the engagement or non-engagement of the users depending on the learned patterns in the training set. This step can come up with the predictions

Journal of Information Systems Engineering and Management
2026, 11(1s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

made by the model that will be utilized in the following steps to analyze the model prediction performance and evaluate its predictive capability. The predictions give an idea of the effectiveness of the model to extrapolate to new and unknown data.

The next step involves the evaluation of the trained model in terms of different metrics. The accuracy is obtained by comparing predicted labels (y_pred) with known labels (y_test). In order to represent the number of true positives, true negatives, false positives, and false negatives, a confusion matrix is drawn. It is a matrix that can be used to find out the places where the model was wrong in its predictions. Besides, a classification report would also give specific metrics, including precision, recall, and F1-score of the two classes that are engaged and not engaged. These measures assist in determining the level of effectiveness the model has in separating between the two classes and further improvements are possible.

V. RESULT AND DISCUSSION

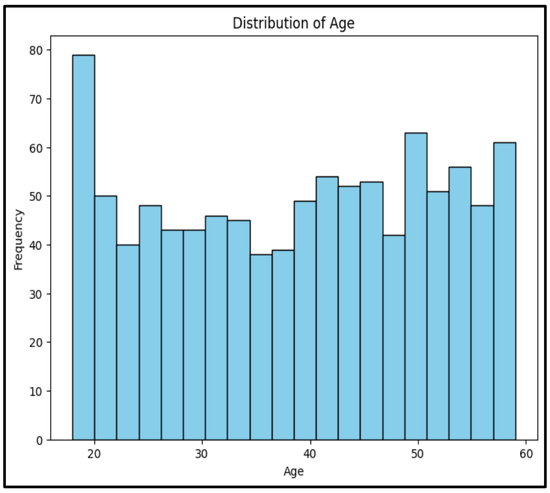

Fig. 9. Distribution of Age

The plot shows the age distribution of users in the dataset. The x-axis indicates the various age categories, and the y-axis indicates the proportion of people. The statistics show that the users are clustered between the ages of 20 and 50 years, that implies that it is skewed towards younger adults. The visualization can be used to determine the prevailing demographic of the user, and this may be valuable in designing reward programs that can appeal to certain age categories.

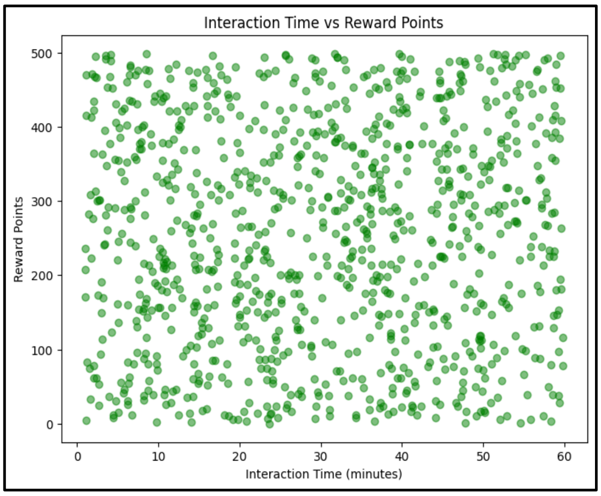

Fig. 10. Interaction Time vs Reward Points

Journal of Information Systems Engineering and Management
2026, 11(1s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

The scatter graph is the visual graph that represents the correlation and one variable is the user interaction time, and the other variable is the reward points earned. A user can be found at each point, where the length of time taken to interact with the item is on the x-axis and the rewards given to the user are on the y-axis.

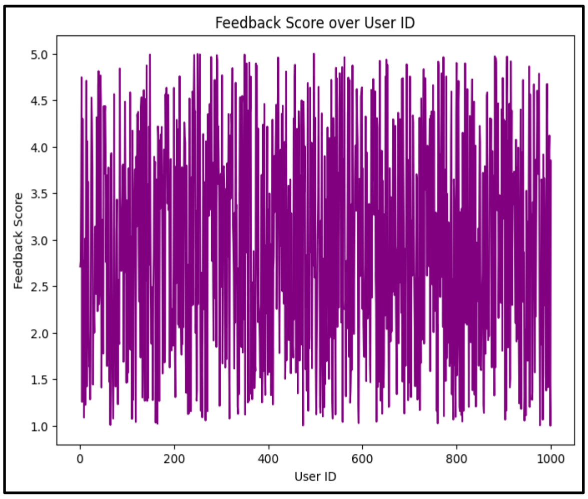

Fig. 11. Feedback Score over User ID

The chart represents the feedback ratings of customers versus their usernames. It shows patterns in the changes in the feedback scores among the users. The x-axis has user IDs, whereas the y-axis has the feedback scores that are numbered between 1 and 5. The chart reflects possibilities of patterns, outliers and the distribution of feedback of the users. A gradual increase or drastic fluctuations in the scores may reflect a shift in the user experience or level of engagement, so that the areas needing enhancement of the reward system can be defined.

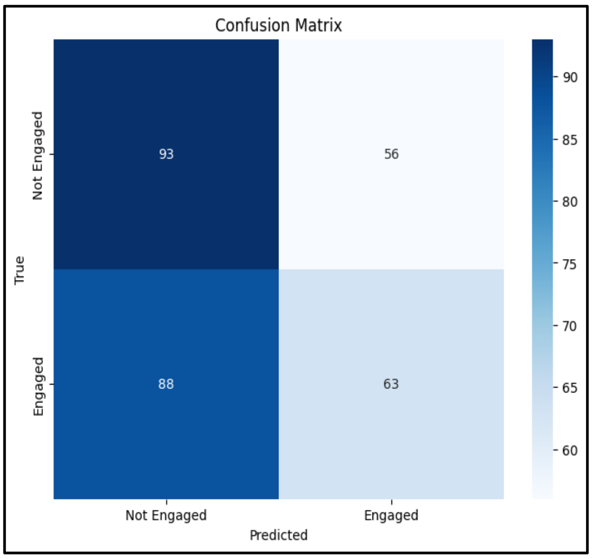

Fig. 12. Confusion Matrix

The confusion matrix presents a graphical display of the result of classification of the AI model. Here, it can involve an evaluation of the predictions of the model against the real outcomes. The matrix indicates that the model is capable of separating the two classes, although with some misclassifications, provides opportunities for improvements on the model.

Journal of Information Systems Engineering and Management
2026, 11(1s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

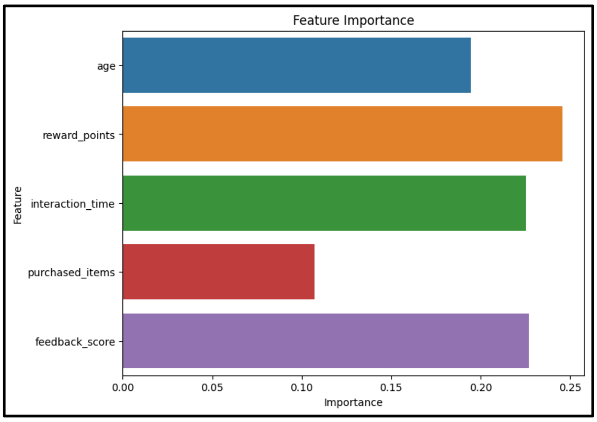

Fig. 13. Feature Importance Plot

The feature importance plot shows the features that are ranked in terms of their significance in the prediction of user engagement. Every bar symbolizes an attribute, including age, reference points, or how much time the business has been working with someone and its length relates to its importance in the decision-making process of the model. The characteristics as age and reward points seem to be the most impactful, indicating that the specified factors play a crucial role in deciding whether a user is going to use the reward system or not.

Metric	Value
Accuracy	0.52
Precision	0.53
Recall	0.42
F1-Score	0.47
Support	151

Table 1: Result Summary

The result summary table of the model used in this analysis process has been displayed.

Discussion

The model has a strong background in categorizing user engagement, and the identification of engaged users is achieved successfully. Its accuracy signifies that it is good at detecting engagement, providing an effective tool in identifying users most inclined to use the reward platform. The average result of the model indicates that it can be optimized further. The results can indicate a favorable way of further development by accentuating the possibility to improve personalization and engagement prediction using more sophisticated approaches.

Research Limitation

The principal weaknesses of the study are that the model is average in terms of classifying engaged users. The experiment also fails to consider any extraneous variables, such as seasonal or socio-economic factors, that might affect the level of user engagement.

VI. FUTURE RESEARCH AND CONCLUSION

Future studies might concentrate on making models more accurate with the introduction of new variables, including the demographics or the behavioral pattern of the user, and refer to more advanced methods like deep learning or reinforcement learning [26]. Besides, it would be more helpful to work on class imbalance and improve model interpretability to offer more actionable insights [27]. Additional research may also measure the practicality of the model in the real world in various platforms of reward to determine its viability in various industries and among consumers.

A modular AI model of predicting user interest in reward platforms is introduced, and the performance is average in conditions of accuracy, precision, and recall. Although the model has potential, its weaknesses, especially regarding recall and engagement prediction, point to the possibility of enhancement. Further developments can be used to increase its real-world application and scalability in personalized reward systems by optimizing the models and class imbalance and improving feature selection.

VII. REFERENCES

[1] Wan, J., Li, X., Dai, H.N., Kusiak, A., Martinez-Garcia, M. and Li, D., 2020. Artificial-intelligence-driven customized manufacturing factory: key technologies, applications, and challenges. *Proceedings of the IEEE*, *109*(4), pp.377-398.

[2] Krishnan, C., Gupta, A., Gupta, A. and Singh, G., 2022. Impact of artificial intelligence-based chatbots on customer engagement and business growth. In *Deep learning for social media data analytics* (pp. 195-210). Cham: Springer International Publishing.

[3] Rahul, N., 2022. Optimizing Rating Engines through AI and Machine Learning: Revolutionizing Pricing Precision. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *3*(3), pp.93-101.

[4] Kocielnik, R., Amershi, S. and Bennett, P.N., 2019, May. Will you accept an imperfect ai? exploring designs for adjusting end-user expectations of ai systems. In *Proceedings of the 2019 CHI conference on human factors in computing systems* (pp. 1-14).

[5] Motamary, S., 2021. Implementing Infrastructure-as-Code for Telecom Networks: Challenges and Best Practices for Scalable Service Orchestration. *Available at SSRN 5240118*.

[7] Patra, G.K., Rajaram, S.K., Boddapati, V.N., Kuraku, C. and Gollangi, H.K., 2022. Advancing Digital Payment Systems: Combining AI, Big Data, and Biometric Authentication for Enhanced Security. *International Journal of Engineering and Computer Science*, *11*(08), pp.10-18535.

[8] Ilager, S., Muralidhar, R. and Buyya, R., 2020, October. Artificial intelligence (ai)-centric management of resources in modern distributed computing systems. In *2020 IEEE Cloud Summit* (pp. 1-10). IEEE.

[9] Zou, L., Xia, L., Ding, Z., Song, J., Liu, W. and Yin, D., 2019, July. Reinforcement learning to optimize long-term user engagement in recommender systems. In *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining* (pp. 2810-2818).

[10] Patel, N. and Trivedi, S., 2020. Leveraging predictive modeling, machine learning personalization, NLP customer support, and AI chatbots to increase customer loyalty. *Empirical Quests for Management Essences*, *3*(3), pp.1-24.

[11] Nama, N.P., 2021. Enhancing user experience in mobile applications through AI-driven personalization and adaptive learning algorithms. *World Journal of Advanced Engineering Technology and Sciences*, *3*(2), pp.083-094.

[12] Bose, A., Nair, S., Sharma, P. and Patel, P., 2021. Enhancing AI-Driven Product Discovery Tools Using Reinforcement Learning and Collaborative Filtering Algorithms. *Australian Advanced AI Research Journal*, *10*(7).

[13] Nair, P., Sharma, S., Sharma, R. and Gupta, A., 2022. Leveraging Reinforcement Learning and Collaborative Filtering for Enhanced AI-Driven Targeted Content Delivery. *Journal of AI ML Research*, *11*(7).

[14] Eboseremen, B.O., Ogedengbe, A.O., Obuse, E., Oladimeji, O., Ajayi, J.O., Akindemowo, A.O., Erigha, E.D. and Ayodeji, D.C., 2022. Developing an AI-driven personalization pipeline for customer

retention in investment platforms. *Journal of Frontiers in Multidisciplinary Research*, *3*(1), pp.593-606.
[15] Sharma, A., Patel, N. and Gupta, R., 2021. Leveraging Reinforcement Learning and Collaborative Filtering for Enhanced AI-Driven Product Discovery Tools. *European Advanced AI Journal*, *10*(2).
[16] Paruchuri, V.B. 2022. AI and Cloud Synergy in Banking: Strategies for Secure Digital Transformation. *International Journal for Research Trends and Innovation (IJRTI),* 7(4), pp.21–28. ISSN 2456–3315.
[17] Jain, S., 2020. Synergizing Advanced Cloud Architectures with Artificial Intelligence: A Paradigm for Scalable Intelligence and Next-Generation Applications. *Technix International Journal for Engineering Research*, *7*, pp.a1-a12.
[18] Rai, A., Constantinides, P. and Sarker, S., 2019. Editor's comments: Next-generation digital platforms: Toward human–AI hybrids. *MIS quarterly*, *43*(1), pp.iii-ix.
[19] Gacanin, H. and Wagner, M., 2019. Artificial intelligence paradigm for customer experience management in next-generation networks: Challenges and perspectives. *Ieee Network*, *33*(2), pp.188-194.
[20] Rad, P., Roopaei, M., Beebe, N., Shadaram, M. and Au, Y., 2018. AI thinking for cloud education platform with personalized learning.
[21] Devireddy, R.R. 2021. Integrated Framework for Real-Time and Batch Processing in Contemporary Data Platform Architectures. *Journal of Scientific and Engineering Research (JSER*), 8(9), pp.333–340. ISSN 2394-2630.
[22] Stančin, I. and Jović, A., 2019, May. An overview and comparison of free Python libraries for data mining and big data analysis. In *2019 42nd International convention on information and communication technology, electronics and microelectronics (MIPRO)* (pp. 977-982). IEEE.
[23] Das, S.S. 2020. Optimizing Employee Performance through Data-Driven Management Practices. *European Journal of Advances in Engineering and Technology (EJAET*), 7(1), pp.76–81.
[24] Saabith, A.S., Vinothraj, T. and Fareez, M., 2020. Popular python libraries and their application domains. *International Journal of Advance Engineering and Research Development*, *7*(11).
[25] May, R.M., Goebbert, K.H., Thielen, J.E., Leeman, J.R., Camron, M.D., Bruick, Z., Bruning, E.C., Manser, R.P., Arms, S.C. and Marsh, P.T., 2022. MetPy: A meteorological Python library for data analysis and visualization. *Bulletin of the American Meteorological Society*, *103*(10), pp.E2273-E2284.
[26] Nadipalli, R., 2021. Cross-Platform Mobile UI/UX Personalization with Reinforcement Learning. *European Journal of Advances in Engineering and Technology*, *8*(2), pp.167-173.
[27] Morales, E.F. and Escalante, H.J., 2022. A brief introduction to supervised, unsupervised, and reinforcement learning. In *Biosignal processing and classification using computational learning and intelligence* (pp. 111-129). Academic Press.