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A Business-Oriented Recommender System for Insurance Policy and Add-On Upselling Using Implicit Behavioral Data

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Abstract: Recommender systems are now important for making personalised product offers, but using them in the insurance industry is not easy. This study aims to develop a recommender engine suitable for real-world businesses. It will focus on recommending insurance policies and additional coverages to support effective upselling. We look at and compare several recommendation methods based on how well they predict, how hard they are to model, and how much work it takes to tune them to find a solution that is both balanced and scalable. Because there are no clear customer ratings and insurance data is highly sensitive, the proposed system relies on implicit behavioural signals and next-item prediction techniques. Some of the other problems solved were a lack of item diversity, a lack of interaction data, and the difficulty of using customer metadata due to concerns about randomness and bias. The study shows how to address implicit feedback while reducing bias from favouring popular products over less popular ones. The results show that carefully chosen recommendation strategies can deliver real business value while adhering to the rules and limitations that apply to data in the insurance industry.

Keywords: A Generalised Low Rank Model, Nonnegative Matrix Factorisation, Matrix Completion, Universal Recommender, Machine Learning, Correlated Cross-Occurrence Algorithm, K-Fold Cross-Validation

Introduction

The insurance business is highly competitive, and there is significant room for growth in sales. The traditional way of using mediators to sell more insurance policies is what holds this industry back [29]. It just adds an extra step to the whole process that doesn't need to be there. Using a recommender system is one of the best ways to do this [32]. Even so, recommender systems are used in many fields and applications, but they are not used enough in the insurance industry [37]. This is because the insurance industry has built-in problems, such as a limited number of target products, a large number of user features and training data, and gaps in recorded data because financial tech services place a lot of emphasis on privacy [35]. These problems need to be solved before recommender systems can work in the insurance industry. The goal is to create a recommender system that addresses the problems mentioned above and can be used in real time in business settings [39].

The goal is to build a recommender engine that businesses can use [34[. Different ways to suggest insurance policies and additional coverage to customers are compared, and the approach that performs best in terms of predictive power, modelling effort, and tuning time is chosen. For optimal coverage upselling, the approach must work with next-item data[31]. The inherent challenges of data management in the insurance sector pose significant obstacles to the application of basic or conventional methodologies in the development of recommender systems. Because this field has a lot of customer privacy, it is hard to use unlabelled data for training [38]. It's not good that the data doesn't have any clear ratings, so we have to guess ratings and use implicit data. It's also hard to use customer metadata and profile information because there is a random element. It's also harder to train people in the insurance industry because there aren't many predictable items [28]. This creates bias against popular and unpopular products.

The project is about machine learning and financial services. More specifically, it examines how AI and machine learning can automate tasks in the financial sector [33]. It makes a solution for the insurance industry that is specific to that business. The scope includes a working model that handles missing user data and a robust data-cleaning effort that addresses problems with implicit and unrated data [36]. A learning strategy that lets you make predictions with low item counts and a suggested backend method for easy business use are also put in place [30]. It helps insurance companies suggest as many policies as they can to customers. It wants to help people find the right policy for their needs [40].

Project Description

There are several recommender systems already in place for insurance policies. The generalised low-rank model-based recommender system proposed by Spedicato and Savino is one of these [42]. A generalised low-rank model (GLRM) is a way to use a low-rank matrix to approximate a data set represented by a matrix. GLRM can work with any kind of dataset, including numeric, true/false, categorical, ordinal, and more [48]. This framework includes many well-known data analysis methods, such as nonnegative matrix factorisation and matrix completion [46]. This system employs machine learning methods to identify statistically significant correlations between products and consumers, and it has been effectively implemented across diverse business sectors. IGI Global has also proposed a recommendation system for life insurance [44]. This system makes it easier to identify client risks and opportunities for up-selling and cross-selling, and provides a clear, simple platform for insurance products, literature, and marketing facts and figures to speed up the sales cycle [49].

Recommendation engines can help both customers and insurance companies [47]. Recommendation engines can move data to the cloud with insurers and keep it up to date in real time. Recommendation engines can also help determine which areas will generate the most revenue from productized insurance [45]. There are still many problems with using recommender systems in the insurance industry, even with these improvements. One of the main problems is that there aren't many products to choose from, which makes classical recommender system models less useful [41]. Also, many of the methods used in recommender system analyses are very different from those actuaries use all the time. It's hard to fully understand a customer's needs because insurance policies use complicated language and have many parts [43]. There are also concerns about privacy and data security when gathering and analysing customer information.

Literature Review

RevMan uses the Valence Aware Dictionary and Sentiment Reasoner framework, along with simple machine learning methods such as logistic regression and multinomial Naive Bayes, to make sentiment-based recommendations [4]. This method is easy to use and inexpensive to run, but its simplicity makes it less useful for predicting in complex recommendation scenarios [22]. The model can't pick up on subtle user preferences or sequential behaviour because it only looks at sentiment polarity. Also, not having access to rich and varied datasets makes it much harder to generalise and validate models. RevMan struggles to go beyond controlled experiments without substantial data from the same field [9]. Because of this, the method is easy to understand and doesn't take up much space, but it doesn't meet the robustness and accuracy standards that modern, data-heavy recommender systems require.

The K-Nearest Neighbours method uses similarity-based learning to make recommendations and has been shown to perform better than older sentiment-based models [23]. This method is said to perform about 15% better than the baseline by combining a decision tree algorithm with neighbourhood-based learning [16]. Its strength comes from its easy-to-understand logic and its ability to quickly adapt to patterns in local data. But KNN-based systems often struggle with scalability as the dataset size grows, because calculating distances becomes more expensive [26]. The model's performance also depends on the distance metric and the value of K, which can vary across datasets. Even with these problems, KNN remains a useful step up from simpler models when you need a moderate increase in accuracy without making the model overly complex [7].

Support Vector Machine-based methods, improved with gradient regression boosting techniques, make a better modelling framework for recommendation tasks [12]. When properly tuned, these models can uncover complex nonlinear relationships in data, making them very good at predicting. But this strength comes with a lot of time spent tuning and a lot of work spent modelling [3]. It takes a lot of testing and field knowledge to choose the right kernels, regularisation parameters, and boosting settings. In addition, the extra work required to train and test these models can be too much for businesses that need to move quickly or operate at scale [18]. So, even though SVM-based systems can be very accurate, they are often not very useful because they require substantial resources and take a long time to develop.

Recommendation systems that use Natural Language Processing rely on predicting the value of an item's attributes to figure out what a user likes [14]. Many studies build custom engines to demonstrate that it is possible to extract semantic meaning from text descriptions and user interactions. These methods are often new and interesting because they go beyond simple numbers to more complex representations of context [24]. However, their use in the real world is limited because they require high-quality text data and extensive preprocessing. Custom engines might not work well across different fields or handle large amounts of data in production settings [6]. Consequently, despite their innovation, NLP-driven recommender systems often face challenges in operational deployment, particularly in industries where structured interaction data dominates over textual inputs.

Hybrid recommendation models aim to leverage the best features of different methods by combining them. However, many implementations still use outdated methods and basic collaborative filtering techniques [2]. These systems often lack the advanced features needed to address modern challenges such as sparsity, scalability, and changing user behaviour. Using simple hybrids can lead to bad predictions because they don't combine parts in a useful or optimised way [11]. Also, old methods may not work well with implicit feedback or changing item catalogues. So, even though hybrid models sound good in theory, poorly designed implementations can perform worse than more focused, up-to-date single-method approaches [21].

Explainable AI models use both collaborative filtering and content-based filtering to provide clear, understandable recommendations. These systems have good predictive power and can explain why certain recommendations are made, which is useful in areas where trust is important or where rules are strict [15]. But they often have problems with clustering, where users or items are grouped too broadly, leading to overly general predictions. This can make things less personalised and miss the small differences between users [19]. Furthermore, achieving a balance between explainability and accuracy is difficult because making models easier to understand can hurt performance [8]. Even with these problems, XAI-based methods represent a significant step toward making recommender systems accountable and trustworthy for users.

Matrix factorisation techniques use both collaborative filtering and neural network ideas to find hidden connections between users and items [10]. The use of weighted alternating least squares enables these models to handle implicit feedback effectively while maintaining computational efficiency. One of the best things about matrix factorisation is that it can help with the cold-start problem by learning general latent features [17]. This makes it a good fit for sparse interaction data, which is common across many fields. However, the quality of recommendations depends heavily on the choice of latent dimensions and regularisation parameters [5]. When properly tuned, matrix factorisation offers a strong balance between scalability, accuracy, and practical applicability in business-oriented recommender systems.

Finding patterns of items that happen together is the main goal of association rule mining [27]. This is how recommendations are made. These methods frequently juxtapose various rule-based methodologies and assess performance through metrics such as Mean Absolute Error [20]. MAE, on the other hand, is not a good choice for recommendation tasks because it doesn't effectively measure ranking quality or user relevance [1]. Additionally, association rule mining often yields a large number of trivial or redundant rules, making interpretation and deployment challenging [25]. Testing model-based, user-based, content-based, and item-based recommendations gives a lot of information. Still, the lack of good evaluation metrics and personalisation makes them less useful in real life [13]. As a result, association rule mining is better suited to exploratory analysis than to recommendation systems that work well.

Issues with Existing System

Recommender systems have been successfully implemented across various domains, including e-commerce and entertainment. But the insurance industry hasn't paid much attention to them [52]. One of the biggest problems with using recommender systems in the insurance industry is the limited product selection, which makes classical recommender system models less useful. When there aren't many products, it's hard to find similar users, since active users have only rated a few products [51]. This is called the sparsity problem, and it makes it hard for the system to give good suggestions [54]. The cold start problem occurs when the system can't provide good recommendations because it lacks sufficient information about users. Also, many of the methods used in recommender system analyses are very different from those actuaries use all the time [50]. It's hard to fully understand a customer's needs because insurance policies have many complex terms and features. There are also concerns about privacy and data security when gathering and analysing customer information [53].

Design

The project tries to use a cross-domain recommender algorithm to guess what customers will like [71]. We made this choice rather than testing how well the alternating least squares algorithm performs, which is a lower-quality version. We also try to adjust the model to reduce training costs [60]. We try to address problems that arise when working with insurance data using specific methods.

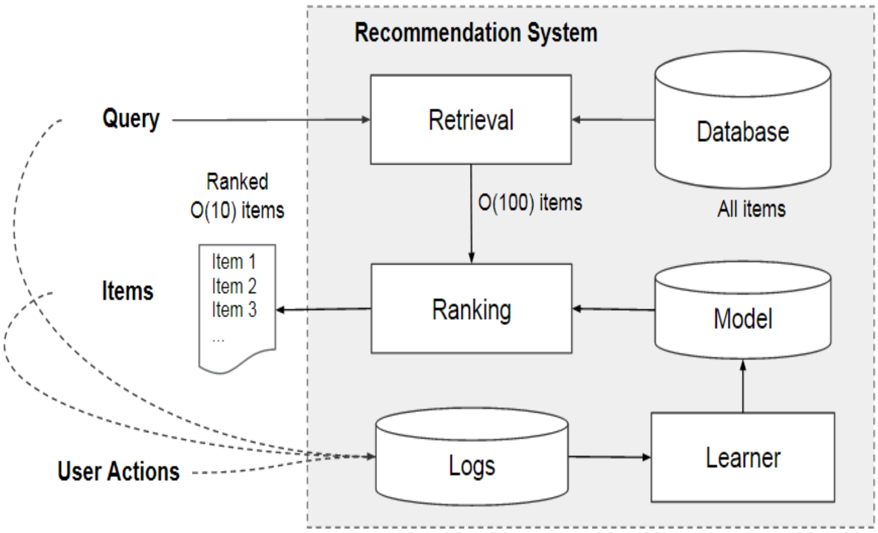

Figure 1. Architecture Diagram

The user's question is what starts the recommender system working. For us, this is the customer's user data input and their choice of insurance policy [64]. The trained model gets the query and compares the customer's data to data from previous users. Then, it makes a list of the most relevant insurance policies [77]. A selective list from this ranking is shown to the user, which makes it easier for them to decide (Figure 1).

Design Phase

The Universal Recommender (UR) is a collaborative filtering system that uses the Correlated Cross-Occurrence algorithm to analyse any number of user actions, events, profile data, and contextual information to guess what users will like [98]. This recommender system is very flexible and can be used in many areas, including e-commerce, entertainment, and insurance [58]. Many businesses and organisations, such as ActionML, which provides end-to-end machine learning solutions, have successfully adopted the UR. This service was the inspiration for the design of the recommender system [70]. From previous tests, we know that the alternating least squares model can make fairly accurate predictions. Still, it didn't address the problems that come with using implicit unrated data and low target item counts. We use the cross-occurrence correlation model to fill gaps when it's hard to rate historical customer data, and we use k-fold cross-validation to address the problem of too few target items [93]. K-fold cross-validation is a method for evaluating how well a machine learning model performs. The dataset is split into k parts, or folds. The model is trained and tested k times, with each fold used as the validation set. The other k-1 folds are used to train the model. Then, the scores from each test are averaged to get a single performance metric for the model [81]. K-fold cross-validation is a good way to estimate how well a model will perform on new data, and it can also help prevent overfitting.

- A Kafka cluster is a distributed system composed of multiple Kafka nodes. It is a free, open-source, distributed event streaming platform for collecting, processing, storing, and combining large amounts of data [63]. At any scale, Kafka takes in, stores, and processes streams of data as they are created. Kafka Streams is a library for clients that lets you make applications and microservices that read and analyse data stored in Kafka [97]. It gives you a quick, easy way to perform calculations on event streams in real time.
- Spark cluster: An Apache Spark cluster is a distributed computing system made up of many nodes [99]. Each node can process data simultaneously. People use Spark clusters to work with large datasets and perform complex tasks such as machine learning, graph processing, and stream processing [69]. This lets Spark work with large datasets much faster than older systems with a single node.
- Backing store database: A database that stores data that the computer's memory isn't currently using. It can be used to save the trained recommender system's model [84].
- Solr server: Solr is an open-source enterprise search platform built on the Apache Lucene search engine library. It is a separate search server that has a REST-like API for indexing and searching data. Solr can handle a lot of data, is fault-tolerant, and lets you index, replicate, and query data across multiple servers [78]. Many of the world's biggest websites use it to power their search and navigation features. It can be used to retrieve ranked insurance policies from the backing store's database [91].

Module Description

Data Cleaning Module

Cleaning data is an important step in preparing it for machine learning. Finding and fixing, or removing, mistakes, inconsistencies, and inaccuracies in the data is part of the process [76]. When cleaning up data for an insurance prediction dataset, there may be several steps to take. For example, duplicate records can throw off the results of a machine learning model [89]. It is important to identify and remove any duplicate records in the dataset. A machine learning model can also be less accurate if it has missing values. Imputation and deletion (Figure 2) are just two of the many ways to deal with missing values [57]. For simplicity, we delete the missing values. Outliers are data points that are very different from the rest of the data in a dataset. Outliers can occur due to measurement errors or other factors, and they can make a machine learning model less accurate [96]. So, we identify and remove the outliers. To standardise data, you need to scale it so that its mean is zero and its standard deviation is one [68]. This helps our algorithm work better. Categorical variables are variables that can take only a few values, such as gender or job. Our algorithm usually requires numerical values, so we need to convert categorical variables into numbers. There isn't much extra data in the original dataset we used [87]. We removed some outliers and applied one-hot encoding to some features. Now we're on to the training module (Figure 3).

	Age	Driving_License	Region_Code	Previously_Insured	Annual_Premium	Policy_Sales_Channel	Vintage
count	508146.00	508146.00	508146.00	508146.00	508146.00	508146.00	508146.00
mean	38.81	1.00	26.41	0.46	30554.45	111.98	154.34
std	15.50	0.05	13.22	0.50	17146.57	54.25	83.67
min	20.00	0.00	0.00	0.00	2630.00	1.00	10.00
25%	25.00	1.00	15.00	0.00	24381.00	26.00	82.00
50%	36.00	1.00	28.00	0.00	31661.00	133.00	154.00
75%	49.00	1.00	35.00	1.00	39403.75	152.00	227.00
max	85.00	1.00	52.00	1.00	540165.00	163.00	299.00

Figure 2. Description of the Dataset

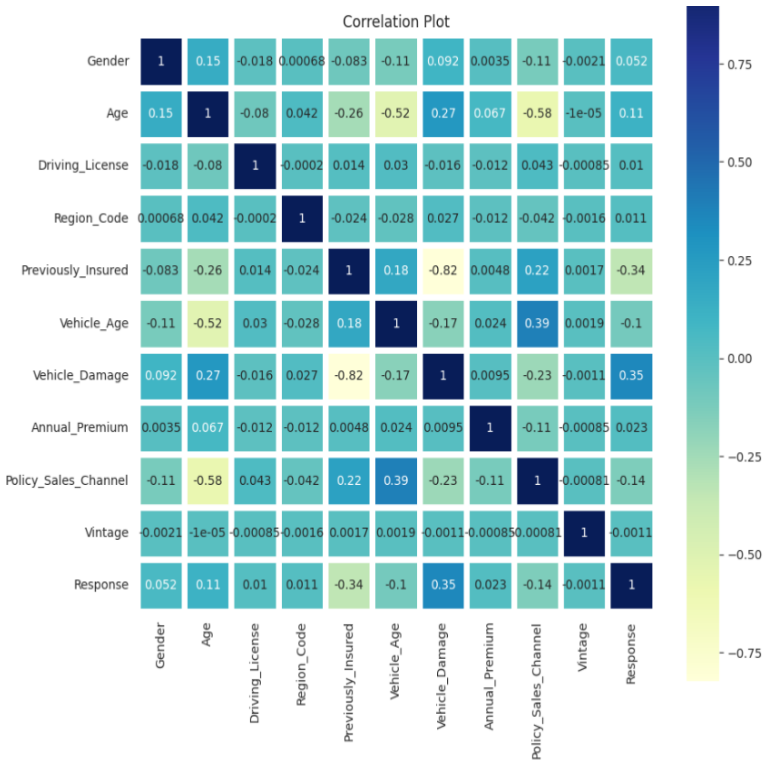

Figure 3. Correlation Plot of Features

Data Splitting Module

Even though it costs more to train, we have used k-fold cross-validation to cover more ground and improve our predictive performance [83]. K-fold cross-validation is a method for evaluating how well a machine learning model performs. The dataset is split into k parts, or folds [92]. The model is trained and tested k times, with each fold used as the validation set. The other k-1 folds are used to train the model [67]. Then, the results of each evaluation are combined into a single performance metric for the model. K-fold cross-validation is a good way to assess how a model will perform on new data and can help prevent overfitting. In k-fold cross-validation, the dataset is split into k equal-sized groups at random [59]. One of the k subsamples is used as validation data to test the model, and the other k-1 subsamples are used as training data. The cross-validation procedure is subsequently executed k times, utilising each of the k subsamples precisely once as the validation dataset. You can then average the k results from the folds to get one estimate [75]. When working with small datasets or datasets with an unbalanced class distribution, K-fold cross-validation is very helpful. It can also help the model generalise better and prevent overfitting (Figure 4) [100].

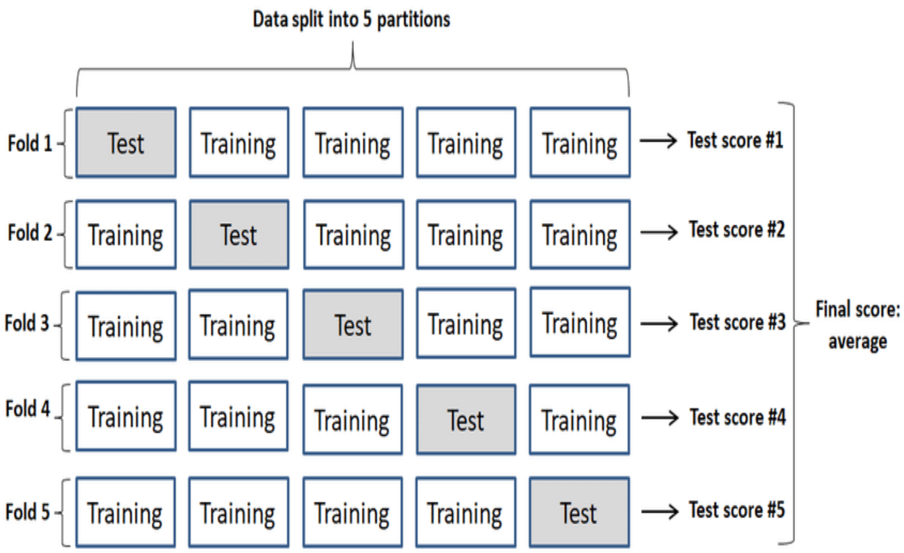

Figure 4. K-Fold Splitting Technique

Data Training Module

We begin by training the train split using a random forest model as a starting point. A baseline model is a simple model that lets you compare how well more complicated models work. Baseline models help you determine whether a more complex model performs better [65]. If a model doesn't perform better than the baseline, it means there are problems with the data or the method. Baseline models can also help you find the most important parts of a dataset and give you a way to judge how useful new parts are [90]. It is important to compare a machine learning model to a baseline model to ensure the model is learning something useful from the data. It also helps identify potential problems with the data or method that may be preventing the model from performing as well as it should [72]. You can find out which model is best for a certain job by comparing several models to a baseline. A ROC (Receiver Operating Characteristic) curve is a graph that shows how well a binary classifier model works at different threshold values [56]. The ROC curve shows the true positive rate (TPR) and the false positive rate (FPR) at each threshold setting. The TPR, also called sensitivity, recall, or hit rate, is the number of true positives divided by the number of true positives plus false negatives. The FPR is the ratio of false positives to positives [85]. The ROC curve shows how sensitive and specific a certain classifier is. A common way to measure how well a binary classifier performs is to evaluate the area under the ROC curve (AUC). An AUC of 1.0 means that the classifier is perfect, and an AUC of 0.5 means that it is random. We compare the results to the alternating least squares model and the cross-occurrence correlation model (Figure 5) after we have obtained them [95].

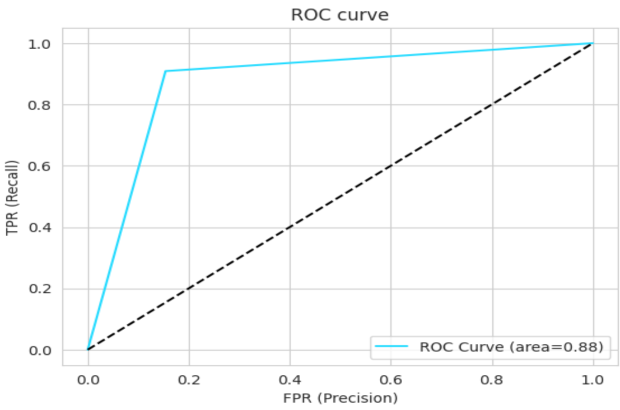

Figure 5. Performance of the Algorithm

Algorithm Module

The Random Forest model is the base model we use. Random forests are well-known machine learning algorithms that are part of the supervised learning method [74]. In machine learning, it can be used for both regression and classification problems. The idea behind random forests is ensemble learning, which means combining several classifiers to solve a hard problem and improve the model's performance. The random forest doesn't rely on a single decision tree [61]. Instead, it takes the predictions from each tree and uses the majority to make its own prediction. More trees in the forest mean greater accuracy and a lower risk of overfitting [94]. Random forests are a good starting point because they are easy to set up, require minimal data preprocessing, and can handle both categorical and continuous variables[82]. It also helps you identify important features in a dataset, which can aid you in choosing features for more complex models.

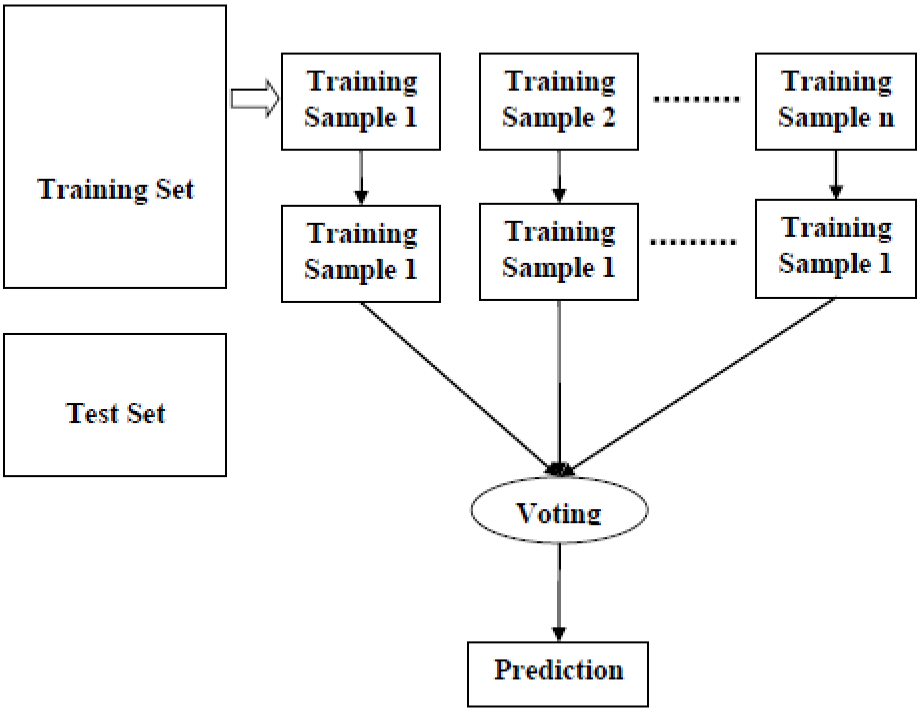

Figure 6. Random Forests Model

Next, we use the Alternating Least Squares model. Alternating Least Squares (ALS) is a matrix factorisation method that is used in recommender systems for collaborative filtering [79]. ALS tries to estimate the ratings matrix R by multiplying two lower-rank matrices, X and Y, so that R

= X * Y^T. These approximations are usually called "factor" matrices [62]. The overall method is iterative. In each iteration, one of the factor matrices stays the same, and the other is solved for using least squares. Then the two-factor matrices switch roles, and the process repeats until convergence [86]. ALS is particularly useful for large-scale collaborative filtering problems where explicit feedback data is not available (Figure 6).

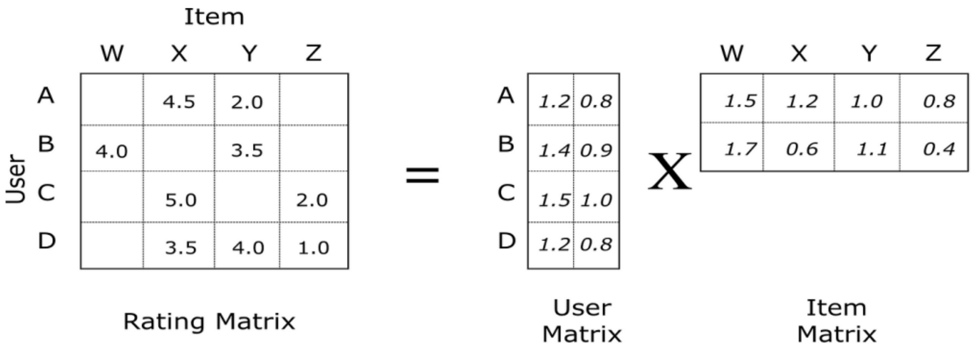

Figure 7. Alternating Least Squares Model

The last step is to train the cross-occurrence correlation model on the data. The Correlated Cross-Occurrence (CCO) algorithm is a collaborative filtering method used in recommender systems [80]. It is a new kind of collaborative filtering recommender that uses an algorithm that can work with data from many different user preference indicators. The CCO algorithm finds statistically significant links between products and customers [55]. The algorithm finds items bought together in the same transaction and then determines how closely related they are. The CCO algorithm is great for suggesting items related to more than one area [73]. The CCO algorithm is based on the idea of cross-occurrence, which measures how often two events occur together in the same transaction. The CCO algorithm finds statistically significant connections between products and customers by examining how often they co-occur [66]. Then, using these connections, the algorithm suggests content to users based on what they like. The CCO algorithm has been successfully used across many business areas, including insurance, e-commerce, and entertainment. Figure 7 shows that it works to find hidden connections between items and users that aren't clear from the data alone [88].

Results and Discussions

Performance and Implementation

Testing Classification Report:

	precision	recall	f1-score	support
0	0.89	0.90	0.90	83537
1	0.90	0.89	0.89	83663
accuracy			0.90	167200
macro avg	0.90	0.90	0.90	167200
weighted avg	0.90	0.90	0.90	167200

Figure 8. Classification Report

A classification report is a summary of how well a classification model works [113]. It includes metrics like precision, recall, F1 score, and support. The confusion matrix is a table that shows how many predictions the model got right and wrong. These metrics are based on that table. Precision is the percentage of true positives (correctly predicted positive cases) out of all the positive predictions the model made [104]. TP is the number of true positives, and FP is the number of false positives. To find it, divide TP by (TP + FP). If the model has high precision, it means it makes fewer false-positive predictions [106]. Recall tells you how many of the actual positive cases in the data are correctly identified as true positives. To find it, divide TP by (TP + FN), where FN is the number of false negatives [111]. A high recall means that the model makes fewer wrong negative predictions. The F1 score is the average of precision and recall. To find it, multiply the precision and recall by 2 and then divide by the sum of the two. F1 score balances precision and recall, and it is often used as the sole metric for evaluating classification models [102]. The number of times each class actually happens in the dataset is called "support." It is helpful when working with unbalanced samples, and it can reveal structural problems in the classifier's reported scores (Figure 8) [114].

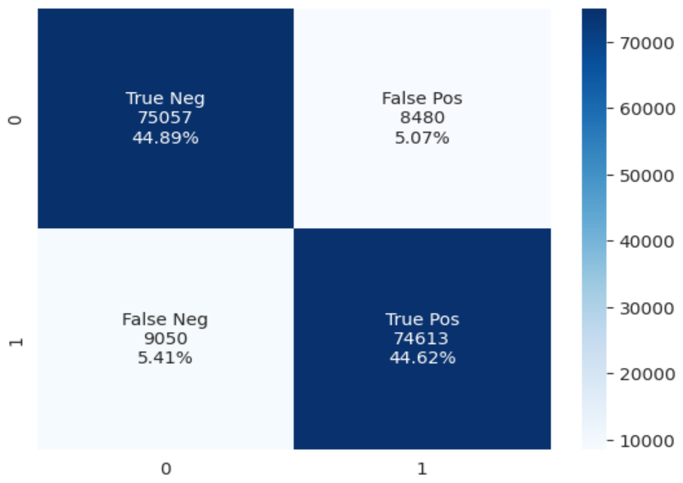

Figure 9. Confusion Matrix

A confusion matrix is a table that shows how well a machine learning model did on a set of test data. People often use it to see how well classification models work [103]. These models try to guess a category label for each input instance. The matrix shows the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) the model found in the test data (Figure 9) [110].

- True Positive (TP): The total number of counts in which both the predicted and actual values are positive.
- True Negative (TN): This is the total number of counts where both the predicted and actual values are negative.
- False Positive (FP): The total number of counts in which the prediction is positive but the actual value is negative.
- False Negative (FN): This is the total number of counts that say something is negative when it is actually positive.

Business Viability

To assess whether the recommender system is a good business idea, we need to consider how well the model processes information in real time [107]. The Correlated Cross-Occurrence (CCO) algorithm is a great tool for businesses that want to control how data behaves. The Universal Recommender and Behavioural Search both have this as a key new idea [112]. Cross-correlation is a way to see how two or more time series move in relation to each other. It is used to compare several time series and determine how well they match, especially when the best match is found. Cross-correlation can also show any patterns that repeat in the data [101]. You can use the CCO algorithm to find patterns in how different users or groups of users act [115]. This can help businesses learn more about how their customers use the insurance policies they offer. For instance, it can help you figure out which insurance policies are often bought together, which ones are often looked at together, and which ones are often left behind [109]. The CCO algorithm can also identify patterns in a single user's actions. This can help businesses tailor their products and services to each customer's needs [105]. Also, using Kafka, Spark, and Solr is the cheapest way to process user recommendations in real time.

Conclusion and Future Enhancement

Conclusion

The correlation cross-occurrence model is clearly better than the baseline model based on these results. An accuracy score of 89% is pretty good, since it shows how accurate the ranking of an insurance policy is. The model's ROC area indicates that it can distinguish between things well. The model can accurately estimate the likelihood that a user will buy an insurance policy on their own and then rank these policies based on that estimate. It is also clear that the correlated cross-occurrence algorithm requires much less tuning than the alternating least squares model, even though the two models achieve the same performance metrics. So, it's safe to say that the correlation cross-occurrence model is the best choice for recommending and ranking insurance policies in a business setting because it performs well and can be tuned to improve performance.

Future Enhancements

The conversion rate for insurance policies is the percentage of people who are given the chance to buy one and then do so. This number is used to determine how well marketing campaigns and sales strategies work to attract and retain customers. On the other hand, actual revenue is the total amount of money an insurance company earns from selling insurance policies. This metric considers more than just the number of policies sold; it also accounts for their price and length. Conversion rate is a good way to see how well marketing and sales strategies are working, but it doesn't always show how much money an insurance company is actually making. If the policies sold are cheap or only last a short time, a high conversion rate doesn't necessarily translate into high revenue. So, insurance companies need to pay attention to both metrics to ensure they remain profitable and grow over time. So, future versions of the recommender system can use this factor along with the pure customer conversion rate to help the business make more money.

The holdout set method is a way to test how well a machine learning model works by dividing the data into two groups: a training set and a test set. The training set is used to train the model, and the test set is used to evaluate how well it performs. But this method has some problems. One of the main problems is that it assumes that the training and test sets come from the same distribution. This assumption might not hold in many real-world situations, especially when working with time-series data. To fix this problem, it is best to use two distinct data sets from different time periods to train and test the model. This method is called temporal validation or temporal cross-validation. In this method, the model learns from data from a time before it was tested and then tests it on data from a time after it was trained. This ensures the model is tested on data more like what happens in the real world. When working with time-series data whose distribution changes over time, temporal validation is especially helpful. It can also help the model generalise better and avoid overfitting to the training data.

References

[1] S. Borg Bruun, M. Maistro, and C. Lioma, “Learning recommendations from user actions in the item-poor insurance domain,” in Sixteenth ACM Conference on Recommender Systems, Washington, United States of America, 2022.

[2] S. Nagar, “An impact of performance of companies with sustainability goal on stock market

movements," European Economic Letters, vol. 13, no. 3, pp. 417–420, 2023.
[3] S. Nagar and P. Mahajan, "An assessment of effectiveness of remote work mode in job internships," The Online Journal of Distance Education and E-Learning (TOJDEL), vol. 11, no. 2, p. 1154, 2023.
[4] P. Jothilingam, "Towards autonomous commissioning: Integrating digital twins, artificial intelligence and smart sensors for next-generation process control systems," Certified Journal of International Research (CJIR), vol. 5, no. 1, pp. 1-8, Mar. 2025.
[5] P. Jothilingam, "Edge computing for industrial automation and control: Enabling real-time processing, scalable architectures and secure operations," Certified Journal of International Research (CJIR), vol. 5, no. 1, pp. 1–8, Mar. 2025.
[6] P. Jothilingam, "Advancing cybersecurity in industrial control systems: Frameworks, threat modeling, and resilience strategies," International Journal of Supportive Research (IJSR), vol. 2, no. 2, pp. 69–75, Jul. 2024.
[7] D. R. Janardhana, K. Shivanna, M. Ghouse Shukur, C. P. Vijay, H. R. Mahalingegowda, and H. V. Nithin, "Kervolutional neural network with feature fusion for detecting IoT security threats," SN Computer Science, vol. 6, no. 8, p. 979, 2025.
[8] J. D. Rangappa, A. P. Manu, S. Kariyappa, S. K. Chinnababu, G. H. Lokesh, and F. Flammini, "A lightweight blockchain to secure data communication in IoT network on healthcare system," International Journal of Safety & Security Engineering, vol. 13, no. 6, pp. 1015–1024, 2023.
[9] K. Shivanna, H. P. Hema, D. R. Janardhana, and P. M. Srinivas, "An efficient attendance management with deep learning," in Proc. 2024 Int. Conf. on Computing, Semiconductor, Mechatronics, Intelligent Systems and Communications (COSMIC), Nov. 2024, pp. 18–23.
[10] S. J. Niranjan, R. M. Lingaraju, B. V. B. Prabhu, and V. N. Vinaykumar, "Coconut disease prediction using neural attention mechanism with Adamax optimizer-based convolutional neural network," International Journal of Environmental Sciences, vol. 11, no. 5, pp. 2352–2360, 2025.
[11] S. J. Niranjan, R. M. Lingaraju, and J. A. Babu, "Spiralizer strategy with wolf pack algorithm and temporal convolution network–gated recurrent unit for coconut crop yield prediction," SN Computer Science, vol. 5, Art. no. 1108, 2024.
[12] V. V. N. Nagaraju, A. B. Jayachandra, A. Stateczny, S. H. Yogesh, R. M. Lingaraju, and B. P. B. Veeranna, "Dual strategy based improved swarm intelligence and stacked LSTM with residual connection for land use land cover classification," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 18, pp. 4188–4198, 2025.
[13] D. Narasappa, "Integrating Zero Trust Architecture with Automation and Analytics for Resilient Cybersecurity," 2025 3rd International Conference on Data Science and Network Security (ICDSNS), Tiptur, India, 2025, pp. 1-6.
[14] B. Lakshmikanth and T. Jesudas, "Influence of stainless steel short fibres as reinforcements in enhancing the performance of aluminium 7075 alloy matrix composites," Transactions of the Indian Institute of Metals, vol. 77, pp. 495–501, 2024.
[15] T. Jesudas, S. Ramesh, and R. M. Arunachalam, "Prediction and optimization of micro EDM process parameter using multiple regression and artificial neural network," Elixir Mechanical Engineering, vol. 66, pp. 20895–20900, 2014.
[16] J. R. Rogers, Y. Wang, N. F. Khan, K. Mott, V. K. Nomula, D. Wang, P. C. Fiduccia, M. Burcu, and X. Liu, "Landscape assessment of clone-censor-weight methodology application in real-world data studies: A scoping review," in Proceedings of the Pharmacoepidemiology and Drug Safety Conference, vol. 33, pp. 424–424, Nov. 1, 2024.
[17] S. K. R. Padur, "Empowering Developer & Operations Self-Service: Oracle APEX + ORDS as an Enterprise Platform for Productivity and Agility," Int. J. Sci. Res. Sci. Eng. Technol., vol. 4, no. 11, pp. 364–372, 2018.
[18] S. K. R. Padur, "The Future of Enterprise ERP Modernization with AI: From Monolithic Systems to Generative, Composable, and Autonomous Platforms," J. Artif. Intell. Mach. Learn. & Data Sci., vol. 3, no. 1, pp. 2958–2961, 2025.
[19] S. K. R. Padur, "Automation-First Post-Merger IT Integration: From ERP Migration

Challenges to AI-Driven Governance and Multi-Cloud Orchestration," Int. J. Sci. Res. Sci. Eng. Technol., vol. 12, no. 5, pp. 270–280, 2025.
[20] S. K. R. Padur, "Network Modernization in Large Enterprises: Firewall Transformation, Subnet Re-Architecture, and Cross-Platform Virtualization," Int. J. Sci. Res. Sci. Eng. Technol., vol. 2, no. 5, 2016, Zenodo.
[21] I. A. Mohammed, "Artificial Intelligence in Supplier Selection and Performance Monitoring: A Framework for Supply Chain Managers," Educational Administration: Theory and Practice, vol. 29, no. 3, pp. 1186–1198, 2023.
[22] I. A. Mohammed, "The Role of Artificial Intelligence in Enhancing Business Efficiency and Supply Chain Management," Journal of Information Systems Engineering and Management, vol. 10, no. 10s, pp. 509–518, Feb. 2025.
[23] I. A. Mohammed, "AI-Powered Risk Management Frameworks for Ensuring Supplier Quality in Carbon Capture and Energy Storage Supply Chains," International Journal of Intelligent Systems and Applications in Engineering, vol. 12, no. 1, pp. 854–, Dec. 2023.
[24] I. A. Mohammed, "Optimizing Carbon Capture Supply Chains with AI-Driven Supplier Quality Management and Predictive Analytics," Journal of Next-Generation Research 5.0, Dec. 2024.
[25] I. A. Mohammed, "Machine Learning-Driven Predictive Models for Enhancing Supplier Reliability in Renewable Energy Storage Supply Chains," International Journal of Intelligent Systems and Applications in Engineering, pp. 767–770, 2022.
[26] N. Gupta, M. Adawadkar, I. A. Mohammed, S. Verma, and M. Dubey, "Predictive Insights: Leveraging Artificial Intelligence for Strategic Business Decision-Making," Advances in Consumer Research, vol. 2, pp. 98–105, 2025.
[27] S. Dhanalakshmi, T. Jesudas, and M. Pradeep Kumar, "A stir casting process-based experimental analysis of the wear properties of an Al 6063 alloy reinforced with ceramic particles," Romanian Journal of Materials, vol. 55, no. 2, pp. 107–120, 2025.
[28] J. Dineshkumar and T. Jesudas, "Hybrid polymer matrix development using cashew nut shell liquid as an additive into epoxy resin," Journal of the Chinese Institute of Engineers, vol. 46, no. 4, pp. 380–388, 2023.
[29] H. R. Laskar, "Adoption of fintech and digital financial services (DFS) by young professionals," Int. J. Adv. Res. Eng. Technol., vol. 11, no. 1, pp. 537–561, 2020.
[30] H. R. Laskar, "Factors influencing saving and investment behavior of government and private sector employees," Indian Journal of Economics and Business, vol. 20, no. 1, pp. 1168–1192, 2021.
[31] S. Roushon and H. R. Laskar, "Influence of Neural Behaviour on Decision Making," IOSR Journal of Humanities and Social Science, vol. 29, no. 5, ser. 13, pp. 35–42, May 2024.
[32] Z. Alam and H. R. Laskar, "The Influence of Neural Behavior on Individuals' Financial Decisions," Journal of Economics, Finance and Management Studies, vol. 7, no. 6, pp. 3298–3306, Jun. 2024.
[33] S. Laskar, H. R. Laskar, and M. N. I. Barbhuyan, "Perception of Women Entrepreneurs Regarding Social Media Marketing," Bangladesh Journal of Multidisciplinary Scientific Research, vol. 9, no. 5, pp. 10–18, Nov. 2024.
[34] D. Narasappa, "AI-Driven Security Measures for IoT Networks Utilizing Machine Learning for Anomaly Detection," 2025 IEEE 4th World Conference on Applied Intelligence and Computing (AIC), GB Nagar, Gwalior, India, 2025, pp. 134-139.
[35] Kumar, P.R., Mohammad, G.B., Narsimhulu, P., Narasappa, D., Maguluri, L.P. et al. (2025). Computer Modeling Approaches for Blockchain-Driven Supply Chain Intelligence: A Review on Enhancing Transparency, Security, and Efficiency. Computer Modeling in Engineering & Sciences, 144(3), 2779–2818.
[36] I. Ganie and S. Jagannathan, "Online learning-driven human intent estimation and control for human–robot interaction," Proc. 2025 Amer. Control Conf. (ACC), Denver, CO, USA, 2025, pp. 5160–5165.
[37] I. Ganie and S. Jagannathan, "Online lifelong optimal tracking control of nonlinear continuous-time strict-feedback systems using deep neural networks," Neural Netw., vol.

191, 107793, 2025.
[38] I. Ganie and S. Jagannathan, “Optimal trajectory tracking of uncertain nonlinear continuous-time strict-feedback systems with dynamic constraints,” Int. J. Control, pp. 1–15, 2024.
[39] P. M. Srinivas, K. Shivanna, D. R. Janardhana, and S. Samarth, “SAAI—Smart automated anti-violence intervention,” in Proc. 2024 Int. Conf. on Computing, Semiconductor, Mechatronics, Intelligent Systems and Communications (COSMIC), Nov. 2024, pp. 82–87.
[40] D. R. Janardhana, K. Shivanna, and A. P. Manu, “Security and privacy in military application using blockchain,” in Artificial Intelligence for Military Applications with Blockchain. Boca Raton, FL, USA: CRC Press, 2025, pp. 1–18.
[41] D. R. Janardhana, A. P. Manu, K. Shivanna, and K. C. Suhas, “Malware analysis and its mitigation tools,” in Malware Analysis and Intrusion Detection in Cyber-Physical Systems. Hershey, PA, USA: IGI Global, 2023, pp. 263–284.
[42] A. Satyanaga and H. Rahardjo, "Role of unsaturated soil properties in the development of slope susceptibility map," Proc. Inst. Civ. Eng. – Geotech. Eng., vol. 175, no. 3, pp. 276–288, 2022.
[43] Q. Zhai, H. Rahardjo, A. Satyanaga, and G. Dai, "Estimation of tensile strength of sandy soil from soil–water characteristic curve," Acta Geotechnica, vol. 15, pp. 3371–3381, 2020.
[44] H. Rahardjo, Nio, A. Satyanaga, F. R. Harnas, and E. C. Leong, "Comprehensive instrumentation for real time monitoring of flux boundary conditions in slope," Procedia Earth Planet. Sci., vol. 9, pp. 23–43, 2014.
[45] Y. Kim, H. Rahardjo, M. M. Nistor, A. Satyanaga, E. C. Leong, and A. W. L. Sham, "Assessment of critical rainfall scenarios for slope stability analyses based on historical rainfall records in Singapore," Environ. Earth Sci., vol. 81, no. 2, p. 39, 2022.
[46] A. Satyanaga, H. Rahardjo, and C. J. Hua, "Numerical simulation of capillary barrier system under rainfall infiltration in Singapore," ISSMGE Int. J. Geoengineering Case Hist., vol. 5, no. 1, pp. 43–54, 2019.
[47] H. Rahardjo, M. M. Nistor, N. Gofar, A. Satyanaga, Q. Xiaosheng, and S. I. C. Yee, "Spatial distribution, variation and trend of five-day antecedent rainfall in Singapore," Georisk: Assess. Manag. Risk Eng. Syst. Geohazards, vol. 14, no. 3, pp. 177–191, 2020.
[48] A. Satyanaga, H. Rahardjo, Z. H. Koh, and H. Mohamed, "Measurement of a soil-water characteristic curve and unsaturated permeability using the evaporation method and the chilled-mirror method," J. Zhejiang Univ. – SCIENCE A, vol. 20, no. 5, pp. 368–374, 2019.
[49] H. Rahardjo and A. Satyanaga, "Sensing and monitoring for assessment of rainfall-induced slope failures in residual soil," Proc. Inst. Civ. Eng. – Geotech. Eng., vol. 172, no. 6, pp. 496–506, 2019.
[50] A. Satyanaga, N. Bairakhmetov, J. R. Kim, and S.-W. Moon, "Role of bimodal water retention curve on the unsaturated shear strength," Appl. Sci., vol. 12, no. 3, p. 1266, 2022.
[51] Y. Kim, A. Satyanaga, H. Rahardjo, H. Park, and A. W. L. Sham, "Estimation of effective cohesion using artificial neural networks based on index soil properties: a Singapore case," Eng. Geol., vol. 289, Art. no. 106163, Aug. 2021.
[52] S. K. Somayajula, "Enterprise Data Migration Success Patterns: Lessons from Large-Scale Transformations," International Journal of Research in Computer Applications and Information Technology (IJRCAIT), vol. 8, no. 1, pp. 757-776, Jan.-Feb. 2025.
[53] S. K. Somayajula, "Demystifying Modern Data Warehousing: From Traditional to Cloud-Native Solutions," International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 2025.
[54] S. K. Somayajula, "Building a Career in Enterprise Data Architecture: A Practical Guide," International Research Journal of Modernization in Engineering Technology and Science (IRJMETS), vol. 7, no. 1, Jan. 2025.
[55] S. K. Somayajula, "Advanced ETL Optimization: A Framework for Next-Generation Data Integration," International Journal of Computer Engineering and Technology (IJCET), vol. 16, no. 1, pp. 381-406, Jan.-Feb. 2025.
[56] S. Somayajula and A. Orlovsky, "Proof, Truth and Contradiction in the System and Meta-System: Comprehensive Mathematical Solutions and Implementation Framework," 2025.

[57] P. Jothilingam, “Cybersecurity in water and wastewater systems: Protecting critical infrastructure from emerging threats and ensuring operational resilience,” in Proc. International Conference on Recent Advances in Science, Engineering, Technology and Management, India, Mar. 2024, pp. 550–558.
[58] P. Jothilingam, “Digital twin technologies for ICS: Leveraging virtualization and sensor data for FAT/SAT, commissioning and predictive risk detection,” International IT Journal of Research, vol. 1, no. 1, pp. 45–49, Oct. 2023.
[59] P. Nutalapati, "Automated Incident Response Using AI in Cloud Security," Journal of Artificial Intelligence, Machine Learning and Data Science, vol. 2, no. 1, pp. 1301–1311, 2024
[60] P. Nutalapati, "Data Leakage Prevention Strategies in Cloud Computing," European Journal of Advances in Engineering and Technology, vol. 8, no. 9, pp. 118–123, 2025.
[61] P. Nutalapati, "Security Considerations for Hybrid Cloud Deployments in Fintech Using Blockchain," Journal of Artificial Intelligence, Machine Learning and Data Science, vol. 1, no. 1, URF Publishers, 2025.
[62] P. Nutalapati, "Zero Trust Architecture in Cloud-Based Fintech Applications," Journal of Artificial Intelligence & Cloud Computing, vol. 2, no. 1, pp. 1–8, 2023.
[63] P. Nutalapati, J. R. Vummadi, S. Dodda and N. Kamuni, "Advancing Network Intrusion Detection: A Comparative Study of Clustering and Classification on NSL-KDD Data," 2025 International Conference on Data Science and Its Applications (ICoDSA), Jakarta, Indonesia, 2025, pp. 880-885.
[64] P. Nutalapati, S. M. Dhavale, A. Shrivastava, R. V. S. Praveen, H. K. Vemuri and R. RiadHwsein, "IoT and Machine Learning-Enhanced Energy Management in Enabled Smart Grids for Predictive Load Balancing," 2025 World Skills Conference on Universal Data Analytics and Sciences (WorldSUAS), Indore, India, 2025, pp. 1-6.
[65] P. Nutralapati, “Disaster Recovery and Business Continuity Planning in Cloud-Blockchain Infrastructures,” SSRN Electron. J., Jun. 2020. Available: https://ssrn.com/abstract=5219038.
[66] S. Arul Krishnan, V. P. Rameshkumaar, K. Prakash, and D. Sugandaran, "Impact of celebrity endorsement on cause-related marketing and purchase intention of FMCG consumers in Chennai," Journal of Statistics & Management Systems, vol. 26, no. 7, pp. 1627–1641, 2023.
[67] S. Arul Krishnan, V. P. Rameshkumaar, R. Sathya Aarthi, and S. Karthikeyan, "Role of job design on institutional support and work-life equilibrium of women teachers in Chennai," Journal of Statistics & Management Systems, vol. 26, no. 7, pp. 1549–1563, 2023.
[68] S. Karthikeyan, V. P. Rameshkumaar, and B. Balaji, "Subscribers of Indian Mobile Telecom: Satisfaction with Experience and Loyalty," International Journal of Management, vol. 11, no. 9, Oct. 15, 2020.
[69] S. Pundir, V. G. Murugan, P. Raman, V. P. Rameshkumaar, and P. Sudharsan, "Automatic Stock Price Prediction and Classification Based on Hybrid with AI Feature Selection Method," in Proc. 2024 5th International Conference on Recent Trends in Computer Science and Technology (ICRTCST), pp. 149–154, Apr. 9, 2024. IEEE.
[70] P. Praba Devi and S. P. Dharshini U. M., "Social Media Marketing: A Review," Strad Research, vol. 8, no. 3, pp. 281-287, 2021.
[71] P. Praba Devi, "A literary review on conflict management strategies," AIP Conference Proceedings, vol. 3306, no. 1, p. 030080, 2025.
[72] P. Praba Devi, C. V. Sabiya, M. Nitish, A. S. Rouban, and S. Sanjay, "Green consumerism from the perspective of theory of planned behaviour," Cahiers Magellanes-Ns, vol. 6, no. 2, pp. 7344-7350, 2024.
[73] P. Prabadevi, "A study on organizational commitment of employees in life insurance companies," Global Management Review, vol. 9, no. 1, Nov. 1, 2014.
[74] S. G. K. Peddireddy, “Advancing Threat Detection in Cybersecurity through Deep Learning Algorithms,” FMDB Transactions on Sustainable Intelligent Networks., vol.1, no. 4, pp. 190–200, 2024.
[75] S. G. K. Peddireddy, “Integrating AI for Proactive Network Defense against Emerging

Security Vulnerabilities," FMDB Transactions on Sustainable Computer Letters., vol. 2, no. 4, pp. 232–241, 2024.
[76] S. G. K. Peddireddy, "Optimizing Resource Allocation in Multi-Cloud Environments for Cost Efficiency and Scalability," FMDB Transactions on Sustainable Computing Systems., vol. 2, no. 4, pp. 167–177, 2024.
[77] V. Hiremath, "Quantum Networking: Strategic Imperatives for Enterprises and Service Providers in the Emerging Quantum Era," Journal of Computational Analysis and Applications (JoCAAA), vol. 31, no. 3, pp. 617–631, Dec. 2023.
[78] V. Hiremath, "AI-Optimized Adaptive Routing for High-Performance Data Centers: A Predictive Framework for Dynamic Network Optimization," 2025 IEEE 4th World Conference on Applied Intelligence and Computing (AIC), GB Nagar, Gwalior, India, 2025, pp. 152-157.
[79] V. Hiremath, "Optimizing SDN Controller Placement for Enhanced Performance and Scalability in Large-Scale Networks," 2025 International Conference on Intelligent Communication Networks and Computational Techniques (ICICNCT), Bidar, India, 2025, pp. 1-6.
[80] S. Nagar, "Augmentation of insurance business in India: Role of commercial banks," in India Banking and Finance Report 2024, National Institute of Bank Management (NIBM), pp. 81–94, 2024.
[81] S. Nagar, "Cointegration of Indian stock market with global stock markets: An empirical analysis," European Economic Letters, vol. 14, no. 2, pp. 2457–2464, 2024.
[82] S. Kumar, "Challenges in higher education for sustainable development," South Eastern European Journal of Public Health, vol. 26, no. s1, pp. 4194–4204, Feb. 2025.
[83] D. K. Arora et al., "An in vitro assessment of microleakage of pit and fissure sealants and restorative materials using dye penetration method," Journal of Pharmacy and Bioallied Sciences, Feb. 2025.
[84] R. Nagar et al., "In vitro analysis of compressive strength of three different aesthetic restorative materials," Journal of Pharmacy and Bioallied Sciences, Feb. 2025.
[85] N. Maiti et al., "Assessment of the efficacy of photobiomodulation (PBM) therapy in periodontal treatment: a longitudinal study," Journal of Pharmacy and Bioallied Sciences, vol. 16, no. Suppl 3, pp. S2449–S2451, Jul. 2024.
[86] V. S. A. Anala, A. R. Pothu, and S. Chintapalli, "Enhancing Preventive Healthcare with Wearable Health Technology for Early Intervention," FMDB Transactions on Sustainable Health Science Letters., vol.2, no.4, pp. 211–220, 2024.
[87] V. S. A. Anala and S. Chintapalli, "Scalable Data Partitioning Strategies for Efficient Query Optimization in Cloud Data Warehouses," FMDB Transactions on Sustainable Computer Letters., vol. 2, no. 4, pp. 195–206, 2024.
[88] G. Imran and R. Parveen, "Impact of Note Taking in Higher Education: A Case Study of Bilingual Students of Saudi Arabia," Journal of Education, Society and Behavioral Science, vol. 25, no. 4, pp. 1–14, 2018
[89] H. Mahmood, S. Hassan, R. Parveen, and M. Tanveer, "Role of Rule of Law in the Renewal Energy Transition in Saudi Arabia: A Review and Analysis," Academic Journal of Interdisciplinary Studies, vol. 13, no. 4, pp. 186-197, Jul. 2024.
[90] H. Mehraj, D. Jayadevappa, S. L. A. Haleem, R. Parveen, A. Madduri, M. R. Ayyagari, and D. Dhabliya, "Protection Motivation Theory Using Multi-Factor Authentication for Providing Security over Social Networking Sites," Pattern Recognition Letters, vol. 152, pp. 218–224, Dec. 2021.
[91] J. Zhang, M. Raza, R. Khalid, R. Parveen, and E. H. Ramírez-Asís, "Impact of Team Knowledge Management, Problem Solving Competence, Interpersonal Conflicts, Organizational Trust on Project Performance: A Mediating Role of Psychological Capital," Annals of Operations Research, vol. 326, no. Suppl 1, pp. 41–42, 2023.
[92] L. Zhang, R. Khalid, M. Raza, N. Chanrawang, and R. Parveen, "The Impact of Psychological Factors on Women Entrepreneurial Inclination: Mediating Role of Self-Leadership," Frontiers in Psychology, vol. 12, pp 1-13, Dec. 2021.

[93] M. Z. M. Nomani and R. Parveen, "Contextualizing Epidemic Diseases (Amendment) Ordinance, 2020 in Epidemic-Pandemic Syndrome of COVID-19 in India," Systematic Reviews in Pharmacy, vol. 11, no. 8, pp. 156–160, 2020.
[94] M. Z. M. Nomani and R. Parveen, "COVID-19 Pandemic and Application of Disaster Management Act, 2005: Promises and Pitfalls," International Journal of Pharmaceutical Research, vol. 12, no. 4, pp. 3730–3734, 2020.
[95] M. Z. M. Nomani and R. Parveen, "COVID-19 Pandemic and Disaster Preparedness in the Context of Public Health Laws and Policies," Bangladesh Journal of Medical Science, vol. 20, no. 5, pp. 41–48, 2021.
[96] M. Z. M. Nomani and R. Parveen, "Legal Connotations of Biological Resources and Its Ripple Effect on Conservation Research in India and Abroad," International Journal of Conservation Science, vol. 12, no. 2, pp. 571–576, 2021.
[97] M. Z. M. Nomani and R. Parveen, "Legal Dimensions of Public Health with Special Reference to COVID-19 Pandemic in India," Systematic Reviews in Pharmacy, vol. 11, no. 7, pp. 131–134, 2020.
[98] M. Z. M. Nomani and R. Parveen, "Medico-Legal Insights into COVID-19 Pandemic and the Platter of Health Law Reform in India," International Journal of Pharmaceutical Research, vol. 12, no. 1 Suppl, pp. 2328–2332, 2020.
[99] M. Z. M. Nomani and R. Parveen, "Prevention of Chronic Diseases in Climate Change Scenario in India," Environmental Justice, vol. 13, no. 4, pp. 97–100, 2020.
[100] M. Z. M. Nomani and R. Parveen, "Socioeconomic Disparities in Times of COVID-19 Pandemic in India," Environmental Justice, vol. 15, no. 5, pp. 212–220, Oct. 2022.
[101] R. A. A. Alkhayyal and R. Parveen, "The Impact of Implementing Value-Added Tax on the Islamic Banking Practices," International Journal of Religion, vol. 5, no. 2, pp. 452–458, Feb. 2024.
[102] R. Parveen and A. Alajmi, "An Overview of Bitcoin's Legal and Technical Challenges," Journal of Legal, Ethical and Regulatory Issues, vol. 22, no. 1, pp. 1–11, 2019.
[103] R. Parveen and A. Alajmi, "Global Environmental, Social and Economic Issues in the Fast Fashion Industry," in Proceedings of the 32nd International Business Information Management Association Conference, 2018, pp. 1234–1245.
[104] R. Parveen and A. Alajmi, "Globalization, Climate Change and Emergence of Global Environmental Law," in Proceedings of the 32nd International Business Information Management Association Conference, 2018, pp. 1246–1257.
[105] R. Parveen and B. Nasir, "The Role of Legal Framework in Attracting Foreign Investments: The Case Study of Tourism Sector in Saudi Arabia," Russian Law Journal, vol. 12, no. 1, pp. 1123–1132, 2024.
[106] R. Parveen and E. Chikhaoui, "Legal Issues and Challenges in Educational Cloud Computing in the Kingdom of Saudi Arabia," International Journal of Economic Research, vol. 14, no. 20, pp. 357–371, 2017.
[107] R. Parveen and Y. J. Amuda, "Exploring Multidimensional Impacts of COVID-19 on Children in Nigeria," Journal of Infrastructure, Policy and Development, vol. 8, no. 10, pp.1-20, 2024.
[108] R. Parveen, "Artificial Intelligence in Construction Industry: Legal Issues and Regulatory Challenges," International Journal of Civil Engineering and Technology, vol. 9, no. 13, pp. 957–962, Dec. 2018.
[109] R. Parveen, "Challenges in Cloud Computing Adoption: An Empirical Study of Educational Sectors of Saudi Arabia," Indian Journal of Science and Technology, vol. 11, no. 48, pp. 1–9, Dec. 2018.
[110] R. Parveen, "Corporate Governance in Saudi Arabia: Analysis of Current Practices," Journal of Legal, Ethical and Regulatory Issues, vol. 24, Special Issue 1, pp. 1–5, 2021.
[111] R. Parveen, "Issues and Challenges in Cloud Computing in Mechanical Engineering," International Journal of Mechanical Engineering and Technology, vol. 9, no. 10, pp. 380–386, Oct. 2018.
[112] R. Parveen, Y. J. Amuda, and S. Hassan, "Effects of Corruption on the Human Social

Economic Development: A Case Study of India, Nigeria and Bangladesh," International Journal of Economic Research, vol. 14, no. 20, pp. 373–388, 2017.
[113] S. Hassan, Y. J. Amuda, and R. Parveen, "Persecuted Muslim Minority: Zakat, Waqf, and Sadaqah as Financial Instrument for Human Development," International Journal of Applied Business and Economic Research, vol. 15, no. 25, pp. 475–484, 2017.
[114] Y. J. Amuda and R. Parveen, "Environmental Legal Frameworks and Practices for Attaining Sustainable Development Goals in Nigeria and Student Academic Performance," Journal of Posthumanism, vol. 5, no. 5, pp. 2539–2560, 2025.
[115] Y. J. Amuda, and R. Parveen, "Public-Private Partnerships in Driving Sustainable Agricultural Growth for Addressing Poverty and Food Insecurity in Nigeria," Journal of Ecohumanism, vol. 3, no. 4, pp. 3228–3240, 2024.