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ORIGINAL ARTICLE

Enhancing customer-centric retailing through AI-driven total offer management strategies for airline users

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Abstract
The new distribution capability has extended a new world of customer- centric total offer management strategies for airline users, where airlines must respond to each customer's booking instantly with a personalized set of offers and prices. Currently the process of creating offers is unrefined and is controlled by several organizations, procedures, and IT (Information Technology) systems. However, the present method is inadequate and the path to profitability lies in maintaining a continuous offer management system within an integrated total offer management framework. The extant research on customer-centric personalized offer management is lacking in terms of Total Offer Management systems (TOMs). The researchers primarily concentrated on creating a single offer along with a limited number of ancillary options, often neglecting to consider customer behavior in the process. This is where the deficiency in Total Offer Management Systems (TOMs) to the customers become evident. The current research introduces an innovative solution for addressing the total offer management problem outlined by (Wang KK, Wittman MD, Fiig T (2023) Dynamic offer creation for airline ancillaries using a Markov chain choice model. J Revenue Pricing Manag 22(2):103–121) and (Kummara MR, Guntreddy BR, Vega IG, Tai YH (2021) Dynamic pricing of ancillaries using machine learning: one step closer to full offer optimization. J Revenue Pricing Manag 20(6):646–653). This work advances existing knowledge by considering four different segments of customers, each associated with multiple ancillary options. In this research the proposed approach was compared with the existing algorithms in terms of purchase probability. The results obtained from the current work demonstrate a substantial 14.5% increase in the likelihood of offer purchases for each segment of customers. The research is expanded by generating all essential rules and patterns from the customer database to assess the effectiveness of the proposed methodology.

Keywords Dynamic pricing · Customization · Total offer management system · Personalization · Association rules · Pricing strategy

1 Introduction

The rise of digital first services, e-shopping and customer expectations of consistent digital experiences and personalization are at all-time high. Travelers are increasingly demanding better experiences from the airline industry whenever they are planning for a trip. To meet all those demands the airline sector is continuously trying to become stronger retailers to improve the customer experience and translate it into incremental revenue. To become better retailers, personalized offer optimization is only one of the key solutions. An offer is the set of core elements such as airfares, flight crew and ancillary services such as extra baggage allowance, survival guide, car facilities, etc. However, offer construction is quite primitive today. Through the use of revenue management systems, which have developed over the course of nearly 40 years, the aviation product is properly priced. Paradoxically, the selection and pricing of ancillary products have not received comparable attention. This critical aspect is presently managed through two

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discrete processes: RMS and Merchandising. These processes operate within distinct organizational entities, each governed by its own set of protocols and facilitated by separate IT systems. The role of RMS is centered around maximizing revenue derived solely from flight products, whereas Merchandising focuses on broadening the customer's shopping experience by incorporating upselling, cross-selling, and the sale of ancillary products. Regrettably, there is currently a lack of emphasis on delivering personalized and highly pertinent offers. In typical shopping session airline industry used to display the ancillaries to customers sequentially. For example, while booking customers got the list of available flight itenaries along with some static branded offers and once customer select one among them after that some optional ancillary services are displayed for which extra cost will get added in the total fare if customer chooses any among them. Certain airlines show linked deals, which are static in nature—that is, based on prior booking patterns of customers—that combine a flight with one or more supplementary services at a fixed cost. We think that the current approach is insufficient and that using an integrated offer management system (OMS) to handle offers consistently is the key to profitability. Today, for a variety of reasons, this is not feasible.

The very first reason is traditional distribution system I.e., GDS (Global distribution channel) which limit the ways in which airline can construct fully customer centric offers, service bundled offers and in which contacting end user directly is impossible. Even on airline own direct distribution channels, due to technological crisis often restrict the airline to construct and display dynamic offers for all their individual passengers. Another reason is due to various silos in every airline organization which leads to constructing and managing every element of offer ala carte. For instance, the scheduling and network planning departments specify the range of possible itenaries, while the pricing and revenue management (RM) sections determine which fare items and fare classes are available. The benefits of the loyalty programs are created by the marketing department, and the auxiliary services are priced. Airlines must also follow regulations for the usage of client data and tariff filing procedures while making reservations; these regulations can be difficult to follow and vary by nation. Due to these obstacles, the airline sector is unable to use modern e-commerce techniques and take advantage of their potential benefits (Krishnamurthy and Krishnan 2021). These restrictions are explained in more detail below.

1.1 Limitations of existing revenue management system

- During a shopping session, the focus is mainly on whether flights are available and how much they cost. The extra things you can buy along with the flight are not given much importance.
- The airline doesn't make the best choices or set the prices for all the things they sell as a package. They decide on each thing separately.
- Everyone pays the same price for the same stuff, without considering user purchase pattern.
- The sales display cannot be tailored to a customer in a way that affects his or her purchase behavior.

The extant research has focused on setting dynamic prices for extra services and creating offers, but it mostly concentrated on making just single offer with a limited ancillary option. Often, it didn't consider how customers behave. This new research suggests a different approach to solve the problem of managing all the offers. This study goes further by looking at four different groups of customers, each with various ancillary's options. The comparison between the new method and existing ones involved assessing how likely customers were to buy the offers. The results revealed a significant 14.5% increase in the probability of customers purchasing offers in each group. Further details regarding the proposed solution for managing all offers are elaborated below.

1.2 Contribution through this research

In this paper, we'll outline our vision for Total Offer Management System (TOMs) and talk about potential solutions of all the above stated drawbacks. Nevertheless, no single study can address every aspect of an OMS. To provide depth, this research gives the solution of most important components of the total offer management i.e.,

- User persona identification using K-Mode clustering and XG Boost algorithm.
- Dynamic customized offer set construction and recommendation using Singular Value Decomposition (SVD) and Restricted Boltzmann Machine (RBM) algorithm.
- Prediction of maximum margin for each bundled offer using random forest regression algorithm.
- Prediction of optimal price for each bundled offer using neural networks.
- Selection of best optimal packages for each individual user.

The methodology utilized possesses attractive qualitative characteristics. The selection of offers and their corresponding prices is structured in a manner that dissuades the purchase of less profitable options. Instead, it guides customers towards more lucrative choices. Consequently, the methodology recommends relevant offers to individual users. This is vital, as including irrelevant offers in the selection can diminish both revenue and the rate at which additional items are purchased. Additionally, The research is expanded by generating all essential rules and patterns from the customer database to assess the effectiveness of the proposed methodology using association rule mining approach.

1.3 Organization of the paper

The paper is structured as follows: Sect. 2 highlights the related work done in prior years which is showcased with the help of Annotated IATA Capability Matrix. Section 3 provides the detailed information about proposed customer centric comprehensive solution. In Sect. 4 we discussed about implementation and results in which comprehensive presentation of our approach revolves around three key components, each playing a distinct role. The journey begins with a thorough exploration of the model's operational process, where we break down its progression into five sequential steps. This detailed breakdown offers a clear understanding of how the model functions. Moving forward, the study delves into the intricate task of extracting association rules using the FP-growth algorithm. These rules serve the crucial purpose of revealing which products are best suited for user recommendations, spanning various scenarios within the test dataset. Lastly, we delve into the practical significance of these extracted rules, emphasizing their potential to impact strategic decisions and contribute significantly to the growth of the business. In Sect. 5 conclusion and future research direction from this research is highlighted.

2 Related work done

This section presents an overview of prior research conducted in the context of the problem definition, with the purpose of identifying existing gaps and highlighting the significant contribution of this manuscript in addressing the challenges related to total customized offer management systems. We use IATA's dynamic offer capabilities model matrix (Touraine and Coles 2018), which is replicated in Fig. 1, to assess the advancements made in real-world overall customized offer management. A selection of pertinent works covering a range of matrix corners are included in the matrix. A rising degree of complexity and dynamics in the determination of prices (horizontal axis) or product offerings (vertical axis) is represented by each corner. Prior research efforts have primarily concentrated on resolving the challenges found in the bottom left lower corner of the matrix, characterized by static itineraries and fixed ancillary items with predefined price points. For instance, (Belobaba 1987) proposed the EMSRb model to maximize airline revenue by assuming independent demand. Building upon

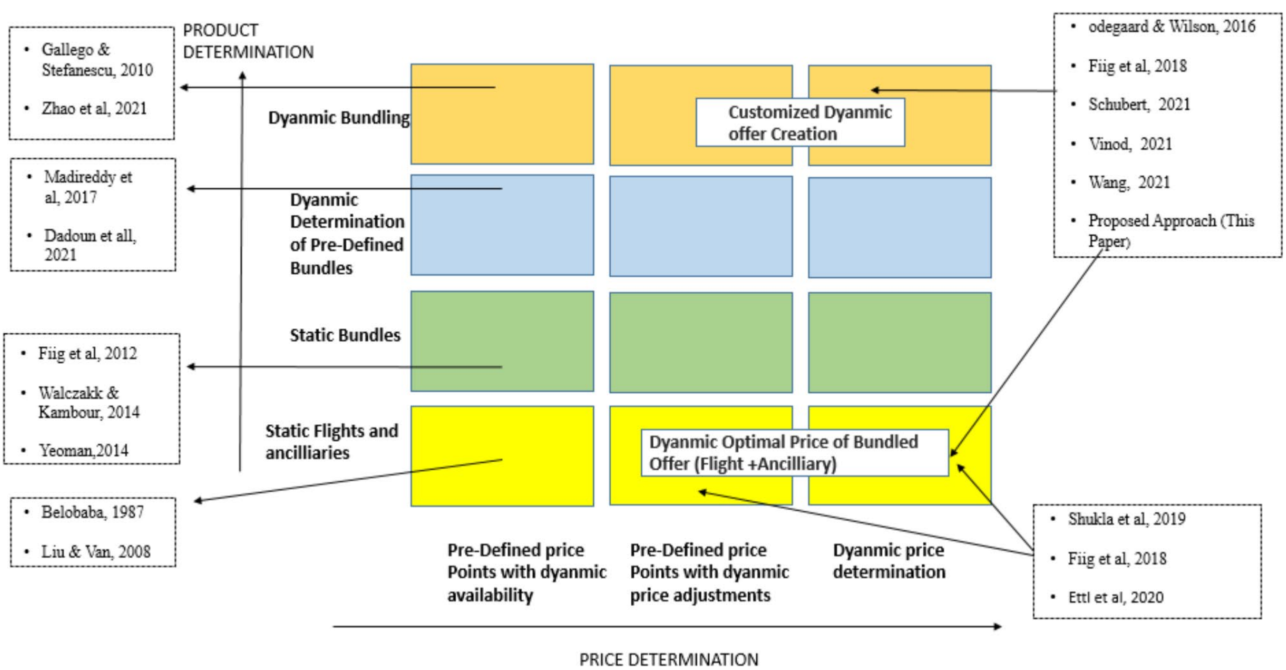

Fig. 1 Proposed annotated IATA capability matrix for research contribution (Touraine and Coles 2018)

this work, (Liu & Van Ryzin 2008), introduced a Choice-based Deterministic Linear Programming model (CDLP) to analyze revenue management based on fixed offer sets. Additionally, (Fiig et al. 2012) made some modifications to develop a fare forecaster for two defined sets of fare families, considering customers' willingness to pay and their preference for the flex or economy product relative to the price gap between them.

Moving one column ahead of the matrix of traditional revenue management where some modification in terms of customer choice was added to increase overall revenue. (Walczak and Kambour 2014) presented how marginal revenue transformation might involve consumer choice across fare families. (Yeoman 2014) suggested the fuzzy demand model for overbooking airline tickets and a metaheuristics-based GA to control overall income by reducing the number of vacant seats and the number of people that are turned away.

Each of the above manuscripts chooses the current price from a list of predetermined pricing values for each product. Continuing to move ahead next we have construction of bundled offers for customers having pre-defined price points. (Madireddy et al. 2017) shows how one airline product having seat and ancillary can be bundled by estimating customer willingness to pay using frequent itemset approach. According on client past purchase history, (Dadoun et al. 2021) showed how recommender systems can be utilized to make personalized offers. The authors have discussed how the algorithm used in conventional recommender systems can help control airline revenue. They did not, however, discuss offer pricing in their research.

Much more attention has been paid to the dynamic pricing of individual flights and ancillary services, as the bottom right of the matrix illustrates. In order to establish rates for a single primary good and one supplementary service, baggage. (Ødegaard & Wilson 2016) presented a unique multi-period dynamic pricing model. Every time a representative sample of customers enters the store at random, they may belong to one of three groups: those who are interested only in the primary products; those who would purchase the ancillary service at a reasonable price; or individuals who only buy the primary product and the ancillary service. (Fiig et al. 2018) suggested a technique for dynamic pricing modification based on the environment of the shopping experience to combat itinerary prices. (Shukla et al. 2019) describes the dynamic pricing model that gives recommendation as per specific customer and optimizes expected revenue management system. In this study, authors compared three dynamic ancillary pricing strategies with varying degrees of sophistication, including a single-stage end-to-end deep neural network that suggests the best price and two-stage models that use deep neural networks and logistic mapping functions for forecasting and optimization. (Zhao et al. 2021) develops a dynamic pricing scheme for ancillary services based on traveler preferences using binary logistic model. However, these manuscripts have focused on dynamic pricing portion of total offer management problem but do not explain how set of products will be displayed to the customers.

There is very limited study done on dynamic bundling of offers but (Gallego andStefanescu 2010) discussed the creation of specialized bundles for various consumer segments based on the valuation of each product for each category. Their model calculates bundle prices as the sum of the costs of each component that makes up the bundle; but they have not considered bundle discounts.

The top right part of matrix focusses on dynamic offer construction and pricing. Related to this, (Schubert et al. 2021) creates a conceptual architecture for personalized real-time offer administration with machine learning framework. The research aims to improve pricing decisions and customer satisfaction through personalized offers and more accurate willingness-to-pay estimates. (Vinod 2021) presents all the components of total offer management with the help of machine learning framework for leisure travelers and corporate travelers. Study that concentrates on issues with overall offer management typically take into account modest bundles of travel with one or two ancillaries. Discounts for bundles and mixed bundling are not specifically taken into account. The flight and ancillary bundling problem is solved by (Wang 2021), who focuses on the best possible bundling. It is theoretically conceivable to add more services to their probit-based customer choice model, but doing so would significantly increase the complexity. (Ettl et al. 2020) consider 11 ancillaries where a client can select from multiple services or a single, personalized bundle that can be offered at a reduced price compared to the usual cost. Based on their research, personalized pricing and bundling can raise revenue by 2–7% when compared to a fixed-price base scenario without bundling. They fail to take into account the potential for several packages within an offer set.

To overcome all the above discussed issues, this manuscript focusses on total personalized offer management problem that consists of five autonomous problems such as User persona identification, Dynamic customized offer set construction and recommendation, Prediction of maximum margin for each bundled offer and prediction of optimal price for each bundled offer and selection of best optimal packages for each individual user. This research has covered all the areas of the given matrix in detail in the sections below. This research also focusses on four segments of customers I.e., business travelers, solo travelers, group travelers and leisure travelers. As seen from the above survey the manuscripts considered total offer management problem consider very minimal numbers of ancillaries (one or two) along with one flight. But this research has considered all top-rated ancillaries as per survey results.

3 Proposed customer centric comprehensive solution

The focus of this section of the article is on the conventional airline revenue management system, which is illustrated in Fig. 2. In-depth details regarding the data sources that were used to confirm the suggested solution's results are provided in Sect. 3.1. Moreover, basic ideas are presented in Sect. 3.2, decomposing the Total Offer Management System (TOMs) problem into five independent subproblems:

- User persona identification.
- Dynamic customized offer set construction and recommendation.
- Prediction of the maximum margin for each bundled offer.
- Prediction of the optimal price for each bundled offer.
- Selection of the best optimal packages for each individual user.

A detailed description of the proposed algorithm's method for solving the dynamic offer set price optimization problem is given in Sect. 3.2. It is shown that factors including willingness-to-pay, flight bid price, and the cost of delivering additional services naturally affect the resulting costs. Additionally, the process for choosing the variety of offers to maximize expected revenue per user is explained in Sect. 3.3. Furthermore, the impact of offer quality and consumers' willingness to pay on variations in the preferred offer selection is examined.

Through this comprehensive analysis and proposed approach, we aim to contribute significantly to the field of total customized offer management systems, offering valuable insights and optimal solutions for airline revenue management.

3.1 Dataset collection

The dataset used in this research was gathered in three stages. In preliminary stage (data collection) data was collected from transportation of bureau statistics for the year 2019–2022. The origin and destination dataset referred has attributes such as origin, destination, unique itenary ID, passengers, price, is round trip, trip break, flight class, etc. Due to very limited information obtained from this data source, during second stage live web scraping is done from kayak to get impact of travel search difference, day week preference, passengers, flight class, time to fly on price. Based on the results obtained, the hypothesis was designed to fill missing

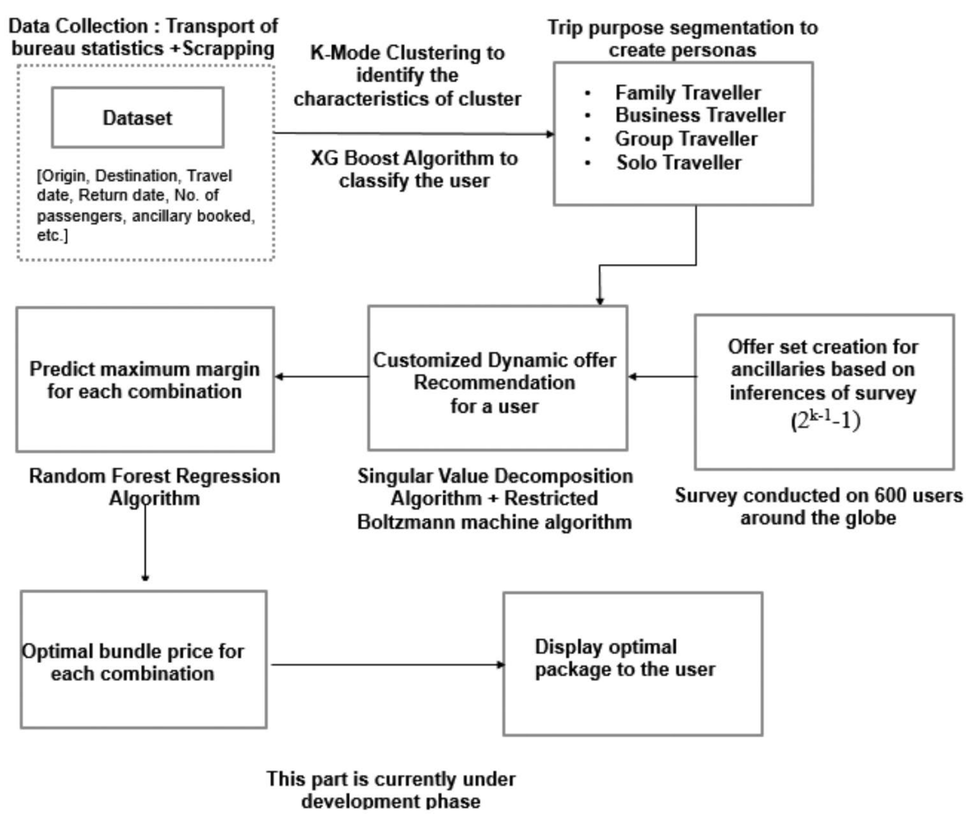

Fig. 2 Proposed solution of total offer management system (TOMs) problem

data points. In addition, data about ancillaries preferred was collected through surveys conducted on various sites to get authentic information about all categories of users (different age, demographics, etc.).

3.2 User persona identification

To design a useful offer, it is essential to recognize each individual customer based on their behavior. Determining the traveler type (e.g., business, family, solo, and group) based on passenger details is not enough. Factors like origin, destination, book travel window, trip span, etc.) also has a powerful influence on the customer purchased itineraries. In order to bundle offers, traveler-type segmentation is also essential. On one end of the scale, we had a one-size-fits-all strategy, where all the requesting customers got the same product. This is obviously insignificant because we are aware that different customer groups have different tastes. On the opposite end of the scale, we have a strategy where we can address each client individually. With segmentation, one can operate under the presumption that various customer groups have varied preferences by classifying people who exhibit similar behavior patterns into groups. All the prior research done on customer segmentation has focused on customer demographic information to partition them under same category. Consideration of booking GDS data is the important element in developing client personas. According to the Travelport survey, this study proposes a novel customer segmentation approach to predict the type of traveler, such as family traveler, group traveler, business traveler, and solo traveler. The segmentation is based on distinctive features, including user origin, destination, flight class, price, travel search category, trip span, time of flight, number of passengers, trip break, and whether it is a round trip. The study uses K-Mode clustering, which determines the most ideal clusters within the data points, to find patterns in the data (Chaturvedi et al. 2001). The XG Boost method (Chen et al. 2015) is used to forecast the traveler's class, and the results of the machine learning model are explained using Shapley Additive Explanations value analysis. As shown in Fig. 3, the strategy employs a four-phase process to help decision-makers enhance service quality and client happiness. Figure 4 depicts the process flow of the segmentation analyzer on the dataset utilized in this study.

3.3 Dynamic customized offer construction and recommendation

According to the International Air Transport Association (IATA), dynamic customized offer construction refers to the process of creating an offer using the entire available set of products and services, subject to specific conditions. Each offer package comprises one or more offers, which, in turn, include both a flight and one or more ancillary services. The set of offers represents a subset or selection from the vast array of potential offers that the airline can offer, depending on its flight schedule and supplementary services. To encompass all possible offers that can be generated from these components, we calculate the powerset $\Omega = P(A)$, where A denotes the set of ancillaries offered by the airline. We define an unpriced offer set S = {O0, O1, O2……ON}, where $S \subseteq \Omega$, as a collection of one or more offers that can be presented to the customer without specified prices. We can generate all non-empty offers sets S Ω by considering the powerset $P(\Omega)$, which has cardinality of 2^k-1. Note that customers always have the option not to purchase any ancillary, so each offer set includes a possibility of no purchase (O0 = Ø). Based on personas created from segmentation and survey results, a total of 30,000 offer sets are generated. These offer sets are then used as input for our recommender system to determine the most suitable offers for a particular user with the highest likelihood of conversion, as depicted in Fig. 5. Customers are called users and items are the products in the catalogue in the context of recommender systems. Consequently, a recommender system may be thought of as a method of estimating the likelihood that a user will interact with an item and using that likelihood to suggest the most pertinent subset of items to the user. The primary

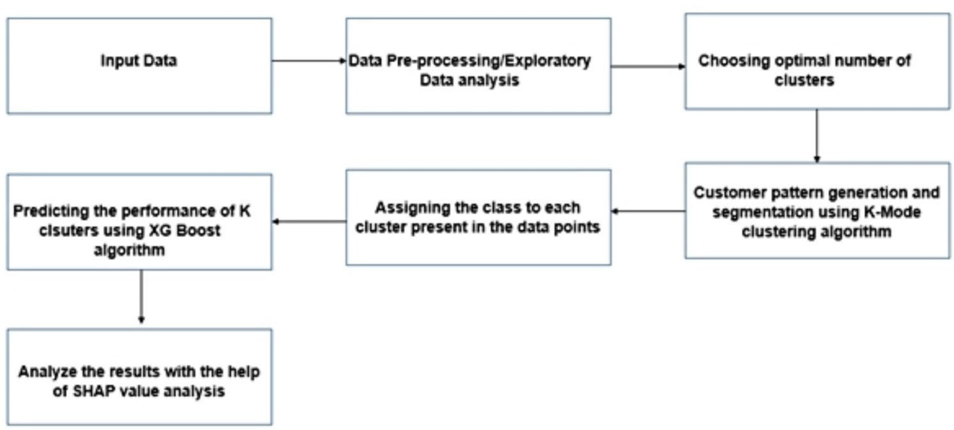

Fig. 3 Research flow of the proposed framework (Mahendru and Singh 2023)

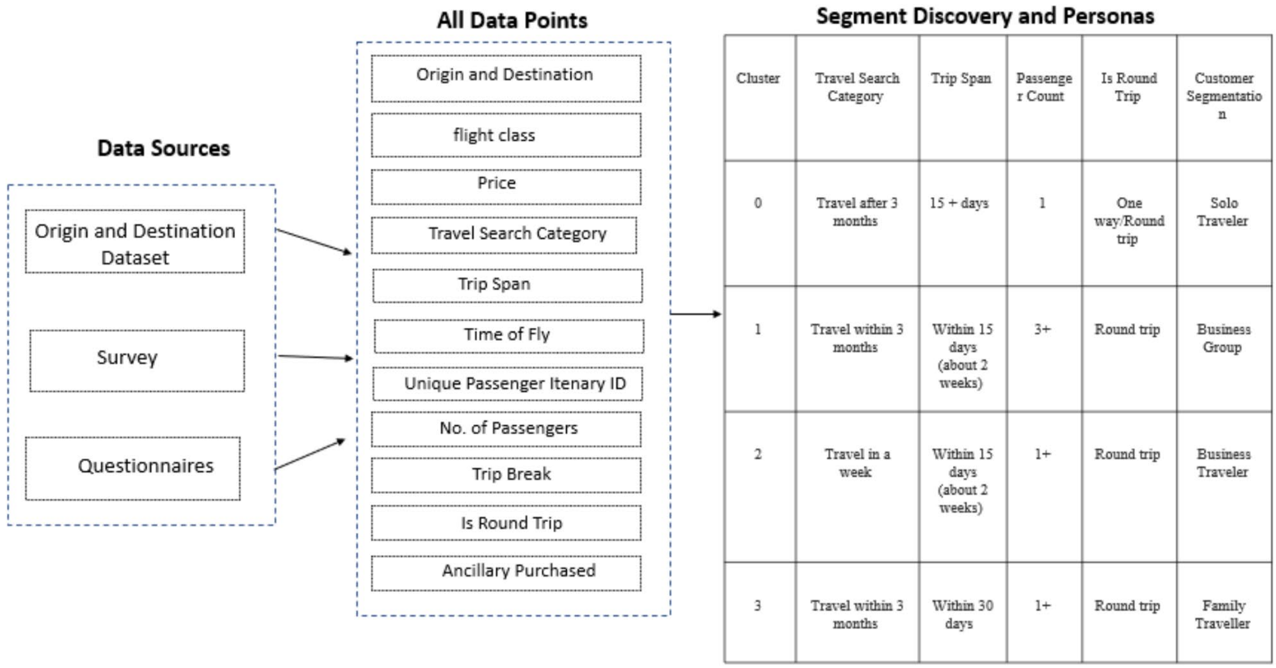

Fig. 4 Customer segmentation and personas (Mahendru and Singh 2023)

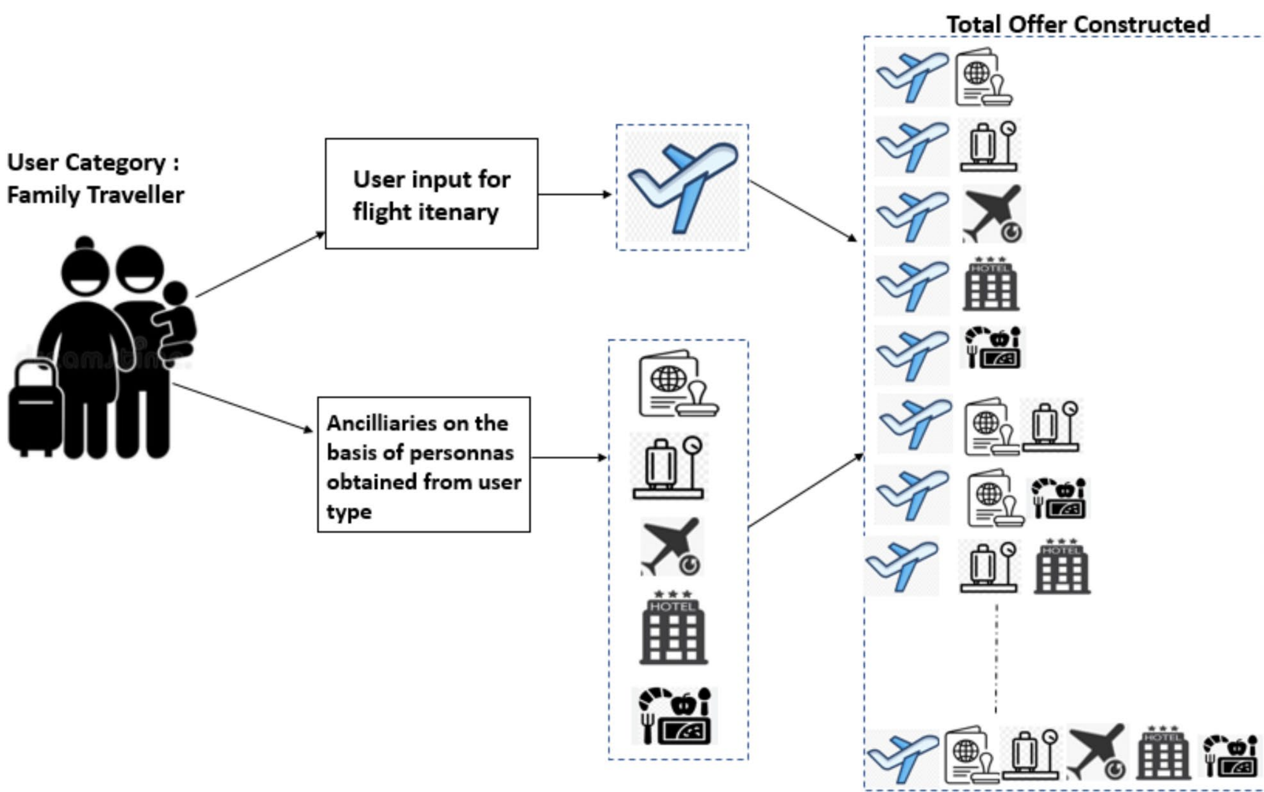

Fig. 5 Top 30 offers recommended as per user characteristics

goal of any recommender system is to establish a connection between the user and the product, aiming to maximize user-product engagement. Numerous recommender systems have been developed to improve users' ability to find better products (Dadoun et al. 2021).

A key method employed in personalised recommender systems that falls within the memory- and model-based categories is collaborative filtering (CF) (Behera & Nain 2022). CF operates on the fundamental premise that users will likely continue to prefer certain items if their past preferences were similar. These recommendations are based on both explicit and implicit user evaluations, as well as user history. In the classic CF approach, the user-item matrix is created solely based on the user's previously provided preferences. However, this approach faces significant challenges such as cold start and data scarcity. When a new user or item is introduced, the system is unable to provide recommendations because it lacks sufficient knowledge of the user's preferences. This is known as the "cold start" issue. The user-item matrix becomes relatively sparse if an additional item has no user preferences, leading to a significant decrease in the likelihood of providing recommendations.

To address the problem of data sparsity, matrix factorization is widely used as a filtering method. This approach maps users and items to latent properties by factorizing the user-item interaction matrix. Based on similarities between users and items, the recommender system then makes a tailored selection of items to each distinct user in the latent space. Matrix factorization has the advantage of accurately discovering hidden patterns within the data. Principal Component Analysis (PCA), Singular Value Decomposition (SVD), Probabilistic Matrix Factorization (PMF), and Non-Negative Matrix Factorization (NMF) are examples of decomposition methods that are frequently employed (Isinkaye 2021) (Martins et al. 2020). Despite these benefits, this approach has drawbacks, such as limiting the dimensionality of the data, which may prevent the development of prediction accuracy.

To address the a forementioned issues, this research employs a deep learning-based hybrid recommendation method. The proposed model is described as follows:

- Explicit ratings are produced together with a user-item relationship matrix. The matrix is integrated with Singular Value Decomposition (SVD), which decomposes the matrix into the best lower rank approximation of the original matrix.
- Subsequently, incorporate the user-item matrix into the Restricted Boltzmann Machine (RBM) DNN (deep neural networks) model for learning latent features to forecast user preferences.
- Lastly, the ratings for each prediction made using the SVD and RBM techniques are provided. Utilizing a weighted hybridization to experiment with weight values W1 and W2, these two values are combined to create the hybrid final prediction result.

3.3.1 Proposed hybrid model

Having a common interface across all recommenders, a hybrid recommendation model can simply mix multiple algorithms that may do completely different things.

3.3.1.1 Singular value decomposition (SVD) One of the most used techniques in linear algebra for factoring matrices is SVD. A technique like this would minimise the characteristics and reduce the dimensions from N to K. The matrix is created by SVD and contains a row of users, columns of items, and all entries are ratings provided by users for those items. Let's look at a matrix A with a size of m x n and a rank of r. The factors for SVD (A) are derived from the factorization of a high-level (user-item-rating) matrix by splitting the matrix into three additional matrices.

$$\mathrm{A} = \mathrm{USV}^{\mathrm{T}} \tag{1}$$

Where U denotes the user matrix * latent factors of size (m x m), V denotes item matrix *latent factors of size (n x n), and S denotes diagonal matrix of size (m x n) which denotes the strength of each latent factor. The set of first r values of S $(s_1, s_2, \ldots \ldots, s_r)$ are all positive with $s_1 \geq s_2 \geq s_3, \ldots \ldots \ldots,$ $\geq s_r$. The initial r columns of U are eigen vectors of AAT and represent the left singular vectors of A. Similarly, the first r columns of V are eigen vectors of $A\ TA$ and represent the right singular vectors of A. SVD supplies the best lower approximation matrix of original matrix A. It is obtained by holding the initial x diagonal values of, by removing $r -$ x columns from U and by removing $r -$ x rows from V, which can be written as follows:

$$A_{\mathrm{x}} = U_{\mathrm{x}} \times S_{\mathrm{x}} \times V_{\mathrm{x}}^{T} \tag{2}$$

The matrix reconstructed as $A_{\mathrm{x}\ \mathrm{is}}$ the closest approximation of original matrix A. Once the $m \times n$ ratings matrix R is decomposed and reduced into three SVD part matrices with k features U_{x}, S_{x} and V_{x}, prediction can be generated from it by computing the cosine similarities (dot products) between m pseudo-customers $U_{\mathrm{x}}.\ \sqrt{S_{\mathrm{x}}}^{T}$ and n pseudo-products $S_{\mathrm{x}}.\ \sqrt{V_{\mathrm{x}}}^{T}$. In particular, the prediction score Ri, j for the i th customer on the j th product by adding the row average $\overline{\overline{ri}}$ to the similarity.

$$Ri,j = r\bar{i} + U_{\mathrm{x}}.\sqrt{S_{\mathrm{x}}}^{T}(i) + S_{\mathrm{x}}.\sqrt{V_{\mathrm{x}}}^{T}(j) \tag{3}$$

Once the ***SVD*** decomposition is done, the prediction generation process involves only a dot product computation. For more details refer to (Prajna et al. 2022) (Dwivedi et al. 2020).

The SVD is an effective method for dimensionality reduction and for generating low-rank approximations with high accuracy and scalability. The cost of computing the SVD is significantly higher than that of most other techniques. For cold start issues, singular value decomposition offers a poor solution. SVD is therefore not alone proper for recommendation (Li et al. 2022). Although SVD offers a satisfactory solution to recommender systems, it performs less well when novel items do not gather enough data.

3.3.1.2 Restricted boltzmann machine (RBM) RBM is a two-layer stochastic neural network that consists of an input layer, sometimes referred to as the visible layer, and a hidden layer. While the neurons in one layer are capable of communicating with those in the opposite layer, they are unable to do so inside the same layer. When neurons in the visible layer communicate with neurons in the hidden layer, only the hidden layer relays information back to the visible layer. The communication between the visible and hidden layers is carried out by RBMs (Restricted Boltzmann Machines) in order to create a generative model that will aid in predicting if the user would like the item that they have never seen but is comparable to the thing they have rated. A m x n matrix, where m stands for users and n for ancillary's user ratings, is used to provide personalized offers based on consumer preferences. The RBM neural network trains for a predefined number of epochs after receiving a batch of K users and the ratings of their n ancillaries. The inputs to the neural network are given in the form of xs, which stand for individual user ratings for each of the n ancillaries. Consequently, each auxiliary has n nodes in the visible layer. To force the hidden layer to learn the most important elements of the first input as quickly as feasible, we can define the number of nodes in the hidden layer, which is often fewer than the number of nodes in the visible layer. The matching weight W is multiplied by each input value (v0). The connections between the visible and hidden layers are used to learn the weights. Next, the bias vector hb is assigned to the hidden layer. At least some neurons will fire as a result of the bias. The outcome of W*v0 + hb is handled by an activation function. Next, we will select a representative sample using the results of a procedure called Gibbs sampling (Bao et al. 2020, Kuo & Chen 2020). Put another way, the final outputs are generated at random when the hidden layer is activated. This degree of randomness helps to create a more reliable and efficient generative model. Next, in a process called as a backwards pass, the output from the gibbs sampling of h0 is returned to the visible layer. The activations are sent into the hidden layer after Gibbs sampling in the forward pass, and the backward pass multiplies them by the same weight "W" as before. Then, at the visible layer, we introduce vb, a new bias vector.

After this W_h0 + vb has passed via an activation function, Gibbs sampling is carried out. This produces the output v1, which is subsequently used in a subsequent forward run through the neural network and as the new input in the visible layer. This learning probability distribution is what allows RBMs to forecast results for previously unseen data. Based on the user's similarity to other users and the ratings that these ancillaries have received from other users, the RBM will try to predict ratings for ancillaries that the user has not purchased.

Gibbs sampling is done once this W_h0 + vb has passed through an activation function. Consequently, the output v1 is generated. After that, this output is employed in a subsequent forward run through the neural network as the new input in the visible layer. RBMs can use this learnt probability distribution to predict results for data that has never been observed before (See Table 1).

3.4 Prediction of maximum margin for each bundled offer

This section explains the estimation of the highest profit margin which we can get for a particular itenary from the user. To maximize the total predicted revenue of the offer set, this projection is essential. Airlines may strategically priorities their marketing and promotion operations by precisely calculating the maximum profit margins. To increase their profitability, they can decide which offers have the largest profit margins and devote resources accordingly.

Additionally, knowing the maximum margin enables airlines to set up rates that are both customer-friendly and profitable. Airlines can choose the best pricing point by taking the costs of each offer into account and aiming for a particular profit margin. This strategy guarantees that the pricing makes a profit and pays the costs. A significant viewpoint is to choose the features needed for calculation of expected profit margin. Output gathered from the previous step along

Table 1 The performance of various algorithms on dataset

Metric	SVD	NMF	Co clustering	Normal predictor	RBM	Proposed method
RMSE	0.26	1.75	1.65	1.86	1.32	0.23
MAE	0.21	1.44	1.37	1.52	1.21	0.19

with the attributes present in the dataset are passed as input to various machine learning models to evaluate the performance of each algorithm. Dataset used in this research contains number of parameters for each flight: yet not all are needed, so just the accompanying components are,

- Origin
- Destination
- Travel Date
- Return Date (if round trip)
- No. of passengers
- Total Fare
- Unit Price of each ancillary booked

Numerous techniques are provided in machine learning for calculating the maximum profit margin. K-Nearest Neighbor, Linear Regression, Support Vector Machine (SVM), Decision Tree, Multilayer Perceptron, Gradient Boosting, and Random Forest Algorithm are a few examples of the methods (Chakrabarty et al. 2019) (Wang et al. 2019) (Khaksar and Sheikholeslami 2019). R-square, MAE, and MSE are a few of the parameters that are used to evaluate how well these models work. The highest margin that can be charged from each individual client to ensure both customer loyalty and profitability is anticipated by analyzing the results of algorithms like SVM, Decision Tree, KNN, Bagging Tree, Random Forest, and Linear Regression. For the aforementioned dataset, random forest regression is more accurate than other techniques (See Fig 6).

3.5 Prediction of optimal price for each bundled offer

Once calculating the prediction of the maximum profit margin, the next step involves determining the prices for each offer in the offer set to maximize the total expected net revenue of the entire set. Dynamic pricing aims to identify the prices that optimize the contribution of each offer, ultimately leading to the overall revenue maximization for the airline, considering the costs involved. Each buyer is assumed to purchase only one offer from the available set. To achieve this, we optimize a vector of prices $\vec{p}^*$ (S) for the entire offer set S, taking into account the interdependence of one offer's purchase probability on the prices of other offers. This simultaneous optimization allows the algorithm to strategically set prices, such as offering a higher price for one offer to incentivize customers to consider another offer generating higher revenue. The objective of offer set price optimization can be defined as follows:

Find the prices $\vec{p}^*$ for each offer Oi in the offer set S that maximize the total expected net revenue of the offer set.

$$
\begin{aligned}
\mathrm{E}(S) : & p^{\rightarrow} * (S) = \arg\max{}^{\rightarrow} p\, \mathrm{E}(S) \\
& = \arg\max{}^{\rightarrow} p \sum Oi \in S(pi - ci)\, P\left(Oi|^{\rightarrow} p(S)\right)
\end{aligned}
$$

By optimizing the prices in this manner, the goal is to increase the overall revenue while considering the costs associated with each offer. This dynamic pricing strategy takes into account customers' preferences and behaviors, allowing the airline to offer tailored and attractive pricing to maximize the revenue potential of the entire offer set. This module utilizes the following parameters as input:

- The list of offers Oi in the offer set S (from the previous section).
- For each offer, a function that relates the cost to the likelihood that a customer will make a purchase, often utilizing a probability distribution of the customer's willingness to pay.
- For each offer, the maximum profit margin that can be charged from each individual customer (calculated in the previous step).

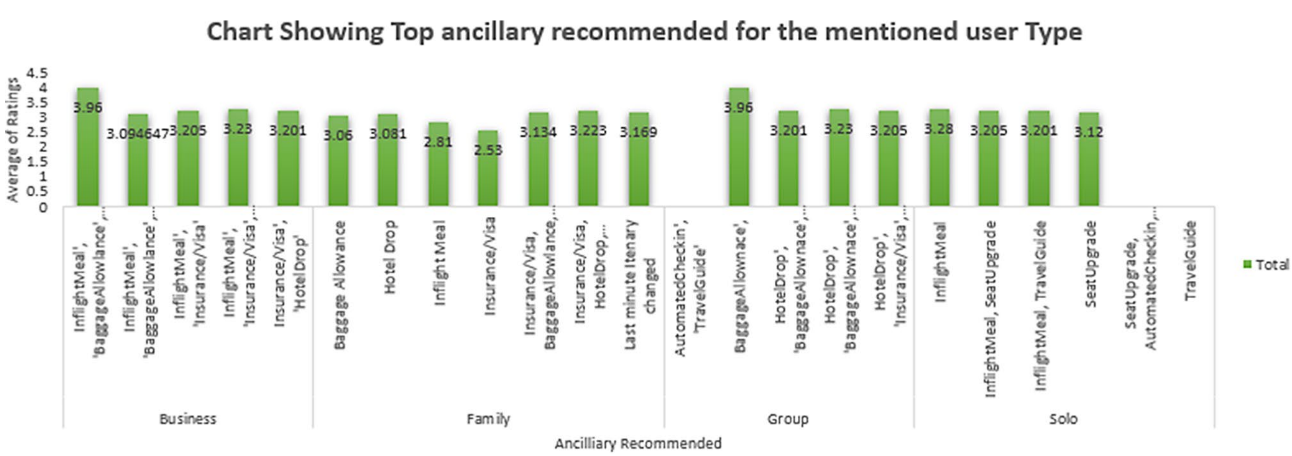

Fig. 6 Top ancillary recommended to user type

The willingness to pay for an offer is determined by summing the willingness to pay for each of its components, which is obtained from a global survey ranking provided by each individual customer. The cost of an offer is calculated as the sum of the costs of the flight and all the ancillaries associated with it, denoted by $ci = cf + \sum ak \in Oi\, cak$.

To recommend the final optimal price for each bundled offer, we employ a neural network with two layers (LeCun et al. 2015), utilizing an end-to-end learning approach. While this technique enables the model to learn a wide range of correlations between customer behavior and pricing, it may pose challenges in terms of interpretation due to its integrated structure. Since there is no precise "ground truth" signal for the ideal price, as past data only indicates whether the customer purchased the ancillary at the suggested price, we acknowledge the potential limitations in precisely determining the optimal price. We are aware that a customer's willingness to pay might have been higher if they had made a purchase and vice versa if they had not. For instance, if a buyer paid \$20 for a product, their actual willingness to pay might have been \$22. In this model, our primary focus is on determining the ideal pricing rather than forecasting the specific price at which an item was purchased in previous user sessions.

To address this challenge, we have designed a unique loss function that considers both the regret of setting prices too low and an additional penalty for setting prices too high. This formulation builds upon the concepts presented in prior studies (Ye et al. 2018) (Al-Bazi et al. 2019). The loss function teaches the model to learn in a manner that aligns with sensible prior experiences. For instance, if a previous customer did not pay \$10 for a product, it logically follows that the model shouldn't charge that much or more for another customer with similar characteristics. If the model outputs \$13 for such a customer during training, the loss would be significant, penalizing the model to lower the price. This model proves useful in determining upper and lower bounds for the willingness to pay, thereby providing richer reward signals for multiple models to learn the willingness to pay. Furthermore, depending on the customer category, booking time, and the availability of the revenue management system, both the willingness-to-pay estimates and the costs may vary in the model. For instance, the average willingness to pay for the flight may increase with changes in demand from early booking leisure passengers to late booking business passengers, while the average willingness to pay for a checked bag may decrease. The airline could potentially employ separate metrics for business and leisure passengers and classify booking requests as business, leisure, or group to derive different offer pricing for each consumer segment through optimization.

3.6 Prediction of five optimal packages for each user

The method of choosing the best packages to show to users is the focus of this section. The selection process is based on three key factors: margin, optimal price (which has been calculated in earlier steps), and user characteristics. By integrating margin, optimal price, and user characteristics, the research endeavors to improve the overall user experience. Packages that strike a balance between profitability, affordability, and personalized appeal are more likely to resonate with users. This, in turn, can lead to increased user retention, positive feedback, and enhanced brand loyalty.

4 Implementation and results

In this section, we break down our results into four key components, each serving a distinct role in presenting our approach comprehensively. Firstly, there's a detailed explanation of how the model operates, breaking down its steps to illustrate how it works. Following this, study delve into the intricate task of extraction of association rules using the FP-growth algorithm. These rules serve the purpose of shedding light on the products that are most suitable for user recommendations across diverse scenarios within the test dataset. Additionally, we verify the outcomes derived from our proposed approach by conducting an extensive comparison between the projected results and the association rules generated for particular user scenarios. Lastly, the practical significance of these extracted rules is explored, highlighting how they can influence strategic decisions and contribute to business development. By seamlessly blending these four elements, the research offers insights into the usefulness of the approach for making decisions and advancing industries.

4.1 Model workflow

This part describes the whole flow of the model in five sequential steps as discussed above. To evaluate the performance of the model on all the scenarios, one common case is considered for all the user types where user origin is Columbia (CAE), destination is Fort Lauderdale (FLL) USA, travel date is within 3 months and trip type is round trip. Keeping all the above attributes fixed, multiple scenarios are considered for the user types as shown below (See Table 2).

As mentioned in the above section, total offer management (TOM) problem is collection of five autonomous subproblems: Offer set recommendation, offer set pricing optimization, and offer set selection.

Table 2 Common scenario conditions for all the user types

User type	Origin	Destination	Trip period	Trip type	No. of passengers
Family	CAE	FLL	Within 3 months	Round Trip	2 C + 2 A + 1 S
Business	CAE	FLL	Within 3 months	Round Trip	2 A
Group	CAE	FLL	Within 3 months	Round Trip	10 A
Solo	CAE	FLL	Within 3 months	Round Trip	1 A

Table 3 Comparison between (Wang et al. 2023), (Kummara et al. 2021) and proposed approach on input dataset

(Kummara et al. 2021)	(Wang et al. 2023)	Total offer management solution (Proposed)
66% (approx.)	68% (approx.)	78%

4.1.1 Dynamic customized offer recommendation

As described in Sect. 3.3 our recommender recommends the top 30 offers per user. In the visualization presented in the paper, we have chosen to focus on the top five offers based on the highest ratings for each scenario discussed. Due to the limitations of space and feasibility, it is not possible to display visualizations for all 30 offers constructed for every individual user in the study. However, by showcasing the top-rated offers, we aim to provide a representative snapshot of the personalized pricing strategy's effectiveness and customer preferences. The graph illustrates the preferences and ratings of different traveler types for the specific case of a round trip from Columbia (CAE), USA, to Fort Lauderdale (FLL), USA, with a travel date within 3 months.

Based on the data presented, it is evident that business travelers tend to prioritize inflight meals and baggage allowance, as indicated by their highest rating of 3.56 for these features. On the other hand, group travelers show a preference for automated check-in and travel guides, which received the highest rating from this traveler segment. Family travelers, when considering the same case, rated baggage allowance as their top priority. Lastly, solo travelers displayed a preference for inflight meals, which received the highest rating among this group.

It is significant to note that these preferences are particular to the present situation, and the ratings reflect the proportionate weight that each traveler type has given to each choice. These data can help airlines and other travel companies adjust their services to the unique requirements and tastes of various traveler categories, improving client happiness and the overall travel experience (See Table 3).

4.1.2 Prediction of maximum margin for each bundled offer

The graph provides a visual representation of the highest profit margins that each customer is eligible to pay for a specific itinerary. The graph offers a thorough look at the profit possibilities linked to various pricing methods catered to various traveler types. The graph illustrates the scenario for the specific case of a round trip from Columbia (CAE), USA, to Fort Lauderdale (FLL), USA, with a travel date within 3 months. Based on the data presented it is observed that for a business traveler inflight meal, baggage allowance, insurance visa and hotel drop give the highest profit margin value. Whereas for family travelers the highest profit margin can be set for baggage allowance, inflight meal and hotel drop facilities. The same can be visualized for group and solo travelers from the graph below (See Fig 7).

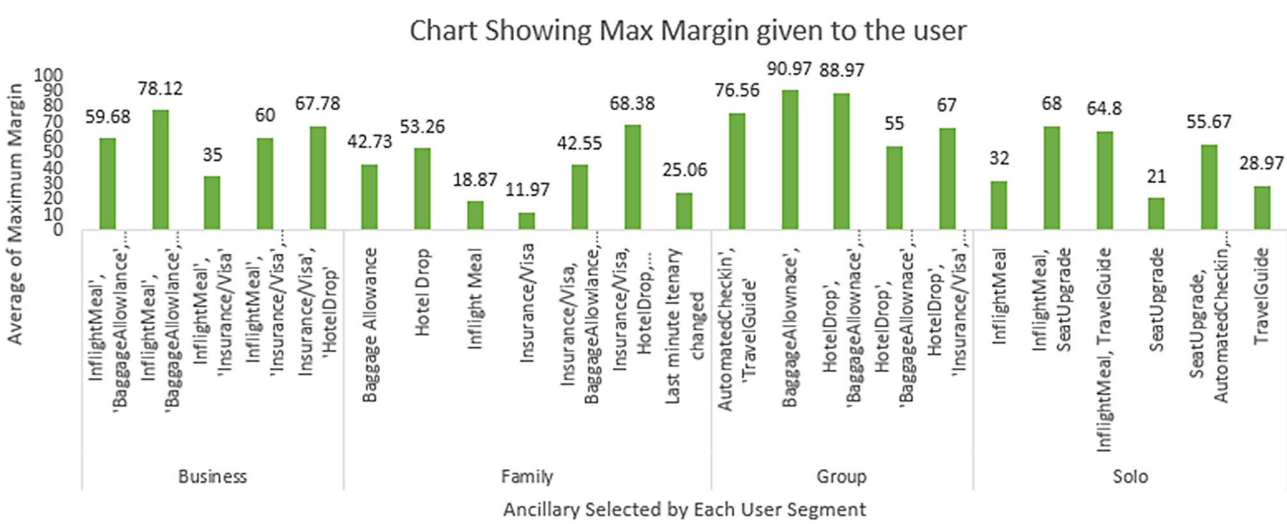

Fig. 7 Maximum margin given to the user on each offer

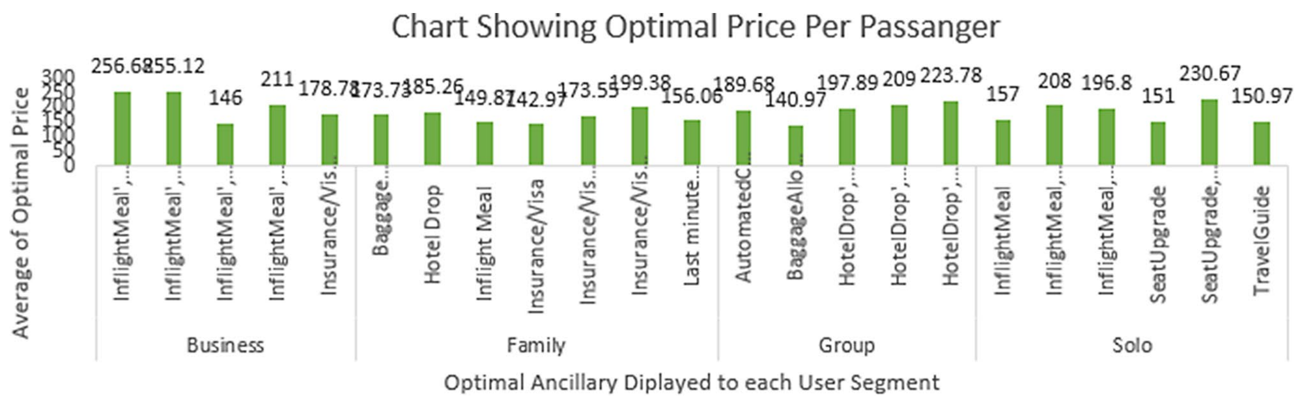

Fig. 8 Optimal price per passenger

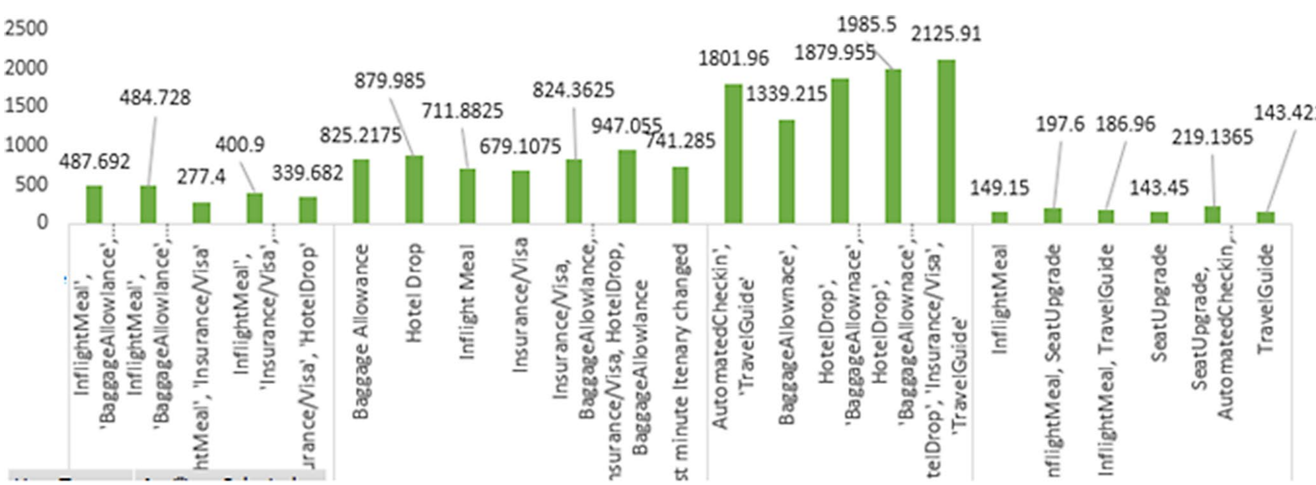

Fig. 9 Top 5 optimal package for the user

4.1.3 Prediction of optimal price for each bundled offer

This section focuses on determining the ultimate optimal pricing for each offer after determining the highest profit margin for each offer and creating a function that connects price to the likelihood that a user will make a purchase. The section illustrates the final optimal price of each offer that is displayed to customer while booking as shown below (See Fig 8).

4.1.4 Prediction of five optimal packages for each user

This section highlights the top 5 packages displayed at user's end along with the optimal price for the scenario discussed above as shown in graph below. This prediction derived through a meticulous selection process that considers three crucial factors: margin, optimal price (previously calculated through a rigorous analysis), and user characteristics. The integration of these key factors in the selection process aims to significantly enhance the overall user experience (See Fig 9).

4.2 Comparison between (Wang et al. 2023), (Kummara et al. 2021) and proposed approach on the basis of increase in purchase probability

This study incorporates methodologies from prior research by (Wang et al. 2023; Kummara et al. 2021), alongside introducing a new solution. The main objective was to enhance purchase probability within our research domain through these methods. The experiment resulted in a notable improvement in purchase probability, particularly evident with the implementation of the proposed solution. To assess the effectiveness of proposed approach compared to existing methods, a comprehensive analysis was conducted, primarily focusing on purchase probability as the key metric. The results obtained from the experiment demonstrate a substantial 14.5% increase in the likelihood of offer purchases for each segment of customers. The comparative results are summarized and visually presented in the subsequent table, providing insights into the relative performance of the algorithms.

4.3 Association rules extraction using FP-growth algorithm

The FP-Growth technique was used in this research to derive useful association rules that illuminated the nuanced relationships in the dataset used in this study. The fundamental purpose of employing this methodology is to uncover interesting patterns of user behavior, thereby facilitating the development of tailored offers that cater to individual user preferences. The formulation of these rules is measured using essential metrics including confidence, lift, leverage, and conviction. These metrics collectively assess the strength and applicability of the established rules. The detailed table provided below demonstrates how these rules provide insights into product recommendations adapted to various user contexts. These rules serve as a blueprint for tailoring recommendations to passengers' preferences, resulting in enhanced personalized travel experiences (See Table 4).

4.4 Validation and comparison

In this section, we validate the results obtained from our proposed approach, as discussed in Sect. 4.1, by conducting a comprehensive comparison between the predicted outcomes and the association rules generated for specific user scenarios. The evaluation is focused on scenarios where the origin is Columbia (CAE), the destination is Fort Lauderdale (FLL) in the USA, the travel date is within 3 months, and the trip type is round trip. Table 5 presents an in-depth comparison between the anticipated personalized ancillary offers derived from our proposed approach and

Table 4 Common scenario conditions for all the user types

S.no	Association Rules	Confidence	Lift	Leverage	Conviction
1	User Category-Family Passenger Category-(2) Time to Fly-NIGHT Trip Break-Multi stop===> Buy Seat upgrade, Hotel Drop, Travel Guide, Automated Check-in	0.994	1.000	0.01	10.000
2	User Category-Family Passenger Category-(5–6) Travel Category-Travel in 1 to 3 months Trip Type-Round Trip ===> Inflight Meal, Insurance/Visa, Baggage Allowance	0.99	1.003	0.01	10.026
3	User Category-Family Price Category- $200-$300 or $100-$200 ===> Buy Seat Upgrade, Automated Check in, Hotel Drop	0.93	1.002	0.01	10.018
4	User Category-Family Trip Type-One Way Trip Break-Multi Stop===> Buy Automated Check-in Seat Upgrade, Baggage Allowance	0.896	0.998	0.01	9.985
5	User Category- Family Passenger Category-(2) Time to Fly-NIGHT Trip Break-Multi stop===> Buy Baggage Allowance, Hotel Drop, Automated Check-in	0.989	0.998	0.03	9.985
6	User Category- Family Buy-Automated Check in Seat Upgrade, Insurance/Visa Price Category- under $500 ===> Maximum Margin-$163	0.813	1.000	0.01	9.999
7	Trip Span- One way User Category-Family===> Buy Seat Upgrade, Automated Check in, Hotel Drop, Travel Guide	0.959	0.982	0.01	9.880
8	Travel Search Category-Travel after 6 months User Category-Family===> Buy Travel Guide, Automated Check in Seat Upgrade Maximum Margin-$200	0.943	1.003	0.01	10.025
9	Trip Span Category-Return in 60–90 Days Travel Category-Travel in 1–3 months, Price Category -$100-$150 ===> Buy Automated Check in, Baggage Allowance Maximum margin- $150	0.795	1.003	0.01	10.027
10	Passanger Category- (3–6)===> Buy Hotel Drop, Seat Upgrade, Automated Check in Insurance/Visa Maximum Margin-$150	0.994	1.067	0.01	10.467
11	Trip Break- Multi Stop Buy Hotel Drop, Inflight Meal Passanger Category- (2) User Category-Family===> Buy Seat Upgrade, Automated Check in, Baggage Allowance	0.912	1.003	0.02	10.031
12	User Category-Solo Passanger Category- (1) Trip Break-Multi Stop===> Buy Insurance/Visa Automated Check in Last minute itenarary change, hotel Drop	0.932	0.929	0.01	9.632
13	User Category - Solo Trip Break-Non Stop Travel Search Category- 1–3 Month Trip Span-Round Trip ===> Buy Inflight Meal, Seat Upgrade and Automated Check in.	0.956	1.008	0.01	10.077
14	User Category- Solo Trip Break Multi Stop ===> Inflight Meal, Insurance/Visa	0.986	0.930	0.01	9.633
15	User Category -Solo Travel Search Category-After 6 Month ===> Seat Upgrade, Last minute itenary change	0.876	1.003	0.01	10.025
16	User Category -Solo ===> Maximum Margin $100	0.886	1.002	0.01	10.024
17	User Category -Solo Trip Break-Multi Stop Buy-Hotel Drop, Seat Upgrade ===> Buy Automated Check in	0.898	1.053	0.01	10.362
18	Travel Search Category- Beyond 3 months ===> Buy Last Minute Itenary Change, Insurance/Visa	0.798	1.002	0.01	10.024

Table 4 (continued)

S.no	Association Rules	Confidence	Lift	Leverage	Conviction
19	User Category -Solo Trip Span- Within a week Travel Search Category-In a Week ===> Buy Automated Check in, Insurance/Visa Maximum Margin-$52	0.994	1.053	0.01	10.362
20	User Category- Solo Trip Span- 60–90 Days Buy- Last Minute Itenary Change, Automated Check in===> Buy Baggage Allowance	0.897	1.005	0.03	10.052
21	Buy- Baggage Allowance, Automated Check in ===> Buy Hotel Drop, Insurance/Visa	0.908	0.948	0.01	9.726
22	User Category- Solo Travel Search Category- 1–3 months Trip Span- 15 days Buy Baggage Allowance, Automated Check in Insurance Visa===> Maximum Margin $90	0.967	1.005	0.01	10.052
23	Price Category- $100-$200 User Category- Business Traveler===> Buy Hotel Drop, Insurance/Visa	0.912	0.948	0.01	9.726
24	Trip Span- One way User Category- Business Traveler ===> Buy Insurance/Visa, Hotel Drop	0.82	1.007	0.01	10.075
25	Passanger Category – (2) User Category- Business Traveler===> Buy Seat Upgrade, Insurance/Visa, Hotel Drop, Baggage Allowance Maximum Margin- $163	0.75	0.948	0.01	9.724
26	Time of Fly- Night Buy Last Minute Itenary Change User Category- Business Traveler Trip Span - Return in a Week===> Buy Insurance/Visa, Automated Checkin, Hotel Drop	0.774	1.007	0.01	10.075
27	Passenger Category – 2, User Category- Business Traveler, Travel Search Category- Within 1–3 Months, Trip Type- Round Trip Time of Fly- Morning Trip Break-Multi stop ===> Buy Inflight Meal, Insurance/Visa, Automated Check in and Hotel Drop.	0.821	0.948	0.01	9.724
28	Time of Fly- Night Buy Last Minute Itenary Change User Category - Business Traveler Trip Span- Return in a week ===> Buy Seat Upgrade, Baggage Allowance, Insurance/Visa Automated Check in Maximum Margin - $273	0.789	1.255	0.06	12.035
29	Trip Break- Multi Stop Buy- Hotel Drop Price Category- $50-$100 ===> Buy Insurance/ Visa	0.778	1.002	0.01	10.016
30	Trip Break- Multi Stop Buy- Insurance/Visa Category- $50-$100 ===> Buy Hotel Drop, Inflight Meal	0.941	1.003	0.01	10.031
31	Trip Break- Multi Stop Price Category- $200===> Seat Upgrade, Baggage Allowance, Insurance/Visa, Automated Check in Inflight Meal	0.901	1.002	0.01	10.016
32	User Category- Group Time of Fly - Night Trip Break- Multi stop ===> Buy Hotel Drop, Baggage Allowance, Seat Upgrade, Automated Check in, Insurance /Visa	0.935	1.254	0.01	12.032
33	User Category- Group Time of Fly - Night ===> Buy Hotel Drop, Baggage Allowance, Seat Upgrade, Automated Check in, Insurance /Visa	0.984	1.002	0.01	10.016
34	User Category- Group Price Category-(12) Trip Break-Multi Stop ===> Buy Hotel Drop, Baggage allowance, Seat Upgrade, Automated Check Insurance/Visa Maximum Margin - $220	0.871	1.003	0.02	10.031
35	Time of Fly - Night User Category- Group Trip Break - Multi stop ===> Buy Hotel Drop, Baggage Allowances, Seat Upgrade, Automated Check in	0.994	1.256	0.01	12.050
36	Time of Fly - Morning Travel Search Category - Travel in 30 days ===> Buy Hotel Drop, Automated Check in	0.795	1.003	0.01	10.028
37	User Category-Group Price Category- $300-$400 Passenger Category- (10)===> Buy Hotel Drop, Baggage Allowance, Automated Check in	0.994	1.003	0.03	10.031
38	User Category-Group Time to Fly-Evening Price Category - below $200 ===> Buy Hotel Drop, Baggage Allowance, Seat Upgrade	0.769	1.003	0.02	10.031
39	Buy Hotel Drop Passenger Category – (14) Price Category- above $500===> Buy Inflight Meal, Travel Guide	0.91	1.256	0.01	12.050
40	Trip Span- return in 10 Days Passenger Category – (12) Price Category - $400-$500 ===> Buy Baggage Allowance, Insurance/Visa Hotel Drop	0.928	1.003	0.01	10.028
41	User Category- Group Travel Search Category - After 6 Months ===> Buy Last Minute Itenary Change, Seat Upgrade, Travel Guide	0.906	1.003	0.01	10.028
42	User Category - Group Passenger Category (20) ===> Maximum Margin-$500	0.812	1.256	0.01	12.046
43	User Category-Group Travel Search Category- within 1–3 months, Type- Round Trip Passenger Category- 10===> Buy Baggage Allowance, Automated Check in and Travel Guide.	0.826	1.003	0.01	10.028

Table 5 Comparative analysis of predicted ancillary offers and association rules

Scenario	Model prediction	Association rules	Match/Rule no.
Origin-CAE, Destination-FLL, Trip Type-Round Trip, Travel date: within 3 months, Passenger Category-(5)	Inflight Meal, Insurance/Visa, Baggage Allowance, Hotel Drop	Inflight Meal, Insurance/Visa, Baggage Allowance	Yes/Rule 2
Origin-CAE, Destination-FLL, Trip Type-Round Trip, Travel date: within 3 months, Passenger Category-(1)	Inflight Meal, Seat Upgrade, Last minute itenary change and automated check-in.	Inflight Meal, Seat Upgrade and Automated Check in.	Yes/Rule 13
Origin-CAE, Destination-FLL, Trip Type-Round Trip, Travel date: within 3 months, Passenger Category-(2)	Inflight Meal, Insurance/Visa, Automated Check in and Hotel Drop	Inflight Meal, Insurance/Visa, Automated Check in and Hotel Drop	Yes/Rule 27
Origin-CAE, Destination-FLL, Trip Type-Round Trip, Travel date: within 3 months, Passenger Category-(10)	Baggage Allowance, Automated Check in Travel Guide and inflight-Meal	Baggage Allowance, Automated Check in and Travel Guide	Yes/Rule 43

the recommendations generated by association rules for the specified individual user scenarios.

The analysis of the results presented in Table 5 underscores the effectiveness of our proposed approach in accurately predicting personalized ancillary offers tailored to the unique preferences of individual users. In the "Match" column, we observe instances where our predictions align with the ancillary recommendations derived from association rule-based approaches. It's important to note that our analysis also reveals cases where there are differences between our predictions and the association rule-based recommendations.

4.5 Implications of rules for business development

The comparison between our predicted personalized ancillary offers and association rule-based recommendations holds significant implications for business development within the aviation industry. The alignment between our predictions and recommendations highlights the potential for a more customer-centric approach, fostering elevated customer satisfaction and loyalty. This, in turn, has the power to optimize revenue streams through increased uptake of relevant ancillary offerings. Additionally, understanding the complexities behind both aligned and divergent predictions underscores the importance of data-driven decision-making, enhancing user experience and enabling flexibility in adapting to evolving customer preferences. Overall, this analysis provides valuable insights for refining ancillary strategies, improving customer engagement, and fostering adaptable business development initiatives.

5 Conclusion and future scope

In response to the New Distribution Capability (NDC), airlines are actively looking for new revenue management (RM) models that can support segmented pricing and continuous pricing. NDC enables airlines to more accurately estimate customer valuations and adjust product offerings and pricing accordingly, aligning with the RM objective of providing the right product to the right consumer at the right price and time. The focus of RM has also shifted from merely maximizing flight ticket income to optimizing overall revenue and offer development. As ancillary revenues become increasingly important for airlines, there arises a need for new RM models to optimize ancillary pricing. With the wide range of ancillary services offered by airlines, there is an opportunity to bundle services and create unique product offerings tailored to specific passenger categories. For instance, families on vacation may show more interest in checked baggage and seat assignment services, while business travelers might prefer insurance, visa assistance, and in-flight meals.

This research effectively addresses the critical decision-support challenges faced by airlines as they adopt customer-centric retailing. We introduce the Total Offer Management System (TOMs) and its five autonomous subproblems: User persona identification, Dynamic customized offer set construction and recommendation, Prediction of the maximum margin for each bundled offer, Prediction of the optimal price for each bundled offer, and Selection of the best optimal packages for each individual user. Unlike previous research that often focused on only one or two TOMs subproblems with limited exploration of ancillary aspects, our research significantly advances the field by comprehensively integrating all five subproblems using a substantial dataset, leading to a comprehensive solution. The proposed solution exhibits appealing qualitative characteristics, as the resulting offers and pricing are customized to direct customers towards more profitable offerings and away from less profitable ones. Our approach naturally suggests relevant offers to customers, thereby reducing the presence of irrelevant offers, which can lead to lower revenue and ancillary purchase rates.

The research also demonstrates the intuitive relationships between the generated prices and the input variables of the model. It is observed that the price tends to increase with the cost of providing the service and the passenger's willingness-to-pay (WTP). Bundled offers of flights and ancillary services are priced higher than the flight alone but lower than the combined individual purchase of both services. In conclusion, this research provides valuable insights and practical solutions for airlines seeking to optimize their revenue management and offer more personalized and profitable travel experiences to their customers.

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Declarations

Competing interests The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Al-Bazi A, Üney E, Abu-Monshar A (2019) Developing an overbooking fuzzy-based mathematical optimization model for multi-leg flights. Transp Res Procedia 43:165–177

Bao L, Sun X, Chen Y, Gong D, Zhang Y (2020) Restricted boltzmann machine-driven interactive estimation of distribution algorithm for personalized search. Knowl Based Syst 200:106030

Behera G, Nain N (2022) Trade-off between memory and model-based collaborative filtering recommender system. In *Proceedings of the International Conference on Paradigms of Communication, Computing and Data Sciences: PCCDS 2021* (pp. 137–146). Springer Singapore

Belobaba P (1987) *Air travel demand and airline seat inventory management* (Doctoral dissertation, Massachusetts Institute of Technology)

Chakrabarty N, Kundu T, Dandapat S, Sarkar A, Kole DK (2019) Flight arrival delay prediction using gradient boosting classifier. In *Emerging Technologies in Data Mining and Information Security: Proceedings of IEMIS 2018, Volume 2* (pp. 651–659). Springer Singapore

Chaturvedi A, Green PE, Caroll JD (2001) K-modes clustering. J Classif 18:35–55

Chen T, He T, Benesty M, Khotilovich V, Tang Y, Cho H, Zhou T (2015) Xgboost: extreme gradient boosting. R Package Version 0 4-2 1(4):1–4

Dadoun A, Defoin-Platel M, Fiig T, Landra C, Troncy R (2021) How recommender systems can transform airline offer construction and retailing. J Revenue Pricing Manag 20:301–315

Dwivedi R, Anand A, Johri P, Banerji A, Gaur N (2020) Product Based Recommendation System on Amazon Data. *Researchgate*

Ettl M, Harsha P, Papush A, Perakis G (2020) A data-driven approach to personalized bundle pricing and recommendation. Manuf Service Oper Manage 22(3):461–480

Fiig T, Isler K, Hopperstad C, Olsen SS (2012) Forecasting and optimization of fare families. J Revenue Pricing Manag 11:322–342

Fiig T, Le Guen R, Gauchet M (2018) Dynamic pricing of airline offers. J Revenue Pricing Manag 17(6):381–393

Gallego G, Stefanescu C (2010) *Service engineering: The future of service feature design and pricing*. Working Paper

Isinkaye FO (2021) Matrix factorization in recommender systems: algorithms, applications, and peculiar challenges. IETE J Res, 1–14

Khaksar H, Sheikholeslami A (2019) Airline delay prediction by machine learning algorithms. Scientia Iranica 26(5):2689–2702

Krishnamurthy J, Krishnan Y (2021) New distribution capability (NDC) and its effects on Travel Industry in Oman. Int J Res Entrepreneurship Bus Stud 2(3):15–26

Kummara MR, Guntreddy BR, Vega IG, Tai YH (2021) Dynamic pricing of ancillaries using machine learning: one step closer to full offer optimization. J Revenue Pricing Manag 20(6):646–653

Kuo RJ, Chen JT (2020) An application of differential evolution algorithm-based restricted Boltzmann machine to recommendation systems. J Internet Technol 21(3):701–712

LeCun Y, Bengio Y, Hinton G (2015) Deep Learn Nat 521(7553):436–444

Li C, Li Y, Wang C, Dong S, Gao H, Zhao Q, Wu W (2022) The multimedia recommendation algorithm is based on probability graphical model. Multimedia Tools Appl 81(14):19035–19050

Liu Q, Van Ryzin G (2008) On the choice-based linear programming model for network revenue management. Manuf Service Oper Manage 10(2):288–310

Madireddy M, Sundararajan R, Doreswamy G, Nia MH, Mital A (2017) Constructing bundled offers for airline customers. J Revenue Pricing Manag 16(6):532–552

Mahendru M, Singh A (2023), May Airline Customer Segmentation based on Complex Behavioral Approach using K-Mode and XGBoost Algorithm. In *2023 International Conference on Disruptive Technologies (ICDT)* (pp. 685–689). IEEE

Martins GB, Papa JP, Adeli H (2020) Deep learning techniques for recommender systems based on collaborative filtering. Expert Syst, 37(6), e12647

Ødegaard F, Wilson JG (2016) Dynamic pricing of primary products and ancillary services. Eur J Oper Res 251(2):586–599

Prajna KB, Kothiyal A, Dhanush N, Kumar A (2022), October Implementation Of a Hybrid Recommendation System for Movies. In *2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon)* (pp. 1–7). IEEE

Schubert D, Sys C, Macário R (2021) Customized airlines offer management: a conceptual architecture. J Revenue Pricing Manag, 1–11

Shukla N, Kolbeinsson A, Otwell K, Marla L, Yellepeddi K (2019), July Dynamic pricing for airline ancillaries with customer context. In *Proceedings of the 25th ACM SIGKDD International Conference on knowledge discovery & data mining* (pp. 2174–2182)

Touraine S, Coles H (2018) Dynamic Ofer Creation. IATA Air Industry Retailing White Paper. https://www.iata.org/contentassets/0688c780d9ad4a4fadb461b479d64e0d/air-white-paper-dynamic-ofer-creation.pdf

Vinod B (2021) Offer management. The evolution of Yield Management in the Airline industry: origins to the last Frontier. Springer International Publishing, Cham, pp 241–269

Walczak D, Kambour E (2014) Revenue management for fare families with price-sensitive demand. J Revenue Pricing Manag 13:273–290

Wang K (2021) Ancillary Price Optimization with Thompson Sampling - Initial Tests. Presented at MIT PODS Consortium Conference, November 2021

Wang T, Pouyanfar S, Tian H, Tao Y, Alonso M, Luis S, Chen SC (2019), July A framework for airfare price prediction: a machine learning approach. In *2019 IEEE 20th international conference on information reuse and integration for data science (IRI)* (pp. 200–207). IEEE

Wang KK, Wittman MD, Fiig T (2023) Dynamic offer creation for airline ancillaries using a Markov chain choice model. J Revenue Pricing Manag 22(2):103–121

Ye P, Qian J, Chen J, Wu CH, Zhou Y, De Mars S, Zhang L (2018), July Customized regression model for airbnb dynamic pricing. In *Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining* (pp. 932–940)

Yeoman I (2014) Technical to operations: the diversity of revenue management. J Revenue Pricing Manag 13(4):271–272
Zhao G, Cui Y, Cheng S (2021) Dynamic pricing of ancillary services based on passenger choice behavior. J Air Transp Manage 94:102058