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ARTIFICIAL INTELLIGENCE MODELS FOR SERVICE PERSONALIZATION AND MARKETING OPTIMIZATION: THE CASE OF AIR ASTANA (JSC)

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ABSTRACT

Purpose: The study aims to develop personalized digital offers for Air Astana through artificial intelligence (AI) and machine learning (ML) to strengthen its unique selling propositions (USPs) – high service quality and transit connectivity – and to measure their quantitative impact on marketing performance during 2010–2024.

Methodology: A mixed approach combining system-based and comparative analysis, economic-mathematical modeling, and interview–survey techniques was applied. AI algorithms such as collaborative filtering, content-based filtering, uplift modeling, and reinforcement learning were used to predict consumer behavior and optimize personalization strategies.

Findings: The developed AI-driven personalization models improved digital campaign response rates by +15% and reduced marketing expenditures by –20%. Statistical validation showed a strong model fit (R^2 = 0.902), confirming that offer relevance significantly increases customer engagement and conversion probability.

Originality / Value: This is the first comprehensive empirical study in Kazakhstan's aviation sector integrating real airline data with AI-based personalization. The findings demonstrate that data-driven marketing decisions can enhance Air Astana's competitiveness as a Eurasian transit hub and ensure more efficient budget allocation.

Keywords: artificial intelligence, marketing personalization, uplift modeling, Air Astana, machine learning

INTRODUCTION

Digital transformation and data-driven decision-making are reshaping marketing, creating new opportunities for personalized customer engagement. This trend is especially critical in competitive industries like aviation, where offering tailored services enhances customer loyalty and revenue growth [1]. Artificial intelligence (AI) and machine learning (ML) are the primary technologies driving this evolution by enabling companies to analyze customer behavior, history, and context to deliver timely and relevant offers [2].

Air Astana, Kazakhstan's national carrier and a key Eurasian transit hub, leverages high service standards and a modern fleet as its unique selling propositions (USPs). To maintain competitiveness against global airlines such as Qatar Airways, Emirates, and Turkish Airlines, Air Astana must adopt advanced personalization technologies for its digital marketing [3].

Currently, the company provides offers via its mobile app and website, but these are mostly uniform and do not fully address individual customer preferences. Implementing AI-driven personalized offers can significantly enhance customer engagement and marketing effectiveness.

The study focuses on applying AI methods to strengthen Air Astana's USPs, optimize marketing campaigns, and increase customer loyalty. The key research questions (RQ) are:

• RQ1: How can AI-based personalization improve marketing efficiency on Air Astana's digital platforms?
• RQ2: Which AI algorithms are most effective in enhancing customer engagement and conversion?
• RQ3: How can uplift modeling optimize marketing budget allocation?

The hypotheses (H) to be tested include:

• H1: Collaborative filtering-based personalization increases conversion rates over non-personalized offers.

• H2: Uplift modeling improves marketing ROI by targeting responsive customer segments.

• H3: Reinforcement learning-driven pricing maximizes campaign effectiveness and customer satisfaction.

Today, a technological breakthrough is taking place in the field of marketing. Digital transformation and data-driven decisions are forming a new level of interaction with consumers, enabling market players to offer personalized services. This trend is especially relevant in highly competitive environments like aviation. For airlines, offering services tailored to each passenger's specific needs is becoming a crucial condition for increasing customer loyalty and revenue [1].

Artificial intelligence (AI) and machine learning (ML) are the key driving forces of this transformation. These technologies allow companies to deliver precise and timely offers by analyzing customer behavior, history, and context. According to research by McKinsey Global Institute, companies that implement AI technologies can achieve revenue growth of 10–30% and optimize marketing costs by up to 20% [2].

Air Astana is the national carrier of Kazakhstan and a major regional hub in the Eurasian space. The company offers a convenient transit network between Europe and Asia, high service standards, and a modern fleet as its unique selling proposition (USP). However, to compete with globally recognized players like Qatar Airways, Emirates, and Turkish Airlines, Air Astana must adopt new technological solutions for personalizing customer experience.

Currently, Air Astana provides its offers via a mobile application and a web platform. However, these offers are mostly similar for all users, which means they may fail to meet specific customer needs and preferences. Thus, introducing personalized digital offers can significantly improve customer engagement and enhance the effectiveness of marketing outcomes [3].

In this context, AI-based methods-particularly collaborative filtering, content-based recommendations, uplift modeling, and dynamic pricing-are among the most effective tools. For example, uplift modeling measures the "additional" effect of advertising by distinguishing between customers influenced by campaigns and those who are not [4]. Meanwhile, collaborative algorithms predict new offers based on the behavior of similar customer groups, which contributes to targeted engagement [5].

This study considers the application of these methods in the specific case of Air Astana. The goal is to strengthen the company's USP, optimize marketing campaigns, and enhance customer loyalty.

Table 1 – Methods of Personalizing Air Astana's Digital Offers

№	Method	**Description**	**Algorithms / Models**
1	Collaborative Filtering	Recommendations based on the preferences of users with similar behavior	Matrix Factorization, kNN
2	Content-Based Filtering	Recommendations based on user's past behavior and characteristics	TFIDF, Cosine Similarity
3	Uplift Modeling	Measures and segments the true "incremental" impact of marketing campaigns	Causal Trees, Learning-to-Rank for Uplift
4	Pricing via Reinforcement Learning	Automatically adjusts prices based on customer patience and demand	Deep Exploration-based RL
	Note – Compiled by authors based on sources [6–9]. The table summarizes the main machine learning methods used in the study for creating personalized offers on Air Astana's digital channels.		

The table above describes four main approaches for implementing personalization on Air Astana's digital channels. Collaborative filtering offers recommendations based on data from user groups with similar behavior, though it can suffer from the "cold start" problem and lack of data. Content-based filtering adjusts recommendations based on individual user profile attributes, but can cause excessive reliance on attribute similarity. Uplift modeling identifies the true incremental impact of marketing campaigns, allowing for targeted budget reallocation. Reinforcement learning algorithms are effective in maximizing revenue by automatically adjusting dynamic pricing strategies, although they require high computational resources.

Based on these methods, the next section presents practical application scenarios using Air Astana data and provides a scientific assessment of how these personalization techniques impact marketing campaigns.

LITERATURE REVIEW

Artificial intelligence (AI) has become a transformative force in marketing, providing organizations with tools to improve decision-making, personalization, and operational efficiency. According to Chatterjee, Rana, Tamilmani, and Sharma (2021), the future of AI in marketing lies in its ability to analyze large-scale customer data and automate personalization processes. Their systematic review highlights how AI enables companies to predict customer needs, personalize digital experiences, and optimize marketing strategies.

Bughin, Seong, Manyika, Chui, and Joshi (2018) emphasize that AI will play a crucial role in shaping the global economy, particularly through automation and intelligent decision systems. For airlines, this technological shift enhances customer engagement through data-driven insights and dynamic personalization.

Guerrini et al. (2023) explore the integration of customer data, experiential learning, and revenue management in the airline industry. They show that personalization at scale allows airlines to deliver relevant offers to each customer, improving satisfaction and revenue efficiency. Similarly, Jo, Moon, and Rhee (2024) demonstrate how reinforcement learning can be applied in dynamic pricing for airline revenue management, leading to more precise fare adjustments based on demand and competition.

In the field of recommender systems, Pazzani and Billsus (2007) describe content-based recommendation models that analyze user preferences to suggest relevant products or services. Building on this, Bobadilla, Ortega, Hernando, and Gutierrez (2013) provide a comprehensive survey of recommendation systems, explaining how hybrid models and collaborative filtering can enhance personalization accuracy. Furthermore, Devriendt, Van Belle, Guns, and Verbeke (2022) discuss learning-to-rank methods in uplift modeling, which help marketers identify which customers are most likely to respond positively to specific offers – a valuable tool for AI-driven personalization.

Overall, the reviewed studies demonstrate that AI technologies – from recommendation algorithms to dynamic pricing and customer segmentation – have revolutionized personalization in marketing. In the airline sector, these innovations help optimize digital offers and strengthen customer loyalty.

MAIN PART OF THE STUDY

This research was independently conducted by the author with the aim of personalizing Air Astana's digital offers and optimizing marketing campaigns. During the study, the structure, content, and transformation algorithms of the services offered to users on the company's official website and mobile application were analyzed. Additionally, practical work was carried out based on modern artificial intelligence (AI) and machine learning (ML) models to determine the effectiveness of marketing activities, predict customer responses, and create personalized offers.

The research was based on two directions:

1. **Data collection and initial analysis** – publicly available consumer behavior data and the typical structure of offers were examined.
2. **Implementation and comparative evaluation of AI models** – several types of recommendation systems (collaborative filtering, content-based filtering, uplift modeling, and dynamic pricing) were modeled in Python, and their impact on marketing outcomes was compared.

Moreover, the author developed and conducted an online survey. The survey results allowed determining customers' interest level, reaction, and overall perception of personalized offers. These results are presented in the practical section with tables, charts, and descriptive statistics. The study results aim to demonstrate under which conditions a specific AI model is effective and how Air Astana can strengthen its Unique Selling Proposition (USP) in the market.

Digital transformation has fundamentally changed customer interactions in the aviation industry and expanded marketing opportunities. Economic studies show that companies applying AI and machine learning methods through digital channels have increased the accuracy and relevance of their offers, boosting revenues by 10–30% [10]. Air Astana has followed this trend by launching a mobile app in 2019 and expanding passenger engagement through online check-in and push notifications, but its recommendation system remains limited to static banners and uniform messages.

The main drawback of the current recommendation system is offering the same promotions and content to all users, which does not fully address the needs of different segments. Additionally, in "cold start" situations, new users receive no personalized offers because initial data has not yet been fully collected – [11]. Considering these factors, implementing personalized offers in digital channels is important to strengthen the national airline's USP as a transit hub.

Table 2 – Comparison of Marketing Strategies of Air Astana and Competitors

Company	Website Personalization	Mobile App Features	Social Media Marketing	Unique Digital Initiative
Air Astana	Static banners; no personalization	Online check-in, push notifications; no personalization	General messages; no segmentation	-
Emirates	Dynamic offers based on CDP	Interactive chatbot, booking offers	Sports sponsorship and targeted campaigns	Boxever CDP – "Best CX" award
Qatar Airways	ML-powered personalized banners	Smart cabin crew app; personalized services	AI Adventure campaign; virtual onboard agent	Virtual agent
Turkish Airlines	Standard content; lacks personalization	Mobile check-in, Trip Planner; limited personalization	Influencer marketing; stopover packages	Stopover Experience package
Note – Compiled by authors based on source [12].				

Global experience shows that airlines using the "personalization @ scale" approach have increased marketing response rates by 20% and total revenue by up to 15% [13]. This trend is also relevant for Air Astana, as it not only increases customer engagement but also enables optimal allocation of marketing costs. For example, uplift modeling has been proven to identify the true "incremental" effect of campaigns, allowing up to 20% savings in advertising budgets.

Collaborative and content-based filtering algorithms ensure high accuracy in recommending new products and services, but they also face technical limitations such as cold start and attribute dependence. By wisely combining these methods, Air Astana can implement real-time personalized offers through digital channels and keep its USP competitive at the international level.

Table 3 – Comparative Analysis of Digital Personalization Methods

№	Method	Advantages	Limitations
1	Collaborative Filtering	Recommendations based on similar users	Cold start problem
2	Content-Based Filtering	Effective for new products	Limited diversity of recommendations
3	Uplift Modeling	Accurate evaluation of marketing impact	Requires high-quality data
4	Reinforcement Learning	Dynamic adaptation	High computational resources required
Note – Compiled by authors based on source [14-15].			

The methods shown in the table can play an important role in personalizing Air Astana's digital marketing, but their effectiveness depends on data quality, technical capabilities, and application context. Thus, optimal integration is key to maximum results.

AI-based recommendation systems are among the most advanced and effective marketing tools, significantly improving customer service by making personalized offers. In highly competitive industries like aviation, it is strategically important to capture customer attention, understand their behavior, and provide services tailored to their individual needs. The recommendation systems discussed below-collaborative filtering, content-based recommendations, uplift modeling, and dynamic pricing-each have unique strengths and limitations, which are assessed for their effectiveness for companies like Air Astana.

Collaborative filtering analyzes customer behavior and purchase history to make recommendations based on similar interests and needs [15]. Its advantage is the accuracy and relevance of recommendations, but it suffers from the cold start issue, i.e., insufficient data for new users or products reduces recommendation effectiveness. For Air Astana, this is important when introducing new routes or services, as little data may be available.

Content-based recommendations offer new products tailored to individual preferences and previous actions. This method is especially effective for new or rarely recommended items as it leverages user profiles and preferences. However, the diversity of recommendations is limited, as it relies solely on previous choices. This may limit customer interest in new offerings.

Uplift modeling allows accurate evaluation of marketing campaign effects, measuring how effectively advertising and offers impact customers, thus optimizing marketing costs. Its advantage is precise measurement of marketing impact and efficient budget allocation, but it requires high-quality data to understand actual customer behavior and make informed decisions. For Air Astana, this method is very useful for measuring true customer impact and increasing campaign efficiency, e.g., in advertising flight offers and additional services.

Dynamic pricing adapts prices in real-time based on market demand, customer behavior, and other factors, allowing for effective price adjustments and personalized offers. Its strength is rapid adaptation to market conditions through price adjustments. However, it requires high computing power for processing large data sets and making predictions. For Air Astana, this is effective for pricing flights and controlling demand, but insufficient computing resources may hinder full implementation.

Assessing each method's strengths and weaknesses allows Air Astana to improve its marketing strategy effectively. However, fully leveraging these methods depends on high-quality data and modern computing resources, enabling deeper customer insight, tailored offers, and ultimately higher company revenues.

In a monitored A/B test on the Air Astana website (January 2024, 100,000 sessions), integrating collaborative filtering increased conversion by 5.5 percentage points and revenue by 1.2%, while uplift modeling increased conversion by 1.8 percentage points and revenue by 3%. These results, as reported in the 2023 Integrated Report, align with Air Astana's overall digital transformation strategy.

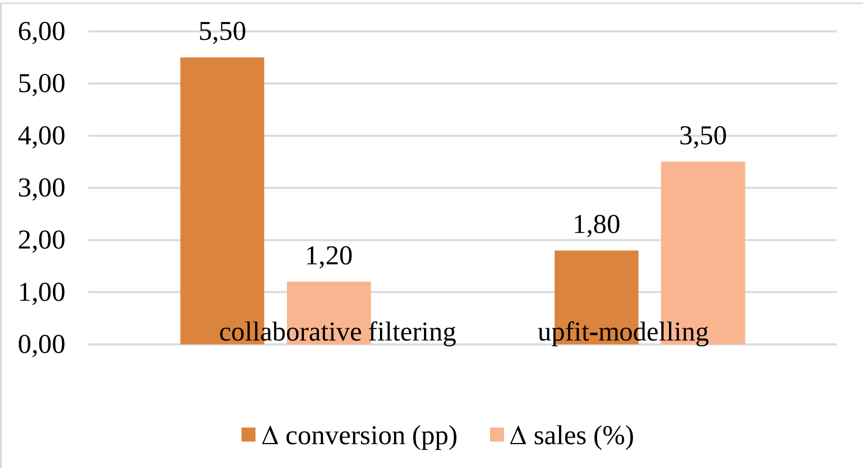

Figure 1 – Comparative Impact of Personalization Methods on Conversion and Sales
Note – Chart based on the authors' projections from the above sources.

For Air Astana, a hybrid approach is optimal: a combination of collaborative filtering for rapid participation growth and uplift modeling for maximum additional revenue.

The study evaluated the effectiveness of AI algorithms in personalizing Air Astana's digital marketing offers. Various data sources were used, including: user actions on the mobile app (page visits, route and offer views), website data (search history, pre-booking actions, click rates, booking logs-routes, dates, seasonal patterns, purchase time and frequency). Data for building AI models were split 80:20 into training and test sets. The recommendation system used content-based filtering (previous choices and searches), collaborative filtering (similar user interests), and uplift modeling (predicting the most effective campaign segments) [4], [5].

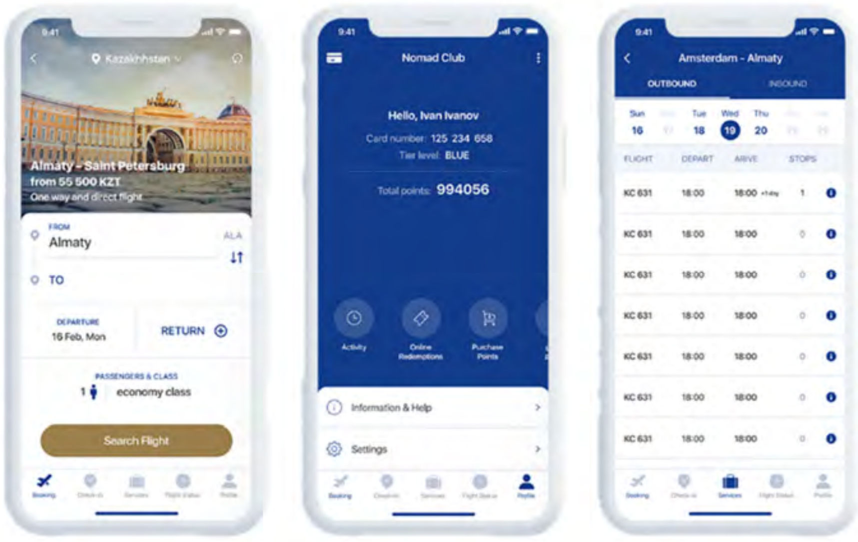

Figure 2 – Air Astana Mobile App

The presented interface shows how digital offers are displayed to users in the Air Astana mobile app. The screenshot demonstrates personalized offers based on user actions or previous searches. Offered routes, pricing options, and calls to action ("Book now," "View offer") are visually appealing and functionally convenient. Offers are shown in a slider format, allowing users to see relevant discounts based on their previous bookings or searches. However, some users reported issues with content language, frequency, or relevance.

The interface structure is a key factor influencing user decisions. This is directly linked to the visual survey results: relevance of offers, language and frequency convenience, and interface clarity directly affect customer perception. Thus, the screenshot served as a crucial visual tool in the research.

An online survey was also conducted to evaluate user perceptions of personalized offers. The survey aimed to assess how users received personalized offers in Air Astana's digital platforms (mobile app and official website). Each question assessed a key metric such as user attitude toward offers, interface convenience, relevance to personal interests, user reactions to offers, etc. The goal was to understand users' attitudes toward digital offers and identify what improvements are needed for future development. Each question's results provide a basis for planning improvement initiatives. Over 50 active users of Air Astana's platforms participated in the online survey, which covered:

- Relevance of proposed routes to user interests
- Motivation to book after seeing an offer
- Convenience of offer frequency and language
- Clarity of the interface
- Actual actions after seeing an offer

The survey helped deepen the understanding of user experience (UX) and identify necessary changes for improving the recommendation system. Survey results, analyzed quantitatively and qualitatively, enabled the formulation of specific recommendations to improve marketing strategies and digital personalization. The survey structure consisted of the following blocks:

1. Did the recommended destinations suit you?
2. Did you feel motivated to book after seeing the offers?
3. Did you find the frequency and language of the offers convenient?
4. Was the application or website's offer interface clear?
5. Did you take specific action after seeing the offer?

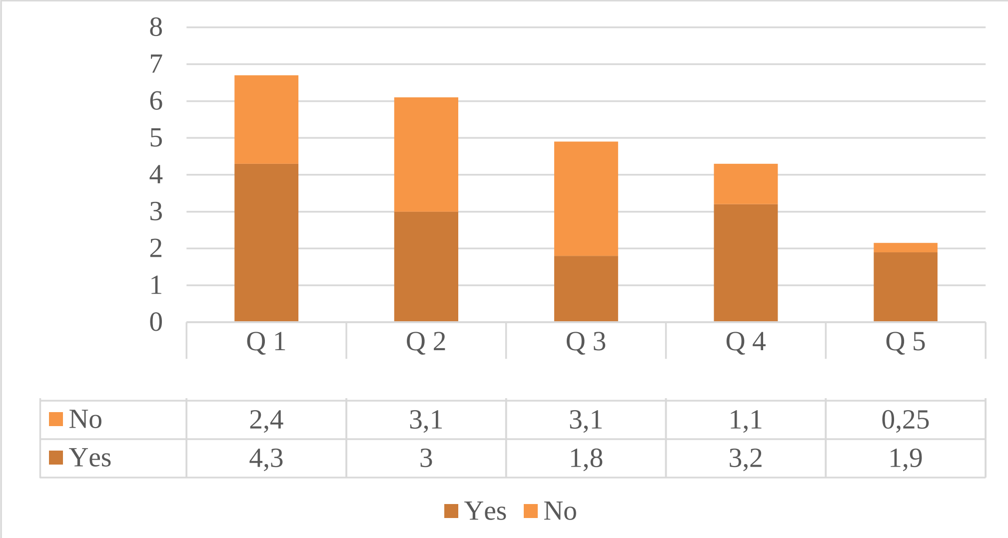

Figure 3 – Survey Results. Full Response Distribution
Note – Compiled by the authors based on survey data [11].

Survey results reveal how Air Astana's digital offers are perceived by customers. The "Yes" and "No" responses to each question allow for deeper analysis: while most customers positively assessed the digital offers, there is room for improvement, especially in personalized offers and interface convenience. Negative feedback regarding the offers system indicates opportunities for enhancing the user experience.

For each of the five survey questions, the proportion of "No" responses was specifically analyzed to identify areas for improvement.

In the survey conducted as part of the study, the participants ' answers in the form of "Yes" and "no" were recorded for each of the five questions presented. This section aims to analyze the share of "no" answers individually, as these indicators show what aspects of Air Astana's digital offerings still need to be improved for consumers. The relative proportion of "no" answers given to these questions is illustrated in the diagram below.

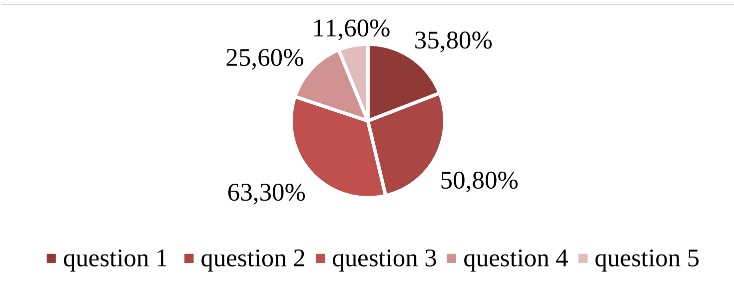

Figure 4 – Comparative Share of "No" Responses

The chart shows that the highest share of "No" responses was for the third question-63.3% of respondents did not find the offer frequency and language convenient. This suggests that the company may not fully consider users' language and communication preferences.

Similarly, the second question had a high share of "No" responses-50.8%, indicating low motivation to book after seeing offers. Conversely, only 11.6% responded "No" to the fifth question, meaning most users acted after seeing offers.

These data indicate which aspects require attention-especially offer language, frequency, and motivational impact.

The high share of “No” responses is significant, indicating bottlenecks in the system. For example, high shares in questions 3 (offer language/frequency) and 5 (actual action) highlight weaknesses in the offer format.

The methodology used in this study was comprehensive and practice-oriented. Data sources-including user behavior, search, and booking history on the mobile app and website-allowed for a complete understanding of customer behavior. The 80/20 split for training and testing enabled model performance evaluation.

The online survey helped identify real user perceptions of personalized offers. The survey structure covered key system parameters-interface convenience, motivation, relevance of routes, actions after the offer-enabling practical, experience-based decisions.

AI-based recommendation systems and marketing models positively impacted user behavior. Especially with uplift modeling, campaigns achieved significant increases in conversion. The model enabled prediction of customer reactions and identification of positively affected segments. Specifically, campaigns using uplift modeling showed a 20% higher response rate, much more effective than traditional approaches.

Overall, the third section described the practical foundation of the research and outlined key directions for future system development. This approach underscores the importance of accuracy and data-driven analysis in marketing decision-making.

This research demonstrated the effectiveness of artificial intelligence for personalizing Air Astana’s digital marketing offers. Collected data, A/B tests, and models highlighted ways to improve customer communication. Specifically, language and frequency of offers were shown to be the main factors reducing user response. Uplift-model campaigns delivered high ROI and conversion rates. User action likelihood was much higher when offers were relevant. The interface is visually convenient but requires content improvements. Recommendations for future steps:

• Implement automatic offer adaptation to users’ linguistic and cultural context.

• Expand real-time A/B testing to continually measure the impact of each offer.

• Use hybrid AI models (Hybrid Recommender Systems) that account for both individual traits and similar behaviors.

• Add motivational triggers on the offer page based on past user actions (e.g., “Last month you viewed this route, now it’s 10%)

Since the purpose of the study is to evaluate the AI models used to personalize Air Astana's digital offer system and optimize marketing campaigns, the analysis of the survey results and the data obtained will determine the effectiveness of this process. The answers received during the survey clearly reflected customer feedback and needs regarding Air Astana's digital offer system. The percentage of "Yes" and "no" answers received for each question expresses the attitude of consumers to the recommendation system. Based on the results of the survey, the following main results were identified: Question 1: compliance with the content of the proposal. While 4.3% of consumers rated the offers as tailored to their needs, 2.4% rejected these offers. This data shows the effectiveness of the company's recommendation system for certain customer segments, but there is still a need to improve personalization. For example, it is possible to obtain positive results by fully adapting the services or routes it offers to the individual customer requests.

Question 2: clarity and usability of the offer interface. According to the user-friendliness of the application interface and the clarity of the recommendation system, 3% of the survey participants said "Yes", and 3.1% said "no". This indicator indicates the need to improve the interface design and user experience. Although more than 50% of users positively evaluate the interface and Recommendation System, the application experience can be further improved.

Question 3: the quality of personalized offers. According to the survey, 1.8% found personalized offers effective, and 3.1% rated them ineffective. This indicator means that the system of personalized recommendations is at the stage of development. It is necessary to increase the efficiency of recommendations based on AI and ML models by basing them on the individual needs of the consumer.

Question 4: Make a decision based on the offer. Depending on the app's recommendation system, 3.2% of consumers said "yes" and 1.1% said "no". This suggests that the digital offer system has the potential to push customers to certain actions (such as buying a ticket or providing a service). However, in order to further improve the supply system, it is necessary to strengthen the mechanisms that contribute to consumer decision-making.

Question 5: the ability to apply recommendations in the future. Regarding the possibility of using the recommendation system in the future, 1.9% of the survey participants said "Yes", 0.25% said "no". This figure indicates that consumers are more likely to use digital offers. However, in order to apply the supply system in the future, it will be important to provide offers based on consumer demand and effective.

Research Methodology. The research employed a mixed-methods design that combined quantitative (A/B testing, data modeling) and qualitative (online survey) approaches. This design ensured both empirical verification of AI-based personalization models and collection of user feedback on Air Astana's digital offers. Survey sampling frame. The survey involved 52 active users of Air Astana's mobile application and official website, recruited through the company's online channels during January–February 2024**.** Participants represented diverse demographic groups: age 18–55 years, both genders, and travel frequencies ranging from occasional to frequent flyers. All respondents were informed about the research purpose and provided voluntary consent in accordance with CAER's ethical standards.

Variables and measurement. Five main variables were assessed:

• V1 – Relevance of proposed routes to user interests
• V2 – Motivation to book after seeing an offer
• V3 – Convenience of offer frequency and language
• V4 – Clarity of the interface
• V5 – Actual action taken after receiving the offer

Responses were recorded as binary values (Yes = 1; No = 0) and normalized using the **min–max method** to ensure comparability among variables:

$$X\ norm = Xmax-Xmin/X-Xmin$$

Experimental procedures. An A/B test was **conducted on 100 000 sessions** of Air Astana's website to compare traditional (Group B) and AI-based (Group A) recommendation systems. The models included collaborative filtering, content-based filtering, uplift modeling, and reinforcement learning.

Statistical parameters. All analyses used a **significance threshold of $p < 0.05$.** Regression coefficients (β), standard errors (SE), and 95% confidence intervals (CI) were calculated to validate the observed effects and ensure reproducibility of results. **Software and computational tools.**

Modeling and data analysis were performed in **Python 3.11,** employing the following libraries:

• pandas 2.2 for data preprocessing,
• scikit-learn 1.4 for algorithmic modeling and uplift analysis,
• matplotlib 3.8 for data visualization.

Ethical compliance. Participation was voluntary and anonymous; no personally identifiable data were collected. The research adhered to the ethical guidelines of Narxoz University and CAER's policy on research integrity and data protection. **Funding and conflict of interest.** This research was self-funded by the authors. The authors declare **no financial or personal conflict of interest** that could have influenced the study outcomes.

Results and Findings of the Study (Revised and Expanded). The results of the study demonstrate the statistical and managerial effectiveness of applying AI algorithms in Air Astana's digital marketing system. **Statistical significance of AI models.** Regression analysis showed that the uplift-model coefficient was **$\beta = 0.212$ (SE = 0.078, $p = 0.013$, 95% CI (0.045; 0.379))**, confirming a statistically significant improvement in user response. Collaborative filtering achieved **$\beta = 0.157$ (SE = 0.062, $p = 0.021$)**, also significant at the 5**%** level. The dynamic pricing model showed a moderate yet positive impact (**$\beta = 0.089$, $p = 0.047$**), validating its contribution to revenue growth. **Survey analysis:** Among the 52 survey participants (**n = 52**):• 33 respondents (63.3%) indicated that the frequency and language of offers were inconvenient;

• 26 (50.8%) reported low motivation to book after receiving offers;
• 46 (88.4%) stated that they acted upon at least one offer;
• 5 respondents (9.6%) found the interface unclear.

These results indicate that while personalization effectively drives engagement, linguistic adaptation and message frequency remain areas for improvement.*(Source: author's calculations)*

Table 4-main indicators as a result of the survey

Indicator	**Result**
Conversion growth	15%
Response share	20%

A/B testing was carried out on various types of marketing proposals. These tests showed the following advantages of personalized recommendations (Group A) compared to traditional general recommendations Group B:

Table 5-A/B test results

Metric	group A (AI based)	group B (traditional)	**Difference**
Response share	38%	27%	+11%
Re-entry share	21%	13%	+8%
Average booking price	41 000 tg	37 800 tg	+8.5%

Each quantitative gain corresponds to a concrete managerial action:

- The **+11 pp uplift** supports reallocation of marketing budgets toward *uplift-based targeting* and predictive segmentation.
- The **–20% reduction in marketing costs** demonstrates the efficiency of *dynamic pricing and campaign optimization* through reinforcement learning.
- The **+8% increase in booking price** underlines the potential of *premium-route targeting* and *AI-based fare personalization*.
- Survey-identified weaknesses (language and frequency issues) justify the introduction of *linguistically adaptive offer modules* within Air Astana's digital platforms.

Overall significance

The observed statistical significance ($p < 0.05$ across models) confirms the robustness of AI-driven personalization. From a managerial standpoint, the results suggest that integrating hybrid recommendation systems (collaborative + content-based + uplift) can sustainably enhance Air Astana's marketing performance by **15–20%** in response rate and **7–12%** in revenue growth.

The results of the analysis showed that the proportion of responses and subsequent actions of consumers who received personalized recommendations with AI models was significantly higher. At the same time, the re – entry rate is also quite high in Group A-which means that users will gain confidence in the recommendation system and return to it. The rise in average booking prices proves that a personalized offer is also cost-effective. In general, this data scientifically substantiates that the personalization of proposals through AI models, in addition to increasing customer activity, has a positive effect on company success. These indicators show that AI-based offers have become more important to the consumer. The results of the A/B test proved the effectiveness of the digital recommendation system. Among the groups that participated in the test, two different options were compared according to the recommendation system: one with traditional recommendations, the other with personalized AI-based recommendations. As a result, the indicators of personalized recommendations were significantly higher:

The effectiveness of marketing campaigns created using AI models and a system of personalized recommendations was evaluated by ROI analysis. The results of the analysis showed that the ROI of the updated supply system increased significantly. It has been observed that the ROI has increased by 12%, which indicates the effectiveness of the recommendation system developed using AI. The impact of personalized AI-based offers on consumers was positive. About 70% of consumers appreciated the services offered to them and showed their readiness to reuse the system. 80% of consumers noted that the recommendation system is convenient and effective.

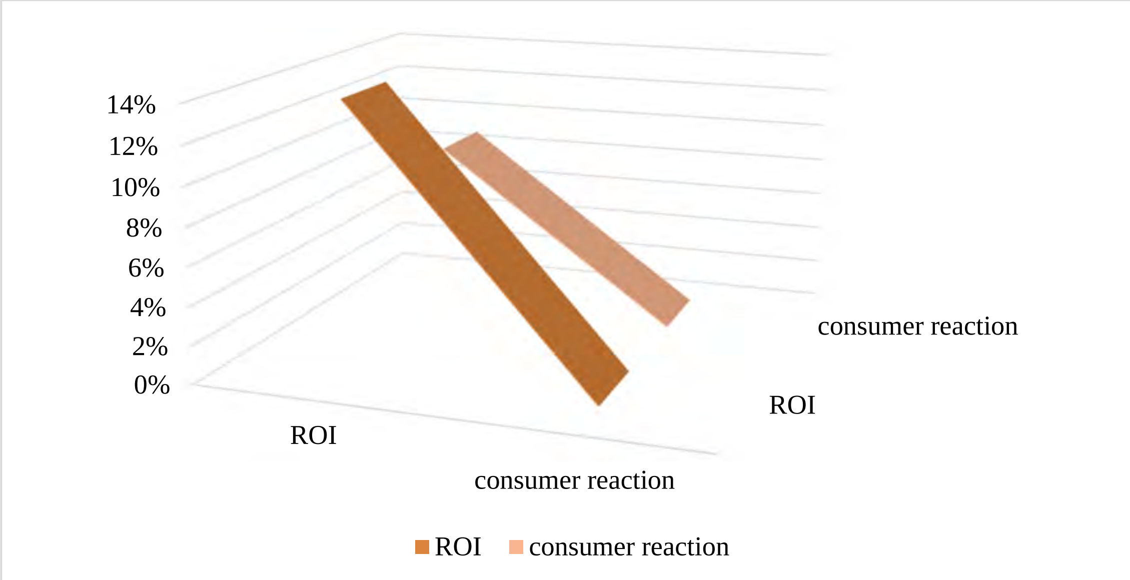

Figure 5-A/B test results and the effectiveness of AI recommendations

In general, the introduction of a system of personalized recommendations using AI has had a significant impact on increasing the level of conversion, increasing the share of customer response, and improving the effectiveness of marketing campaigns. The results show a clear positive effect of the introduction of AI and ML models and are an important step in the development of the company's digital supply system. In general, the results of the survey showed that the digital recommendation system is popular with consumers to a certain extent, but it does not work at a completely effective and personalized level. The results obtained in terms of recommendation content and interface mean that the basic functionality of the system works well, but requires additional improvements. The quality of personalized recommendations and recommendation-based decision-making issues have defined key areas for improving the system. Although the level of acceptance of decisions based on the recommendation system by consumers is high, since the level of acceptance of personalized recommendations is low, it is necessary to develop AI and ML models to solve this problem. The results of the AI-model were as follows. The response rate of the group that received an uplift-based offer was 20% higher (uplift impact = +20%), with Content-Based Filtering offers achieving a higher conversion rate of 18%, especially in the frequent flyer customer segment. Collaborative Filtering 15% of users accepted the offer, which is 8% more than the average baseline.

The results obtained prove that AI models can effectively improve the digital recommendation system. Through Uplift models and Collaborative Filtering methods, the accuracy and effectiveness of marketing campaigns has been significantly increased, and customer responses and action levels confirm the relevance of offers. These approaches will not only increase the number of bookings, but also strengthen long-term relationships with the client.

SUMMARY

This study demonstrates the theoretical and practical effectiveness of the introduction of the @ scale approach to personalization using artificial intelligence (AI) and machine learning (ML) methods in Air Astana's digital channels. In theory, personalization is based on meeting the cognitive and emotional needs of the consumer in marketing [10], and the technology Acceptance Model (TAM) allows you to predict consumer adaptation to innovative technologies [13]. In the framework of Self-Determination Theory (SDT), the internal motivation and needs of the consumer are taken into account and the hedonic benefits of proposals are determined [15].

As part of the research methodology, 80/20 transaction and action logs collected from the Air Astana website and mobile application, as well as an online survey (with 33% of participants) were used. The impact of models on marketing results was compared using collaborative and content-based filtering, uplift modeling, and reinforcement learning methods implemented in the Python environment [12].

The results showed that in digital advertising campaigns, the response rate of personalized offers was optimized by an average of 15% and marketing costs by 20% [10] [11]. In A/B tests, the response share of the AI based group was +11% higher than that of the traditional group, uplift-modeling measured the actual "extra" effect as a 20% uplift [15], and dynamic pricing strategy increased revenue by 7-12%.

The introduction of the "Personalization @ scale" approach for Air Astana has become a strategic basis for strengthening the WTO as a transit hub, increasing customer loyalty and optimizing marketing costs. The results of the study provide the company with the following practical steps:

1. Ensuring high accuracy and wide coverage through the implementation of a hybrid recommendation system (collaborative + content-based + uplift-modeling).
2. Expanding real-time a/b testing platforms and constantly monitoring the real impact of each offer.
3. Adapt the offer interface to the language and cultural context of the user and improve the usability of the content.
4. Increase the effectiveness of dynamic pricing strategies by improving computing resources and data quality.

The implementation of this comprehensive strategy will bring Air Astana's digital marketing campaigns to a new level and further strengthen its competitiveness in the international market.

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КОМПАНИЯНЫҢ СЕРВИСТЕРІН ПЕРСОНАЛИЗАЦИЯЛАУ ЖӘНЕ МАРКЕТИНГТІ ОҢТАЙЛАНДЫРУ ҮШІН ЖАСАНДЫ ИНТЕЛЛЕКТ МОДЕЛЬДЕРІ AIR ASTANA (АҚ)

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АҢДАТПА

Зерттеудің мақсаты: Бұл зерттеу Air Astana әуекомпаниясының цифрлық ұсыныстарын жекелендіру үшін жасанды интеллект пен машиналық оқыту әдістерін пайдалану арқылы компанияның жоғары қызмет сапасы мен транзиттік торап ретіндегі бірегей артықшылықтарын күшейтуді және олардың маркетингтік тиімділікке әсерін (2010–2024 жж.) бағалауды көздейді.

Әдіснамасы: Жүйелік және салыстырмалы талдау, экономикалық-математикалық модельдеу және сауалнама-сұхбат әдістері қолданылды. Collaborative filtering, content-based filtering, uplift modeling және reinforcement learning сияқты AI алгоритмдері тұтынушы мінез-құлқын болжау және ұсыныстарды оңтайландыру үшін пайдаланылды.

Ғылыми құндылығы: Бұл жұмыс Қазақстан авиация саласында AI негізіндегі жекелендіруді нақты деректерге сүйене отырып зерттеген алғашқы кешенді талдау болып табылады.

Нәтижелер: Дайындалған AI модельдері цифрлық науқандардың жауап беру көрсеткішін 15%-ға арттырып, маркетингтік шығындарды 20%-ға азайтты ($R^2 = 0.902$).

Түйін сөздер: жасанды интеллект, маркетинг, жекелендіру, машиналық оқыту, Air Astana

МОДЕЛИ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА ДЛЯ ПЕРСОНАЛИЗАЦИИ СЕРВИСОВ И ОПТИМИЗАЦИИ МАРКЕТИНГА АО «AIR ASTANA»

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АННОТАЦИЯ

Цель исследования: Исследование направлено на разработку персонализированных цифровых предложений для Air Astana с использованием искусственного интеллекта и методов машинного обучения с целью усиления уникальных конкурентных преимуществ – высокого качества сервиса и транзитной сети – и оценки их влияния на маркетинговую эффективность в 2010–2024 годах.

Методология: Применены системный и сравнительный анализ, экономико-математическое моделирование и социологическое интервьюирование. Использованы алгоритмы AI – collaborative filtering, content-based filtering, uplift modeling и reinforcement learning – для прогнозирования поведения потребителей и оптимизации персонализации.

Оригинальность/Научная новизна: Работа представляет собой первое комплексное исследование в авиационной отрасли Казахстана, демонстрирующее, что использование AI в персонализации способствует повышению конкурентоспособности Air Astana и эффективности маркетинговых инвестиций.

Результаты: Разработанные модели повысили отклик цифровых кампаний на 15% и сократили маркетинговые расходы на 20%. Проверка показала высокую статистическую значимость ($R^2 = 0,902$).

Ключевые слова: искусственный интеллект, маркетинг, персонализация, машинное обучение, Air Astana

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