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Driving Service Innovation through AI Chatbot Adoption in Aviation

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Tanikan Pipitwanichakarn[1*]

Abstract

The AI chatbot, a cutting-edge technology powered by artificial intelligence, is transforming the aviation industry. Understanding what drives consumers to adopt chatbots is essential to realize their potential benefits, including boosting revenue and increasing customer lifetime value. Moreover, chatbot adoption has practical implications for marketing strategies tailored to distinct user segments. This study aims to develop an effective model for forecasting AI chatbot adoption. To achieve this, several machine learning techniques were evaluated, with the Random Forest algorithm demonstrating the highest predictive performance and thus selected as the final model. The findings reveal that perceived personalization, perceived usefulness, and perceived ease of use are key predictors of adoption. By examining consumers' decision-making routes toward AI chatbot adoption in aviation, this study increases the granularity of our understanding of the customer journey—a journey that culminates in ticket purchases and enhanced overall satisfaction, which in turn foster greater engagement. These insights can help aviation businesses design marketing strategies that emphasize personalization, thereby encouraging stronger user engagement across their websites.

Keywords: technology acceptance model, machine learning, artificial intelligence, chatbot, aviation

Introduction

In the two decades prior to 2010, the expansion of online business transformed the global landscape, driving rapid advances in digital integration and enabling seamless interactions between businesses and customers. Following this transformation, and particularly since 2022, generative artificial intelligence (AI) has emerged as a key driver of innovation, with applications already embedded in the aviation socio-technical ecosystem and expected to expand further (Ziakkas & Pechlivanis, 2023). One such application, the chatbot, has become increasingly important in airline customer service. Designed to simulate human conversation through text or voice, chatbots enable passengers to interact naturally with digital systems and are widely used for customer service, information retrieval, and transaction processing (Ozuem et al., 2025). They also support pre-flight assistance, handle inquiries, and facilitate bookings, ultimately enhancing the customer journey (Garcia et al., 2024).

Chatbots have also become central tools for airlines as they navigate intense industry competition and rising customer expectations. Despite the absence of physical stores, the airline industry remains highly competitive, and airlines increasingly rely on machine learning and AI chatbots across the customer journey (Mishra et al., 2025). From flight search and fare comparison to booking, chatbots provide tailored solutions, such as dynamic pricing. Meanwhile, their post-purchase functions—including product bundling, customer lifetime value prediction, and customer segmentation—strengthen airlines' competitiveness and operational efficiency (Teichert et al., 2008). These advantages translate into measurable business outcomes for airlines, particularly in reducing costs, enhancing customer satisfaction, and driving marketing impact.

[1] Head of Digital Business and Innovation, UTCC Business School, University of the Thai Chamber of Commerce

Research Objective

Against this backdrop, the present study pursues three main objectives. First, to better understand AI chatbot adoption, it extends the Technology Acceptance Model (TAM) by incorporating additional constructs relevant to chatbot adoption, including trust, perceived personalization, and social influence. Second, it develops a consumer decision model for forecasting AI chatbot adoption, with a particular focus on consumers' use of chatbots for information search and personalized ticket assistance. Third, it enhances the predictive power of this model by systematically refining the model's parameters and validating the refined model on a dedicated testing dataset. This approach enables a rigorous assessment of the model's performance and ensures that the final model can accurately forecast AI chatbot adoption in real-world applications.

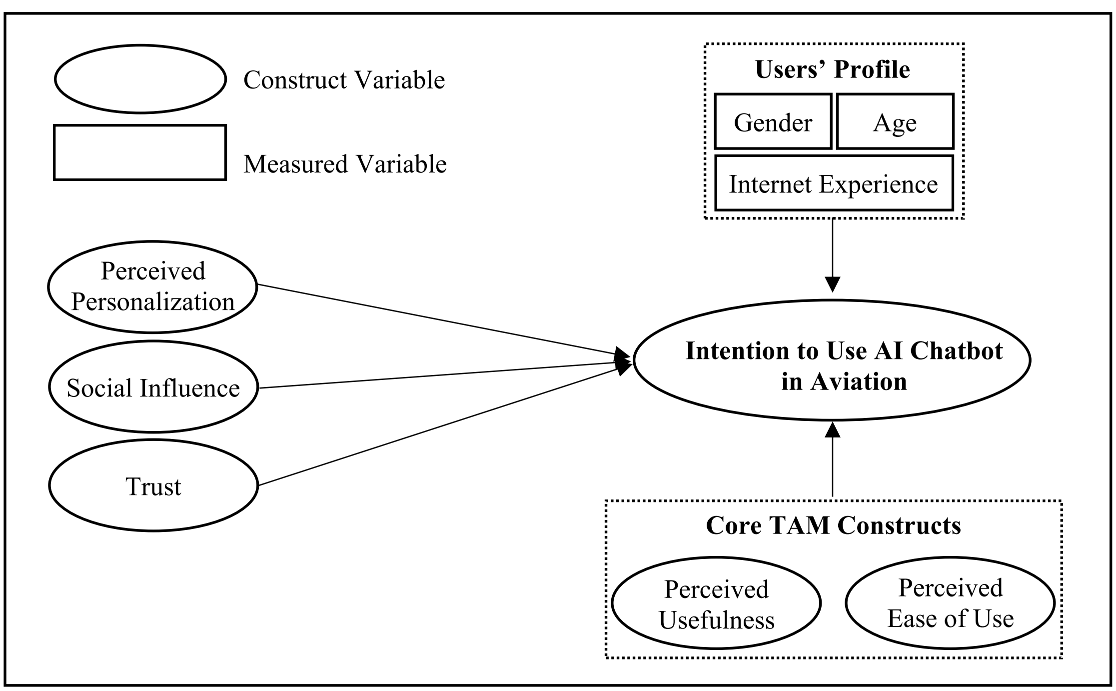
The remainder of the article is structured as follows. The next section reviews TAM and the factors relevant to consumer adoption of AI chatbots. Thereafter, the article presents research methodology. Finally, the article discusses the results, contributions, limitations, and directions for future research.

Literature Review

The Technology Acceptance Model (TAM) is one of the most respected frameworks for explaining user adoption of new technologies. It consists of two key technological characteristics: perceived usefulness and perceived ease of use (Davis et al., 1989). Perceived usefulness is defined as the degree to which a user believes that adopting a technology will improve their job performance, while perceived ease of use refers to the extent to which a user believes that adopting a technology will be effortless.

Research in hospitality and tourism confirms that the technological characteristics of AI-based chatbots—such as information quality and interaction quality—shape customers' adoption intentions (Pillai & Sivathanu, 2020). Specifically, system-related qualities like information quality strengthen perceived usefulness, while interaction quality enhances perceived ease of use (Khrouf et al., 2025). In the context of aviation, perceived usefulness has been shown to significantly influence passengers' behavioral intention to use chatbots (Alotaibi & Hidayat-ur-Rehman, 2025; Hidayat-ur-Rehman, 2025). However, the original TAM focuses largely on users' cognitive evaluations and does not fully account for socio-emotional, experiential, or interpersonal factors that play a crucial role in AI-driven conversational interactions. AI chatbots operate as interactive agents rather than static information systems. In other words, additional determinants—such as users' trust, personalization experiences, and social influences—are essential to explaining acceptance but fall outside TAM's core constructs. Therefore, extending the model is necessary to align TAM with the nature of AI-based conversational technologies. To address these theoretical gaps and build a more comprehensive framework, this study incorporates additional constructs—including trust (Pavlou, 2003), perceived personalization (Niu, et al., 2025), and social influence (Venkatesh et al., 2003)—into the AI chatbot adoption model.

Figure 1. Research Framework for Describing AI Chatbot Adoption



Trust

Trust is a critical element in technology acceptance and is essential when sensitive personal information is shared online, as it reduces uncertainty and assures users that service providers will not engage in undesirable behaviors (Pavlou, 2003). As such, trust has been strongly linked to chatbot usage intention and user experience (Miraz et al., 2024). Users' faith in a chatbot's ability to communicate information accurately and effectively is largely shaped by the efficacy of communication; thus, when interactions are clear, customers are more willing to use AI chatbots. Moreover, familiarity with generative AI further enhances perceived trust in AI-assisted travel planning, which subsequently increases intention to use (Topsakal, 2025). Notably, prior research highlights an interesting paradox in chatbot interactions. Both technology anxiety and the need for human interaction significantly increase perceived "creepiness" of chatbots. However, perceived creepiness can have a positive effect on customer satisfaction, which in turn mediates the relationship between perceived creepiness and customer loyalty (Lacap et al., 2025).

Perceived Personalization

Personalization has been widely studied across fields such as psychology, information systems, and marketing. It refers to the process of changing the functionality, interface, information access, content, or distinctiveness of a technology to increase its personal relevance for an individual or group of individuals (Fan & Poole, 2003). Perceived personalization provides several benefits: it makes technology easier to use, more understandable, and more natural, while reducing the time and effort required to search for information (Garcia et al., 2024). Even if consumers react negatively to personalized advertising, perceived personalization is associated with reduced advertising avoidance (Nyheim et al., 2015). Advances in automation technologies like AI have further expanded personalization opportunities by enabling large-scale data collection and pattern recognition for improved matching. In the context of chatbot use, personalization is positively associated with customers' continuance intention (Zhang, 2023). In addition, anthropomorphic chatbots enhance perceived product personalization and increase willingness to pay, particularly among lonely consumers (Sidlauskiene, et al., 2023).

Social Influence

Social influence theory has been described as a core determinant of human behavior, persuasion, and digital transformation. Social influence refers to the extent to which an individual's thoughts, feelings, attitudes, or behaviors result from interaction with another person or a group (Rashotte, 2007). In adoption technology, it reflects the degree to which individuals perceive that important others believe they should use a new system, with this perception influencing their adoption decision (Venkatesh et al., 2003). Social influence has been demonstrated to significantly shape positive brand attitudes and increase purchase intention (Kbaier, et al., 2025).

Research Methodology

Population and Sample

The target population consisted of Thai travelers who had prior experience in air travel, had previously booked airline tickets online, had taken flights, and acted as decision-makers in the use of technology. The survey was distributed through travel-related social media platforms to reach potential respondents who met these criteria.

After the data cleaning process, which involved the removal of two incomplete responses, a total of 248 valid questionnaires were retained for analysis. The sample reflected an equal gender distribution, with participants aged between 21 and 36 years ($M = 27.97$, $SD = 2.51$). On average, respondents reported 10.4 years of internet use. Following the descriptive analysis of participant characteristics, the next step involved preparing the target variable for classification. The split was determined based on the median value of the intention rating scale (Overall, I intend to use the AI chatbot'). Participants who scored above the median were classified as high-intention, and those who scored below it were classified as low-intention. The dataset was then categorized into two class labels—high-intention (56.9%) and low-intention (43.1%)—reflecting a reasonably balanced distribution suitable for machine-learning classification. The descriptive distribution of respondents is presented in Table 1.

Table 1: The Descriptive Distribution of Respondents

Gender	**Frequency**	**Percentage**
Male	124	50.0
Female	124	50.0
Age (year)		
21-25	82	33.1
26-30	85	34.3
31-36	81	32.6
Intention to Use AI Chatbot		
High-Intention Group	141	56.9
Low-Intention Group	107	43.1

The measurement model consisted of 15 indicators across five constructs (Perceived Usefulness, Perceived Ease of Use, Trust, Perceived Personalization, and Social Influence), along with three control variables—gender, age, and internet experience. Following the sample-size guideline proposed by Hair et al. (2019), which recommends approximately 5–10 respondents per observed variable, the minimum required sample size ranges from 90 to 180 cases based on 18 observed variables. With 248 valid responses retained for analysis, the sample size exceeds the conservative upper bound of this recommendation and is therefore considered sufficient for reliable machine learning analysis.

Research Tools

The data collection instrument used in this study was a web-based questionnaire developed and administered through Google Forms. This platform was selected for its accessibility and ability to facilitate efficient online data collection from participants across different locations.

Research Tools Development

To ensure that respondents had a clear understanding of the study's context, the questionnaire began with an introduction to AI chatbots in aviation. These chatbots were described as automated virtual assistants that support services such as flight bookings, customer support, check-in assistance, baggage tracking, and real-time flight status updates. By leveraging AI technology, these systems provide personalized services, thereby enhancing operational efficiency and improving passenger experience.

The study focused specifically on the process of purchasing airline tickets, from searching for flights to completing transactions, as this phase represents a critical stage in customer decision-making and a primary source of airline revenue. The questionnaire items were designed within this context to capture travelers' attitudes and behavioral intentions toward AI chatbot adoption.

Statistical Techniques

To develop an AI chatbot adoption model, Python 3.13.7 was used as the primary analytical tool. The data analysis followed five main phases: Data partitioning, Modeling, Evaluation, Cross-validation, and Result interpretation. The dataset of 248 valid cases was partitioned into training and testing sets, with 80% (198 responses) used for training the model and 20% (50 responses) reserved for testing. In the modeling phase, eight machine learning algorithms were employed to construct predictive models: logistic regression, decision tree, multilayer perceptron, K-nearest neighbors (KNN), random forest, eXtreme gradient boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and gradient boosting. Using multiple algorithms enabled a comparative assessment of predictive performance. Model evaluation was primarily based on the area under the ROC curve (AUC), supplemented by additional metrics including F1-score, accuracy, precision, and recall. To ensure the reliability and generalizability of the models, five-fold cross-validation was conducted on the training dataset before final model evaluation, and ROC (Receiver Operating Characteristic) curve analysis was performed to assess the discriminative capability of the final selected model.

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Results and Discussion

An initial predictive model was developed using eight algorithms: logistic regression, decision tree, multilayer perceptron, K-nearest neighbors (KNN), random forest, eXtreme gradient boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and gradient boosting. Among these, the random forest model achieved the highest AUC (area under the ROC curve) on the testing dataset, with a value of 0.941 (Table 2).

Subsequently, five-fold cross-validation was conducted on the training dataset, producing five testing rounds. The random forest model achieved an average AUC of 0.856 across these rounds. To further improve performance, parameter tuning was performed to identify the optimal configuration. The parameters considered included the number of estimators (10, 20, 30, 40, 50, 60, 70, 100), maximum depth (3, 5, 7, 9), minimum samples split (2, 3, 4, 5), and minimum samples leaf (1, 2, 3, 4, 5).

Next, GridSearchCV was employed to systematically evaluate all possible parameter combinations, resulting in 640 distinct configurations ($8 \times 4 \times 4 \times 5$). The optimal configuration was determined to be 30 estimators, a maximum depth of 7, a minimum samples split of 2, and a minimum samples leaf of 3. This model achieved an average cross-validation AUC of 0.886. Consequently, the optimized random forest was selected as the final model, demonstrating an AUC of 0.986 on the training data and 0.949 on the testing data (Table 3).

Table 2: Results of Initial Model Comparison for AI Chatbot Adoption Prediction

Algorithm	AUC	F1-Score	Accuracy	Precision	Recall
Random Forest	0.941	0.860	0.870	0.851	0.875
Logistic Regression	0.934	0.823	0.833	0.816	0.847
Gradient Boosting	0.934	0.860	0.870	0.851	0.875
LightGBM	0.932	0.841	0.852	0.832	0.861
XGBoost	0.924	0.823	0.833	0.816	0.847
Multilayer Perceptron	0.889	0.742	0.778	0.752	0.736
Decision Tree	0.750	0.727	0.741	0.725	0.750
K-Nearest Neighbors	0.746	0.661	0.722	0.686	0.653

Table 3: Results of Final Model for AI Chatbot Adoption Prediction

Algorithm	AUC	F1-Score	Accuracy	Precision	Recall
Random Forest	0.949	0.944	0.926	0.944	0.944

To further assess how well the model distinguishes between the two classes, ROC curves were generated for both the training and testing datasets using the predicted probabilities. The ROC (Figure 2) curve illustrates the trade-off between the true positive rate and false positive rate across different thresholds, with curves closer to the upper-left corner indicating stronger discriminative performance. Consistent with the AUC values of 0.986 for the training data and 0.949 for the testing data, both ROC curves showed a strong upward trend, visually confirming that the optimized model demonstrates high predictive accuracy with minimal overfitting.

The feature importance analysis, conducted using the random forest model with its optimal configuration on the training dataset, identified perceived personalization, perceived usefulness, perceived ease of use, trust in service provider, and social influence as the most important features. The values of all features related to chatbot acceptance are presented in Figure 3.

The rationale for perceived personalization becoming more important than perceived usefulness and perceived ease of use is that it offers emotional, psychological, and relational value beyond basic functionality. In contexts where users expect conversational intelligence, this added value strengthens emotional connection and increases engagement. These findings extend the TAM framework by suggesting that personalization functions as an additional determinant of user engagement, highlighting the need for practitioners to incorporate adaptive and personalized interaction strategies to foster long-term adoption and continued use. Furthermore, trust in the service provider and social influence play an important role in shaping chatbot acceptance. Within a collectivist cultural context such as Thailand, users place considerable weight on opinions and recommendations from peers, which further amplifies their intention to adopt and engage with personalized chatbot services.

Figure 2. Receiver Operating Characteristic Curves for the Optimized Random Forest Model

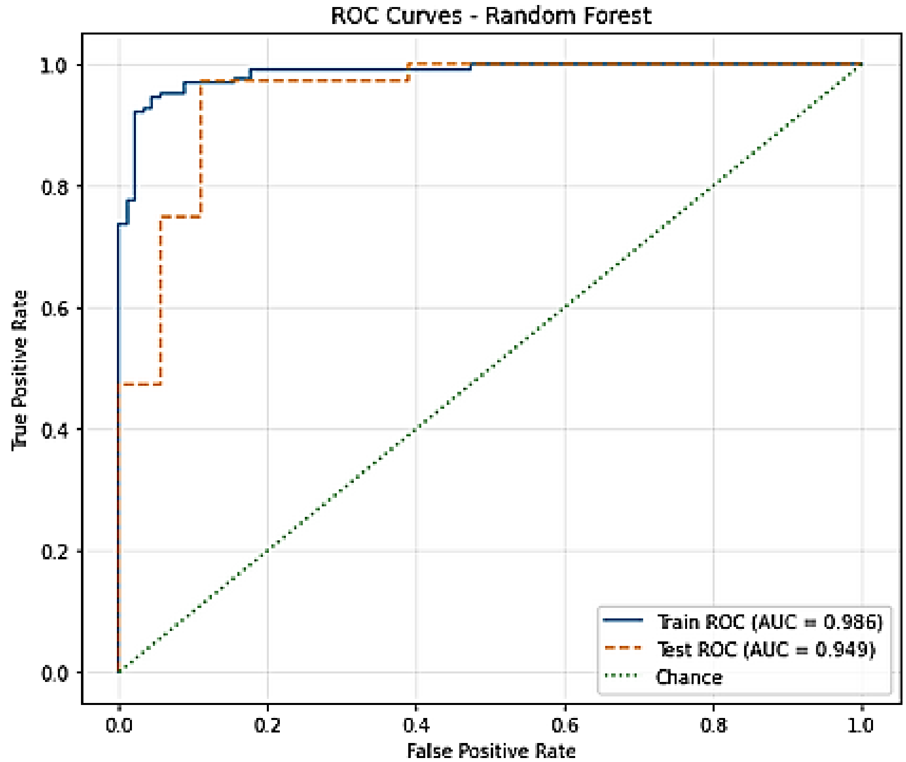
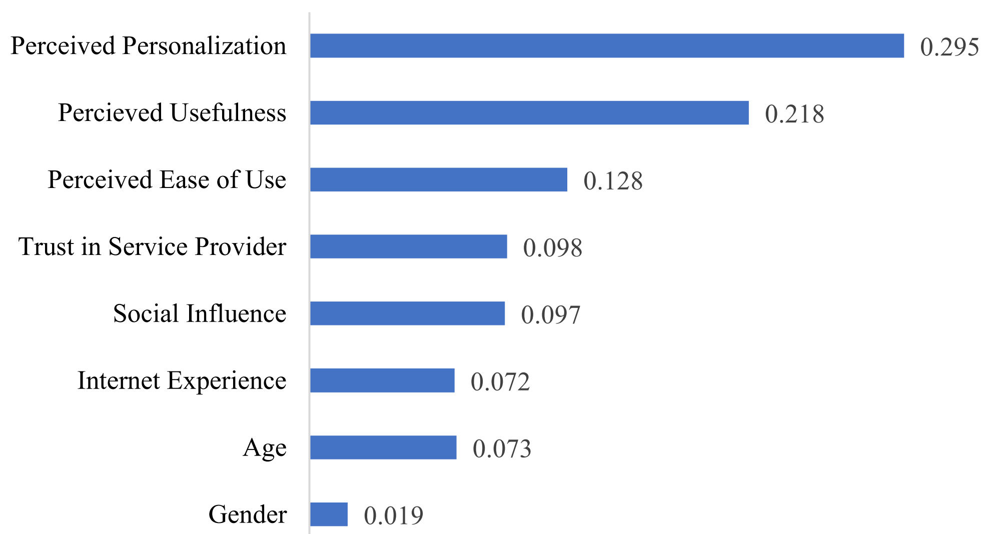


Figure 3. Importance Features in a User's Adoption of AI Chatbot in Aviation



Contribution

Theoretical Contribution

When the Technology Acceptance Model (TAM) was applied to this study's dataset on AI chatbot adoption, The results reinforce TAM's applicability to AI-driven technologies and provide a foundation for identifying the key determinants of chatbot adoption in aviation. Grounded in this validation, the findings indicate that perceived personalization, perceived usefulness, and perceived ease of use are the three most crucial determinants of behavioral intention. Personalization plays an important role in the ticket-search stage, where travelers must evaluate complex factors such as airline, price, destination, and travel dates. Providing tailored responses at this stage supports decision-making and enhances user confidence

Consistent with prior research, perceived usefulness and perceived ease of use remain central drivers of adoption. However, trust in service providers is also essential, as passengers balance the sophistication of AI chatbots with potential concerns about "creepiness" and ethics. In addition, social influence plays a significant role. In Thailand's collectivist culture, individuals often rely on the opinions of others when making decisions. This reliance facilitates higher adoption rates and leads to positive post-adoption behaviors, including purchase intention, satisfaction, and repurchase.

Managerial Contribution

This study, which applied data-mining techniques, highlights both theoretical implications and managerial implications. Shifting the focus to practical contributions, the findings suggest that airlines should design real-time strategies that are closely aligned with users' behavioral patterns, with personalization emerging as a key approach. For instance, dwell time can serve as an indicator of purchase intent. Travelers who show longer dwell times during the search process are more likely to complete bookings, and offering targeted discounts may increase conversions. In contrast, users with shorter dwell times may not require retargeting, thereby reducing unnecessary marketing costs.

More broadly, by addressing user needs—such as personalization during ticket searches, clear and reliable information, and ease of interaction—AI chatbots can play a strategic role in increasing customers' willingness to adopt the technology. This, in turn, can generate higher revenue while fostering customer retention and loyalty in the long run. Conversely, a failure to adopt innovation-driven strategies that leverage user data and dynamic expectations could diminish airlines' competitive advantage in the international market.

Limitations and Future Research Directions

Although this study proposed applications of the Technology Acceptance Model (TAM) in AI chatbot adoption, the essential question of which AI technologies truly drive consumer adoption remains under debate. This issue requires examination from multiple perspectives. Based on the findings, two key directions for future research can be identified.

First, while this study employed machine learning–based predictive models, future research could apply other statistical techniques such as Structural Equation Modeling (SEM) and regression analysis. These approaches could validate relationships among constructs more rigorously and test complex interaction and mediating effects. For example, SEM could be used to evaluate whether perceived usefulness mediates the effect of anthropomorphism on user adoption. Furthermore, SEM with multigroup comparisons could allow researchers to explore AI chatbot adoption across different cultural contexts. For instance, Thai users may differ significantly from users in the US or UK in terms of individualism, collectivism, and social influence. Measuring and comparing such cultural variations could yield valuable insights, as they may shape attitudes toward AI chatbots in culture-specific ways.

Second, characteristics of technology-related variables should be incorporated to address existing research gaps. For instance, anthropomorphism—the extent to which AI chatbots are perceived as human-like—may strongly influence user trust and acceptance in AI contexts. Exploring such psychological and social variables could provide deeper insights into adoption behavior and extend the explanatory power of TAM in AI research.

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