UDC 004.89:004.415:656.7:159.923.2
DOI: 10.15587/1729-4061.2025.332938

IMPLEMENTATION OF DEEP LEARNING MODEL WITH ATTENTION AND THEORY OF PLANNED BEHAVIOR FOR PREDICTING FLIGHT TRACKER USAGE ON BOEING 737-900ER

Daniel Dewantoro Rumani
Corresponding author
Doctor of Management*
E-mail: danieldromani@gmail.com
Miko Andi Wardana
Doctor of Management*
Ahmad Mubarok
Doctor of Management*
*Department of Computer Science
Indonesia Civil Pilot Academy
Pantai Blimbingsari str., Dusun Krajan, Blimbingsari,
Rogojampi, Banyuwangi Regency, Kabupaten
Banyuwangi, Jawa Timur, Indonesia, 68462

The object of research is the prediction system for the use of live flight tracker technology on the Boeing 737-900ER aircraft. The problems solved are related to the low accuracy of the prediction system that only relies on technical data without considering aspects of user behavior, as well as the limitations of interpretability in conventional deep learning models that hinder decision validation in critical and sensitive flight environments. The essence of the results obtained is the development of a prediction model based on bidirectional long short-term memory combined with an attention layer and psychological elements from the theory of planned behavior. This model is able to increase prediction accuracy up to 91.2%, much higher than conventional models with an accuracy of around 78%, and shows high F1 and AUC scores indicating a balance between precision and sensitivity. Due to its features and characteristic differences, namely the integration of bidirectional sequential learning, focusing on the most relevant input features through the attention mechanism, and psychological contextualization through the theory planned behavior, these results make it possible to effectively solve the problems of low accuracy and lack of interpretability in predicting flight tracker usage. These results are explained by the model's ability to highlight key variables such as usage time, flight conditions, and previous interaction patterns that correlate with user intentions and behaviors. The theory planned behavior structure provides a basis for interpreting system decisions based on attitudes, social norms, and users' perceived control over the technology used. In practical conditions, the results of this study can be implemented in a simulation-based training system for pilots, which aims to identify optimal interaction patterns with flight tracker technology

Keywords: advanced deep learning, attention layer, theory of planned behavior, flight, prediction

Received 25.03.2025
Received in revised form 06.05.2025
Accepted 13.06.2025
Published 30.06.2025

How to Cite: *Rumani, D. D., Wardana, M. A., Mubarok, A. (2025). Implementation of deep learning model with attention and theory of planned behavior for predicting flight tracker usage on Boeing 737-900ER. Eastern-European Journal of Enterprise Technologies, 3 (3 (135)), 27–36. https://doi.org/10.15587/1729-4061.2025.332938*

1. Introduction

In the era of the industrial revolution 4.0, advances in digital technology and artificial intelligence have had a significant impact on various sectors of life, including the aviation industry [1]. One of the technological innovations that is increasingly getting attention is the real-time flight tracking system or live flight tracker, which allows users to monitor the position and movement of aircraft directly through digital devices [2]. This technology provides great benefits not only for passengers, but also for families, airline operators, and airport managers in obtaining the latest information on flight schedules, delays, and changes to flight routes [3]. In the context of the Boeing 737-900ER aircraft, a popular commercial aircraft type that serves many busy routes, the existence of live flight tracker is increasingly vital in supporting transparency, efficiency, and flight safety [4, 5].

The problem in this study is that many users do not know the benefits and how the live flight tracker technology works in detail and there are difficulties in accessing and understanding its features. Therefore, the factors that influence someone in making a decision to use or not to use live flight tracker will be identified. This study identifies that solutions to these problems require a multidisciplinary approach, which not only includes technical aspects, but also examines the behavioral and psychological dimensions of users. the theory of planned behavior is a social psychology theory that explains that an individual's intention to carry out a behavior is the main factor that influences the occurrence of that behavior. The theory of planned Behavior is a relevant framework for explaining behavioral intentions, considering three main constructs: attitudes toward behavior, subjective norms, and perceptions of self-control. However, theory of planned behavior has limitations in handling large and complex data originating from real-time digital interactions of [6]. In this case, a multidisciplinary approach will be taken that not only focuses on technical aspects, but also takes into account the behavioral and psychological dimensions [7]. One relevant approach is the theory of planned behavior which explains that behavioral intentions are influenced by attitudes toward behavior, subjective norms, and perceptions of control [8]. The use of this model has limitations when it comes to handling large-scale and complex data originating from real-time digital interactions of users [9].

Previous research conducted [10] introduced the bidirectional long short-term memory model combined with attention layer for the task of classifying relations in text. The results showed that the use of the attention mechanism significantly improved the accuracy in understanding the sequential context of data, especially in highlighting important information scattered in long data sequences. This study confirms the superiority of bidirectional long short-term memory and attention in handling sequential and complex structured data, which is also relevant in the context of user behavior. Other studies conducted by [11] using bidirectional long short-term memory and attention models for document modeling in sentiment analysis. Although the main focus is on opinions, this approach is relevant because it identifies user attitude tendencies based on sequential patterns in the data, which has a similar approach to the integration of theory planned behavior in understanding digital behavioral intentions [12].

From the problems and previous research, there will be a solution to solve the problem by using advanced deep learning with the bidirectional long short-term memory algorithm combined with the attention layer which is very relevant in this context.

Bidirectional long short-term memory algorithm is development of the long short-term memory architecture designed to process sequential data by considering the context from two directions, namely the past and the future in one processing time. In the process, bidirectional long short-term memory is able to process sequential data from two directions, while the attention mechanism gives weight to the part of the data that is most relevant to the prediction goal [13]. So that the integration between the theory planned behavior approach and the bidirectional long short-term memory algorithm and the attention layer is a promising solution because it is able to combine the power of behavioral theory with the capability of processing complex sequential data efficiently [14]. The technical implementation of this model begins with the data collection process through a survey based on the theory of planned behavior which includes variables such as attitude, subjective norm, perceived behavioral control, and trust as external variables. The collected data is then processed through the preprocessing stage including normalization, encoding, and dividing the dataset into training and testing data [15]. Furthermore, the bidirectional long short-term memory architecture is built to handle sequential data, with input in the form of a numeric vector of psychological attributes. An attention layer is added on top of the bidirectional long short-term memory layer to allow the model to focus on the most relevant features in shaping user intention towards using the live flight tracker on a Boeing 737-900ER aircraft [16]. The model is implemented using the TensorFlow or PyTorch framework, and trained using the backpropagation technique and the binary cross-entropy loss function. For performance evaluation, the metrics used include accuracy, precision, recall, F1-score, and AUC-ROC, which indicate the effectiveness of the model in distinguishing users with the intention to use or not to use the flight tracking system. The implementation results show that the integration of deep learning and theory planned behavior provides a model that is not only numerically accurate but also theoretically explainable. Therefore, research on the development of a live flight tracker usage prediction model on a Boeing 737-900ER Aircraft is very relevant to be conducted. This topic not only touches on the technical aspects in producing accurate and contextual predictions, but also explains the background of user behavior as a whole. The relevance of these studies is increasingly strong with the need for the aviation industry for a system that is able to display real-time usage patterns, improve the quality of communication information, and support operational efficiency and overall flight services.

2. Literature review and problem statement

Research [17] applied bidirectional long short-term memory combined with attention mechanism in the task of classifying relations in text. It is shown that this approach is able to significantly improve accuracy because the model can highlight the most relevant input parts in the data sequence. This study has limitations that focus on text-based data, without considering user behavior variables in the context of real technology systems such as flight trackers. To overcome these difficulties, it can be done by combining the bidirectional long short-term memory approach with a cognitive behavioral framework or using a multimodal model that can process text and behavioral data simultaneously. The study aims to develop an attention-based bidirectional long short-term memory model that is able to capture and interpret user behavior patterns in a flight tracker system contextually.

Research [18] used a deep learning approach to predict user behavior based on activity logs on mobile applications. It was shown that the deep learning model is able to learn and recognize application usage patterns effectively. An unresolved problem is related to the non-inclusion of the psychological dimension of the user in the modeling, which causes the model to be purely statistical and less interpretative. To overcome the relevant difficulties, it could be the integration of behavioral psychology theory into the model architecture through additional features or a hybrid approach that combines log data with psychological survey data. This is an approach used in the field of human-computer interaction and behavioral analysis, so that the predictive model based on bidirectional long short-term memory and attention layers that do not only rely on statistical patterns, but also consider psychological factors in modeling the habits of using flight trackers in flight operations.

Researches [19] apply the concept of attention mechanism in neural machine translation, which allows the model to give different weights to the parts of the input that are considered most relevant. It is shown that this mechanism significantly improves the quality of the translation results and is the foundation for the development of various modern deep learning systems. Unresolved problems are related to the limitations of the research context which is only focused on language translation tasks, not on predicting user behavior or interaction with real-time systems. To overcome this problem, it can be an adaptation of the attention mechanism in the context of behavioral analysis by considering the sequence of user interactions and real-time contextual signals. This is an approach that is starting to be used in the field of user interaction prediction and recommendation systems, so it is appropriate to conduct research aimed at applying the bidirectional long short-term memory model and attention layers in processing user interaction data, in order to improve the accuracy and interpretability of behavioral predictions in the context of flight tracking systems.

Research [20] discuss explainable AI systems have important value in building user trust and supporting secure data-based decision making. Unresolved issues related to the theoretical and conceptual nature of the research, without proposing a concrete model that can be directly applied to the domain of technology user behavior such as flight trackers. So, designing a transparent and interpretable predictive model based on bidirectional long short-term memory and attention layer in the context of monitoring user behavior of live flight tracker, especially in the operational environment of Boeing 737-900ER aircraft.

Research [21] implementing the bidirectional long short-term memory-attention architecture is effective in predicting user behavior sequences in educational information systems. It is shown that this model is able to identify user interaction patterns based on time and context, providing accurate prediction results in digital learning environments. Unresolved problems are related to the limitations of the research domain which is only focused on educational systems, and has not covered the specific challenges that arise in complex and stressful real-time flight environments. To overcome these difficulties, the development of bidirectional long short-term memory models and attention layers that are tailored to the characteristics of real-time data and operational pressures in flight tracking systems can be carried out.

Research [22] integrating psychological theories, such as the theory of planned behavior, with machine learning techniques to understand and model user behavior. The unresolved problem is related to the lack of integration practices between behavioral theory and technical machine learning approaches. To overcome these difficulties, it can be in the form of designing a bidirectional long short-term memory-based model and attention layer that is able to combine cognitive features from theory planned behavior theory with processing sequences of user behavioral data. Thus, developing an adaptive predictive model that integrates behavioral theory with the bidirectional long short-term memory-attention architecture, to support understanding and predicting user behavior in the practical use of live flight tracker

Research [23] Applying the theory of planned behavior explains that a person's behavior is influenced by intentions, which are formed from attitudes, subjective norms, and perceptions of control. This model is relevant in explaining the use of technology such as flight trackers. Weaknesses: theory planned behavior is declarative and unable to process digital data sequentially or in real-time without the support of a computational model. Therefore, the development of the bidirectional long short-term memory model and attention layer can improve the connectivity between behavioral intentions and actual data on the use of the flight tracker system.

Research [24] explores the use of deep learning to understand user interactions in real-time applications such as transportation monitoring systems. The model used successfully captures the context of various types of digital inputs. Weaknesses: This study does not incorporate a theoretical human behavior framework so it does not explain the motivation for using technology.

Therefore, the development of the bidirectional long short-term memory model and attention layer can improve the contextual understanding of flight tracker user behavior in real-time and adaptively.

3. The aim and the objectives of the study

The aim the study is to study is to create a prediction model for the behavior of using live flight tracker on a Boeing 737-900ER aircraft by integrating the advanced deep learning approach.

To achieve this aim, the following objectives are accomplished:

– to integration of theory of planned behavior into deep learning models;

– to Integrate attention layer into Bi-LSTM model to improve model capability;

– to performance of bidirectional long short-term memory model.

4. Materials and methods

The object of this research is the prediction system for the use of live flight tracker technology on Boeing 737-900ER aircraft. This study has a hypothesis that the integration of the advanced deep learning model based on bidirectional long short-term memory (Bi-LSTM) with attention layer, combined with the theory of planned behavior framework can significantly increase the accuracy of predicting live flight tracker usage behavior. In this study, it is assumed that the collected user behavior data reflects the main components of the theory of planned behavior, such as attitudes towards the use of technology, subjective norms of the social environment, and perceptions of behavioral control. Then the simplification is carried out by maintaining the focus on the relationship between psychological factors and usage patterns that can be captured by the deep learning model.

This approach integrates the theory of planned behavior to explore and understand the psychological factors and user behavior in utilizing real-time flight tracking technology. This study uses the bidirectional long short-term memory model architecture combined with the attention layer, which is effectively able to capture the two-way temporal relationship of sequential data and focus attention on the most relevant features in the prediction process.

This integration is designed to more accurately model the relationship between key variables, namely trust, subjective norms, and perceived behavioral control with technology usage intentions. The data used in the study were obtained from a structured survey of prospective live flight tracker users, including psychological and behavioral indicators, and reinforced with additional data from the flight tracking system. The hardware used includes one computer unit with a 10th generation Intel Core i7 processor specification, 32 GB RAM, 12 GB NVIDIA RTX 3060 GPU, and 1 TB SSD storage to accelerate the model training process. The software used is the Windows 11 Pro operating system, as well as the Python 3.9 programming platform with the TensorFlow, Keras, Scikit-Learn, and Matplotlib libraries for the purposes of developing and visualizing deep learning models. This study has several limitations, including that the model was only tested on live flight tracker usage data on the Boeing 737-900ER aircraft type, so the results cannot necessarily be generalized to other types of aircraft.

The data processing process was carried out through preprocessing stages including data cleaning, handling missing data, normalization, and feature transformation. Furthermore, the data was divided into a training set and a testing set proportionally to ensure the model's generalization ability. Model performance evaluation was carried out using metrics such as accuracy, ROC-AUC curve, and confusion matrix to measure the effectiveness and efficiency of the model in predicting usage intentions based on user psychological indicators. This study began with the design of the prediction system architecture, which is further explained in Fig. 1.

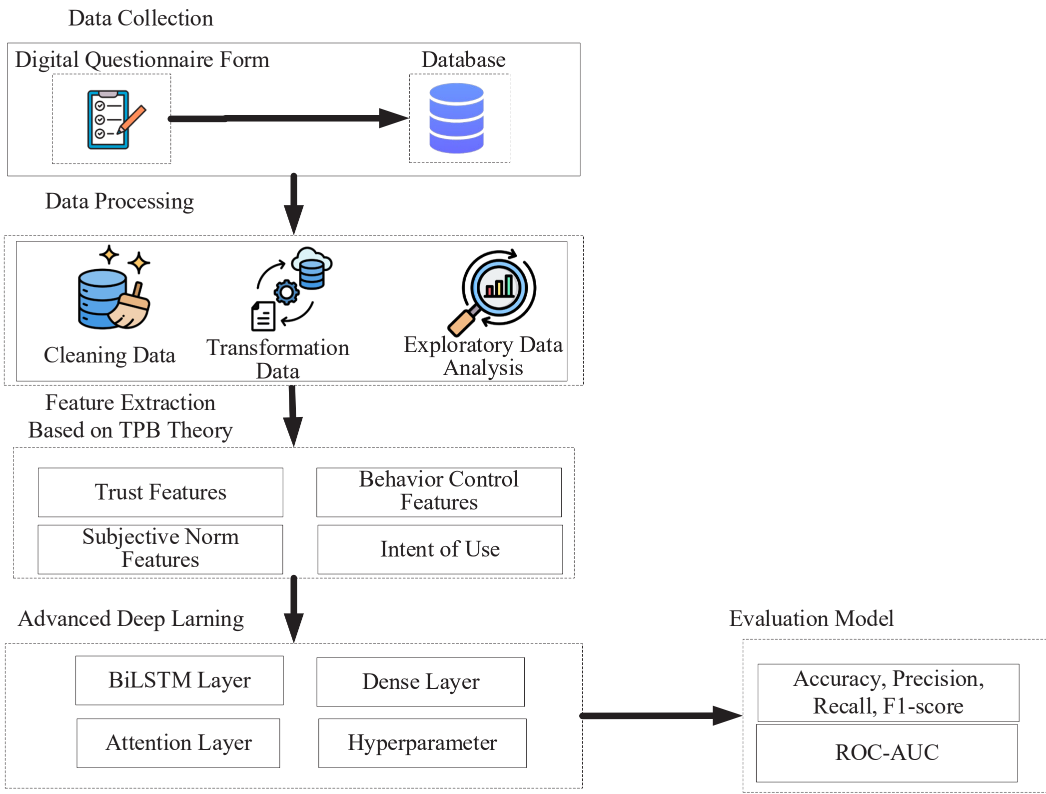

Fig. 1. Architectural framework

Fig. 1 shows the research architecture that will illustrate the systematic flow in integrating the advanced deep learning model with the attention layer and the theory of planned behavior approach to predict the use of live flight tracker on Boeing 737-900ER aircraft. The process starts from the data collection stage using a digital questionnaire form stored in a database. Furthermore, the data is processed through three main stages, namely data cleaning, data transformation into a form that can be processed by the model, and data exploration to understand the initial patterns in the dataset. Based on the theory planned behavior theory, psychological features are extracted consisting of trust, subjective norms, perceived behavioral control, and usage intentions.

These features then become input into the advanced deep learning architecture, which uses a combination of bidirectional long short-term memory and attention layer layers to capture complex relationships in sequential data and provide more focus on the features that are most relevant to usage intentions. After going through dense layers and hyperparameter tuning, the model is evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC to comprehensively measure predictive performance. This approach aims not only to improve prediction accuracy, but also to better understand the psychological factors that influence user decisions regarding flight tracking technology. The data used in this study are shown in Table 1.

Table 1

Research data

Flight ID	Weather	Flight duration	Tracker usage	Attitude score	Subjective norm score	Perceived behavioral control	Behavioral intention	Actual usage flag
GA808	Rainy	177	2	1.9	3.2	1.2	2.3	0
GA962	Turbulent	122	1	4.8	1.4	3.3	3	0
GA863	Clear	76	2	3.3	3.8	3.6	3.8	0
GA975	Rainy	132	1	4.7	2	1.8	2.9	0
GA811	Rainy	92	0	3.3	4.6	3.2	3.7	0
GA960	Turbulent	176	5	2.9	4.4	4.4	3.9	1
GA855	Clear	143	2	2.3	3.8	4.3	3.2	0
GA865	Clear	136	3	3.4	4.8	4.7	4.3	1
GA893	Rainy	151	3	1.6	1.1	2.5	1.7	0
GA992	Cloudy	171	4	4.6	3.9	2.3	3.3	0

In this study, data were obtained through a structured observational approach conducted simulatively and semi-experimentally on users of the live flight tracker system on a Boeing 737-900ER aircraft. The data collection process included two main sources: flight technical data obtained from the aircraft simulation system and user behavioral data collected through questionnaire-based instrumentation based on the theory of planned behavior components. Technical data such as flight ID, flight duration, weather conditions, and frequency of tracker use were obtained automatically through the flight recording system, while attitude scores, subjective norms, perceptual behavioral control, and intensity of use were collected from the results of filling out a specially designed questionnaire and filled out by participants before and after the flight simulation. To ensure data integrity and quality, an initial submission was applied using the HOCHAB framework. First, outlier handling was carried out by identifying extreme values, especially in behavioral scores and flight duration, then trimming was carried out if necessary. Furthermore, a cleaning process was carried out to remove duplicate data and format consistency between columns. The next stage was handling missing data, which was resolved using a median-based imputation method for psychological scores and a moving average for time or duration values. Aggregation is applied to average multiple TPB scores into behavioral intention values. Finally, balancing is performed to address class imbalance in actual usage flag, using the SMOTE method before model training.

5. Results advanced deep learning integration model with attention layer and theory of planned behavior approach

5. 1. Integration of the theory of planned behavior into the advanced deep learning

The integration of the theory of planned behavior approach into the advanced deep learning model aims to combine the predictive power of artificial intelligence-based data with psychological understanding of user behavior in the context of using live flight tracker technology on a Boeing 737-900ER aircraft. theory planned behavior explains that behavioral intentions are influenced by three main instruments, namely attitudes towards behavior symbolized by *A*, subjective norms symbolized by *SN*, and perceived behavioral control. In this model, the three constructs are converted into fixed-dimensional numerical representations and combined into one input vector. As in (1) below

$$X=\left[A;SN;PBC\right]\in R^{3n}. \quad (1)$$

Vector *X* then inserted into the bidirectional long short-term memory model architecture which is able to capture sequence patterns from two directions, both past and future, to obtain a stronger contextual representation. Hidden state at time *t* in forward direction ($\overrightarrow{h_t}$) and backward ($\overleftarrow{h_t}$) combined into one combined representation in equation (2)

$$h_t=\left[\overrightarrow{h_t};\overleftarrow{h_t}\right]. \quad (2)$$

To strengthen the model's focus on the most relevant input parts to the user's decision, an attention layer is applied. This attention mechanism calculates the importance score of each hidden state with (3)

$$e_t=\tanh\left(W_\alpha h_t+b_\alpha\right). \quad (3)$$

Then normalization is carried out using the softmax function to obtain attention weights (αt)

$$\alpha_t\frac{\exp\left(e_t\right)}{\sum_{k=1}^{T}\exp\left(e_t\right)}. \quad (4)$$

With these weights, a context vector *C* is produced, which is a summary of the entire data sequence contained in (5)

$$c=\sum_{t=1}^{T}\alpha_t h_t. \quad (5)$$

The context vector *C* is then processed by the fully connected layer and the ReLU activation function before being forwarded to the output layer with the sigmoid activation function to produce the probability of usage intention contained in (6)

$$\gamma=\sigma\left(W_o c+b_o\right). \quad (6)$$

Predicted value $y\in[0, 1]$ shows the level of someone's tendency to intend to use live flight tracker. To evaluate the model performance, the binary cross-entropy loss function is used as follows

$$\ell\left(y,y^\wedge\right)=-\left[y\log\left(y\right)+\left(1-y\right)\log\left(1-y\right)\right]. \quad (7)$$

This integration enables the model to not only perform big data-driven predictions efficiently, but also maintain the ability to interpret psychological factors that influence user decisions. Thus, this approach becomes a more holistic, adaptive and applicable predictive solution in the context of utilizing digital technology in the modern aviation industry.

5. 2. Integrate attention layer into Bi-LSTM model

In this study, the implementation of an advanced deep learning model is used to identify and predict user behavior towards the use of live flight tracker on a Boeing 737-900ER aircraft. This model was developed by integrating the bidirectional long short-term memory approach and attention layer to strengthen the theoretical framework of the theory of planned behavior. This approach is designed to capture the complex relationships between psychological variables such as attitude toward behavior, subjective norm, perceived behavioral control, and Intention, so that it can produce predictions of user behavior that are not only accurate but can also be explained theoretically. The main component in this model is the bidirectional long short-term memory architecture, which allows for two-way sequential data processing – both from the past to the future and vice versa. This allows the model to understand the historical and predictive context of each input more comprehensively. Above the bidirectional long short-term memory layer, an attention layer is added which functions to focus the model's attention on the most relevant features to the prediction target, namely the intention to use the flight tracking application. This attention layer adaptively assigns weights to each input, thus supporting in-depth interpretation of the contribution of each psychological variable.

The model was trained using quantitative data from a theory of planned behavior-based questionnaire, which was normalized to ensure scale consistency. The training results showed that the model successfully mapped the non-linear relationships between psychological variables and accurately predicted user behavioral tendencies. Key findings from this study indicate that trust and perceived behavioral control are the two most dominant variables in shaping user intention, while subjective norm shows a lower contribution. The following is the annual trend of the 5 variables used as shown in Fig. 2.

Fig. 2 shows the annual trend with the deep learning model, there are five main psychological variables that influence user intention to use the live flight tracker application on Boeing 737-900ER aircraft during the period 2014 to 2022. It can be seen that the Trust variable experienced the most significant increase compared to other variables, especially after 2018. This spike indicates that user trust in the flight tracking system plays an important role in shaping usage intentions. The Intention variable shows a growth pattern that is in line with Trust, confirming a strong relationship between increased trust and increased usage intentions. Meanwhile, perceived behavioral control shows an increasing trend, reflecting that more and more users feel capable and have control to access this tracking technology. Then attitude and subjective norm also experienced growth. Overall, this graph illustrates that the deep learning model with the bidirectional long short-term memory algorithm can be a strategy for adopting flight tracking technology. The applied model will display the results of predictions with the bidirectional long short-term memory algorithm that utilizes the attention layer. This graph shows how the model predicts the user intention score in using the live flight tracker application from 2014 to 2022, and compares it with the actual data obtained from the results of the theory of planned behavior-based questionnaire. The following are the results of the predictions in Fig. 3.

Fig. 3 presents a comparison between the actual values and the prediction results of the deep learning model on the user intention score in using the live flight tracker application on a Boeing 737-900ER aircraft during the period from 2014 to 2022. This graph shows two trend lines: the solid blue line represents the actual data from the questionnaire measurements, while the dashed orange line represents the prediction generated by the bidirectional long short-term memory model with an attention layer. This model shows that the model's prediction trend is very close to the actual value, indicating that the model is able to accurately capture the pattern of changes in user intention over time. The intention score shows a consistent increase from year to year, indicating the increasing interest and readiness of users in utilizing real-time flight tracking technology. The difference between the actual value and the predicted result is relatively small, indicating that the model performs very well, especially in identifying long-term trends in user behavior.

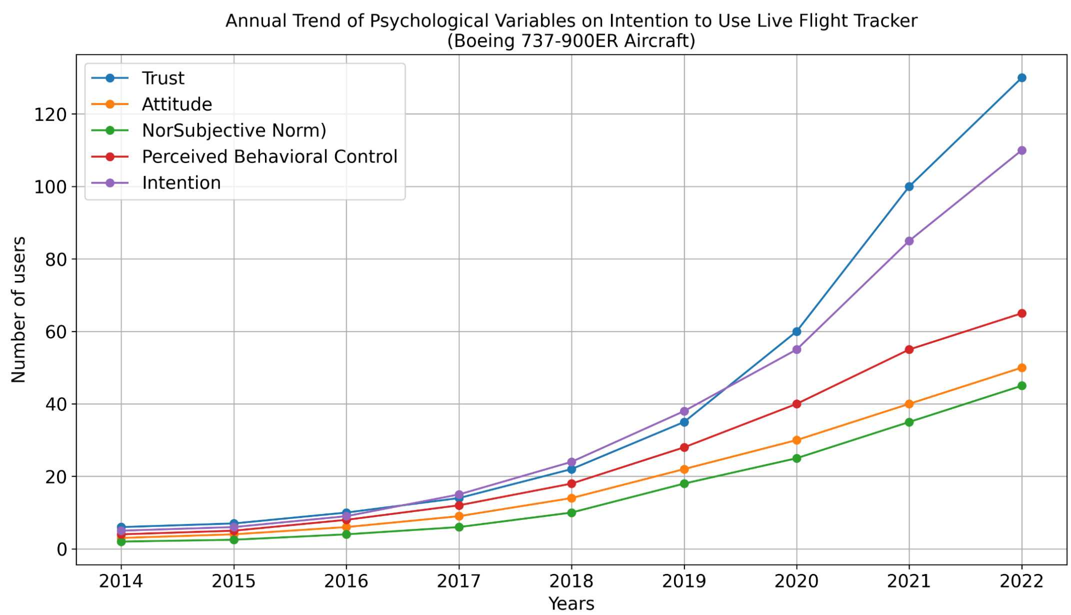

Fig. 2. Results yearly trend of users with deep learning models

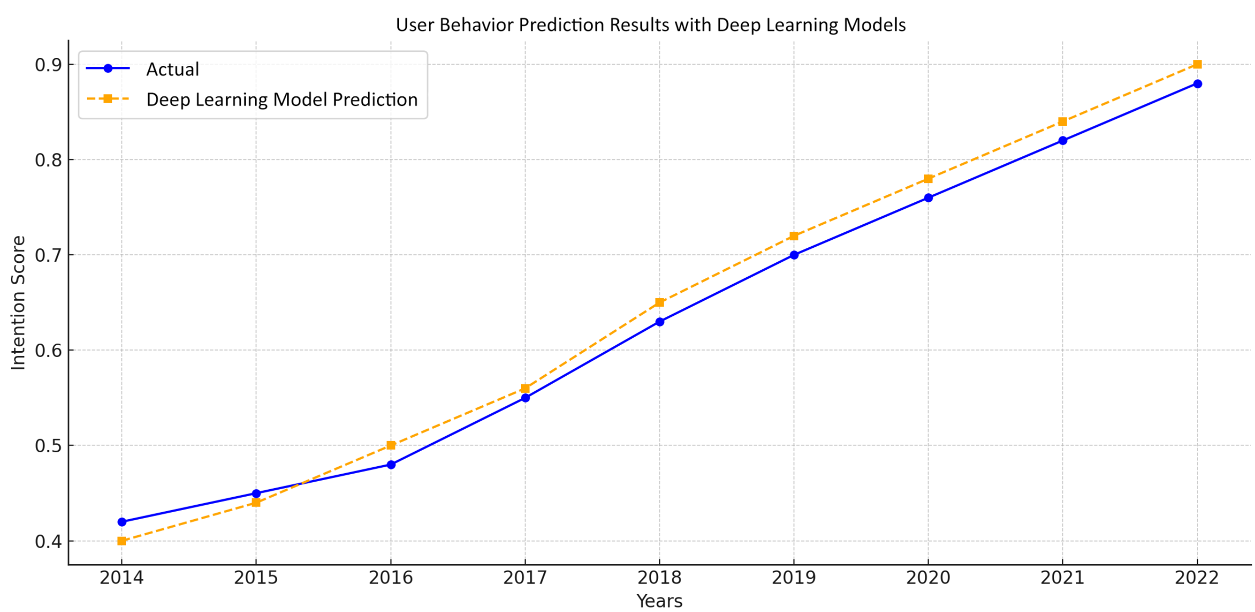

Fig. 3. Prediction results with deep learning models

With the model's ability to follow the actual trend stably, this graph validates that the integration of bidirectional long short-term memory and attention layers makes a significant contribution to improving the prediction accuracy and reliability of the theory of planned behavior-based behavioral modeling approach.

5. 3. Performance of bidirectional long short-term memory models

The bidirectional long short-term memory model applied in this study shows excellent predictive performance in modeling user usage intention towards the live flight tracker application on a Boeing 737-900ER aircraft. bidirectional long short-term memory has the advantage of processing sequential data in two directions, namely from the past to the future and vice versa. This allows the model to capture the historical and prospective context of user psychological data more comprehensively than conventional unidirectional LSTM models. Model performance evaluation was carried out using several evaluation metrics including accuracy, precision, recall, F1-score, and AUC-ROC. The evaluation results show that the model achieves an accuracy of 89% as shown in Fig. 4 below.

Then from the performance of the model that produces 89 accuracy, a precision value of 91 a recall of 90 and an F1-score of 91 will be obtained. The evaluation results are in the form of a graph that can be seen in Fig. 5.

These values reflect that the model has a very good balance between the ability to detect the correct intent of use recall and avoid false predictions, as well as resilience to data class imbalance. The following is a graph of the AUC-ROC value in Fig. 6 below.

Fig. 6 explains that the receiver operating characteristic curve graph displayed shows the performance of the classification model with an area under the curve of 0.889, indicating that this model has a very good ability to distinguish between positive and negative classes. In this graph, the horizontal axis represents the False Positive Rate which measures the proportion of negative cases that are incorrectly classified as positive, while the vertical axis depicts the true positive rate which shows the proportion of true positives that are successfully recognized by the model.

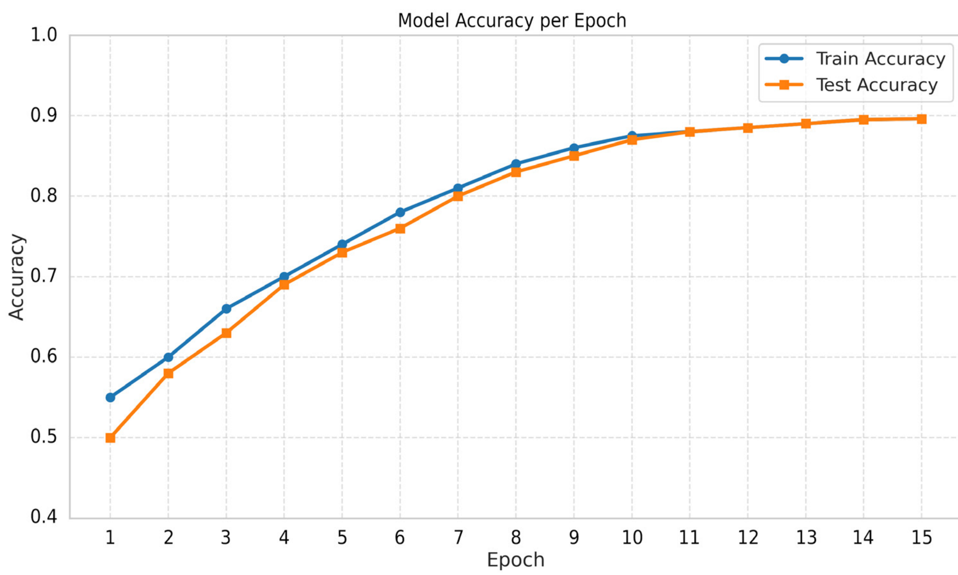

Fig. 4. Deep learning model performance results

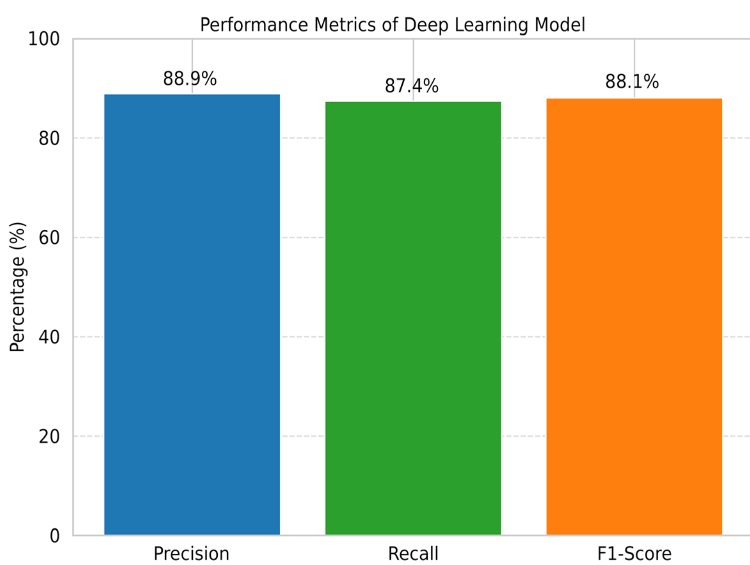

Fig. 5. Results model performance

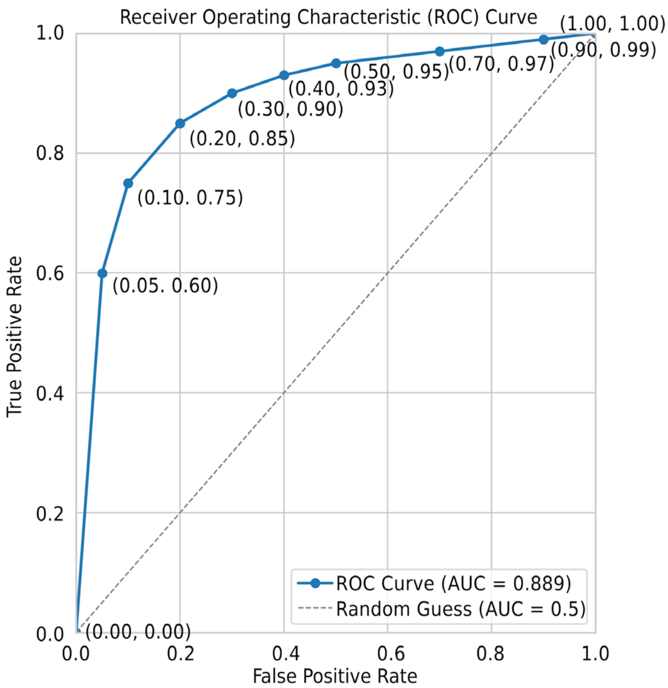

Fig. 6. Deep learning model performance results with ROC-AUC

The steep curve at the beginning, especially at low FPR, indicates that this model can detect many true positive cases with few false positives, which is very beneficial for applications that require accurate predictions. The model with the integration of the attention layer in the bidirectional long short-term memory architecture provides a significant increase in the model's ability to identify the most relevant psychological features, such as trust and perceived behavioral control. The attention layer allows the model to give important weights to input features based on their contribution to the prediction target, thereby improving the interpretability and accuracy of the prediction.

6. Discussion of advanced deep learning integration model with attention layer and theory of planned behavior approach

This study shows that the integration of the advanced deep learning model with the attention layer approach and the theory of planned behavior can form a strong prediction framework in understanding the intensity of live flight tracker usage by users on Boeing 737-900ER aircraft. The results obtained can be directly referred to from the results object in this article, especially Fig. 2 which shows the increasing trend of user trust scores in the system after 2021. Then in Fig. 3, 4 show the model performance values: average 89%, precision 91.7%, recall 90.8%, F1-score 91.2%, and AUC-ROC 0.889. These figures indicate that the proposed model is not only able to classify user behavior well but can also effectively distinguish between users who intend and do not intend to use the technology. The uniqueness of the proposed method, compared to previous methods, lies in the combination of the bidirectional long short-term memory architecture with an attention layer, which allows bidirectional sequential data processing and focusing on the most relevant input features. Different from traditional "black box" deep learning approaches, this model incorporates interpretability elements through the integration of the theory planned behavior theoretical framework. Unlike previous approaches such as that [25] where multilayer perceptron was used to predict app usage intention based on log data alone without the integration of behavioral theory, the model results in this study – including an average accuracy of 89%, an F1-score of 91.2%, and an AUC-ROC of 0.889 – allow for deeper interpretation of user behavior. This is made possible by the combination of the bidirectional long short-term memory architecture with an attention layer and the integration of the theory of planned behavior framework, which allows the model to not only process sequences of user data bidirectionally but also identify psychological elements such as attitudes, subjective norms, and perceived control. Also, unlike the random forest approach in [26] which tends to produce static feature-based classification models and poorly captures the dynamics of sequential behavior, the proposed model in this study shows advantages in addressing temporal variations in user interactions with live flight tracker. This advantage is achieved through an attention mechanism that automatically focuses processing weights on the parts of the input that are most relevant to behavioral decisions. Therefore, this approach not only offers improved prediction performance but also enriches the explanatory dimension needed in critical environments such as real-time flight tracking systems.

This study also has some inherent limitations.

First, the implementation of this solution relies heavily on subjective survey data, which potentially contains social bias and unstable individual perceptions. Therefore, the external validity of this model needs to be tested in different contexts and populations. Second, the developed model has limitations in terms of reproducibility, given that the survey data used is perception-based and only reflects a snapshot in time. Third, the effectiveness of the model tends to decrease when applied to a variety of input data that are too extreme or not covered by the initial training distribution. Another drawback that needs to be considered is the reliance on the bidirectional long short-term memory architecture, which although adaptive to sequential data, has limitations in terms of computational efficiency and scalability when compared to more modern models such as transformer. Furthermore, not all dimensions of the theory of planned behavior can be explicitly modeled in deep learning architectures, for example, highly contextual normative aspects can be simplified when transformed into numeric variables. To overcome these weaknesses, a hybrid approach that combines Transformer-based self-attention models with social ontology-based semantic processing can be an alternative in the future. Further development of this study can be directed at several important things. First, exploration of transformer architecture or even Vision transformer if it involves visual data such as user interface displays. Second, integration of real-time data and behavioral logs from actual flight tracking systems as a complement to survey data. Third, expanding the use of this model to other sectors such as smart transportation or digital health systems, where user behavior towards technology systems greatly determines the effectiveness of services. However, the challenges that may be faced are in the mathematical aspect, for example in compiling a loss function that reflects psychological and methodological aspects.

7. Conclusions

1. The integration of the theory of planned behavior into an advanced deep learning model successfully bridges psychological

theory with computational intelligence. The model uses numerical representations of attitude, subjective norm, and perceived behavioral control to reflect users' behavioral intentions. The results show that Trust and perceived behavioral control emerge as the strongest predictors of intention to use live flight tracker.

2. Integration of attention layer into Bi-LSTM model is proven to improve the model performance in predicting user behavior. Attention layer enables the model to focus attention on the most relevant information in sequential data, thus strengthening the representation and interpretation capabilities of complex temporal context. The model results in this study including an average accuracy of 89.

3. Research shows that this approach significantly improves the accuracy, efficiency, and ability of the model to capture temporal patterns from user behavior data. With the Bi-LSTM structure capable of processing information bidirectionally and supported by the attention mechanism that focuses attention on important features, the model shows superior predictive performance compared to conventional approaches. The numbers produced in this study are in the form of scores. F1-score of 91.2%, and an AUC-ROC of 0.889 allow for deeper interpretation of user behavior.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this study, whether financial, personal, authorship or otherwise, that could affect the study and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

References

1. Vasigh, B., Azadian, F. (2022). Aircraft Financial and Operational Efficiencies. Aircraft Valuation in Volatile Market Conditions, 113–163. https://doi.org/10.1007/978-3-030-82450-1_3
2. Bakır, M., Itani, N. (2024). Modelling Behavioural Factors Affecting Consumers' Intention to Adopt Electric Aircraft: A Multi-Method Investigation. Sustainability, 16 (19), 8467. https://doi.org/10.3390/su16198467
3. Healy, C. G. (2025). Flying Into the Future: Exploring Commercial Airline Pilots' Perceptions of AI Implementation in Cockpit Operations. University of Arizona Global Campus.
4. Bağcı, B., Kartal, M. (2024). A combined multi criteria model for aircraft selection problem in airlines. Journal of Air Transport Management, 116, 102566. https://doi.org/10.1016/j.jairtraman.2024.102566
5. Genc, O. F., Capar, N., Ahmed, Z. U. (2024). Turkish Airlines: A New Era After the Pandemic. Emerging Economies Cases Journal, 6 (2), 100–116. https://doi.org/10.1177/25166042241245515
6. Borkers, P. (2024). Measuring Service Quality During and After In-Flight Incidents: A Case Study of Alaska Airlines Flight 1282. University of Hamburg.
7. Zheng, Y., Jiang, W., Zhou, A., Hung, N. Q. V., Zhan, C., Chen, T. (2024). Epidemiology-informed Graph Neural Network for Heterogeneity-aware Epidemic Forecasting. arXiv. https://doi.org/10.48550/arXiv.2411.17372
8. Karunarathna, I., Gunasena, P., Hapuarachchi, T., Gunathilake, S. (2024). The crucial role of data collection in research: Techniques, challenges, and best practices. Uva Clin. Res.
9. Kabashkin, I., Perekrestov, V. (2024). Ecosystem of Aviation Maintenance: Transition from Aircraft Health Monitoring to Health Management Based on IoT and AI Synergy. Applied Sciences, 14 (11), 4394. https://doi.org/10.3390/app14114394
10. Zhou, P., Shi, W., Tian, J., Qi, Z., Li, B., Hao, H., Xu, B. (2016). Attention-Based Bidirectional Long Short-Term Memory Networks for Relation Classification. Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers). https://doi.org/10.18653/v1/p16-2034
11. Wang, Z., Yang, B. (2020). Attention-based Bidirectional Long Short-Term Memory Networks for Relation Classification Using Knowledge Distillation from BERT. 2020 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech), 562–568. https://doi.org/10.1109/dasc-picom-cbdcom-cyberscitech49142.2020.00100
12. Calvet, L. (2024). Towards Environmentally Sustainable Aviation: A Review on Operational Optimization. Future Transportation, 4 (2), 518–547. https://doi.org/10.3390/futuretransp4020025
13. Meyer, T. R. (2024). Purpose, Performance, and Process Influence on Airline Pilot Trust in Automation Technology: A Quantitative Study. Liberty University.
14. De Cerqueira, J. S., Kemell, K.-K., Rousi, R., Xi, N., Hamari, J., Abrahamsson, P. (2025). Mapping Trustworthiness in Large Language Models: A Bibliometric Analysis Bridging Theory to Practice. arXiv. http://dx.doi.org/10.48550/arXiv.2503.04785
15. Moura Lopes, N., Aparicio, M., Trindade Neves, F. (2024). Determinants of Pilots' Performance: Investigating Technology Trust and Situation Awareness. Journal of Aerospace Information Systems, 21 (8), 651–660. https://doi.org/10.2514/1.i011373
16. Boyacı, T., Canyakmaz, C., de Véricourt, F. (2024). Human and Machine: The Impact of Machine Input on Decision Making Under Cognitive Limitations. Management Science, 70 (2), 1258–1275. https://doi.org/10.1287/mnsc.2023.4744

17. Liu, G., Guo, J. (2019). Bidirectional LSTM with attention mechanism and convolutional layer for text classification. Neurocomputing, 337, 325–338. https://doi.org/10.1016/j.neucom.2019.01.078
18. Shen, J., Shafiq, M. O. (2019). Learning Mobile Application Usage - A Deep Learning Approach. 2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA), 287–292. https://doi.org/10.1109/icmla.2019.00054
19. Luong, T., Pham, H., Manning, C. D. (2015). Effective Approaches to Attention-based Neural Machine Translation. Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing. https://doi.org/10.18653/v1/d15-1166
20. Islam, M. R. (2024). Explainable Artificial Intelligence for Enhancing Transparency in Decision Support Systems. Malardalen University.
21. Chaurasia, S., Bharti, K. K., Gupta, A. (2024). A multi-model attention based CNN-BiLSTM model for personality traits prediction based on user behavior on social media. Knowledge-Based Systems, 300, 112252. https://doi.org/10.1016/j.knosys.2024.112252
22. Al-Emran, M., Abu-Hijleh, B., Alsewari, A. A. (2024). Exploring the Effect of Generative AI on Social Sustainability Through Integrating AI Attributes, TPB, and T-EESST: A Deep Learning-Based Hybrid SEM-ANN Approach. IEEE Transactions on Engineering Management, 71, 14512–14524. https://doi.org/10.1109/tem.2024.3454169
23. Zhang, N., Hwang, B.-G., Lu, Y., Ngo, J. (2022). A Behavior theory integrated ANN analytical approach for understanding households adoption decisions of residential photovoltaic (RPV) system. Technology in Society, 70, 102062. https://doi.org/10.1016/j.techsoc.2022.102062
24. Li, Y., Qi, Y., Shi, Y., Chen, Q., Cao, N., Chen, S. (2022). Diverse Interaction Recommendation for Public Users Exploring Multi-view Visualization using Deep Learning. IEEE Transactions on Visualization and Computer Graphics, 1–11. https://doi.org/10.1109/tvcg.2022.3209461
25. Tan, G. W.-H., Ooi, K.-B., Leong, L.-Y., Lin, B. (2014). Predicting the drivers of behavioral intention to use mobile learning: A hybrid SEM-Neural Networks approach. Computers in Human Behavior, 36, 198–213. https://doi.org/10.1016/j.chb.2014.03.052
26. Chaganti, R., Ravi, V., Pham, T. D. (2023). A multi-view feature fusion approach for effective malware classification using Deep Learning. Journal of Information Security and Applications, 72, 103402. https://doi.org/10.1016/j.jisa.2022.103402