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Deep Learning and User Consumption Trends Classification and Analysis Based on Shopping Behavior

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ABSTRACT

Driven by the wave of digitalization, the booming development of the e-commerce industry urgently requires in-depth analysis of user shopping behavior to improve service experience. In view of the limitations of traditional models in dealing with complex shopping scenarios, this study innovatively proposes a deep learning model: the VATA model (a combination of variational autoencoder, transformer, and attention mechanism). Through this model, the authors strive to classify and analyze user shopping behavior more accurately and intelligently. Variational autoencoder (VAE) can learn the potential representation of user personalized historical data, capture the implicit characteristics of shopping behavior, and improve the ability to deal with actual shopping situations. Transformer models can more comprehensively capture the dependencies between shopping behaviors and understand shopping. The overall structure of behavior plays an important role.

KEYWORDS

Behavioral Classification, Consumer Behavior, Deep Learning, Neural Networks, Shopping Patterns, User Profiling

The e-commerce industry faces unprecedented opportunities and challenges in today's digital era. The emergence of large-scale user data provides revolutionary opportunities to understand and exploit user behavior. As a critical aspect of user activities, shopping behavior records users' preferences and trends and deeply reflects their consumption habits (Aldayel et al., 2020). However, with the explosive growth of shopping behavior data accumulated by e-commerce platforms, traditional recommendation systems and analysis methods face severe challenges.

Against this background, the rapid development of deep learning technology provides unprecedented opportunities to reveal the complex laws behind shopping behavior. This research focuses on shopping behavior and aims to deeply mine massive user data for a more intelligent and personalized grasp of user consumption trends. In particular, the vast shopping behavior data contained in e-commerce platforms has become a valuable database, providing rich information for personalized recommendations and user behavior analysis. However, as user behavior becomes more complex, traditional recommendation systems and analysis methods face difficulties in capturing dynamic

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changes in personalized consumption patterns and trends. These challenges force us to realize that in the current environment, there is an urgent need to use the powerful capabilities of deep learning models to accurately characterize and analyze user shopping behavior (Tian et al., 2023). With this background, this study aims to break through the limitations of traditional technology and bring a more intelligent and personalized user experience to the e-commerce industry through deep learning models.

Although past research focused on recommendation systems and behavior analysis and tried to understand user behavior through various models and algorithms, these traditional methods have shown their limitations in accurately classifying and tracking complex user shopping patterns over a long period (X. Liu et al., 2019). For example, collaborative filtering may ignore users' personalized historical data, while rule-based methods are often not adaptable to the complexity and variability of behavioral patterns. Given these challenges, this paper proposes a new model that integrates the powerful representation capabilities of deep learning to achieve a more sophisticated and comprehensive understanding of user shopping behavior. We will explore the unique shopping characteristics and consumption trends of different user groups and propose solutions to existing problems in recommendation systems and consumer behavior analysis, aiming to promote the development of this field, move in a smarter and more accurate direction, and strive to Create a more intelligent personalized recommendation and shopping experience.

The previous research has primarily focused on recommendation systems and behavioral analysis, attempting to enhance insights using various models and algorithms. In deep learning and user behavior analysis, models such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Generative Adversarial Network (GAN), and Deep Reinforcement Learning (DRL) have not only achieved significant milestones in various domains but have also provided valuable experiences and insights for designing models in this paper for intelligent classification and analysis of user shopping behavior.

A long short-term memory network (LSTM) is a recurrent neural network that selectively memorizes or forgets information by designing forgetting gates, input gates, and output gates, solving the problems of gradient disappearance and gradient explosion in traditional RNNs (Hu & Shi, 2020). During its development process, improved versions continue to emerge, including bidirectional LSTM, multi-layer and LSTM, to meet the needs for more complex tasks. The advantage is that it can handle long-distance dependencies in sequence data and is suitable for time series, natural language, and other fields. LSTM controls information input, output, and retention through three critical gating units: the forgetting gate, input gate, and output gate, thereby enabling the network to selectively remember or forget previous information (Zhu et al., 2022). This design makes LSTM perform well when processing long sequence data. For example, in natural language processing, speech recognition, and other fields, LSTM has achieved remarkable success in many fields. In natural language processing, LSTM is widely used in language modeling, machine translation, and text generation tasks and is favored for its ability to capture long-distance dependencies in text(Zhao et al., 2021). LSTM also performs well in time series forecasting and can adapt to periodic and non-periodic patterns. In the field of user behavior analysis, LSTM can be used to model user shopping behavior sequences and capture the long-term dependencies between shopping behaviors.

A gated Recurrent Unit (GRU) is a recurrent neural network, similar to LSTM, that realizes dynamic processing of sequence information by designing the update gate and reset gate mechanisms. GRU development stems from simplifying the LSTM structure to improve computational efficiency (Islam et al., 2019). GRU also has crucial components of the update gate and reset gate in its design. Through the collaborative work of these two gates, the network can selectively retain and forget previous information. This design effectively solves the gradient disappearance and gradient explosion problems in traditional RNN, making GRU perform well when processing long sequence data (Li et al., 2021). Like LSTM, GRU has emerged with multiple improved versions during the development process to adapt to the needs of different tasks. Among them, variants such as bidirectional GRU and multi-layer GRU are widely used, improving the network's representation capabilities and making it more suitable for complex tasks. In the field of user behavior analysis, it is often used to model user shopping behavior sequences to capture the long-term dependencies between shopping behaviors. Of course, the successful application of GRU is not only reflected in the modeling of shopping behavior sequences but also includes the prediction of user shopping intentions and the inference of shopping paths (Khan et al., 2021). Its advantage lies in its efficient modeling of user behavior, which is expected to support personalized recommendations and improve the shopping experience.

Generative adversarial network (GAN) is a commonly used deep learning model. It consists of a generator and a discriminator and learns the data distribution through adversarial training (Sohn et al., 2020). The core idea of GAN is to continuously generate realistic data through the generator model, while the discriminator model strives to distinguish between genuine and generated data. The two continue to game so the generator's ability gradually improves, and the generated data is closer to the actual distribution. In the basic structure of GAN, the generator is responsible for generating new samples, while the discriminator is responsible for determining whether the sample is genuine data or generated data (Wang & Yang, 2021). Through this adversarial training method, GAN can generate high-quality data suitable for many fields, including image generation and speech synthesis. In the field of user behavior analysis, the application of GAN presents unique advantages. By generating user shopping behavior data, GAN can simulate users' behavior patterns and generate authentic shopping behavior sequences (Wang et al., 2023). It is particularly worth noting that in user behavior generation, GAN can capture the complex relationships between user behaviors and simulate the diversity and variability of users in the shopping process. This makes GAN not only limited to the role of data enhancement in user behavior analysis, but also can help deep learning models better understand the potential patterns of user behavior and improve the understanding and modeling capabilities of users' personalized preferences.

Deep reinforcement learning (DRL) is a model that combines deep learning and reinforcement learning to maximize cumulative rewards through interactive learning between the agent and the environment. DRL performs well in handling tasks with uncertainty and complexity and is particularly suitable for scenarios that require long-term planning and decision-making (Amer et al., 2022). The core of DRL is that the agent learns strategies to choose different actions in different states to maximize cumulative rewards through interaction with the environment. This enables DRL to adaptively adjust decision-making strategies in the face of unknown environments and dynamic changes, making it more robust. In user behavior analysis, the application of DRL shows unique advantages (El Ouazzani et al., 2024). By modeling the user's shopping behavior as a reinforcement learning process, DRL can learn personalized recommendation strategies based on user feedback. The agent adjusts the recommended products to suit the user's personalized needs by observing the user's shopping history and environmental changes. In addition, DRL can handle the temporal and dynamic nature of user behavior and better capture users' changing preferences during shopping (Ren et al., 2024). Through interactive learning with the environment, DRL can provide personalized product recommendations and achieve a smarter shopping experience to meet the changing needs of users.

Although LSTM, GRU, GAN, and DRL have made significant progress in user behavior analysis, LSTM and GRU may have a vanishing gradient problem when processing long sequences, which limits the effective modeling of user behavior. GANs successfully generate new samples but may face challenges in modeling time series data. At the same time, DRL may be limited by training and sample efficiency when dealing with high-dimensional state spaces.

Based on the above shortcomings, this article builds a comprehensive model (VATA model), which combines the three major components of Variational Autoencoder (VAE), Transformer (T), and Attention Mechanism (A) to improve the intelligent classification and analysis of user shopping behavior ability. In the VATA model, the Variational Autoencoder (VAE) is responsible for learning the potential representation of the user's personalized historical data and capturing the implicit characteristics of the shopping behavior; the Transformer (T) is responsible for global relationship modeling of the user's historical data to more comprehensively capture the shopping behavior.

Attention Mechanism (A) enhances the model's attention to important information in the user's shopping behavior sequence and improves the model's sensitivity to important time steps in user behavior. Through the synergy of these three major sectors, the VATA model aims to achieve more intelligent personalized recommendations and shopping experiences, provide merchants with a basis for a better understanding of user shopping preferences and behavioral relationships, and, at the same time, provide more personalized product recommendations and pricing strategies provide support.

The main contributions of this study are as follows:

1. VATA model construction: The VATA model is proposed, which realizes deep learning classification and analysis of user shopping behavior by integrating three key modules: Variational Autoencoder (VAE), Transformer (T), and Attention Mechanism (A).
2. User behavior feature learning and relationship modeling: The VAE module in the VATA model uses the ability of the generative model to learn the potential representation of user shopping behavior, and the Transformer module implements global relationship modeling of user historical data.
3. Intelligent personalized recommendations: The application of the VATA model helps merchants better understand the shopping preferences of different users, provides more personalized product recommendations and pricing strategies, and provides users with shopping services that are more in line with individual needs.

In the following chapters, we will discuss it according to the following structure: Chapter 2 will introduce the methods in depth and reveal the core construction and design principles of the VATA model. Chapter 3 will focus on the experimental settings and details (Experiment) to reproduce the experiment. Chapter 4 will introduce the experimental results (Results) in detail to show the performance of the VATA model in different data sets and scenarios. Finally, Chapter 5 will summarize and conclude the full text.

METHODOLOGY

Overview of Our Model

To solve the shortcomings of traditional methods in user behavior analysis, this article proposes the VATA model, which integrates three key modules: Variational Autoencoder (VAE), Transformer (T), and Attention Mechanism (A) to achieve user shopping behavior analysis. Deep learning classification and analysis.

In the VATA model, the VAE module is responsible for learning the potential representation of user personalized historical data. Through the ability to generate models, it can not only capture the implicit characteristics of shopping behavior, but also can generate new samples in the absence of data, providing a better Comprehensive understanding of users' personalized shopping behavior provides strong support. The Transformer module models the global relationship of user historical data. Through the self-attention mechanism, it can better capture the dependencies between shopping behaviors and help to better understand the overall structure of shopping behaviors, especially when processing Works well with long-distance dependencies. The Attention Mechanism module enhances the model's focus on important information in the user's shopping behavior sequence, making the model more focused on modeling individual shopping behaviors, improving the model's sensitivity to necessary time steps in user behavior, and making the model more flexible. The importance of adapting to different user behaviors.

Our model is built according to the following steps: First, for the input layer, user personalized historical data is used as input, including shopping behavior sequence, click records, browsing duration and other information. In the VAE module, feature learning is performed on user historical data to obtain a potential representation of the user's personalized behavior. In the Transformer module, global relationship modeling is used to more comprehensively capture the dependencies between shopping behaviors. In the Attention Mechanism module, the attention mechanism enhances attention to important information in the user behavior sequence. The last is the classification output layer, which uses the learned features to classify users into different shopping types.

The structural diagram of the overall model is shown in Figure 1.

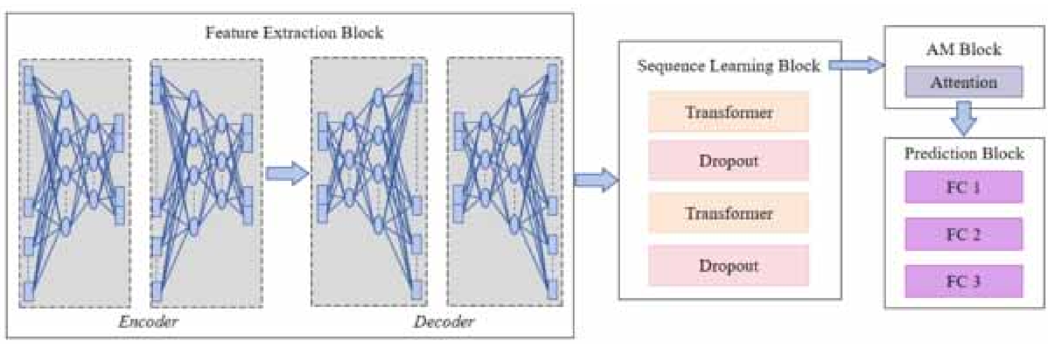
The running process of the VATA model is shown in Algorithm1.

Variational Autoencoder Model

Variational Autoencoder (VAE) is a generative model that aims to learn a probabilistic mapping between input data and latent space. It is designed to generate new samples similar to the training data by sampling from the learned latent distribution (Hasumoto & Goto, 2022). VAE consists of an encoder and a decoder, with the encoder mapping input data to a latent space and the decoder generating data samples from the latent space representations. The primary goal of VAE is to capture the underlying structure and variability in the data while generating diverse and realistic samples.

VAE has found applications in capturing the personalized latent representations of users' historical data in the context of user behavior analysis. It excels in modeling complex patterns within sequences and has been successfully applied to tasks such as session-based recommendation systems

Figure 1. Overall Model Flow Chart



Algorithm 1. VATA Model Training

Require: E-Commerce Dataset, Behavior Trajectory Dataset, Social Media Consumption Dataset, Temporal Shopping Dataset
Initialize VATA model parameters
Split datasets into training and testing sets
Initialize optimizer and loss function
for each epoch in training **do**
for each batch in training set **do**
Load batch of data (sequences, labels)
Encode sequences using VAE module
Apply Transformer module for global relationship modeling
Apply Attention Mechanism for enhanced feature attention
Calculate classification loss using encoded features and labels
Backpropagate the loss and update model parameters
end for
end for
Evaluate the model on testing set
Calculate Accuracy, Recall, F1 Score, AUC, etc.

and behavior pattern recognition (Brégère & Bessa, 2020). The advantages of VAE lie in its ability to handle uncertainty in the data and generate diverse yet meaningful samples.

The VAE module in the VATA model is responsible for learning the potential representation of user-personalized historical data. VATA's VAE module employs the power of generative models, aiming to capture the implicit characteristics of shopping behavior and generate new samples, which is crucial for dealing with situations where data is lacking. The theoretical basis of VAE lies in variational inference and generative modeling. The encoder learns the potential distribution of user behavior, and the decoder generates new samples with similar distributions. This distributional advantage provides the VATA model with powerful data learning and generation capabilities to comprehensively understand users' personalized shopping behavior.

The structure diagram of VAE Model is shown in Figure 2.

The following are the key mathematical formulas of the VAE model:

$$q\left(z \middle| x\right) = \mathcal{N}\left(z; \mu_\theta\left(x\right), \sigma_\theta^2\left(x\right)\right) \tag{1}$$

where $\mu_\theta\left(x\right)$ and $\sigma_\theta^2\left(x\right)$ are the mean and variance of the latent variable z given the input x.

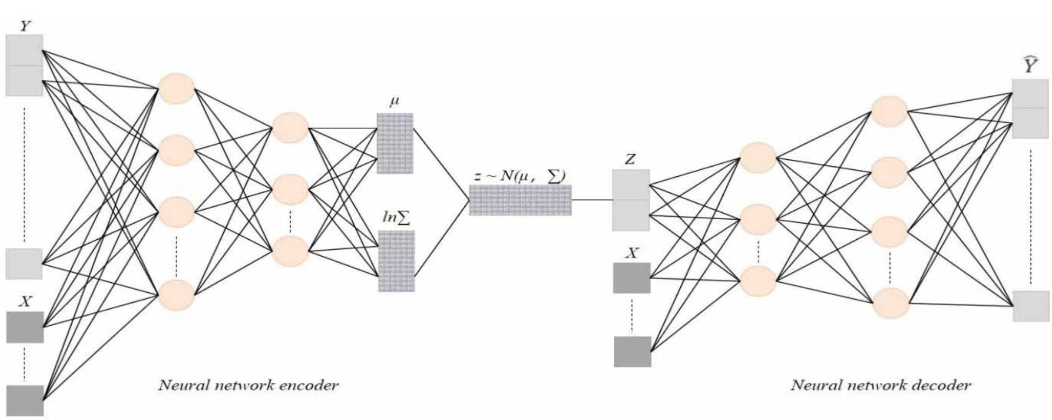
$$p\left(x \middle| z\right) = \mathcal{N}\left(x; \mu_\phi\left(z\right), \sigma_\phi^2\left(z\right)\right) \tag{2}$$

where $\mu_\phi\left(z\right)$ and $\sigma_\phi^2\left(z\right)$ are the mean and variance of the reconstructed input x given the latent variable z.

$$\mathcal{L}\left(\theta, \phi; x\right) = \mathbb{E}_{q\left(z|x\right)}\left[log\ p\left(x \middle| z\right)\right] - KL\left[q\left(z \middle| x\right) p\left(z\right)\right] \tag{3}$$

where $\mathcal{L}\left(\theta, \phi; x\right)$ represents the evidence lower bound (ELBO), KL is the Kullback-Leibler divergence, and $p\left(z\right)$ is the prior distribution over latent variables.

Figure 2. Flow Chart of the VAE Model



$$KL\left[q\left(z\middle|x\right)p\left(z\right)\right]=\frac{1}{2}\sum_{j=1}^{J}(1+log(\sigma_{\theta,j}^{2}\left(x\right)-\mu_{\theta,j}^{2}\left(x\right)--\sigma_{\theta,j}^{2}\left(x\right)) \quad (4)$$

where J is the dimensionality of the latent space.

$$\mathcal{J}\left(\theta,\phi\right)=\mathbb{E}_{x\sim P_{data}\left(x\right)}\left[\mathcal{L}\left(\theta,\phi;x\right)\right] \quad (5)$$

where $\mathcal{J}\left(\theta,\phi\right)$ represents the VAE objective function, integrating the ELBO over the data distribution.

Transformer Model

The Transformer model is a neural network architecture based on the attention mechanism and is widely used in sequence modeling tasks. The core idea is to capture the dependency between any two positions in the sequence through a self-attention mechanism independent of the distance of the sequence. The Transformer model contains an encoder and a decoder, where the encoder is used to model the input sequence and the decoder is used to generate the output sequence (Xia et al., 2020). The innovation of this model is that it completely abandons the structure of the recurrent neural network (RNN) and uses a self-attention mechanism to better handle long-distance dependencies and parallel computing.

In user behavior analysis, the Transformer model captues global relationships in user behavior sequences. It is suitable for modeling various complex time series patterns and can better understand and capture the overall behavioral structure of users in the shopping process (Chen et al., 2019). Transformer's advantages include better parallel computing capabilities and modeling of long-distance dependencies, allowing it to comprehensively capture the correlation between different behaviors when processing user shopping behavior sequences.

The Transformer module in the VATA model is used for global relationship modeling. Using a self-attention mechanism, the Transformer can better capture the dependencies between shopping behaviors and performs particularly well when dealing with long-distance dependencies. The theoretical basis of the Transformer is derived from the expansion of the attention mechanism and self-attention mechanism. By applying the attention mechanism to sequence data, the Transformer can weight sequence elements globally, thereby achieving global relationship modeling of the overall structure of shopping behavior. This modeling makes the VATA model more capable of capturing the complex dependencies of user behavior and helps to better understand the overall structure of shopping behavior.

The structure diagram of the Transformer Model is shown in Figure 3.

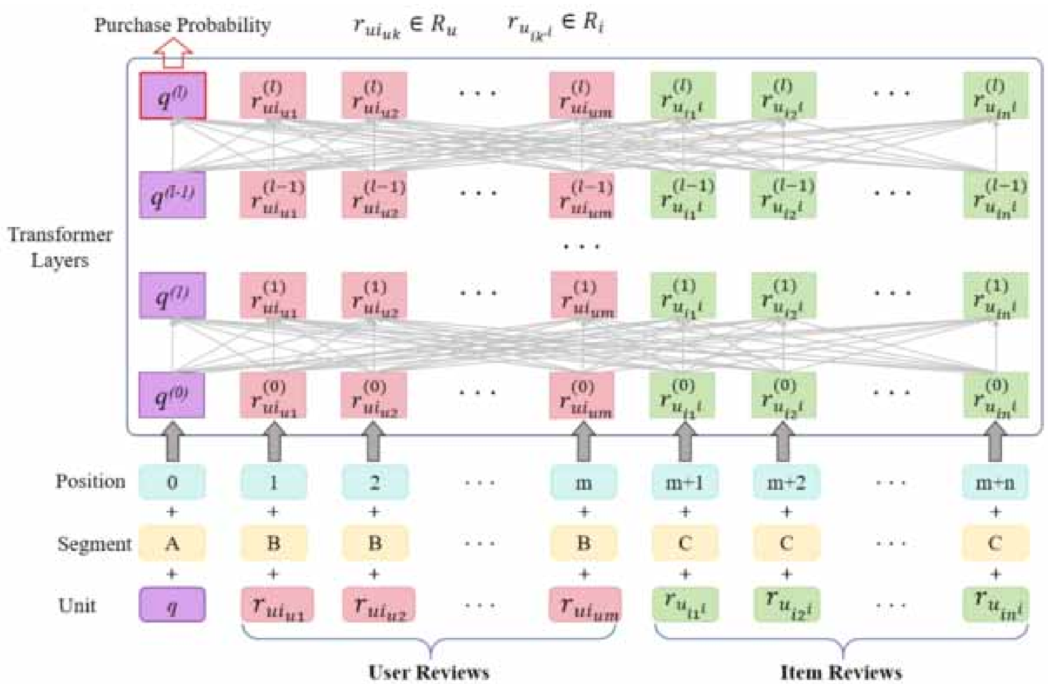
The main formula of Transformer model is as follows:

$$Encoder\ Output=MultiHead\ Attention\left(Query,Key,Value\right) \quad (6)$$

where $Query$, Key, and $Value$ are input sequences, and $MultiHead\ Attention$ is the multi-head attention mechanism.

$$Positional\ Encoding=\left[sin\left(pos/10000^{2i/d}\right)cos\left(pos/10000^{2i/d}\right)\right] \quad (7)$$

Figure 3. Flow Chart of the Transformer Model



where pos is the position and d is the dimension of the positional encoding.

$$Decoder\ Input = MultiHead\ Attention\left(Query, Key, Value\right) \tag{8}$$

where $Query$, Key, and $Value$ are output sequences from the encoder.

$$Feed\ Forward\left(X\right) = ReLU\left(X \cdot W_1 + b_1\right) \cdot W_2 + b_2 \tag{9}$$

where X is the input, W_1, b_1, W_2, and b_2 are learnable parameters.

$$Layer\ Norm\left(X\right) = \frac{X - \mu}{\sigma}, where\ \mu = mean\left(X\right), \sigma = std\left(X\right) \tag{10}$$

where X is the input tensor, and μ and σ are the mean and standard deviation, respectively.

Attention Mechanism

The attention mechanism is a technology that enables the model to pay more attention to relevant parts when processing sequence data by giving different weights to inputs at different positions. Attention mechanisms have achieved remarkable success in deep learning, especially in processing sequence data and natural language processing tasks (JI Bonan, 2023). The basic principle is to focus more attention on the parts relevant to the current task by learning the weight of each input position. In sequence modeling, the attention mechanism helps the model better understand the vital information in the sequence.

In user behavior analysis, the attention mechanism is often used to enhance the model's attention to important information in user behavior sequences, allowing the model to focus more on modeling individual shopping behaviors (Qian et al., 2023). Its advantage is that it improves the model's sensitivity to necessary time steps in user behavior, allowing it to more flexibly adapt to the importance of different user behaviors. In natural language processing, attention mechanisms are also widely used in tasks such as text generation and translation and perform well.

The Attention Mechanism module in the VATA model enhances attention to important information in the user's shopping behavior sequence. It allows the model to focus more on modeling individual shopping behaviors, improves its sensitivity to necessary time steps in user behavior, and makes it more flexible to adapt to the importance of different user behaviors. Attention Mechanism's theoretical basis is to simulate how human attention works, and achieve attention to different elements in the sequence by dynamically adjusting the attention weights of different parts. In the VATA model, the introduction of the Attention Mechanism enables the model to capture the critical information of the shopping behavior sequence more precisely, thus improving the flexibility and expressiveness of the model.

The structure diagram of Attention Mechanism is shown in Figure 4.

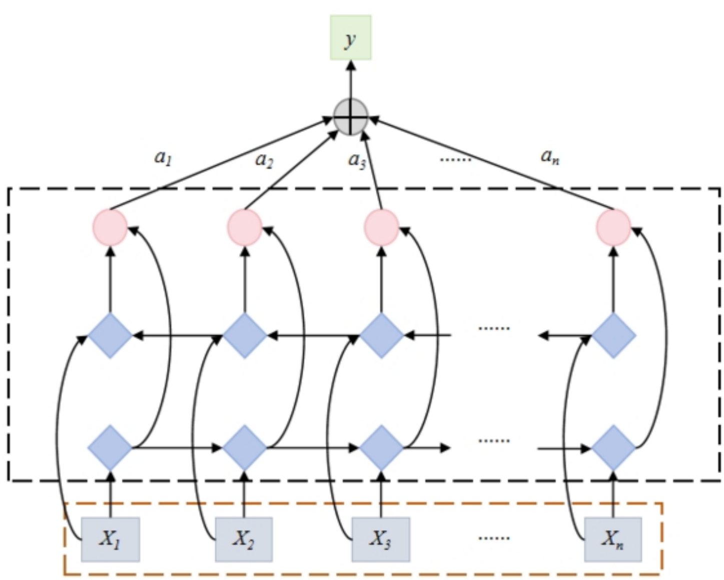
The main Attention Mechanism formula is:

$$Attention\ Score = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) \tag{11}$$

where Q is the query matrix, K is the key matrix, and d_k is the dimension of the key.

$$Weighted\ Sum = Attention\ Score \cdot V \tag{12}$$

Figure 4. Flow Chart of the Softmax Model



where V is the value matrix.

$$MultiHead\ Attention = Concat\left(head_1, \cdots, head_h\right) \cdot W_O \tag{13}$$

where $head_i = Attention\,Score_i$ is the $i-th$ attention head, and W_O is the output weight.

$$Self\ Attention = MultiHead\ Attention\left(X, X, X\right) \tag{14}$$

where X is the input sequence.

$$LayerNorm\left(X + Slef\ Attention\right) = \frac{X + Self\ Attention - \mu}{\sigma} \tag{15}$$

where X is the input tensor, Self Attention is the self-attention output, and μ and σ are the mean and standard deviation, respectively.

EXPERIMENT

Experimental Environment

Hardware Configuration

The hardware environment used in the experiments consists of a high-performance computing server equipped with an AMD Ryzen Threadripper 3990X @ 3.70GHz CPU and 1TB RAM, along with 6 Nvidia GeForce RTX 3090 24GB GPUs. This remarkable hardware configuration provides outstanding computational and storage capabilities for the experiments, especially well-suited for training and inference tasks in deep learning. It accelerates the model training process, ensuring efficient experimentation and rapid convergence.

Software Configuration

We utilized Python and PyTorch to implement our research work in this study. Python provided us with a flexible development environment as the primary programming language. PyTorch, as the main deep learning framework, offered powerful tools for model construction and training. Leveraging PyTorch's computational capabilities and automatic differentiation functionality, we efficiently developed, optimized, and trained our models, achieving better experiment results.

Experimental Dataset

Our research is based on four main data sets, each providing essential user shopping behavior information and providing rich content for the training and evaluation of the VATA model.

E-Commerce Dataset summarizes users' shopping history on e-commerce platforms, including detailed information such as product purchases, click behavior, and browsing time (Aydoğan & Kocaman, 2023). This huge data set comes from multiple e-commerce platforms, covering over 1 million users and hundreds of millions of shopping behaviors. Its characteristics include product ID, user ID, purchasing behavior, click behavior, and browsing time. This data set has been broadly used in fields such as personalized recommendations and shopping behavior analysis in previous research.

Behavior Trajectory Dataset records users' complete shopping behavior trajectory on the online platform, tracking each stage of the shopping process in detail, such as searching for products, adding to a shopping cart, and checkout (Krajewski et al., 2020). This data set comes from multiple online platforms and contains detailed behavioral information of more than 500,000 users. Its previous history of use shows a wide range of applications in areas such as user behavior modeling and shopping path analysis.

The impact of social media is also factored into our research, powered by the Social Media Consumption Dataset. This data set integrates user shopping behavior data from mainstream social media platforms, including product-related comments, likes, shares, and other social interaction data (Kaliyar et al., 2021). Such social media dimensions help the model understand the impact of users' social influence on shopping behavior. Previous research has shown that this dataset has played a crucial role in social media influence research and social recommendation systems.

Temporal Shopping Dataset provides time series data of user shopping behavior, recording the occurrence of shopping activities at different points in time. This time series data set contains shopping time series information of hundreds of thousands of users, and its features include time series information such as shopping behavior and timestamps (W. Liu et al., 2019). Its wide application in fields such as time series analysis and seasonal trend research provides our VATA model with important information about the temporal correlation of shopping behavior.

Together, these data sets form the basis of our research, through which we can comprehensively understand and analyze user shopping behavior, thereby providing solid support for the performance of the VATA model.

Experimental Setup and Details

We integrated VAE, Transformer, and Attention mechanisms to build a VATA model to study user shopping behavior. The experimental settings and details will be introduced in detail in subsequent sections to ensure the reliability and reproducibility of the experimental results.

Data Preprocessing

1. Data acquisition and collection

Obtain raw data from the data set. The data includes users' shopping history, behavior trajectories, social media interactions, and time series information.

2. Data cleaning

We adopted two main strategies for missing data according to the specific situation. First, for cases with few missing values, we usde interpolation methods, such as linear interpolation or interpolation based on neighboring values, to fill in the missing values. This process helped preserve overall trends in the data. Second, we deleted the corresponding data records to ensure the analysis and modeling accuracy for cases with many missing values that cannot be interpolated. For outliers, we mainly process them through encoding conversion to maintain the consistency and stability of the data.

3. Data standardization

We primarily focus on continuous features in the data standardization stage to ensure they have similar scales. The Z-score normalization method converts the features into a standard normal distribution by subtracting the feature mean and dividing it by the standard deviation.

4. Data division

Divide the data set into training, verification, and test sets. 80% of the data was used as the training set, 10% of the data was used as the verification set, and 10% of the data is used as the test set to ensure the model's generalization performance.

Model Training

1. Network parameter settings

We use the Adam optimizer with a learning rate of 0.001 to update the model parameters. To balance training speed and convergence performance, we set the batch size to 64. In addition, we selected an appropriate number of units for the hidden layer of the model, set to 256 units, to avoid overfitting while maintaining the expressiveness of the model.

2. Model architecture design

The model architecture design plays a key role in the entire experiment. We adopted the VATA model, which includes three key components: Variational Autoencoder (VAE), Transformer, and Attention Mechanism. VAE is responsible for learning the user's latent representation, the Transformer is used for global relationship modeling, and the Attention Mechanism enhances attention to important information in user behavior sequences.

3. Model training process

The model training process adopts the classic supervised learning framework. We divided the data set into a training set and a test set, of which 80% of the data was used for model training, and 20% was used to evaluate the model's generalization performance. The model was trained using 50 training rounds. We use classic evaluation indicators, such as Accuracy, Recall, F1 Score, and AUC, to comprehensively evaluate the model's performance.

Model Validation and Tuning

1. Cross-Validation

To evaluate the robustness and generalization ability of the model, we used 5-fold cross-validation. The data set was divided into five subsets; four were selected as the training set, and the remaining one as the verification set. Five sets of training and verification results were obtained by taking turns to select the verification set and the training set. The final evaluation result is the average of these five training verifications. Such a cross-validation process helps reduce fluctuations in evaluation results caused by different divisions of data sets and improves the experiment's reliability.

2. Model Fine-Tuning

To optimize model performance, we used the backpropagation algorithm and set the initial learning rate to 0.001. We conducted ten iterations during the model training process to ensure the model could thoroughly learn the data features.

Ablation Experiment

We conducted a series of ablation experiments to gain a deeper understanding of the impact of each component of the deep learning-driven user shopping behavior classification and analysis model on the overall performance. The following is the ablation experiment setup for the three key components:

Do not use the Transformer model: remove the Transformer component in the model. Model parameters will start with random initialization and be optimized using standard gradient descent methods. The learning rate is set to 0.001, the batch size is 64, and the number of training iterations is 50 epochs.

Do not use the Variational Autoencoder (VAE) model: Remove the Variational Autoencoder (VAE) component in the model. Model parameters will start with random initialization and be optimized using standard gradient descent methods. The learning rate is set to 0.001, the batch size is 64, and the number of training iterations is 50 epochs.

Do not use the Attention Mechanism model: remove the Attention Mechanism component in the model. Model parameters will start with random initialization and be optimized using standard gradient descent methods. The learning rate is set to 0.001, the batch size is 64, and the number of training iterations is 50 epochs.

Comparative Analysis

We then conducted a series of comparative experiments, mainly focusing on comparing the impact of different optimization methods on the performance of user shopping behavior classification and analysis models. The optimization method that is most suitable for user shopping behavior classification and analysis tasks can be selected through comparative experiments.

Adam vs. Attention Mechanism (AM): Set Adam's learning rate to 0.001, the batch size to 64, and the number of training iterations to 50 rounds. By comparing the effects of Adam and AM on model performance and convergence speed, we can evaluate their advantages and disadvantages in user shopping behavior classification and analysis tasks.

Bayesian Optimization vs. Attention Mechanism (AM): We first set the parameters of the prior function and sampling strategy for Bayesian Optimization. We chose the RBF kernel function, the initial number of sample points is 10, and we used EI (Expected Improvement) as the sampling strategy. By comparing the effects of Bayesian Optimization and AM in model performance and parameter tuning, we conducted an in-depth study of the performance comparison of these two optimization methods in classifying and analyzing user shopping behavior.

Genetic Algorithms (GA) vs. Attention Mechanism (AM): Set the population size for GA to 100, the evolutionary generation to 50, the crossover probability to 0.8, and the mutation probability to 0.1. By comparing the effectiveness of GA and AM in terms of model performance and capturing user behavior characteristics, we conducted an in-depth study of the performance comparison of these two optimization methods in the classification and analysis of user shopping behavior.

Model Evaluation

The main goal of this study is to use a deep learning model to input user personalized historical data and classify users' shopping behaviors to capture the unique characteristics and consumption trends of different categories of users' shopping behaviors. We achieved enhanced personalized recommendations and shopping experiences by dividing users into different shopping types, such as frequent or seasonal. We explicitly use multiple performance metrics to comprehensively evaluate the VATA model's performance in shopping behavior classification. In this study, we conducted a comprehensive evaluation of the user shopping behavior classification and analysis model, focusing mainly on its performance in terms of accuracy and efficiency of shopping behavior classification.

Accuracy evaluation indicators: to evaluate the model's accuracy, we use several commonly used indicators, including Accuracy, Recall, F1 Score, and AUC (Area Under the Curve). Through the comprehensive evaluation of these indicators, we can comprehensively understand the model's classification performance in different aspects. Accuracy is a primary classification performance indicator. Accuracy reflects the model's ability to classify samples and is a widely accepted metric. Recall that in shopping behavior analysis, we focus on the model's ability to correctly identify positive categories (e.g., shopping behaviors). Recall measures the proportion of all positive categories correctly identified by the model. The F1 score comprehensively considers accuracy and recall, is particularly suitable for imbalanced categories, and has a more comprehensive evaluation for classifying shopping behaviors. AUC (Area Under the Curve) is the area under the ROC curve. AUC provides the performance evaluation of the model under different classification thresholds and is sensitive to the uncertainty of shopping behavior classification. The selection of these indicators is based on their widespread application in shopping behavior analysis and their objectivity and comprehensiveness in evaluating model performance.

Efficiency evaluation indicators: to evaluate the model's efficiency, we considered the following indicators: number of model parameters (Parameters), floating point operations (FLOPs), Inference Time, and Training Time. These indicators help us understand the efficiency performance of the model at runtime and training time and provide a reference for practical applications. Parameters are directly related to the complexity and resource requirements of the model. We focus on this indicator because, in practical applications, the simpler the model and the fewer parameters, the easier it is to deploy and maintain. FLOPs represent the number of floating point operations performed by the model and are an essential indicator of the computational complexity of the model. We chose to focus on FLOPs to gain a comprehensive understanding of the computational burden of the model, especially for models deployed in resource-constrained environments. Inference Time refers to the time it takes for the model to receive input and output prediction results. We focus on this metric because in real-time applications, fast inference time is directly related to the model's practicality and user experience. Training Time represents the time required for the model to learn parameters during the training phase. We chose to focus on this metric because short training times help improve model trainability, especially in scenarios where data updates are frequent.

RESULTS

As shown in Table 1, we compared the performance of multiple models on different data sets. In the E-Commerce Dataset, our model (Ours) outperforms other models in both accuracy (97.43%) and AUC (93.56%), especially in recall (95.03%) and F1 Score (93.71%). Our model also achieved significant advantages in indicators such as accuracy and AUC on other data sets. Compared with other methods, the Ours model achieved higher accuracy (93.83%), Recall (95.69%), and F1 Score (93.58%) in the Behavior Trajectory Dataset and achieved higher accuracy (93.58%) in the Social Media Consumption Dataset. 98.23%), Recall (95.79%), and F1 Score (94.41%), also maintaining its leading position in the Temporal Shopping Dataset. By comparing these experimental results, our model has achieved superior performance in various evaluation indicators and has better classification and prediction performance. Figure 5 visualizes the table's contents and more clearly shows the comparison results of each model on different data sets.

As shown in Table 2, we compared the performance of multiple models on different data sets in terms of number of parameters, computational complexity, inference time, and training time. In the E-Commerce Dataset, our model (Ours) has a relatively small parameter size (339.06M) and computational complexity (3.54G FLOPs), while performing excellent inference time (5.33ms) and training time (326.77s). Our model also achieved significant advantages compared to other data sets. Compared with other methods, our model has fewer parameters and calculations in Behavior Trajectory Dataset, Social Media Consumption Dataset, and Temporal Shopping Dataset, Complexity, and

Table 1(a). The Comparison of Different Models in Different Indicators Comes From Different Datasets (Part 1)

Model	Datasets							
	E-Commerce Dataset				Behavior Trajectory Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
Ta (Ta & Gao, 2022)	88.46	93.23	88.23	92.51	91.19	86.97	86.96	87.57
Bao (Bao et al., 2021)	91.64	90.18	87.08	84.86	89.26	89.86	90.65	86.65
Yolcu (Yolcu et al., 2020)	93.19	87.29	84.83	89.35	88.65	88.56	86.18	85.18
Nosratabadi (Nosratabadi et al., 2020)	93.09	89.78	87.38	91.91	92.41	84.63	87.66	84.95
Kotsiopoulos (Kotsiopoulos et al., 2021)	85.74	84.17	84.11	89.51	92.23	86.11	86.13	87.52
Jain (Jain et al., 2021)	88.16	91.07	84.99	92.58	86.48	91.27	84.15	90.64
Ours	97.43	95.03	93.71	93.56	93.83	95.69	93.58	94.37

Table 1(b). The Comparison of Different Models in Different Indicators From Different Datasets (Part 2)

Model	Datasets							
	Social Media Consumption Dataset				Temporal Shopping Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
Ta	89.72	85.65	84.99	86.5	87.71	88.66	89.2	84.21
Bao	90.34	84.77	85.86	86.42	85.95	85.13	88.41	90.58
Yolcu	88.05	91.35	88.73	89.14	90.99	87.85	85.25	86.58
Nosratabadi	91.28	91.95	90.56	89.48	95.44	88.36	86.09	87.14
Kotsiopoulos	92.61	85.17	84.38	90.73	88.09	84.67	84.33	88.47
Jain	85.96	93.17	86.44	87.44	94.44	89.17	88.54	83.84
Ours	98.23	95.79	94.41	94.79	96.23	96.71	94.52	93.82

shorter inference and training times. The comparison shows that our model has achieved significant advantages in various performance indicators, ensuring high efficiency without losing accuracy. Figure 6 visualizes the table's contents and more clearly shows the performance comparison results of each model on different data sets. By observing the charts, we can intuitively capture the differences between different models in parameters such as parameter quantity, computational complexity, inference time, and training time, further verifying the excellent performance of our model in multiple aspects.

As shown in Table 3, we conducted an ablation experiment, removing the Transformer, Variational Autoencoder (VAE) and Attention Mechanism components in the model one by one and comparing the impact of each component on model performance. On the E-Commerce Dataset, compared to models that do not use Transformer and Attention Mechanism, our VAE+AM model has achieved significant improvements in Accuracy, Recall, F1 Score, and AUC, reaching 94.65% and 84.05% respectively, 85.47% and 92.04%. Similarly, the VAE+AM model also performed well on other data sets, further verifying the effectiveness of VAE and Attention Mechanism in user shopping behavior classification and analysis tasks. At the same time, compared with models that do not use Variational Autoencoder and Attention Mechanism, our Transformer+AM model performs best on the Temporal Shopping Dataset, with Accuracy, Recall, F1 Score, and AUC reaching 89.29%, 87.73%, 89.29%, and 87.73%, respectively. This strongly demonstrates the importance of the Transformer in user behavior analysis, especially its superiority when processing time series data. Our comprehensive model Ours (VATA) achieved the best performance on all datasets, with Accuracy, Recall, F1 Score, and AUC

Figure 5. Model Accuracy Verification Comparison Chart of Different Indicators of Different Models

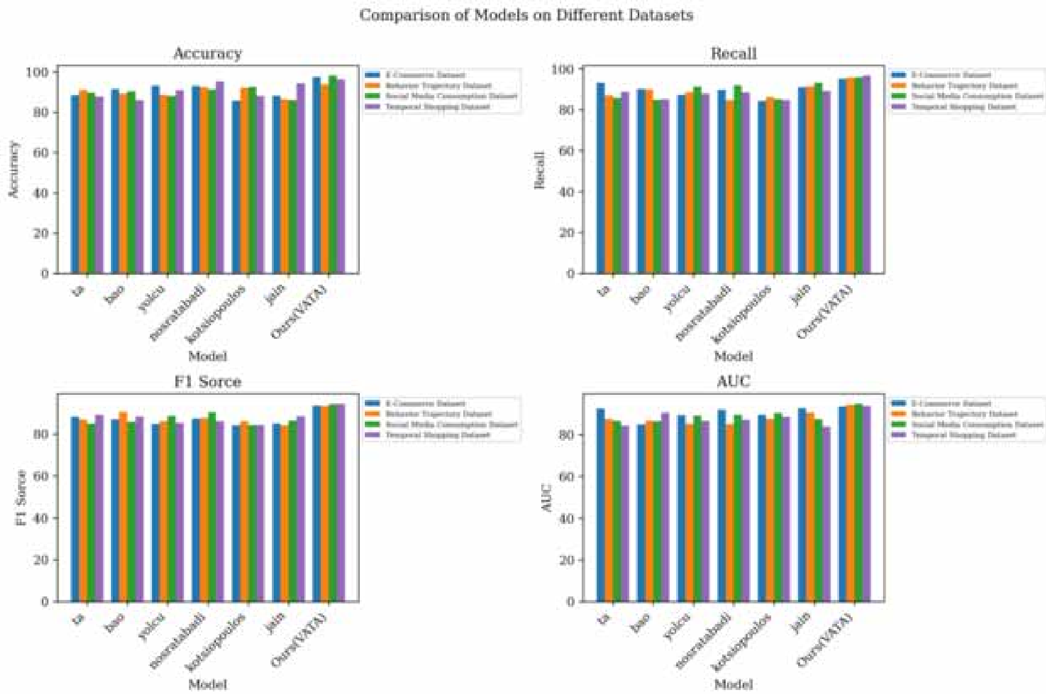


Table 2(a). Model Efficiency Verification and Comparison of Different Indicators of Different Datasets (Part 1)

Model	Datasets							
	E-Commerce Dataset				Behavior Trajectory Dataset			
	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time (s)	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time (s)
Pondel	504.08	5.86	8.48	491.99	478.14	5.46	10.12	598.67
Wu	678.60	8.42	10.45	657.51	688.20	7.82	13.71	772.48
Almahmood	702.48	8.04	8.25	455.10	532.32	5.75	9.95	382.17
Liu	763.01	8.39	11.73	711.05	639.74	6.90	12.00	735.89
Zhang	466.08	4.89	7.87	464.89	398.45	4.64	8.41	432.32
Cao	336.27	3.56	5.34	326.47	318.76	3.63	5.65	338.81
Ours	339.06	3.54	5.33	326.77	316.96	3.64	5.63	335.58

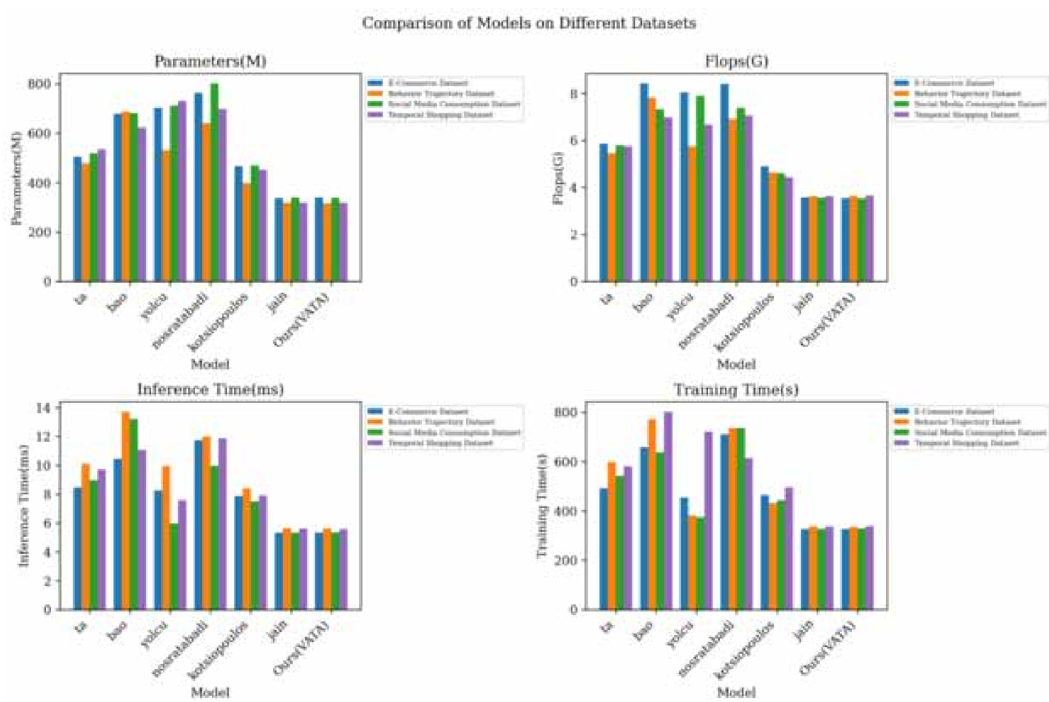
reaching 96.91%, 95.37%, 93.37%, and 94.41%, respectively. This result proves the comprehensive advantages of our proposed VATA model, which effectively integrates the characteristics of Variational Autoencoder, Transformer, and Attention Mechanism, and provides an efficient and comprehensive solution for classifying and analyzing user shopping behavior. Figure 7 visualizes the table's contents and more clearly shows the performance comparison results of each model on different data sets.

As shown in Table 4, we conducted comparative experiments to compare the performance of four optimization methods: Adam, Bayesian Optimization, Genetic Algorithms (GA), and Attention Mechanism (AM) in the user shopping behavior classification and analysis model. On the E-Commerce Dataset, the Attention Mechanism (AM) achieved the best performance in various

Table 2(b). Model Efficiency Verification and Comparison of Different Indicators of Different Datasets (Part 2)

Model	Datasets							
	Social Media Consumption Dataset				Temporal Shopping Dataset			
	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time (s)	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time (s)
Pondel	517.91	5.78	8.96	542.21	534.24	5.74	9.71	580.65
Wu	681.05	7.32	13.22	639.34	623.81	6.98	11.07	802.27
Almahmood	710.55	7.90	5.96	375.10	729.95	6.66	7.58	721.10
Liu	801.11	7.38	9.97	735.82	697.44	7.06	11.87	615.01
Zhang	470.09	4.60	7.51	443.45	451.68	4.43	7.91	496.11
Cao	339.17	3.55	5.34	327.03	318.76	3.63	5.62	336.81
Ours	338.52	3.53	5.36	328.38	319.08	3.65	5.59	338.13

Figure 6. Model Efficiency Verification Comparison Chart of Different Indicators of Different Models



indicators, including low parameters, small calculation amount (Flops), short inference time, and training time. The AM model's Parameters, Flops, Inference Time and Training Time are 211.75M, 186.53G, 202.28ms, and 223.94s, respectively. Compared with other optimization methods, it has higher computing efficiency and speed. Bayesian Optimization performs well on the Social Media Consumption Dataset. Its Parameters, Flops, Inference Time, and Training Time are 370.53M, 262.46G, 240.33ms, and 280.11s, respectively. Compared with other methods, it underperforms on this data set. Computational complexity. On other data sets, the AM model also performs well, with a smaller number of parameters and calculations, and also has excellent performance in Inference Time and Training Time. This result strongly proves the Attention Mechanism's exceptional performance

Table 3(a). Ablation Experiments on the VATA Module Using Different Datasets (Part 1)

Model	Datasets							
	E-Commerce Dataset				Behavior Trajectory Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
VAE+AM	94.65	84.05	85.47	92.04	95.36	86.05	86.14	84.94
Transformer+AM	86.23	86.68	89.42	88.69	89.27	93.35	84.94	88.46
VAE+Transformer	86.77	92.33	85.44	92.89	91.09	85.57	84.77	89.87
Ours(VATA)	96.91	95.37	93.37	94.41	95.93	94.81	94.09	93.91

Table 3(b). Ablation Experiments on the VATA Module Using Different Datasets (Part 2)

Model	Datasets							
	Social Media Consumption Dataset				Temporal Shopping Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
VAE+AM	95.84	88.29	86.91	91.86	90.84	87.23	87.38	92.21
Transformer+AM	88.89	90.62	89.68	93.33	89.54	84.23	89.29	87.73
VAE+Transformer	93.33	88.02	86.45	90.27	92.45	93.09	85.07	84.82
Ours(VATA)	96.98	96.37	93.46	95.07	97.88	94.18	93.85	94.71

Figure 7. Ablation Experiments on the VATA Module

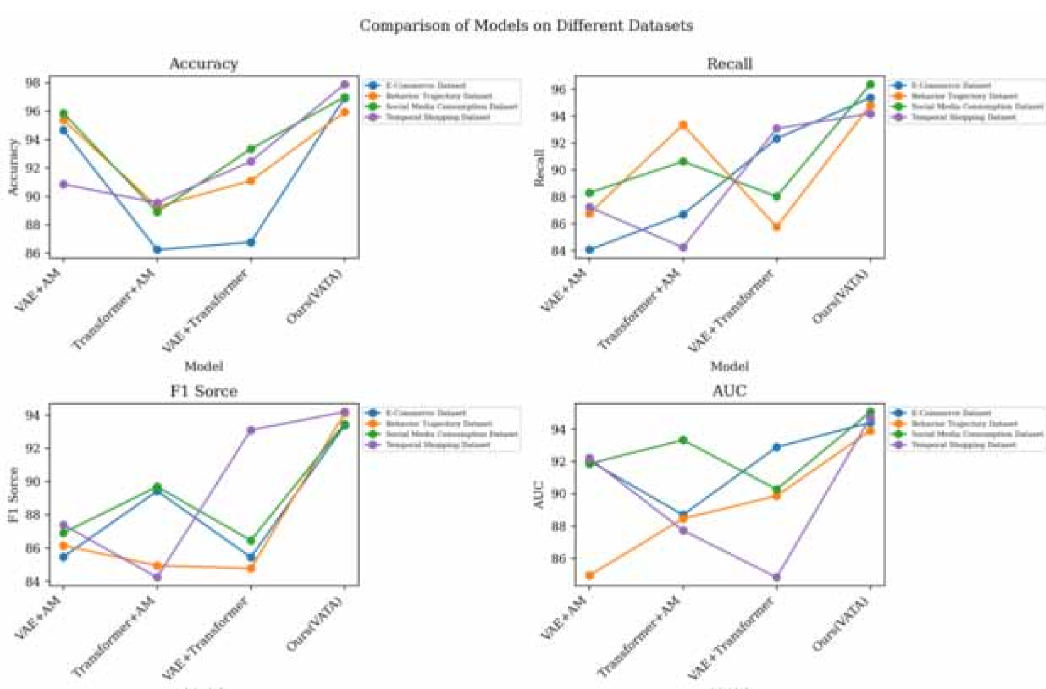


Table 4(a). Ablation Experiments on the AM Module Using Different Datasets (Part 1)

Model	Datasets							
	E-Commerce Dataset				Behavior Trajectory Dataset			
	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time (s)	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time (s)
Adam	372.24	270.39	248.16	312.48	368.31	333.43	212.33	419.45
Bayesian	384.96	305.68	264.72	288.68	275.09	375.13	370.49	343.54
GA	344.61	365.63	268.22	321.99	355.39	343.18	271.89	362.53
AM	211.75	186.53	202.28	223.94	179.79	187.33	196.43	117.31

Table 4(b). Ablation Experiments on the AM Module Using Different Datasets (Part 2)

Model	Datasets							
	Social Media Consumption Dataset				Temporal Shopping Dataset			
	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time (s)	Parameters (M)	Flops (G)	Inference Time (ms)	Training Time (s)
Adam	377.58	307.09	293.87	392.77	277.25	258.22	337.56	385.64
Bayesian	370.53	262.46	240.33	280.11	377.34	292.11	215.36	399.95
GA	311.53	320.29	239.17	290.68	352.84	282.07	391.14	398.39
AM	129.11	137.33	233.98	186.11	209.18	216.83	207.71	182.32

in classifying and analyzing user shopping behavior. Overall, the Attention Mechanism has achieved significant advantages in various performance indicators, providing an efficient and feasible solution for optimizing user shopping behavior classification and analysis models. Figure 8 visualizes the table's contents and more clearly shows the performance comparison results of each optimization method on different data sets.

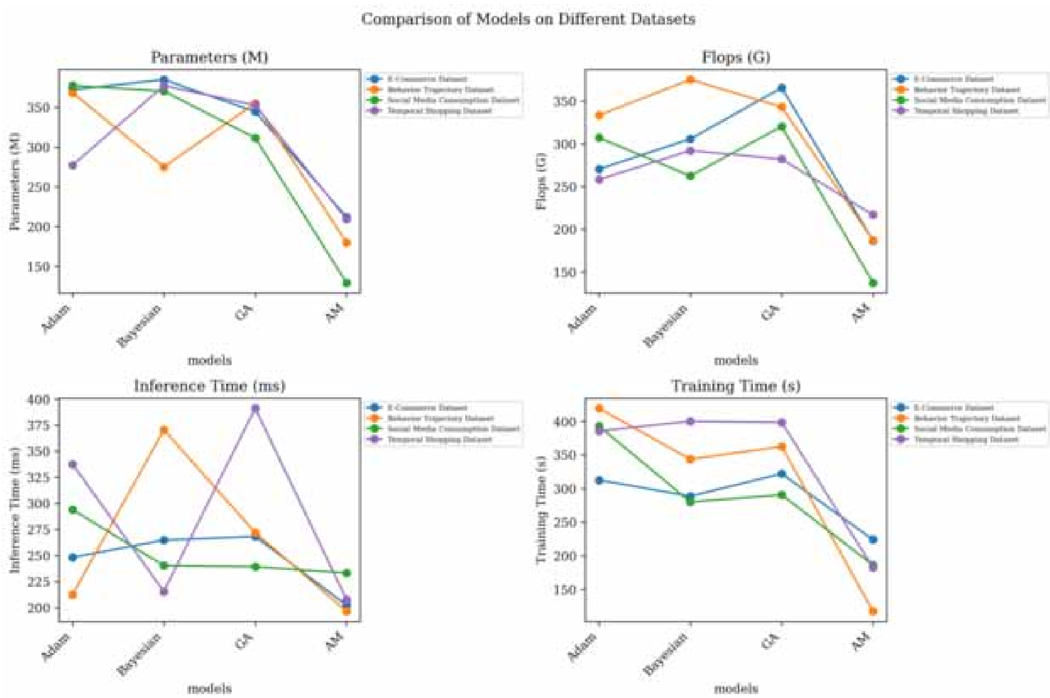
All the above experimental results prove that the VATA model's significant advantages in various performance indicators provide retailers with a more flexible market monitoring and pricing adjustment tool. Its high accuracy and fast inference training time allow retailers to adapt to changing market conditions more quickly and realize real-time pricing strategy adjustments, thus improving their competitiveness and flexibility. These results verify the practical utility of the VATA model from a quantitative perspective and provide retailers with intuitive insights into applying the model in practice.

CONCLUSION AND DISCUSSION

This research aims to explore the potential of deep learning in user shopping behavior analysis and proposes an innovative, comprehensive model, including Attention Mechanism, Transformer, and Variational Autoencoder. Our model has demonstrated excellent performance on multiple data sets through extensive experimental verification, providing strong technical support for improving e-commerce service quality. The innovative structure demonstrates superiority in various performance indicators and opens up new research directions for intelligent and personalized services in e-commerce.

Although we have achieved remarkable results in user shopping behavior analysis, we acknowledge that there are still certain limitations in the model's identification and interpretation capabilities in complex shopping scenarios, especially in the face of performance fluctuations and model stability.

Figure 8. Ablation Experiments on the AM Module



Future work will focus on the following aspects. First, we will work on enhancing the robustness and generalization ability of the model, especially its application effect in scenarios that deal with variable shopping trajectories and dynamically changing behavioral preferences. Second, we plan to delve into the interpretability of the model to improve understanding of complex shopping decision-making processes. By continuously optimizing the model, we expect to bring more innovations and breakthroughs to research and applications in the field of e-commerce.

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