Artificial Intelligence-Based Consumer Emotion Modeling: Quantifying The Interplay Between Self-Depletion, Emotional Compensation And Shopping Addiction

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This paper proposes an AI framework analyzing psychological factors in online shopping addiction and compulsive purchasing behavior. This study utilizes an openly available Mendeley dataset containing behavioural, demographic, and emotional indicators of women's online shopping behaviour. The DEL-GRU-Transformer model extracts emotional embeddings, models sequences, and captures context, achieving 97% accuracy. Results show strong classification of positive, neutral, negative, and stress-driven emotions with low error rates and high Area Under the Curve (AUC). The framework helps understand psychological triggers of compulsive online shopping and supports future prevention and personalized intervention strategies.

Keywords: Consumer Emotion Modelling; Dense Emotional Layer (DEL); GRU-Transformer Hybrid Model; Online Shopping Addiction

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1. Introduction

The swift growth of digital commerce has changed the ways consumers search for products, assess alternatives, and select purchases [1]. Consequently, consumer emotions have become an essential factor shaping online shopping behaviour [2]. Emotional states such as excitement, curiosity, confusion, or hesitation strongly influence how consumers interpret product information and respond to e-commerce platforms [3]. As digital shopping becomes part of daily life, understanding emotional processes is increasingly important to improve engagement, satisfaction, and personalized experiences [4, 5]. Online emotions emerge from psychological, behavioural, and environmental factors including website design, persuasive content, shopping history [6, 7]. To overcome these limitations, this study proposes a new AI architecture. It replaces classical embedding models with a Dense Emotional Layer (DEL) combined with GRU and Transformer architectures to better understand complex consumer emotional states.

Etxaburu [8] found that impulsivity, emotional dependence, and insecure attachment significantly predict buying-shopping disorder in adolescents. Nyrhinen et al. [9] linked online shopping addiction to smartphone overuse and weak self-regulation. David [10] showed emotional problems mediate the relationship between childhood adversity and compulsive buying through emotional dysregulation. Although consumer emotions strongly influence online shopping behavior [11] current computational approaches struggle to detect complex emotional states such as stress-driven purchasing and emotional compensation [12]. Prior studies on online shopping addiction mainly use traditional sentiment analysis techniques or single-architecture deep learning models. These approaches focus primarily on surface-level emotional polarity rather than deeper psychological mechanisms. Existing emotion models use traditional ML, LSTM, or Transformers but lack psychological affect modeling and dynamic emotional evolution; a hybrid framework integrating affective features, temporal transitions, and contextual reasoning is needed. The DEL-GRU-Transformer framework integrates psychological theories: affective intensity theory (DEL) for emotional arousal modeling, emotion regulation theory (GRU) for managing emotional states, and cognitive appraisal theory (Transformer).

2. Materials and methods

Figure 1 shows the hybrid framework where consumer text is preprocessed, emotional features are extracted using DEL. The framework clearly outlines the sequential flow from data preprocessing to emotional feature extraction and hybrid classification. It improves readability.

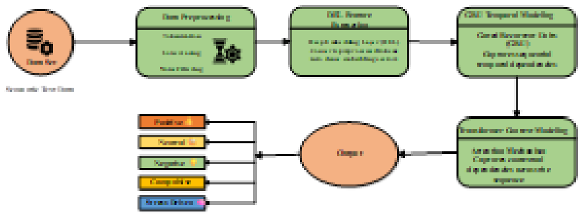

Fig. 1. DEL-GRU-Transformer Architecture

The study uses a Mendeley dataset of 200 women (ages 18-60) emotional relief patterns, and motivational triggers, split into 80% training and 20% testing.[13]. The system processes text, demographic, and behavioural data via dual pathways. Text is tokenized, encoded by DEL, then modelled by GRU and Transformer. Demographic and behavioural features are encoded and fused with emotional embeddings.

Table 1 presents key hyperparameters ensuring stable training, balanced model complexity, efficient convergence, and improved generalization for the DEL-GRU-Transformer architecture.

$$T = \tau(X) = \{t_1, t_2, \ldots, t_n\} \quad (1)$$

Equation. (1) Tokenization splits sentences into tokens, enabling word-level emotional expression.

$$t_i' = \text{lower}\left(t_i\right) \quad (2)$$

Equation. (2) ensures that all words are converted into lowercase form.

Figure 2 shows token embeddings processed with dense layers and attention pooling. Every token embedding is then mapped into the affective feature space using as Equation. (3):

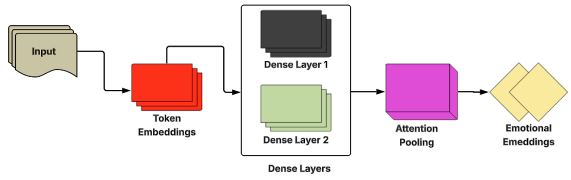

Fig. 2. Attention-Based Emotional Feature Extraction for Consumer Behavior Modeling

$$h_i = \sigma\left(W_1 x_i + b_1\right) \quad (3)$$

Equation. (3) Transforms token embeddings into emotion-aware representations, amplifying emotionally significant words.

$$e_i = \tanh\left(W_2 h_i + b_2\right) \quad (4)$$

Equation. (4) refines features, capturing deeper psychological patterns like stress intensity.

$$E = \sum_{i=1}^{T} \alpha_i e_i \quad (5)$$

Equation. (5) combines token-level emotional features into a single sentence-level vector using attention weights. Emotionally important words contribute more to the final representation.

2.1. Conceptual Framework of the Dense Emotional Layer

The Dense Emotional Layer (DEL) learns domain-specific emotional representations from consumer behavior data, emphasizing stress and compulsive triggers. Attention pooling highlights emotional tokens, producing stable embeddings for GRU-Transformer modeling.

3. Results and discussion

The refined emotional representation is passed through a dense layer. It is then processed by a SoftMax classifier to predict the final emotional state. Figure 3 shows GRU-Transformer architecture combining temporal dependencies and global context for emotional state classification.

GRU models emotional transitions efficiently, capturing sequential emotional evolution.

$$h^{\sim}t = \tanh\left(W\_he\_t + U\_h\left(r\_t \odot h\_(t-1)\right) + b\_h\right) \quad (6)$$

Table 1. Hyperparameter Configuration of the Proposed DEL-GRU-Transformer Model

Hyperparameter	Value	Description
Learning Rate	1×10^{-4}	Adam optimizer step size
Batch Size	32	Number of samples per training batch
GRU Hidden Units	128	Number of hidden neurons in GRU layer
Attention Heads	4	Number of multi-head attention units
Maximum Epochs	20	Training iterations limit
Dropout Rate	0.3	Regularization to prevent overfitting

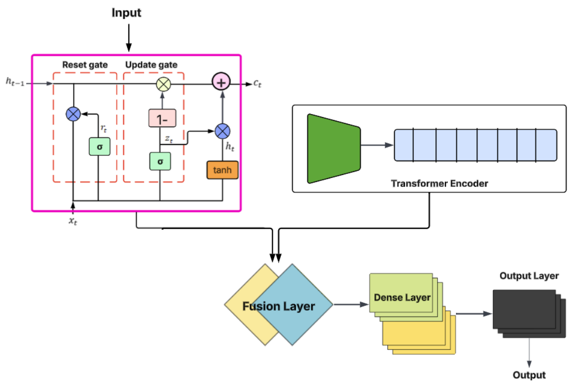

Fig. 3. Hybrid GRU and Transformer Architecture for Emotion classification

Equation (6) computes the candidate emotional state h_t, which represents a temporary emotional activation and the selectively reset previous hidden state $h_{(t-1)}$.

$$h\_t = (1 - z\_t) \odot h\_(t-1) + z\_t \odot h\tilde{\ }t \tag{7}$$

Equation (7) computes the final hidden state h_t by combining the previous emotional state $h_{(t-1)}$ and the candidate emotional state $h^{-}{}_t$, weighted by the update gate z_t.

Figure 4 shows Transformer processing embeddings with attention, feed-forward layers, producing classification probabilities via Softmax. The DEL-GRU-Transformer model achieved 97% accuracy, balanced precision and recall (0.972), and a robust F1-score (0.971).

3.1. Ablation Study Analysis

Table 2 show each module improves performance: DEL extracts affective features, GRU models temporal emotions, Transformer captures context.

3.2. Empirical Validation of the Compensation Mechanism

Empirical tests confirmed the emotional compensation mechanism. GRU gating and Transformer attention captured evolving emotions and stress-to-purchase transitions, reducing misclassification and proving essential for modeling dynamic consumer emotions.

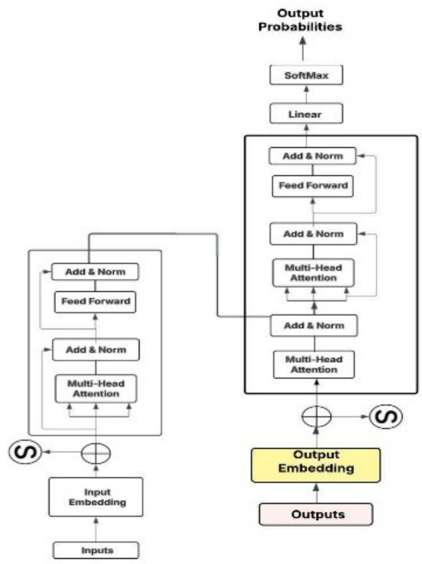

Fig. 4. Transformer Architecture for Sequence Processing and Output Probability Generation

Table 2. Ablation Study Results

Model Variant	Accuracy	F1-Score
GRU + Transformer (without DEL)	0.91	0.90
DEL + Transformer (without GRU)	0.93	0.92
DEL + GRU (without Transformer)	0.94	0.93
Full DEL-GRU-Transformer Model	**0.97**	**0.971**

3.3. Quantitative Interpretability Validation of Emotional Embeddings

Evaluation linked emotional embeddings with addiction, emotional relief, compulsive buying, and mood improvement, with correlation and feature importance confirming meaningful psychological patterns rather than arbitrary representations.

4. Conclusion

Experiments used Python (PyTorch) on a GPU system with an Intel i7 CPU and 16 GB RAM.

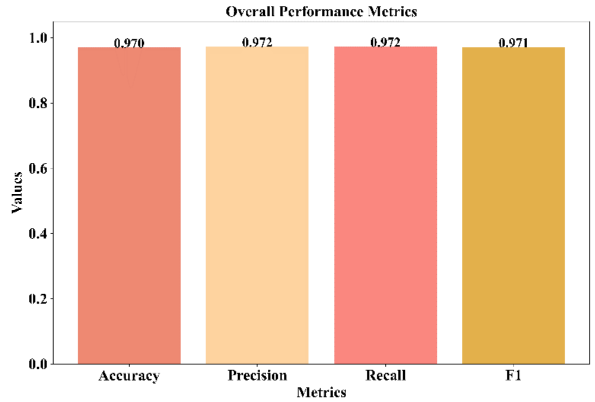

Fig. 5. Overall Performance Metrics of the Hybrid Emotional Classification Model

Figure 5 shows 97% accuracy with balanced precision, recall, and F1-score across emotional state.

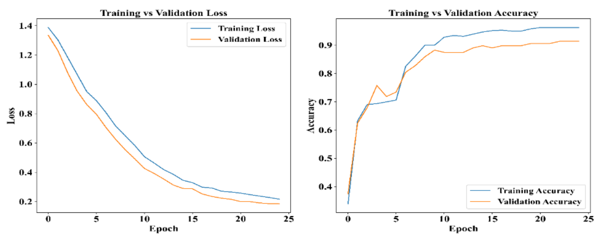

Fig. 6. Model Training vs. Validation Accuracy: Evaluating Model Performance

Figure 6 shows training accuracy rising to 0.9 and validation to 0.85 over 20 epochs, with a small gap indicating good generalization and minimal overfitting.

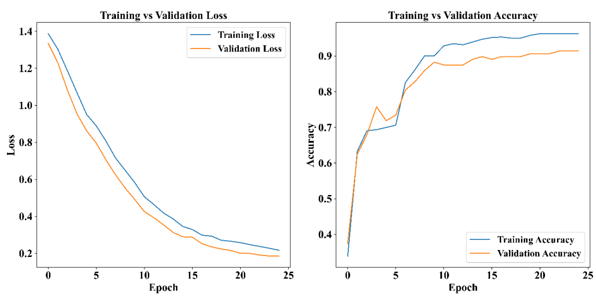

Fig. 7. Model Training vs. Validation Loss: Assessing Learning Progress

Figure 7 shows training and validation loss decreasing across epochs, indicating effective learning.

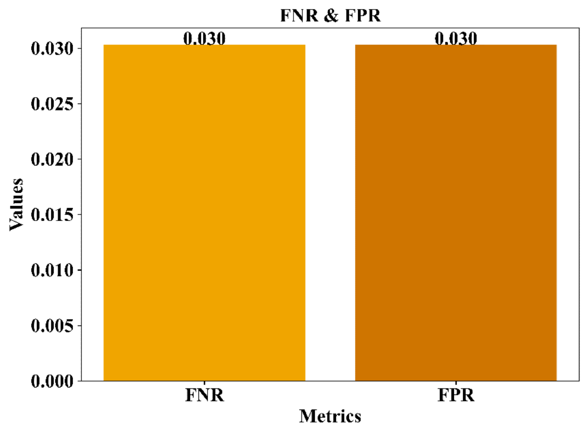

Fig. 8. Confusion Matrix of the Proposed Hybrid Model

Figure 8 shows low error rates (FNR 0.030, FPR 0.030), indicating the model accurately distinguishes emotional states with minimal misclassification and strong calibration.

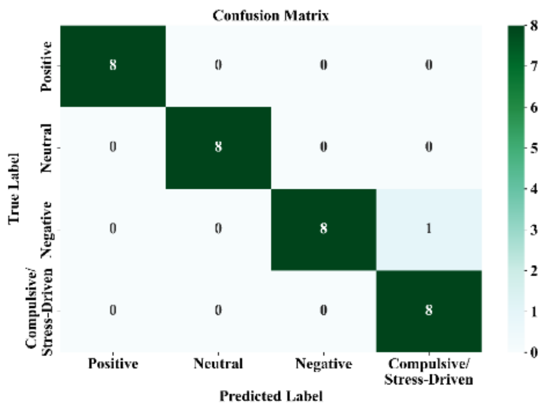

Fig. 9. Confusion Matrix Analyzing Model's Classification Across Emotional States

Figure 9 confusion matrix shows accurate classification with minor Neutral-Negative misclassifications across four emotion categories.

Figure 10 shows the Precision-Recall curve with perfect AP (1.000) for Positive and Neutral, and high AP for Negative (0.989) and Compulsive/Stress-Driven (0.986).

Figure 11 shows addiction, mood improvement, and relief seeking strongly influence predictions, while jewellery-related features show minimal impact.

Figure 12 shows attention heatmap highlighting emotionally significant tokens like stressed, bought, and better,

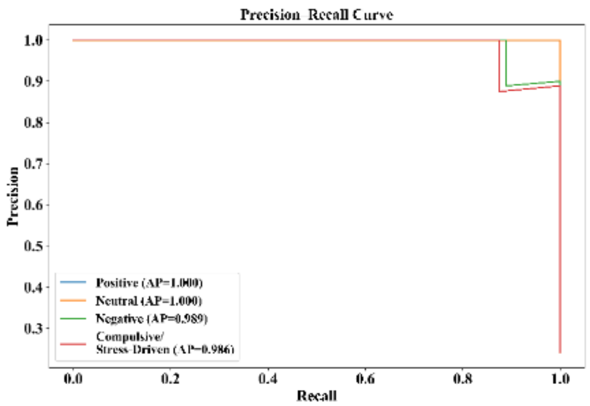

Fig. 10. Precision-Recall Curve: Balancing Precision and Recall

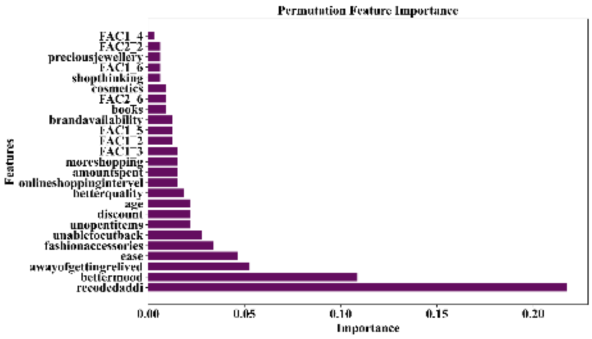

Fig. 11. Permutation Feature Importance: Identifying Key Predictive Features

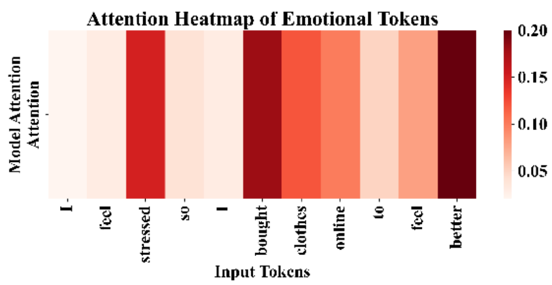

Fig. 12. Attention heatmap highlighting emotionally salient tokens

revealing psychological triggers influencing stress-driven purchasing behavior.

Figure 13 shows t-SNE projection with clear clusters of positive, neutral, negative, and compulsive emotions, confirming meaningful affective representations learned by the DEL layer. Table 3 shows study [14] achieved $\sim 90\%$ accuracy using text mining with LLMs, and [15] reported

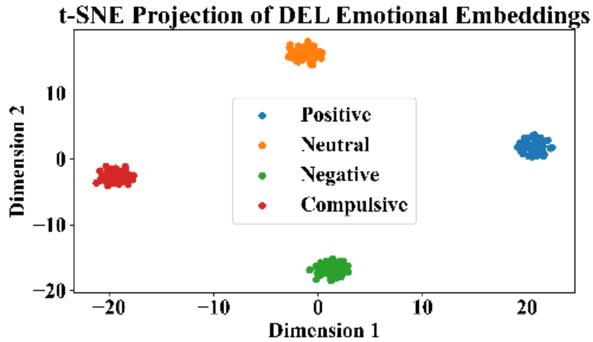

Fig. 13. Attention heatmap highlighting emotionally salient tokens

$82 - 88\%$ using ML classifiers.

Table 3. Performance Comparison of Existing Studies and the Proposed Model

Model	Accuracy (%)	F1-Score
[14]	$\sim 90.0\%$	~ 0.90
[15]	$82 - 88\%$	$0.80 - 0.86$
Proposed Model	97.00%	0.971

The proposed Dense Emotional Layer-GRU-Transformer (DEL-GRU-Transformer) hybrid framework demonstrated strong performance in modeling complex emotions related to online shopping behaviour. Quantitatively, the proposed DEL-GRU-Transformer model achieved an accuracy of 97.0%, precision of 0.972 , recall of 0.972 , and an F1-score of 0.971 , along with an AUC value of 0.98 . The low false positive rate (3%) and false negative rate (3%).

4.1. Ethical Considerations and Responsible AI Deployment

The DEL-GRU-Transformer framework analyzes sensitive consumer emotions. Ethical deployment requires anonymization, secure data handling, transparency, fairness auditing, and regulatory compliance to prevent misuse in targeted marketing.

Acknowledgment

Declarations

Data availability

Not applicable

Conflicts of interest

The author declares that there are no known financial or non-financial conflicts of interest that could have influenced the work reported in this manuscript.

Funding statement

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Author contribution

Haiyang Wu conceptualised the study, developed the model, performed the data analysis, interpreted the results, and prepared the manuscript. The author has read and approved the final version of the manuscript.

Ethical approval

This study uses a publicly available secondary dataset that does not contain any personally identifiable information. Therefore, ethical approval was not required.

Consent to participate

Not applicable, as this study relied solely on an openly available secondary dataset.

Consent to publication

The author consents to the publication of this manuscript.

Competing interests

The author declares no competing interests.

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