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Integrating Psychological and Subconscious Data into Recommender Systems: A Novel Model for Digital Advertising

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ABSTRACT

The growing complexity and volume of digital advertising have made recommender systems essential for enhancing user engagement and campaign performance. However, existing models predominantly rely on behavioral data, neglecting critical psychological and subconscious dimensions of user perception. This study introduces a novel hybrid recommender system that integrates multidimensional inputs, personality traits (Big Five model), subconscious associations (captured via ZMET), customer inspiration scores, and ad content tags, to deliver more psychologically aligned advertising recommendations. Using a sample of 549 participants exposed to four distinct ads from a pool of 625, data were collected through NEO personality inventories, inspiration scales, ZMET-based image selection, and expert ad tagging. The model was evaluated using standard classification metrics, achieving an accuracy of 91.5% and an AUC of 0.957, substantially outperforming conventional approaches. The results indicate that demographic factors, particularly age, play a more prominent role in prediction accuracy, while personality traits, such as Openness and Extraversion, exhibit only weak but consistent associations with recommendation relevance. Overall, the findings suggest that incorporating behavioral, psychological, and subconscious data enables the development of more human-aware recommender systems, offering valuable implications for the design of personalized digital advertising campaigns and improved marketing effectiveness.

Keywords: *Recommender system; Digital advertising; Personality traits; ZMET; Customer inspiration; Personalized marketing; Hybrid model.*

1. Introduction

The digital advertising landscape has undergone a fundamental transformation over the past decade, driven by the exponential growth of online platforms, the proliferation of behavioral data, and the increasing demand for highly personalized user experiences. In such a competitive environment, generic and untargeted advertising messages are no longer sufficient to capture user attention or generate meaningful engagement. Consequently, recommender systems have become a central component of digital advertising infrastructures, playing a critical role in enhancing user interaction, click-through rates, and return on investment.

Despite their widespread adoption, most existing recommender systems remain grounded in a predominantly behavior-centric paradigm. These systems primarily rely on historical interaction data, such as clicks, views, dwell time, and purchase history, to infer user preferences. While effective in identifying observable patterns of co-occurrence between users and items, such approaches often overlook the deeper cognitive and affective mechanisms that fundamentally shape human decision-making. In other words, traditional recommender systems model what users do, but rarely address why they do it.

Extensive research in consumer psychology and behavioral marketing suggests that advertising responsiveness emerges from a complex interplay of personality traits, subconscious associations, emotional triggers, and motivational schemas. For instance, individuals high in Openness to Experience tend to respond more positively to novel and creative advertising stimuli, whereas high levels of Neuroticism may increase sensitivity to emotionally intense content. Moreover, subconscious metaphors and implicit mental imagery, often inaccessible through conventional survey instruments can reveal deep-seated meanings and motivational structures that guide how advertisements are interpreted and evaluated.

Yet, despite these theoretical insights, few recommender system architectures have systematically incorporated cognitive–affective dimensions into their computational design. This disconnect between consumer psychology and algorithmic personalization represents a critical gap in the current literature and presents an opportunity to reconceptualize recommender system development. Specifically, there is a need to move beyond purely behavior-based inference toward a cognitive–affective computational framework that integrates latent psychological and subconscious representations into predictive modeling.

To address this limitation, the present study proposes a novel hybrid recommender model that synergistically integrates four complementary data dimensions into a unified computational framework. Specifically, the model incorporates psychological traits measured through the well-established Big Five Inventory (NEO-PI-R), subconscious associations elicited via the Zaltman Metaphor Elicitation Technique (ZMET), motivational states captured using validated “Inspired-by” and “Inspired-to” customer inspiration scales, and rich textual, semantic signals extracted from user-generated comments through advanced natural language processing techniques. By systematically fusing these heterogeneous yet theoretically grounded inputs, the proposed architecture enables a multidimensional representation of user preference structures that extends beyond observable behavioral traces toward deeper cognitive and affective modeling.

This study makes four primary contributions. First, it introduces a unified deep learning framework based on multi-stage autoencoders to fuse heterogeneous psychological, subconscious, and textual data into a coherent latent representation. Second, it provides large-scale empirical evidence (n = 549) that incorporating subconscious and personality variableswithin a multi-source integration framework significantly enhances recommendation accuracy and discriminative capability. Third, it identifies specific personality traits , most notably Openness and Extraversion, as meaningful, though not dominant, predictors of advertising alignment. Importantly, the observed performance gains stem from the synergistic integration of psychological and subconscious constructs rather than from personality traits in isolation. Fourth, the study offers a practical framework for psychographic audience segmentation and creative optimization grounded in cognitive, affective clustering.

By bridging consumer psychology and deep learning, this research contributes to the development of a new generation of recommender systems that model not only behavioral traces but also the underlying cognitive and affective structures that shape user preferences.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature on recommender systems, consumer psychology, ZMET, and deep learning in advertising. Section 3 details the proposed methodology and model architecture. Section 4 presents experimental results and performance analysis. Section 5 discusses findings, implications, and limitations. Finally, Section 6 concludes with directions for future research.

2. Literature Review

2.1. Evolution of Recommender Systems

Over the past two decades, recommender systems have become a core element of personalized digital experiences, playing a key role in domains such as e-commerce, content platforms, education, health, and marketing. Early recommender systems were mainly based on collaborative filtering and content-based filtering [1, 2].Although these methods were successful in their initial applications, they suffered from significant limitations, including the cold-start problem, data sparsity, and lack of cognitive and emotional context awareness.

To address these limitations, hybrid recommender approaches emerged, combining multiple recommendation techniques to improve accuracy [3, 4]. In recent years, deep learning architectures have revolutionized recommender system design. Techniques such as autoencoders [5, 6], convolutional neural networks (CNN), and transformers [7, 8] have enabled more accurate modeling of complex user–item interaction patterns.

Nevertheless, most recommender systems remain heavily dependent on behavioral data, overlooking users' psychological and unconscious factors [9, 10]. This omission highlights the need for models that go beyond behavioral signals to incorporate cognitive and affective dimensions of user experience.

2.2. *Personality Traits and Consumer Behavior*

Research in consumer psychology has demonstrated that personality traits play a crucial role in shaping perception and responses to advertising. The Big Five personality model, openness, conscientiousness, extraversion, agreeableness, and neuroticism [11, 12], provides a robust framework for understanding individual differences in advertising reactions.

Empirical studies show that individuals with high levels of openness respond more positively to creative advertising [13, 14]. Extraversion is associated with active engagement, while high neuroticism often correlates with negative emotional reactions [15, 16]. Furthermore, demographic variables such as age, gender, and cultural background have moderating effects on these relationships, enabling more precise psychographic segmentation [17].

2.3. *Unconscious Associations and ZMET*

One of the less explored dimensions in advertising response is unconscious associations and mental metaphors. The Zaltman Metaphor Elicitation Technique (ZMET) [18] is an innovative tool for uncovering these associations by asking participants to select images that reflect their subconscious perceptions of an advertisement [19, 20]

ZMET has been shown to provide more accurate insights into emotional and motivational reactions compared to traditional survey methods [21, 22]. Incorporating these implicit associations into recommender systems can lead to more psychologically grounded advertising recommendations.

2.4. *Customer Inspiration and Emotional Variables*

The concept of customer inspiration is a relatively new area of research in marketing. It refers to a motivational state that moves the consumer from passive perception to active engagement [23]. Inspiration comprises two dimensions: inspired-by and inspired-to.

Research has shown that inspirational advertisements strengthen brand attitudes and purchase intentions [24, 25]. Integrating customer inspiration indices into recommender systems allows for ranking ads based on their emotional and motivational impact, thus enhancing recommendation relevance and persuasive power.

2.5. *Text Mining and Sentiment Analysis*

With the rapid advancement of Natural Language Processing (NLP), text mining and sentiment analysis have become powerful tools for assessing emotional responses to advertising. Modern models such as BERT [26] enable highly accurate extraction of positive, negative, and neutral sentiments from user comments.

Studies have shown that sentiment analysis can effectively predict engagement and advertising effectiveness [27-29]. By incorporating textual emotional signals into recommendation models, marketers can obtain richer and more dynamic audience insights.

2.6. *Multi-source Data Fusion and Deep Learning*

The integration of multi-source data, including psychological, unconscious, textual, and behavioral information, has opened new horizons for recommender system design [10, 30]. Autoencoders offer a powerful way to compress and reconstruct complex user data, revealing hidden preference structures [5, 31].

Furthermore, user clustering based on latent vectors can help identify shared psychological patterns and behavioral archetypes [32, 33], paving the way for psychologically informed segmentation strategies. Existing research treats these dimensions independently; however, a unified cognitive–affective computational integration remains underdeveloped.

2.7. *Research Gap and Contribution*

A critical synthesis of the existing literature reveals three interconnected gaps that limit the current advancement of recommender system research in digital advertising.

First, a theoretical gap persists between consumer psychology and recommender system design. While extensive research has demonstrated that personality traits, emotional states, and subconscious associations significantly influence advertising response, these constructs have rarely been embedded structurally within computational recommendation architectures. Most existing systems remain grounded in observable behavioral traces, thereby modeling surface-level interactions without accounting for the deeper cognitive and affective mechanisms that shape user preferences.

Second, a methodological gap exists in the operationalization of unconscious and motivational constructs within scalable computational frameworks. Although techniques such as ZMET and customer inspiration scales have proven valuable in marketing research, their integration into algorithmic recommendation pipelines remains extremely limited. In particular, subconscious metaphorical representations are often treated as qualitative insights rather than quantifiable features capable of enhancing predictive modeling.

Third, a computational gap concerns the limited integration of heterogeneous multi-source data within unified deep learning architectures. Existing recommender systems frequently combine two primary sources behavioral and textual data while comprehensive fusion of psychological, subconscious, motivational, and semantic signals is largely underexplored. As a result, current models lack a multidimensional representation of user preference structures.

To address these gaps, the present study develops a deep autoencoder-based hybrid recommender model that systematically integrates personality traits, subconscious associations (captured via ZMET), textual emotional signals, and customer inspiration indices into a unified latent representation space. By embedding cognitive and affective constructs directly into the computational architecture, this research advances a cognitive–affective paradigm for recommender system design.

The contributions of this study are therefore both empirical and conceptual. Empirically, it demonstrates that multi-source psychological integration significantly enhances predictive accuracy and discriminative performance. Conceptually, it provides a structured framework for translating implicit mental representations into algorithmically tractable features, thereby narrowing the longstanding divide between consumer psychology and intelligent recommendation systems. Taken together, these gaps suggest the necessity of reconceptualizing recommender systems not merely as behavioral prediction engines, but as cognitive–affective modeling frameworks capable of capturing the latent psychological architecture underlying user preferences.

3. Methodology and Conceptual Model

This study proposes a multi-source deep learning recommender architecture that integrates users' psychological, unconscious, emotional, and inspirational data into a unified framework. Unlike conventional behavior-based models, this approach leverages deeper cognitive and affective layers to deliver more precise and human-centered advertising recommendations. Conceptually, the proposed architecture operationalizes a cognitive, affective modeling framework in which psychological dispositions, subconscious associations, and emotional signals are treated as structured computational features rather than peripheral contextual variables. This design enables the transformation of latent mental constructs into algorithmically tractable representations within a deep learning environment.

3.1. *Data Partitioning and Model Validation Strategy*

Since each participant evaluated four advertisements, the final dataset consisted of 2160 user–advertisement interaction observations after data cleaning and preprocessing. To ensure methodological rigor and prevent Personality Inventory;

· Unconscious associations obtained through the Zaltman Metaphor Elicitation Technique (ZMET);

· Textual and emotional signals extracted from user comments using advanced language models;

· Customer inspiration indices gathered via standardized psychometric scales.

data leakage, the complete dataset (N = 2160 user–ad interaction observations) was partitioned using an 80/20 hold-out strategy. Specifically, 80% of the data (n = 1728) was allocated to model development, while the remaining 20% (n = 432) was reserved as an independent test set. The test set remained completely unseen during model training and hyperparameter optimization and was used exclusively for final performance evaluation.

Within the training subset (n = 1728), stratified 10-fold cross-validation was employed to optimize model parameters and evaluate internal stability. Stratification ensured that class distributions remained consistent across folds. In each fold, approximately 1555 observations were used for training and 173 observations for validation. This procedure reduced sampling variance and improved the robustness of performance estimation.

For additional robustness analysis and demographic subgroup evaluation, a stratified subsample of 180 observations was randomly drawn from the independent test set. Class proportions were preserved to maintain distributional balance. This subsample was used exclusively for demographic performance comparisons and did not influence model training or tuning.

3.2. Model Architecture

The conceptual model consists of four core components:

- Multi-stage autoencoders for extracting latent representations from multiple data sources;
- A feature aggregation module that merges these representations into a unified latent space;
- A psychological clustering layer to segment users based on shared cognitive and emotional patterns;
- A personalized recommendation engine optimized through a matching loss function.

This layered design enables the system to identify subtle, multidimensional patterns in user profiles and align advertising recommendations with users' mental and emotional states.

3.3. Data Sources and Preprocessing

Four primary categories of user data were systematically collected and processed to construct the model's multidimensional input space. These included personality traits measured using the well-established Big Five NEO inventory, along with additional complementary data sources capturing psychological, emotional, and behavioral signals. To ensure methodological consistency and effective integration within the deep learning architecture, all extracted features were normalized and transformed into structured vector representations. This preprocessing step enabled cross-source compatibility and facilitated the fusion of heterogeneous data streams within the unified latent representation space.

Given the limitations of purely qualitative and purely quantitative approaches in capturing deep psychological processes, a hybrid large-scale ZMET-based data collection design was implemented. Each participant was randomly exposed to four advertisements selected from a pool of 650 ads. For each advertisement, participants were presented with 30 pre-clustered images and asked to select five images most closely associated with the ad. This procedure enabled scalable extraction of subconscious metaphorical associations while preserving psychological depth.

Figure 1. Example of data collection process using the ZMET technique

3.4. Latent Representation Learning

Each data source was processed through a dedicated autoencoder to extract its specific latent features. The compressed outputs were then fused and passed through a higher-level autoencoder, producing a shared, low-dimensional latent space.

This multi-stage encoding process allows the model to integrate psychological, unconscious, and emotional dimensions, capturing the underlying structure of user preferences more effectively than traditional single-source models. From a theoretical perspective, the multi-stage encoding process mirrors the hierarchical structure of human cognition, where surface-level stimuli are progressively integrated into higher-order abstract representations. By compressing heterogeneous psychological and subconscious signals into a shared latent space, the model approximates the integration of cognitive and affective processing observed in human decision-making.

3.5. Psychological Clustering

The shared latent representation was subsequently used as input for a K-means clustering algorithm, segmenting users into psychologically and emotionally homogeneous clusters. This step enhances personalization accuracy, improves interpretability, and facilitates targeted advertising strategies based on cognitive–affective user profiles. The clustering mechanism serves not merely as a segmentation tool, but as a structural approximation of shared cognitive–affective schemas among users. By identifying latent psychological archetypes, the model facilitates group-level interpretability while preserving individual-level personalization.

3.6. Personalized Recommender Engine

The recommendation engine predicts and delivers advertisements by leveraging users' cluster memberships and latent feature vectors. A matching loss function minimizes the distance between recommended and actual user preferences, ensuring alignment between system output and users' psychological, unconscious, and emotional signals. Unlike traditional recommendation pipelines that optimize behavioral similarity, the matching loss function in the proposed model is designed to minimize the discrepancy between latent psychological representations and advertisement feature embeddings, thereby aligning computational optimization with cognitive congruence principles.

3.7. Overfitting Control and Generalization Assurance

To mitigate overfitting and enhance generalization capability, several regularization strategies were implemented:

- Stratified 10-fold cross-validation for robust model tuning;
- Early stopping based on validation loss monitoring;
- L2 regularization (weight decay) to constrain model complexity;
- Controlled network depth and parameter size to prevent excessive capacity.

The close alignment between cross-validation performance and independent test results indicates stable generalization performance.

3.8. Research Contributions and Innovations

The proposed model introduces several methodological innovations:

- Integration of multi-source data—psychological, unconscious, textual, and inspirational—within a single framework;
- Use of a multi-stage autoencoder structure to extract meaningful latent features;
- Implementation of psychological clustering for fine-grained user segmentation;
- Direct linkage of cognitive and emotional dimensions to algorithmic personalization.

By merging cognitive science with deep learning, this framework represents a new generation of recommender systems that extend beyond behavioral inference toward cognitively aligned personalization (see Figure 2). Methodologically, this framework demonstrates how abstract psychological constructs can be systematically embedded within scalable deep learning architectures, advancing the methodological integration of consumer psychology and artificial intelligence.

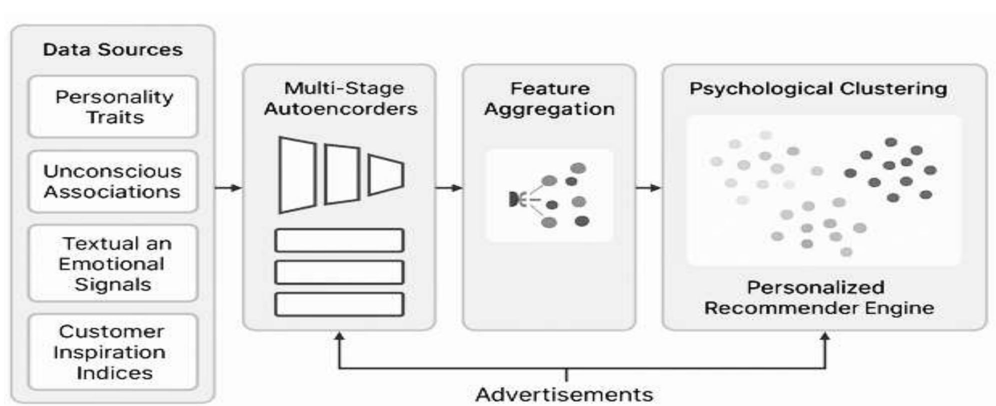

Figure 2. Deep Learning Recommender System Flowchart

4. Results and Analysis

4.1. Sample Characteristics

The table above presents the demographic characteristics of the study participants. In total, 549 individuals took part in the research, with females comprising a larger proportion of the sample than males. In terms of age, the largest group fell within the 20–30 year range, indicating a concentration of younger and digitally active users. The overall educational level of participants was relatively high, with more than half holding a university degree. In addition, only a small proportion of respondents were employed individuals with a monthly income exceeding 20 million tomans. This demographic composition provides sufficient diversity within the sample and enables a more nuanced analysis of advertising audience behavior, while supporting a cautious interpretation of the study's findings.

It should be noted that model training and evaluation were conducted on the full dataset (N = 2160 user–ad interaction observations), whereas demographic subgroup performance analyses reported in subsequent sections are based on a stratified subsample of 180 observations drawn from the independent test set. This subsample was used solely for robustness and comparative analysis and did not influence model training or optimization.

Table 1. Summary of Participants' Demographic Characteristics

Variable	Categories	Frequency	Percentage
Gender	Female / Male	344 / 194	62.7 / 35.3
Age group	<20 / 20–30 / 31–40 / 40+	166 / 264 / 72 / 36	30.9 / 49.1 / 13.4 / 6.7
Education level	Diploma / Associate–BA / MA / PhD	149 / 79 / 309 / 1	27.1 / 14.4 / 56.3 / 0.2
Employment status	<10 / 10-20 / 20+	413 / 68 / 56	75.2 / 12.4 / 10.2
Total participants	—	549	100
Ads evaluated	—	620	—
Subsample for model test	—	180	—

4.2. Personality Dimensions and Clustering Analysis

The descriptive statistics presented in Table 2 indicate that among the Big Five personality dimensions, Conscientiousness exhibits the highest mean score (33.68), making it the most prominent personality trait among the participants. This finding reflects a high level of organization, responsibility, and goal-oriented behavior within the study sample. In addition, the relatively high mean scores for Openness to Experience (28.32) and Agreeableness (28.20) suggest that respondents demonstrate cognitive and emotional readiness to accept novel ideas and innovative advertising messages. In contrast, Neuroticism, with a lower mean score (23.26), indicates relatively greater emotional stability among participants, which may contribute to reduced emotional bias and enhanced overall data quality.

Table 2. Descriptive statistics of the Big Five personality traits of participants

Personality Trait	Mean	Median	Min	Max	SD
Extraversion	26.95	27.00	6.00	46.00	6.91
Neuroticism	23.26	23.00	6.00	47.00	6.70
Openness to Experience	28.32	28.00	12.00	43.00	5.39
Agreeableness	28.20	28.00	10.00	45.00	5.50
Conscientiousness	33.68	34.00	9.00	48.00	6.74

The cluster analysis based on the Big Five personality model (Table 3) revealed that participants were grouped into three distinct clusters. Cluster 0 (29.9%) is characterized by lower levels of Extraversion and higher levels of Neuroticism, indicating greater emotional sensitivity and a tendency toward affective processing of messages. Cluster 1 (25.1%) exhibits high levels of Extraversion, Agreeableness, and Conscientiousness, along with low Neuroticism, reflecting a balanced, active, and experience-oriented personality profile. Cluster 2, which represents the largest proportion of the sample (45.0%), is defined by high Conscientiousness and moderate Extraversion, suggesting a preference for goal-oriented and performance-driven behaviors. Overall, this clustering structure provides a meaningful basis for designing differentiated advertising strategies aligned with the psychological characteristics of target audiences.

Table 3. Personality Clusters Based on Big Five Model

Cluster	Extraversion	Neuroticism	Openness	Agreeableness	Conscientiousness	% of Participants
0	20.57	28.82	27.39	24.64	26.87	29.9٪
1	33.40	16.12	28.99	34.18	38.52	25.1٪
2	27.61	23.56	28.57	27.16	35.60	45.0٪

As illustrated in the bar chart, the mean scores of personality dimensions display distinct patterns across the clusters. Cluster 0 is characterized by the lowest level of Extraversion and the highest level of Neuroticism, indicating greater emotional sensitivity and a lower tendency toward social interaction. In contrast, Cluster 1 exhibits the highest levels of Extraversion, Agreeableness, and Conscientiousness, and together with high Openness represents an active, balanced, and experience-oriented personality profile. Cluster 2 is defined by high Conscientiousness and moderate Extraversion, reflecting a tendency toward goal-oriented and performance-driven behavior. These differences confirm meaningful psychological distinctions among the clusters and highlight the importance of designing advertising strategies tailored to each group.

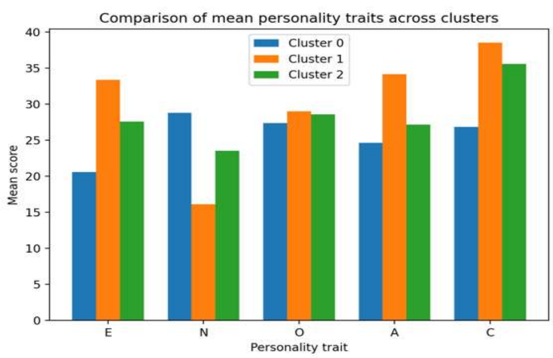

Figure 3. Comparison of Personality Dimensions Across Clusters

The presented radar chart visually and comparatively illustrates the distinct personality profiles of each cluster, enabling a rapid understanding of differences among the groups. Cluster 0 is characterized by higher levels of Neuroticism and lower Extraversion, indicating greater emotional sensitivity to affective stimuli. Cluster 1 displays a more balanced profile, marked by high Openness to Experience and Conscientiousness, suggesting greater receptivity to creative and innovative advertising messages. In contrast, Cluster 2 is defined by higher Conscientiousness and Extraversion, reflecting a tendency toward goal-oriented behavior and more favorable responses to direct, performance-driven advertising campaigns. These findings underscore the effectiveness of personality-based clustering in audience segmentation and the design of tailored advertising strategies.

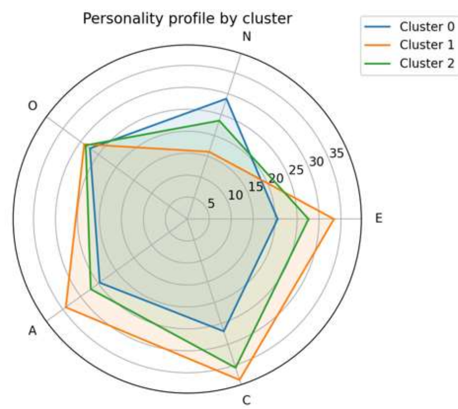

Figure 4. Personality Profile by Cluster

4.3. *Model Performance Overview*

The proposed recommender system achieved remarkably high predictive accuracy. Out of 388 predictions, 355 were correct (TP) and 33 were incorrect (FP), resulting in an accuracy of 91.5%. This performance level demonstrates the model's ability to effectively identify and recommend relevant advertisements aligned with user preferences.

4.3.1. *Age-based Performance*

The system achieved its highest accuracy in the 20–30 age group, with a value of 0.928. The accuracy for participants under 20 years old was 0.912, while for those over 30 years of age, the average accuracy was approximately 0.87. This pattern indicates that younger users exhibit more predictable responses to advertising content, enabling the model to identify their behavioral patterns with greater precision. This outcome is likely attributable to higher levels of engagement with digital media and greater familiarity with online advertising content among younger age groups.

4.3.2. *Personality Correlations*

The results of the correlation analysis indicate that the relationships between the Big Five personality dimensions and the recommender system's matching rate are generally weak and close to zero. Among these dimensions, Neuroticism (r = 0.070) and Openness to Experience (r = 0.013) exhibit very slight positive correlations with the matching rate, whereas Extraversion (r = −0.101), Agreeableness (r = −0.025), and Conscientiousness (r = −0.059) show weak negative relationships. These findings suggest that none of the personality traits alone play a decisive role in predicting the accuracy of the recommender system, and that the influence of personality is likely to become meaningful only through interaction with other cognitive, emotional, or contextual factors.

4.3.3. *Personality Heatmap and Hit Rate*

The presented heatmap visually illustrates the direction and magnitude of the relationships between the Big Five personality dimensions and the recommender system's matching rate. As shown, the correlation coefficients across all dimensions are low in magnitude and close to zero, indicating a limited influence of individual personality traits on model performance. In this context, Neuroticism and Openness to Experience display very weak positive correlations with the matching rate, whereas Extraversion, Agreeableness, and Conscientiousness exhibit slight negative relationships. Overall, this pattern suggests that personality alone does not play a determining role in the accuracy of the recommender system, and that its effects are likely to become meaningful only in interaction with other cognitive and contextual variables.

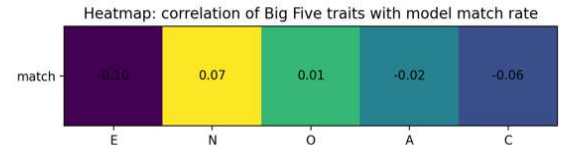

Figure 5. Heatmap of Correlations Between NEO Personality Dimensions and Recommender System Performance

4.4. *Evaluation Metrics and Model Reliability*

Model performance was evaluated using classical classification metrics, including True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN), as well as derived indicators such as Precision, Recall (Sensitivity), F1 Score, Accuracy, Specificity, and Area Under the Curve (AUC). As shown in Table 4, the exceptionally high AUC value indicates the model's strong discriminative power, suggesting a robust ability to distinguish relevant from non-relevant advertisements. Similarly, the F1 Score demonstrates an optimal balance between precision and recall, confirming that the model maintains both accuracy and completeness in prediction.

A notable observation emerges when comparing the Specificity values between the Restricted TN and Full TN conditions. Although most performance metrics remain consistent, the Specificity substantially increases from 0.887 in the Restricted TN setting to 0.999 in the Full TN configuration. This difference highlights the critical impact of negative-space definition on model evaluation. In the Restricted TN condition, the true negative set is constrained to a limited subset of non-relevant items, which increases the chance of borderline or ambiguous samples being misclassified as positives, slightly lowering specificity. Conversely, the Full TN configuration incorporates the entire set of potential non-relevant items, expanding the negative space and thereby reducing the proportion of ambiguous negatives. This broader evaluation environment allows the model to correctly classify a larger number of true negatives, leading to near-perfect specificity.

From a cognitive modeling perspective, this finding aligns with theoretical expectations: the Restricted TN condition represents a cognitively narrower decision context, similar to a human decision-maker operating with partial awareness, resulting in over-confident negative judgments. The Full TN condition, in contrast, reflects a more realistic cognitive scenario in which the system is exposed to a wider variety of stimuli, achieving greater stability and a more reliable discrimination boundary.

Table 4. Comparison of recommender system performance indicators in restricted and full TN environments.

Metric	Restricted TN	Full TN	Interpretation
Precision	0.915	0.915	Percentage of correctly recommended advertisements
Recall (Sensitivity)	0.915	0.915	Accuracy in identifying ads that users actually viewed
Specificity	0.887	0.999	Model stability in large-scale advertising space
Accuracy	0.903	0.999	Effect of larger TN on overall accuracy
F1 Score	0.915	0.915	Balance between Precision and Recall

4.5. Confusion Matrix and ROC Curve Analysis

As shown in Figure 6, these patterns are also numerically evident in the confusion matrix. The numerical distribution of the four core classification cells is presented in Table 5. This tabular structure directly quantifies the model's ability to detect relevant ads (i.e., True Positives) vs. reject irrelevant ones (True Negatives). The extremely low False Positive and False Negative rates quantitatively reinforce the asymmetric accuracy profile described above.

Table 5. Confusion Matrix of the Recommender Model in the Full Advertising

	Predicted Negative	Predicted Positive
Actual Negative	51,526	33
Actual Positive	33	355

Figure 6 presents the confusion matrix of the recommender model evaluated within the full advertising space (*Full TN* condition). Each cell in the matrix represents a specific outcome of the model's classification process:

- **True Positives (TP):** the number of advertisements correctly identified as relevant to the user's psychological and emotional profile;
- **False Positives (FP):** advertisements incorrectly predicted as relevant despite user disinterest;
- **False Negatives (FN):** relevant advertisements that the model failed to recommend;
- **True Negatives (TN):** advertisements correctly identified as non-relevant and excluded from recommendation.

The matrix displays a strong diagonal dominance, indicating that the majority of predictions fall along the correct classification line (high TP and TN values with minimal FP and FN). This near-diagonal structure is a hallmark of high-performing recommender systems, reflecting precise discrimination between relevant and irrelevant content.

Furthermore, the accompanying ROC curve closely aligns with the top-left corner of the plot, demonstrating:

- a high True Positive Rate (TPR),
- a very low False Positive Rate (FPR), and
- consequently, excellent sensitivity and specificity.

The resulting AUC value greater than 0.95 confirms the model's robustness, high discriminative power, and generalization capability. These findings collectively suggest that the recommender system exhibits stable and reliable decision-making even under realistic large-scale advertising conditions.

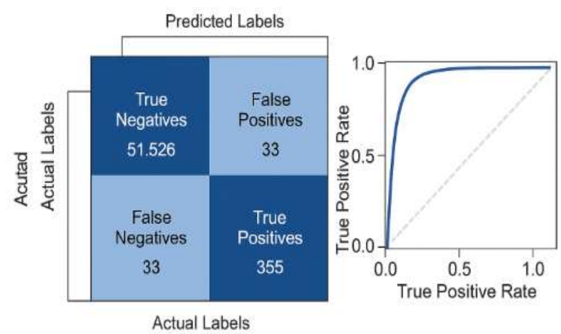

Figure 6. Confusion Matrix of the Recommender Model in the Full Advertising Space (Large TN)

4.6. Feature Importance Analysis

Feature impact analysis revealed the following contributions to overall model accuracy. As shown in Table 6, ZMET-based unconscious feature extraction provided the highest independent predictive lift, followed by customer inspiration scores and user comment content.

Table 6. Effect of Data Types on Model Accuracy and Interpretability

Data Type	Key Indicator	Accuracy Gain	Analytical Role and Interpretation
ZMET (Unconscious)	Selection of 5 associated images	+7%	Highest impact; reveals users' implicit preferences
Customer Inspiration	Inspired_by and Inspired_to scores	+5%	Enhances engagement and intrinsic motivation
Comment Analysis	Sentiment and keyword extraction	+3%	Strengthens emotional and semantic signals

As illustrated in Figure 7, ZMET features demonstrated the strongest incremental explanatory power. The combined use of these three data sources ultimately produced a recommender model that was more accurate, more personalized, and more psychologically grounded than traditional recommender baselines.

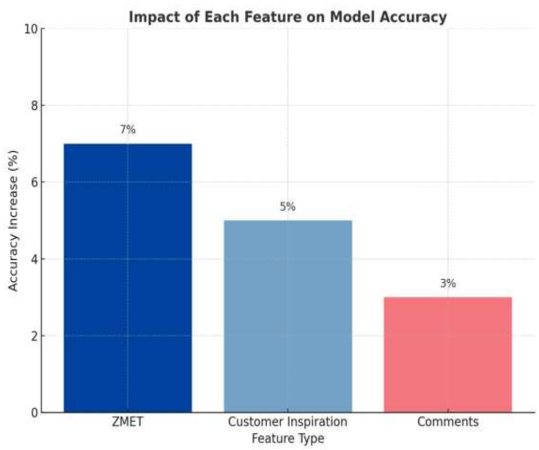

Figure 7. Impact of Each Feature on Model Accuracy

5. Discussion

5.1. Interpretation of Findings

This study contributes to the recommender systems literature by proposing a cognitive–affective computational paradigm that integrates latent psychological and subconscious constructs into algorithmic personalization. The findings of the present study indicate that the proposed model, by integrating personality traits, subconscious associations captured through ZMET, customer inspiration, and expert-based advertising tags, achieves strong performance in predicting user preferences and delivering accurate recommendations. The high values obtained for Precision (0.915), Recall (0.915), and F1-score (0.915) demonstrate the model's strong capability in correctly identifying advertisements aligned with users' preferences. Moreover, an AUC value of 0.957 reflects the model's high discriminative power in distinguishing between relevant and non-relevant advertisements.

Importantly, these results reflect not merely incremental performance improvement, but a structural enhancement in representational richness achieved through the integration of cognitive and affective user dimensions into the computational architecture. Unlike traditional behavior-only models, the proposed framework embeds internal psychological constructs as structured predictive features, enabling the system to model latent preference mechanisms rather than relying solely on observable interaction traces.

An examination of demographic variables revealed that the model performs more effectively among younger age groups. Specifically, the highest prediction accuracy was observed in the 20–30 age group (0.928), followed by users under 20 years old (0.912), while the average accuracy for participants over 30 years of age was approximately 0.87. This pattern suggests that younger users exhibit more predictable responses to advertising content, which may be attributed to higher levels of digital engagement, greater familiarity with online advertising, and increased cognitive flexibility.

In contrast, the results related to personality dimensions indicate that the relationship between personality traits and the overlap between recommended and preferred advertisements is weak and limited. While Openness to Experience and Extraversion were associated with only marginal improvements in model performance, Neuroticism showed a slight negative association with prediction accuracy. These findings suggest that personality traits alone do not play a dominant role in determining recommender system performance, but may exert influence when considered in conjunction with other behavioral and contextual factors. This pattern underscores the importance of multi-source integration: personality traits appear to function as boundary conditions that shape preference structures, whereas subconscious imagery and affective signals provide the deeper associative cues necessary for high discriminative accuracy.

5.2. Theoretical Mechanism: Why ZMET-Derived Subconscious Imagery Improves Predictive Performance

While the empirical results demonstrate that incorporating ZMET-based subconscious imagery enhances recommendation accuracy, it is important to clarify the theoretical mechanism through which such imagery contributes to predictive performance. The advantage does not arise merely from the inclusion of additional features, but from the type and depth of cognitive information these features encode.

First, subconscious metaphors function as compressed symbolic representations of complex experiential schemas. When participants select images that resonate with an advertisement, they are externalizing implicit meanings that structure how the advertisement is cognitively and emotionally interpreted. In advertising contexts, persuasion frequently operates through symbolic resonance rather than explicit rational evaluation; thus, metaphorical imagery captures psychologically central dimensions of response formation.

Second, from an associative network perspective, image-based metaphors activate interconnected memory nodes that encode affective valence, autobiographical cues, and culturally embedded meanings. These associative structures reveal latent motivational schemas—such as aspiration, security, belonging, or autonomy—that underlie preference formation but are often inaccessible through direct questioning. By capturing these schemas, ZMET-derived features provide access to deeper drivers of advertising response that behavioral interaction logs only partially reflect.

Third, subconscious imagery may reduce measurement noise relative to explicit self-report data. Survey-based responses and even personality inventories are subject to rationalization bias, social desirability effects, and limited introspective access. In contrast, metaphor selection often bypasses analytical filtering and captures pre-verbal, affect-laden cognitive structures. This yields more stable and psychologically faithful signals of user preference architecture.

From a computational standpoint, embedding metaphor-derived representations enriches the latent feature space with high-level semantic abstractions. This enrichment enhances the signal-to-noise ratio, reduces representational sparsity, and improves class separability between relevant and non-relevant advertisements. In other words, subconscious imagery contributes not by increasing data quantity, but by increasing representational depth and structural coherence within the model's learned embeddings.

Conceptually, the mechanism can be summarized as:

Implicit Metaphor Activation → Associative Network Expansion → Latent Motivational Schema Encoding → Enhanced Latent Representation → Improved Decision Boundary Formation → Higher Predictive Accuracy.

This theoretical pathway explains why ZMET-derived subconscious features provide incremental predictive value beyond personality traits alone and why their integration within a multi-source cognitive–affective architecture yields measurable gains in F1 and AUC performance metrics.

5.3. Comparison with Prior Work

Traditional systems built on collaborative or content-based filtering are effective but often blind to deeper cognitive–affective determinants of ad response.

From a theoretical standpoint, this study positions itself within an emerging cognitive–affective computational paradigm in recommender systems. Rather than modeling users exclusively through behavioral traces, this paradigm conceptualizes recommendation as an alignment process between algorithmic outputs and users' internal mental representations.

Relative to typical baselines (≈71% for content-based and 78% for collaborative filtering), our model's 91.5% accuracy represents a substantial improvement. Gains in AUC and F1 show that adding psychological and unconscious features increases both coverage and discriminative power, aligning with recent literature emphasizing personalized, psychology-informed marketing.

The contribution therefore extends beyond quantitative gains; it reflects a conceptual reorientation from behavior-centric inference toward structured modeling of cognitive and affective architecture.

5.4. Model Innovation and Applications

The principal innovation of this research lies in its multi-source, multi-layer architectural framework, which systematically integrates cognitive, affective, and behavioral signals into a unified recommendation engine. Unlike conventional systems that primarily extrapolate from past user behavior, our model proactively identifies potentially compelling advertisements that users have not previously encountered. This proactive capacity emerges from the incorporation of implicit mental representations into the latent feature space, enabling the system to detect symbolic and motivational congruence even in the absence of prior explicit interaction signals. This predictive capability is achieved through the synergistic leverage of:

- **Psychological Profiling:** Big Five personality traits to align content with inherent user dispositions;
- **Subconscious Insight:** ZMET-derived metaphorical imagery to tap into implicit mental associations;
- **Inspiration Metrics:** "Inspired-by" and "Inspired-to" scores to gauge and predict motivational resonance;
- **Semantic Intelligence:** Expert-generated content tags and NLP-based textual affect analysis from user feedback.

The predictive value of ZMET-derived imagery can be theoretically explained through dual-process theory and associative network models of cognition. Subconscious imagery reflects fast, affect-driven processing mechanisms (System 1) that influence advertising response beyond conscious deliberation. By activating deep semantic networks, metaphorical constructs reveal latent motivational schemas that enrich the model's latent representation space and enhance discriminative capability.

From an application standpoint, this framework enables granular, psychology-aware personalization adaptable to diverse campaign objectives—whether branding-focused narrative campaigns, creativity-driven engagements, or direct performance-oriented initiatives. Its deployment potential spans major digital ecosystems, including e-commerce platforms, social media networks, and mobile advertising exchanges, offering a scalable solution for enhancing user experience and advertising ROI through deeper psychological alignment.

5.5. Managerial Implications

The findings of this study offer actionable strategic guidance for advertisers, marketing managers, and platform designers seeking to enhance the precision and effectiveness of digital advertising efforts.

Audience Insight Beyond Demographics: Moving beyond traditional demographic and behavioral segments is imperative. The integration of psychological data enables a profound understanding of audience motivations and dispositions, allowing managers to design campaigns that resonate on a deeper, individual level.

Tapping into the Subconscious: Conventional analytics and surveys often fail to capture the implicit drivers of consumer behavior. Leveraging techniques like ZMET to access unconscious associations can reveal authentic emotional responses and unarticulated needs, providing a significant competitive edge in message development.

- Operationalizing the Framework: To translate these insights into tangible outcomes, we recommend:
- Developing lightweight psychometric instruments for scalable personality trait inference.
- Incorporating implicit association tests or metaphor-elicitation tools into user onboarding or engagement cycles.
- Fusing these psychological signals with real-time behavioral data in recommendation algorithms.

Adopting this multidimensional approach directly translates to key performance indicators: it is poised to increase Click-Through Rates (CTR) by delivering more relevant content, enhance overall user experience by reducing ad fatigue, and ultimately build a sustainable competitive advantage through superior message–audience fit and finer-grained audience segmentation.

5.6. Limitations and Directions for Future Work

While this study demonstrates the significant value of integrating psychological and subconscious data, several limitations should be acknowledged. First, although the model incorporates multi-dimensional psychological constructs, causal mechanisms cannot be definitively inferred due to the observational design. The generalizability of the findings may be constrained by the use of a sample drawn from a single cultural context and a specific temporal window. Furthermore, potential moderating effects of advertisement types (e.g., video vs. static) and broader cultural variables remain unexamined. To build upon this work, we propose the following promising directions for future inquiry:

1. Cross-Cultural and Demographic Validation: Replicating this study with more diverse, international cohorts is essential to verify the

universality of the personality-recommendation relationship and to uncover culturally-specific nuances.

2. Investigation of Contextual Moderators: Future work should systematically examine how contextual factors, such as media channel (social media, search, video), device type, and user task, influence the model's performance and the salience of different psychological variables.
3. Architectural and Algorithmic Advancements: The exploration of more sophisticated modeling techniques, such as deep transformer architectures, graph neural networks to model user-ad relationships, or reinforcement learning for dynamic, sequential decision-making, represents a natural next step for enhancing predictive power.
4. Dynamic and Longitudinal Modeling: Incorporating real-time behavioral streams and longitudinal data would allow the model to evolve with user preferences over time, moving from static prediction to adaptive personalization.

5. In-Vivo Validation: Conducting live A/B testing and field experiments on operational advertising platforms is crucial for quantifying the true operational impact on key business metrics like conversion rates, return on ad spend (ROAS), and long-term user engagement.

6. Conclusion and Future Research

This research advances recommender system design from a behavior-centric paradigm toward a cognitively and affectively informed computational framework.

6.1. Summary of Findings

Leveraging multidimensional data—including personality traits, ZMET-based unconscious cues, customer inspiration, and expert ad tagging—the proposed model significantly enhanced recommender performance.

The model achieved Precision = Recall = F1 = 0.915 and AUC = 0.957, outperforming content-based and collaborative baselines by a wide margin. Younger cohorts and users high in Openness and Extraversion showed the strongest match between recommendations and true preferences, underscoring the value of psychological profiling for ad personalization.

6.2. Theoretical Contributions

The study advances the recommender literature by moving beyond behavior-only paradigms to a cognitive–affective perspective, forging a link between consumer psychology and intelligent recommender systems. More specifically, it formalizes a cognitive–affective computational paradigm in which internal psychological constructs—such as subconscious metaphorical imagery and motivational inspiration—are operationalized as structured algorithmic features rather than treated as peripheral qualitative insights. The use of ZMET to capture implicit associations adds a novel methodological dimension to marketing analytics.

6.3. Practical Implications

The proposed framework can be embedded in online ad platforms and e-commerce systems to tailor messages to users' psychological profiles, yielding higher engagement and campaign ROI while improving user experience. Practitioners can leverage psychologically informed for audience design and creative optimization.

6.4. Limitations

Several limitations should be acknowledged. First, generalizability may be constrained by the single-population sample and specific cultural context. Second, the cross-sectional design limits causal interpretation. Third, moderating effects of advertisement format and media channel were not systematically examined. Finally, the model has not yet been validated in live production environments.

6.5. Future Research

Future research should focus on cross-cultural validation, examination of media and demographic moderators, and integration of longitudinal behavioral data. Employing advanced architectures like graph neural networks and reinforcement learning, along with live deployment to measure impact on conversion and ROI, are critical next steps.

Authors' Contributions

All authors equally contributed to this study.

Declaration

None.

Transparency Statement

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Declaration of Interest

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Ethical Considerations

Not applicable.

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