Personality Awareness and Cultural Content Recommendation: A Dual-Process Metacognitive Model of User Perception

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Abstract

Background and Objective: AI recommendation system research mainly focuses on technical aspects, with limited attention to the psychological mechanisms underlying user evaluation. This study investigates how personality awareness influences users' perception of AI-recommended cultural content and behavioral intentions. **Methods:** Based on metacognitive theory and TAM, this research employs MBTI knowledge (Know_MBTI) as an indicator of personality awareness, using a revised AMCA-scale to measure three perceptual dimensions: perceived originality, credibility, and personalization. Data from 521 Taiwanese users were collected through questionnaires and validated using statistical tests and machine learning. **Results:** Know_MBTI significantly influenced all perceptual dimensions and behavioral intentions, with personalization showing the largest effect size (η^2=0.099). A dual-process model was validated: users with high personality awareness rely more on internal cues such as personalization, while those with low awareness depend on external cues. Three user prototypes were identified, with the predictive model achieving 85.1% accuracy. **Conclusions:** Personality awareness represents a significant factor influencing AI recommendation content perception. The proposed metacognitive mechanism and dual-process model provide new perspectives for recommendation system design, while user prototypes offer foundations for personalized strategies, demonstrating theoretical and practical value.

Keywords: Personality awareness, AI recommendation, Metacognition, User perception, User prototype

1 Introduction

AI-driven recommendation systems have profoundly transformed how people access digital content, particularly on social media platforms such as Instagram, TikTok, and YouTube, where algorithms personalize and recommend vast amounts of content, determining what users "see" and influencing how they interpret culture [1-2]. When the recommended content involves geographically-based cultural content (such as folk cultural activities and local history), Luo argues that collaborative filtering and deep learning recommendation models can enhance users' reach to such content, improving user engagement and cultural identification [3]. However, research has also found that despite continuous optimization of algorithmic logic, cultural content itself possesses strong subjective and emotional resonance characteristics. If differences in users' cultural understanding, value identification, and personality preferences are ignored, it may lead to "matching failures" in recommended content, causing cognitive fatigue and decreased acceptance [4-5]. Therefore, optimizing AI recommendation systems relies not only on algorithmic precision but also requires deep understanding of user psychological mechanisms, which is a core issue that current research urgently needs to address.

The integration of recommendation algorithms with user psychological attributes has become a research hotspot. In engineering practice, algorithmic systems often infer personality types through users' behavioral characteristics on social platforms and embed personality vectors into the model training process to optimize the precision and adaptability of personalized recommendations [6-7]. Among these, MBTI (Myers-Briggs Type Indicator), due to its clear structure and distinct dimensions, has become a commonly used tool in personality modeling [8]. However, such personality modeling methods mostly make inferences from external behaviors and seldom focus on users' subjective awareness of their own personality traits—namely, personality awareness [8]. This belongs to the category of "metacognition," emphasizing individuals' ability to perceive and regulate their own psychological states [8]. In the recommendation context, this cognitive ability may influence users' trust, processing, and action pathways regarding recommended content. In other words, even if two users are classified by the system as having the same personality type, if one person clearly knows they possess that personality attribute while the other does not, their reception and behavioral feelings may be completely different. Therefore, this study introduces "personality awareness," focusing on examining how users' knowledge of their own MBTI type (Know_MBTI) influences their perception and usage intention regarding AI-recommended cultural content. MBTI was selected as the research

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framework for the following reasons: first, MBTI is widely disseminated on global social platforms and is a commonly used communication language for user self-identification [1, 8]; second, MBTI's four-dimensional binary structure (E/I, S/N, T/F, J/P) facilitates the construction of cognitive grouping labels [8].

In cross-disciplinary research on AI recommendations, cultural content dissemination, social media, and personal learning, Cifuentes-Faurah and Al-Rahmi [6] used the TAM as a theoretical framework and found that when users perceive higher "usefulness" (Perceived Usefulness, PU) of recommendation systems on social platforms, they are more likely to develop "behavioral intention" (BI) for continued use, thereby actively acquiring, processing, and internalizing relevant cultural information, achieving informal but efficient personal learning pathways [9]. Meanwhile, the AMCA (Algorithmic Media Content Awareness) scale proposed by Zarouali et al. [7], although originally designed to measure users' cognitive awareness of algorithmic mechanisms themselves, including four dimensions of content filtering, automated decision-making, human-machine interaction, and ethical considerations, has also prompted academia to begin focusing on the subjective perceptual structures triggered by recommended content during the acceptance process [10]. Based on TAM model's perception-behavior mechanism and incorporating partial content cognitive perspectives from AMCA, this study reconstructs three key variables of content perception: Perceived Originality (PO), Perceived Credibility (PC), Perceived Personalization (PP). These three perceptual dimensions do not directly adopt the original AMCA-scale but rather reconstruct users' subjective experiences under the technology acceptance pathway, combined with cultural recommendation contexts. To further connect perceptual evaluation with usage behavior, this paper also introduces the behavioral intention (BI) variable from the TAM model [11], measuring whether users are willing to continue using recommendation systems to explore cultural content. Ultimately, this paper proposes a dual-pathway perception model centered on personality awareness (Know_MBTI), theoretically depicting how it influences users' behavioral intention (BI) through three content perceptual dimensions (PO, PC, PP), to construct a cognitive structure model of how metacognition intervenes in the cultural content recommendation acceptance process.

Our research data comes from 521 Taiwanese respondents aged 18-35 who completed a revised AMCA-scale questionnaire survey. Through statistical validation (SPSS) and machine learning techniques (feature selection, clustering, and classification modeling in Weka), we aim to address the following research questions:

1) Does personality awareness (Know_MBTI) significantly influence PO, PC, PP and BI?

2) Which variables are the strongest predictors of personality awareness (Know_MBTI)?

3) Can we identify psychologically meaningful user prototypes through unsupervised learning algorithms to inform personalized recommendation strategies?

2 Literature Review

2.1 From AI Recommendation Systems to Cultural Content Communication on Social Media

2.1.1 "Similarity Matching" to "Cultural Understanding"

Social media algorithms have made technical advances. Algorithms (e.g., Meta's DLRM, Byte Dance's Deep Retrieval) leverage Transformer-based models to track interest changes and predict implicit preferences (e.g., 3-second dwell time without liking) [12]. However, these technical improvements have not solved the challenge of cultural content acceptance [13].

As noted in Tencent Research Institute Algorithm Governance Research Team's report "Breaking the Algorithmic Shell," [14] content understanding and cross-domain transfer learning have addressed cold-start problems. Yet users' responses to cultural content exceed algorithmic prediction. They involve processes of cultural identity and emotional resonance that current algorithms struggle to capture [7].

2.1.2 "Efficiency Optimization" to "Meaning Construction"

Recently, Social media recommendation systems use reinforcement learning for multi-round optimization [15]. However, cultural content recommendation faces a challenge: the subjective nature of cultural content and the complexity of emotional resonance [3-4, 16]. Users' acceptance of cultural content depends on both interest alignment and their individual cultural background, value systems, and identity [17-19].

Even when algorithms accurately predict user behavior, they cannot guarantee recommended content create emotional resonance or cultural connection [19]. Therefore, cultural content recommendation must move beyond simple "user-content" matching toward understanding users' cultural psychology and identity mechanisms.

2.1.3 AI-Generated Content Recognition

With rapid advances in large language models (LLMs) and generative AI, users encounter increasing amounts of AI-generated cultural content on social media [19]. This creates new challenges beyond technical considerations [20-21].

Research from Indonesia shows [19] that 57.5% of respondents incorrectly identified human-created content as AI-generated, demonstrating what researchers call "reverse Turing test failure." Users' ability to distinguish between AI-generated and human-created cultural content affects their perception of content originality, credibility, and personalization [18]. This recognition ability may be closely linked to users' metacognitive levels.

2.2 Metacognitive Theory and Personality Awareness

2.2.1 Personality Awareness as a Metaknowledge Variable in Cognitive Structure

Metacognition is a cognitive psychology concept first proposed by Flavell (1979) [22], referring to individuals' awareness, understanding, and regulation of their own mental activities, emphasizing people's active

consciousness of "how to think" during information processing. Subsequent research (such as Veenman, 2006; Efklides, 2008) further divided metacognition into three major components: metacognitive knowledge, metacognitive monitoring, and metacognitive control [23-24]. Among these, metacognitive knowledge emphasizes individuals' self-understanding of their own cognitive characteristics, cognitive tasks, and strategy use. In algorithmic recommendation contexts, users' self-awareness of their own personality types, preference tendencies, or judgment pathways constitutes "person-related metacognitive knowledge" in their meta-knowledge structure, which may significantly influence their content processing methods and response mechanisms in recommendation contexts [25].

Zarouali et al. pointed out in their AMCA research that users' awareness of "why content is recommended" is essentially a metacognitive process [7], while Kim and Sundar (2022) emphasized the key role of "identity self-perception" in cross-cultural algorithm acceptance [26]. This series of research collectively points to the fact that whether users understand "what kind of person they are": namely, personality awareness — may profoundly influence their content evaluation and recommendation acceptance behavior.

Overall, the effectiveness of AI recommendation systems in cultural content acceptance depends not only on algorithmic modeling itself but is also deeply influenced by users' individual cognitive abilities and psychological pathways. Therefore, exploring users' metacognitive states, especially their cognitive awareness of their own personality types, has become an important entry point for understanding cultural recommendation mechanisms [27].

2.2.2 Personality Traits and Personality Awareness

Although research on personality variables in recommendation systems has established some foundation, mainstream models typically use personality types such as Big Five or MBTI as the basis for user modeling in personalized recommendations [1, 8]. These variables emphasize individuals' stable behavioral tendencies and information preferences, demonstrating certain predictive power in large samples. However, such "static personality trait" models often assume that users are transparent and unchanging regarding their own traits, overlooking whether users truly "realize" their own personality characteristics and how this awareness influences their reception and judgment of recommended content.

This study treats "personality awareness" as users' cognitive degree of their personality type, specifically operationally measured by "whether they know their own MBTI type" (Know_MBTI). This variable differs from personality traits themselves (such as "I am INFJ"); it emphasizes individuals' metacognitive knowledge processing of self-awareness (i.e., "I know that I am INFJ"). This distinction has important psychological significance: among users with the same INTJ type, if one person clearly knows and identifies with this personality label while another is completely unaware of it, their cognitive pathways and interpretative structures when facing recommended content are likely to be very different. Therefore, Know_MBTI is also defined as an operationalized indicator of metacognitive knowledge, introducing a "self-awareness" perspective into content recommendation systems to capture psychological difference mechanisms that traditional modeling methods overlook.

2.2.3 Rationale for Choosing MBTI

Compared to other personality measurement tools (such as Big Five or HEXACO), MBTI has higher prevalence and self-identification among social platform users, particularly Generation Z user groups [28]. Moreover, MBTI's four-dimensional binary structure (E/I, S/N, T/F, J/P) possesses good operability, facilitating users' self-categorization through short assessments or label identification [13]. The abundance of content themed around "MBTI pairing" and "personality type interpretation" on social media platforms (such as Instagram, YouTube, Reddit) demonstrates that users are generally familiar with and use this framework for self-narration and social interaction [18, 29].

Furthermore, MBTI's binary structural characteristics provide natural advantages for metacognitive variable design. In this study, "Know_MBTI" is operationalized in the form of "knowing vs. not knowing," which can logically serve as a categorical variable affecting content processing pathways and can be further used for cluster analysis, feature selection, and classifier modeling. It should be emphasized that this paper does not discuss the scientific validity controversies surrounding MBTI, but rather treats it as a self-awareness label system in social contexts, used to analyze whether users possess personality awareness and whether this cognitive state affects content perception and behavioral intention [30].

While we treat MBTI as a culturally recognized self-categorization framework, we acknowledge ongoing critiques of its psychometric validity [31]. Prior research has identified concerns including limited test–retest reliability low predictive validity in behavioral contexts [23] and the oversimplified dichotomization of continuous personality traits [32-33].

However, this study is not intended to validate MBTI as a diagnostic tool. Rather, we examine how users' familiarity with MBTI as a cognitive–social label informs their self-perception and shapes content evaluation [34].

Additionally, although Know_MBTI is operationalized in binary form for analytical clarity, we recognize that metacognitive awareness likely exists along a continuum. Future research may employ confidence-based scaling (e.g., "How certain are you that you are an INTJ?") or integrate temporal fluctuation modeling to better capture dynamic states of personality self-awareness.

2.3 AMCA-Scale and TAM Model Applications

2.3.1 "AMCA-Scale" to the "PO-PC-PP" Framework

Zarouali et al. [7] developed the AMCA-scale to measure users' awareness of algorithmically recommended content. The original scale includes four dimensions: Content Filtering Awareness, Automated Decision-Making Awareness, Human-Algorithm Interplay Awareness, and Ethical Considerations Awareness.

For this study, we focus specifically on cultural content

in social media contexts. We adapted from AMCA - scale and integrated it with communication theory, the TAM, and metacognitive theory to develop three core perceptual dimensions [33, 35-36]:

1) Perceived Originality (PO) This measures how novel and unique users find the recommended cultural content. It emphasizes the algorithm's ability to expand users' cultural horizons through:

- Cultural diversity exposure: introducing users to previously unfamiliar cultural content or perspectives
- Thematic novelty: covering new topics or distinctive local cultural features
- Active learning facilitation: helping users discover cultural knowledge they wouldn't actively search for

2) Perceived Credibility (PC) This assesses users' evaluation of the accuracy, authority, and reliability of recommended cultural content. Since cultural content often involves historical facts, traditions, and social values, accuracy directly impacts learning quality:

- Content accuracy: whether the cultural information is factually correct
- Source authority: whether content sources are credible and authoritative
- Diverse perspectives: whether content presents multiple viewpoints, especially on sensitive cultural or historical topics

3) Perceived Personalization (PP) This measures how well users believe the recommended content matches their personal cultural learning needs and preferences. Cultural interests are highly individual, so this dimension includes:

- Interest customization: whether content is tailored to users' specific cultural interests
- Learning adaptability: whether the system improves its understanding of user needs over time
- Efficiency advantage: whether recommendations better meet user needs compared to manual searching

2.3.2 Integration with the TAM Model

The TAM model provides a framework for understanding user acceptance of AI recommendation systems [37]. In TAM, "behavioral intention" (BI) measures users' likelihood of continued system use. In this study, BI reflects users' willingness to continue using AI recommendation functions for cultural content exploration and their likelihood of recommending these systems to others. Integrating AMCA dimensions (PO, PC, PP) with TAM's BI, we construct a "awareness - perception - behavior" framework predicting sustained user interaction with AI-recommended cultural content.

3 Methodology

3.1 Research Design

Based on the theoretical framework constructed in the literature review of Chapter 2, this study adopts a staged mixed-methods research design that combines statistical validation with machine learning modeling to systematically explore how personality awareness (Know_MBTI) influences users' perception and usage intention regarding AI-recommended cultural content. The specific research is divided into the following two stages:

Stage 1: Statistical Analysis and Difference Testing

This stage first uses one-way ANOVA to test the main effect differences of whether users know their own MBTI type (Know_MBTI = Yes/No) on AI-recommended content perception (PO, PC, PP) and behavioral intention (BI). Additionally, it further breaks down the four dimensions of MBTI (E/I, S/N, T/F, J/P) to test the significant differences in each perceptual dimension between users in each personality dimension group and users who "don't know their MBTI." Subsequently, Pearson correlation coefficients are used to analyze the linear relationships between PO, PC, PP and BI, establishing a correlation foundation for modeling.

Stage 2: Machine Learning Feature Modeling and User Profile Construction

Based on the validation of statistical correlations, the Information Gain (InfoGain) method in Weka software is used for feature selection to identify key variables that best predict Know_MBTI, including PO_mean, PC_mean, PP_mean, and AI_Identify_Score. Subsequently, K-means++ clustering method is used to perform cluster analysis (K=3) on the above variables to construct user profile prototypes. Finally, multiple supervised classification models are constructed and compared to predict whether users possess personality awareness (Know_MBTI).

This staged research design can be used both for theoretical hypothesis validation and provides operationally viable user modeling strategies for AI cultural recommendation systems, promoting the establishment of metacognition-based personalized recommendation frameworks.

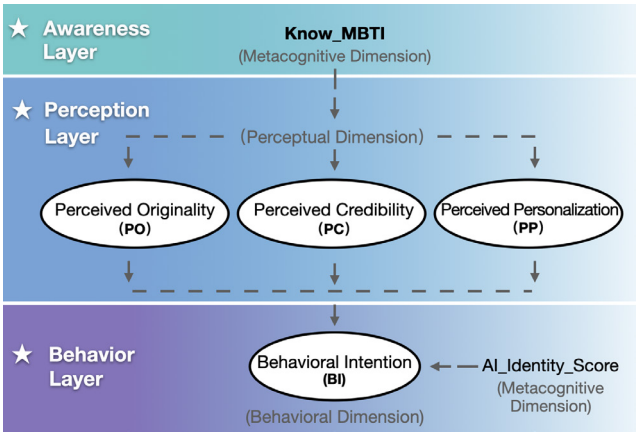

Figure 1. "Awareness - Perception - Behavior" framework

Based on the above content, this paper constructs the following theoretical model to reveal the pathways through which personality awareness affects users' cultural content perception and behavioral intention (see Figure 1). Know_MBTI in the metacognitive dimension serves as a grouping variable, depicting whether users possess personality awareness; the perceptual dimensions (PO, PC, PP) jointly influence BI; AI identification ability (AI_Identify_Score)

in the metacognitive dimension serves as a reference variable, providing background cues for content judgment ability.

3.2 Questionnaire Design and Variable Measurement

The questionnaire consisted of 21 items using a 5-point Likert scale, covering 5 core construct dimensions. The PO, PC, and PP constructs were adapted from the AMCA-scale proposed by Zarouali et al. (2021) and revised for the social media cultural content dissemination context, Detailed measurement items are provided in Appendix A. The BI dimension referenced behavioral intention items from the TAM model. Know_MBTI and ai_identify_score were custom variables created for this research to measure personality awareness and subjective identification ability, respectively. As show in Table 1.

Table 1. Variable measurement and reliability analysis

Construct	Construct variable	Items	Cronbach's α	Description	Source
Perceptual dimension	PO	3	0.811	Novelty of recommended content, cultural horizon expansion	AMCA-scale adapted: FIL1, FIL2, FIL3, FIL4 (awareness of algorithmic filtering and personalized recommendation content)
	PC	3	0.757	Content accuracy, authority, diversity	AMCA-scale adapted: ETH1, ETH2 (whether algorithms are transparent, whether affected by bias)
	PP	3	0.747	Alignment with cultural learning interests and preferences	AMCA-scale adapted: ADM1, ADM3, HAI1, HAI2 (whether algorithms provide personalized recommendations based on user behavioral data)
Behavioral dimension	BI	2	0.752	Willingness to continue using recommendation systems	TAM adapted
Metacognitive dimension	Know_MBTI	1	-	Whether users know their MBTI personality type and their reported personality type	Self-developed
	AI_Identify_Score	1	-	AI Content Recognition Ability	Self-developed (media literacy extension)

Scale Reliability and Validity Testing: We conducted Exploratory Factor Analysis (EFA) using SPSS to verify the structural validity of perceptual and behavioral dimensions. Results showed KMO = 0.894 and Bartlett's test of sphericity $p < 0.001$. Using Principal Axis Factoring with Varimax rotation, we extracted 4 factors that explained 72.6% of the cumulative variance. All item factor loadings exceeded 0.7 with no significant cross-loadings, supporting the existing construct structure.

3.3 Data Collection

Data collection yielded 521 valid responses from Taiwanese participants aged 18-35 (42.9% male, 57.1% female), primarily university students and young professionals. To address cross-platform cultural content interaction patterns, we analyzed participants' engagement across three major platforms: Instagram (78.3% usage for visual cultural content), TikTok (65.2% for short-form cultural videos), and YouTube (54.1% for in-depth cultural documentaries).

Platform-specific usage patterns revealed distinct content consumption behaviors: Instagram users primarily engaged with heritage photography and cultural festivals, TikTok users favored quick cultural facts and trending cultural challenges, while YouTube users sought comprehensive cultural education and historical documentaries. These varied interaction modalities provide important context for understanding how personality awareness (Know_MBTI) may differentially influence content perception across algorithmics. recommendation systems with distinct content formats and user engagement mechanisms.

3.4 Data Analysis Methods

The data analysis in this study employed two main systems: traditional statistical testing and machine learning modeling, executed using SPSS and Weka software respectively.

3.4.1 Statistical Analysis (SPSS)

This study executes the following statistical tests in

SPSS 29.0 software:

1) One-way ANOVA:

Tests the main effect differences of Know_MBTI (whether users know their MBTI type) on PO, PC, PP, and BI.

Supplementary analysis of significant differences in perceptual variables across four MBTI dimensional groups (E/I, S/N, T/F, J/P).

Reports F values, p values, effect size η^2, and 95% confidence intervals.

2) Pearson Correlation Analysis:

Analyzes linear correlations between the three perceptual dimensions (PO, PC, PP) and BI.

Used to test the correlation structure of the "perception-awareness-behavior" pathway hypothesis.

This part of the analysis validates statistical significance and correlations between variables, providing theoretical foundation and feature selection basis for subsequent machine learning modeling.

3.4.2 Machine Learning Analysis

1) Feature Importance Analysis

Feature Selection (InfoGain Attribute Evaluator): The InfoGain algorithm was employed to identify the most important feature variables for predicting Know_MBTI. Based on the information gain formula:

$$IG\,(T, X) = H\,(T) - H\,(T|X)$$

Where:

- $IG\,(T, X)$: Information gain of variable X for target variable T
- $H\,(T)$: Entropy of T
- $H\,(T|X)$: Conditional entropy of T given X

This identifies the input variable constructs with the greatest explanatory power for the target variable (e.g., Know_MBTI).

2) User Profiling and Classification Model Construction and Evaluation

Unsupervised Clustering Analysis: The K-Means++ algorithm was employed to cluster four core constructs (PO, PC, PP, AI_Identify_Score) with K=3, while simultaneously performing comparative clustering on five core constructs (PO, PC, PP, BI, AI_Identify_Score) with K=4. The clustering results from four core constructs with K=3 was ultimately selected as the primary foundation for user profiling analysis.

Classification Model Construction and Evaluation: Binary classification prediction was performed on the Know_MBTI variable using the following six mainstream classifiers:

- Random Forest
- Support Vector Machine (SVM)
- AdaBoost
- Multilayer Perceptron (MLP)
- Decision Tree (J48)
- Naive Bayes

Classification model performance was evaluated using 10-fold cross-validation with the following three core metrics:

- **Accuracy:**

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **F1-Score:**

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

- **ROC-AUC:** Measures the model's overall discriminative ability.

4 Results

4.1 Impact of Personality Awareness on Perception and Behavioral Intention

To examine the impact of personality awareness (Know_MBTI) on three perceptual dimensions (PO, PC, PP) and BI, one-way ANOVA was employed.

The results show that Know_MBTI significantly affects all perceptual dimensions and behavioral intention, with effect sizes ranked as follows:

$$PP > BI > PO > PC$$

As show in Table 2, Perceived personalization showed the strongest effect ($\eta^2 = 0.099$), meaning that Know_MBTI explains 9.9% of the variance in PP.

Table 2. ANOVA results

Perception dimension	Know MBTI group M (SD)	Don't know MBTI group M (SD)	Mean difference	F-value range	p-value	η^2	Effect size	95% CI
PP	3.70 (0.68)	3.17 (0.72)	0.53	28.4-29.0	<.001	0.099	Large	[0.41, 0.65]
BI	3.78 (0.80)	3.30 (0.78)	0.48	16.1-18.8	<.001	0.062	Medium	[0.33, 0.63]
PO	3.71 (0.83)	3.50 (0.74)	0.21	7.9-8.9	<.001	0.03	Small	[0.08, 0.34]
PC	3.32 (0.73)	3.10 (0.66)	0.22	3.8-5.2	<.05	0.017	Small	[0.05, 0.39]

Note: The Know_MBTI group includes all participants who know their MBTI type (E/I, S/N, T/F, J/P). Differences among personality types within the four dimensions were not significant (p > .05).

BI achieved a medium effect size ($\eta^2 = 0.062$), indicating that users with higher personality awareness demonstrate stronger intentions for continued use in cultural content recommendations.

The effect size pattern validates the dual-process cognitive theory: users with high personality awareness rely more on internal standards (PP), while the effects of external standard evaluation (PO, PC) are relatively smaller.

MBTI knowledge is more important than personality type: All four dimensions show the same pattern, indicating that the metacognitive priming effect is more critical than specific personality traits.

4.2 Correlations Between Perceptual Dimensions and Behavioral Intention

As show in Table 3, Pearson correlation analysis was further employed to examine the relationships between PO, PC, PP, and BI:

All three perceptual dimensions showed significant positive correlations with behavioral intention, with the strongest correlation observed between PP and BI ($r = 0.478$). This indicates that "whether recommended content is personalized" directly influences users' willingness to continue using the recommendation system.

This finding aligns with the TAM framework mechanism where "perceived usefulness" promotes "continued usage intention," validating the theoretical soundness of the "perception-behavior" pathway model.

4.3 Feature Selection Results and Key Predictive Variables

Using the InfoGain attribute evaluator in Weka, we identified which variables best predict Know_MBTI. The top 4 variables are as follows, as show in Table 4.

Results Analysis:

AI_Identify_Score (0.2156) and PP_mean (0.1823) are the most important predictive features, far exceeding other variables, indicating that AI recognition ability (AI_Identify_Score) and perceived personalization (PP) are core indicators of personality awareness.

Differences exist among perceptual dimensions: The predictive power of perceived personalization (0.1823) is significantly higher than perceived credibility (0.0982), validating the PP > PC effect pattern observed in the ANOVA analysis.

These results support the metacognitive theory hypothesis: Users with higher metacognitive levels not only have clearer self-awareness of their personality but also possess stronger AI content recognition abilities.

Table 3. Pearson correlation analysis

Variable combination	Pearson r	Significance	95% CI
PO and BI	0.318	$p < 0.001$	[0.24, 0.39]
PC and BI	0.412	$p < 0.001$	[0.34, 0.48]
PP and BI	0.478	$p < 0.001$	[0.41, 0.54]

Table 4. Feature importance ranking (InfoGain)

Rank variable	Information gain	Feature type	Practical interpretation
1 AI_Identify _Score	0.2156	Cognitive Feature	AI recognition ability is highly correlated with metacognitive level
2 PP _ mean	0.1823	Perceptual Feature	Perceived personalization is the strongest predictor of personality awareness
3 PC _ mean	0.0982	Perceptual Feature	Perceived credibility has moderate predictive value
4 PO _mean	0.0491	Perceptual Feature	Perceived originality has relatively weak predictive power

4.4 K-means Clustering Results: User Prototype Classification

4.4.1 Determination of Cluster Number

To identify meaningful user segments, we applied the K-means clustering algorithm using four standardized input variables: AI recognition score, PO, PC and PP. The optimal number of clusters was determined using the Elbow Method, which analyzes the trade-off between within-cluster variance and model complexity.

As illustrated in Table 5, the sharpest decline in within-cluster sum of squares occurred at K=3, indicating that a three-cluster solution offers the most appropriate balance between interpretability and granularity.

Table 5. K-means cluster number selection

K	WCSS (Error)	Error reduction	Category distribution	Balanced	Notes
2	67.877	-	50/50	Yes	Clear elbow point
3	53.015	↓14.862	34/30/36	Yes	Recommended value
4	46.544	↓6.471	23/17/27/32	Yes	Diminishing returns
5	41.157	↓5.387	20/17/15/27/20	No	Continued decline but smaller magnitude

When the number of clusters increased from 2 to 3, the Within-Cluster Sum of Squares (WCSS) decreased from 67.877 to 53.015, with a reduction of 14.862, representing the largest decrease among all K values. However, when moving from K=3 to K=4, the WCSS reduction was only 6.471, showing clear diminishing returns. Therefore, this study determined K=3 as the optimal number of clusters.

To further validate the clustering solution, we applied two additional metrics: silhouette coefficient and Davies–Bouldin index (DB index).

Silhouette coefficients were calculated for K=2 through K=5, with K=3 yielding the highest average silhouette score of 0.547, indicating good cluster cohesion and separation [37] Similarly, the DB index reached its minimum at K=3 (DB = 0.892), further supporting the quality of the three-cluster solution, as values below 1.0 indicate well-separated and compact clusters [38].

Together, these metrics provide convergent evidence that K=3 offers both theoretical interpretability and empirical validity for user segmentation in this context.

4.4.2 User Clustering Characteristic Analysis

Following the K-means clustering with K=3, the user sample was segmented into three distinct groups, each characterized by unique perceptual and cognitive profiles. Table 6 presents the normalized centroid values for each cluster across the four key variables. These centroid patterns reflect differentiated cognitive responses to AI-recommended content and serve as the foundation for constructing user prototypes.

Table 6. Comparison of user characteristics across clusters

User group	Sample size	MBTI awareness rate	AI_Identify _Score	PO	PC	PP	User prototype
Cluster 0	179 (34%)	0.603	0.376	0.577	0.476	0.567	Authority Seekers
Cluster 1	155 (30%)	0.806	0.824	0.545	0.435	0.583	Curious Explorers
Cluster 2	187 (36%)	0.914	0.817	0.816	0.774	0.845	Cognitive Maximizers

In-depth Analysis of User Prototypes:

1) Authority Seekers Type (34%, MBTI Awareness Rate 60.3%)

- Authority Seekers: Lower metacognitive level, relying on traditional evaluation standards
- Curious Explorers: Cautious evaluation of AI recommendations, focusing more on basic content attributes
- Cognitive Maximizers: Strengthen content novelty and authority, reduce recommendation complexity

2) Curious Explorers Type (30%, MBTI Awareness Rate 80.6%)

- Authority Seekers: Beginning to develop personality awareness, but evaluation system not yet mature
- Curious Explorers: Open attitude toward AI technology, willing to try personalized recommendations
- Cognitive Maximizers: Balance personalization with diversity, gradually guide deeper exploration

3) Cognitive Maximizers Type (36%, MBTI Awareness Rate 91.4%)

- Authority Seekers: High personality awareness and AI identify ability
- Curious Explorers: Comprehensive evaluation of recommended content, with clear personal standards
- Cognitive Maximizers: Provide highly personalized precise recommendations, support complex preference expression

These three user prototypes actually reflect three stages of metacognitive development:

Stage 1: Cognitive Ambiguity Period - Self-awareness is unclear, relying on traditional evaluation standards

Stage 2: Cognitive Awakening Period - Beginning to focus on self-compatibility, but evaluation system not yet mature

Stage 3: Cognitive Integration Period - Forming complete self-evaluation system, multidimensional comprehensive judgment

This finding extends the traditional Technology Acceptance Model by emphasizing the moderating role of individual cognitive differences in technology adoption processes.

4.5 Classification Models for Predicting Know_MBTI

Using the aforementioned variables as inputs, six classifiers were employed to model Know_MBTI, with performance evaluated using 10-fold cross-validation. As show in Table 7.

Results Analysis:

1) Random Forest performed best, achieving 85.1% accuracy, F1-score of 0.844, and ROC-AUC of 0.861, indicating that personality awareness can be effectively predicted based on perception variables and AI recognition ability.

2) The 85.1% prediction accuracy has significant practical implications:

- Provides technical feasibility for building human-computer interaction mechanisms centered on "personality awareness"
- In actual recommendation systems, this means accurately identifying over 85% of users with high metacognitive levels
- Provides scientific foundation for precise deployment of personalized recommendation strategies

3) The strong performance of J48 Decision Tree

(83.6%) offers an interpretable rule-based model for business applications, facilitating system implementation and user understanding.

4) Although Naive Bayes showed weaker performance, it serves as a robust baseline, providing a reference standard for model performance evaluation.

Model Application Value:

This predictive model not only validates theoretical hypotheses but also provides technical support for practical applications:

1) User Stratification Strategy: Systems can quickly identify users' metacognitive levels and implement differentiated recommendation strategies [37]

2) Cold Start Optimization: Rapidly establish user profiles through simple perception evaluation questions, reducing data collection costs

3) Dynamic Adjustment Mechanism: As user interactions increase, the model can continuously update assessments of users' metacognitive levels

In summary, this chapter systematically presented the statistical and modeling analysis results of the relationship between personality awareness and AI recommendation content perception, providing solid empirical evidence for the discussion in Chapter 5.

Table 7. Classification model performance comparison

Model	Accuracy (%)	F1-score	ROC-AUC	Features and advantages
Random Forest	85.1	0.844	0.861	Strong feature importance interpretability, good generalization ability
J48 Decision Tree	83.6	0.823	0.842	Rule interpretability, suitable for business understanding
SVM	82.3	0.809	0.837	Strong capability for handling high-dimensional data
MLP Multilayer Perceptron	80.4	0.786	0.813	Strong capability for capturing nonlinear relationships
AdaBoost	78.6	0.763	0.789	Ensemble learning, reduces bias
Naive Bayes	74.8	0.712	0.756	Simple computation, suitable as baseline

5 Discussion

5.1 The Metacognitive Mechanism: From Self-Awareness to Content Evaluation

The systematic pattern of Know_MBTI effects reveals a fundamental shift in how personality-aware users evaluate AI recommendations. Rather than treating all content dimensions equally, these users prioritize self-compatibility (PP) over external validation (PC), suggesting an internalized evaluation schema.

5.1.1 Theoretical Significance of Effect Size Ordering

This sequence perfectly reflects the progressive process from internal self-cognition to external objective evaluation, echoing the metacognitive theory's perspective (as show in Figure 2): individuals with higher self-awareness levels tend to actively process external information and demonstrate greater discriminative ability [22-23] and cognitive clarity in accepting AI-recommended content.

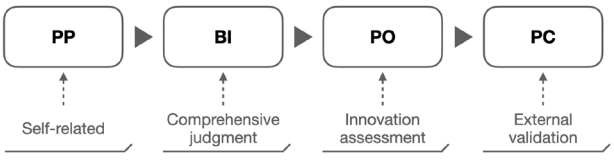

Figure 2. Classification model performance comparison

5.1.2 Implications for Adaptive Algorithm Design

This metacognitive distinction suggests that one-size-fits-all recommendation approaches may be fundamentally misaligned with user cognitive diversity. Systems could leverage personality awareness as a cognitive routing mechanism:

- High-awareness users: Emphasize personalization accuracy and user control
- Low-awareness users: Provide external validation cues and credibility signals.

5.1.3 Interpreting the Practical Impact of Know_MBTI on User Perception and Intention

Know_MBTI significantly enhances users' behavioral intention (η^2=0.062), indicating that when users know who they are and what content suits them, they are more willing to use the system to continue exploring cultural content. The observed effect size for perceived personalization (η^2=0.099) represents a medium-to-large effect by conventional standards [39] explaining approximately 10% of variance in user perception.

While direct translation to satisfaction improvements requires further empirical validation, this effect magnitude suggests meaningful practical significance in recommendation contexts. According to Lakens' [38] Common Language Effect Size interpretation, users with personality awareness have approximately a 68% probability of higher perceived personalization compared to users without such awareness.

5.2 Pathway Significance of Perceptual dimensions on Behavioral Intention and TAM Model Extension

Through correlation analysis, this study preliminarily explored the relationships between PO, PC, and PP with BI. All showed significant positive correlations with correlation coefficients of 0.318, 0.412, and 0.478 respectively. This result further validates the theoretical soundness of the "*perception → behavior*" pathway model, aligning with the TAM framework mechanism where "perceived usefulness" promotes "continued usage behavioral intention."

Notably, PP has the strongest predictive power for BI among all perception variables (r=0.478), holding a central position. This indirectly demonstrates that "personal compatibility" is the key driver for users' decisions to use the system in cultural content recommendation.

This finding has important implications for AI recommendation strategies: systems need to pursue not only accuracy but also understand users' cultural preferences and metacognitive states.

Furthermore, this study provides a metacognitive perspective extension to the traditional TAM model:

- **Traditional TAM** (*External Variables → Perceived Usefulness/Ease of Use → Behavioral Intention*);
- **Metacognitive Extended TAM** (*Metacognitive (Know_MBTI) → Differentiated Perception Weights → Personalized Behavioral Intention*).

This extension emphasizes the moderating role of individual cognitive differences in technology acceptance processes, providing a new theoretical framework for personalized technology acceptance models.

5.3 User Prototypes from Personality Awareness: A Metacognitive Approach to Recommendation Stratification

5.3.1 From User Segmentation to Metacognitive Development Theory

The three-cluster solution reveals more than mere user segmentation-it unveils a developmental progression of metacognitive maturity in technology interactions. This progression challenges traditional demographic-based segmentation by demonstrating how internal cognitive states drive technology acceptance behaviors.

The Authority Seekers Curious Explorers Cognitive Maximizers progression suggests that personality awareness operates as a developmental catalyst, transforming users from external-validation seekers to autonomous evaluators. This finding extends TAM by positioning metacognitive readiness as a precondition for sophisticated technology evaluation rather than a static individual difference.

Implications for adaptive system design:

- **Stage-sensitive onboarding processes**
- **Progressive complexity introduction**
- **Metacognitive scaffolding for lower-awareness users**

5.3.2 Perception Weight Model Construction

To further analyze how personality awareness affects content perception pathway structures, we constructed two sets of linear combination weights based on the standardized average score ratios of Know_MBTI=1 (high awareness) and Know_MBTI=0 (low awareness) groups across PO, PC, and PP constructs. These weights respectively reflect each group's reliance on the three types of perception variables. Coefficients are derived from the proportion of standardized means and normalized (∑w=1).

- **High Personality Awareness Model F_high_awareness:**
  $F_{high} = 0.136 \cdot PO + 0.077 \cdot PC + 0.787 \cdot PP$
- **Low Personality Awareness Model F_low_awareness:**
  $F_{low} = 0.346 \cdot PO + 0.196 \cdot PC + 0.457 \cdot PP$

5.3.3 Model Validation and Recommendation System Optimization

This study validated that personality awareness (Know_MBTI) can be effectively predicted through perceptual variables (PO, PC, PP) and AI content recognition ability. Among the six mainstream classifiers tested, the Random Forest model achieved the highest performance with 85.1% accuracy and an F1-score of 0.844, significantly outperforming others. These findings confirm that personality awareness functions as a modelable metacognitive feature, providing practical feasibility for integration into AI-driven recommendation systems.

Compared with J48 (83.6%) and SVM (82.3%), Random Forest demonstrated superior generalization when handling high-dimensional perceptual variables and latent user cognitive structures. This suggests that metacognitive traits—particularly personality awareness—offer greater predictive power than static demographic or surface behavioral features [40]. Notably, feature selection results ranked AI_Identify_Score and PP_mean as the top two predictors, highlighting users' AI detection ability and perceived personalization as central cognitive signals of personality awareness.

Further mapping of these classification results onto the three user clusters reveals that Cluster 2 (Cognitive Maximizers) was the most accurately classified. Its users displayed stable and centralized perceptual profiles, indicating that cognitive coherence enhances predictability. Conversely, Cluster 0 (Authority Seekers) exhibited volatile perceptual dimensions, leading to blurred classification boundaries. This contrast reinforces the theoretical assertion that cognitive structure stability improves model discriminability and offers practical insights for cold-start scenarios, where minimal data must yield reliable user segmentation.

From a systems design perspective, the validated prediction model offers three key benefits:

1) Rapid User Stratification: Lightweight perception-based questionnaires enable accurate modeling of user cognition in the absence of behavioral data—particularly valuable during onboarding or anonymous interactions.

2) Strategy Differentiation: Prediction outputs can inform whether users are suited for advanced personalization controls (for high metacognitive users) or simplified content delivery (for lower-awareness users).

3) Dynamic Cognitive Feedback Loop: As users interact with the system, continuous behavioral input can refine the model's prediction of their personality awareness, enabling real-time alignment between cognitive pathways and recommendation logic.

In summary, this section establishes personality awareness not only as a statistically significant predictor but also as a technically operational and system-adaptive input for AI-driven personalization. It exemplifies a shift toward cognitively interpretable and psychologically responsive recommendation architecture.

5.4 Implications for Research and Practice

This study demonstrates that personality awareness (Know_MBTI) serves as a pivotal metacognitive variable in AI-recommended cultural content processing. Through integrated statistical and machine learning evidence, we establish that differences in personality awareness not only affect individual perceptions—particularly PP — but also significantly influence BI, reinforcing the value of incorporating user metacognition into recommendation systems design.

Importantly, the results lend strong support to the dual-process cognitive framework proposed. Users with low personality awareness (Know_MBTI=0) tend to engage in heuristic processing, distributing attention more evenly across PO, PC, and PP. In contrast, users with high personality awareness (Know_MBTI=1) exhibit systematic processing, prioritizing PP while also demonstrating higher AI content recognition ability (AI_Identify_Score). This divergence suggests that users' evaluation paths are not merely shaped by content attributes, but by internalized cognitive schemas that guide the weighting and processing of those attributes.

Beyond individual consumption, personality awareness likely extends to social engagement behaviors. High-awareness users may be more selective in sharing content that aligns with their identity and more deliberate in cultural topic interactions. This suggests that the dual-process framework operates not only at individual perception levels but also governs social amplification patterns.

The implications of this model are twofold. First, from a theoretical standpoint, it expands existing technology acceptance and metacognition literature by positioning personality awareness as a gating variable for perception–intention pathways. Rather than treating users as passive receivers of algorithmic output, this approach highlights the active role of metacognitive readiness in shaping content engagement.

Second, from a system design perspective, the validated prediction model offers practical avenues for adaptive recommendation strategies. Cognitive profiling using lightweight, perception-based questionnaires allows systems to rapidly stratify users without relying on behavioral histories. These user types—reflected in the three cognitive prototypes derived from clustering analysis—can then be linked to differentiated recommendation strategies. For example, conservative-traditional users benefit from content structured around credibility and clarity, while rational-comprehensive users prefer deeper personalization and control. This stratified logic not only improves user experience but also enhances algorithm efficiency by reducing mismatched recommendations.

Figure 3 presents the dual-process model. The left side shows heuristic processing (Know_MBTI=0) where PO, PC, and PP jointly influence BI with flat weights. The right side shows systematic processing (Know_MBTI=1) where PP dominates BI formation, with AI_Identify_Score as an auxiliary indicator. This framework formalizes cognitive distinctions and provides a tool for designing cognition-sensitive AI systems.

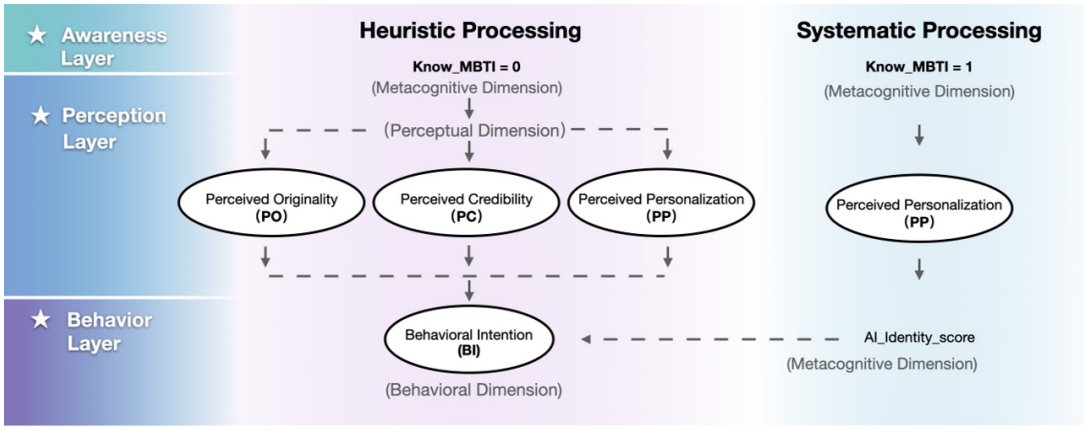

Figure 3. Dual-process metacognitive model of user perception moderated by personality awareness (Know_MBTI)

6 Conclusion

This study proposed a dual-process metacognitive model of user perception in AI-driven recommendation systems, positioning personality awareness—operationalized via MBTI knowledge (Know_MBTI)—as a critical moderator of content evaluation and behavioral intention. Drawing on survey data from 521 Taiwanese

users, we demonstrated that Know_MBTI significantly influences three perceptual dimensions (PP, PC and PO)—as well as behavioral intention (BI), particularly with personalization exhibiting the strongest effect size (η^2 = 0.099).

Four core contributions emerged from this research. First, we extended metacognitive theory into the context of AI content recommendation by conceptualizing personality awareness as a priming mechanism that activates users' internal evaluation schemas. Second, we developed and validated a dual-process cognitive framework (see Figure 3) that differentiates between heuristic and systematic processing paths, providing a theoretical explanation for the variation in perceptual weightings based on metacognitive readiness. Third, unsupervised clustering revealed three cognitively stratified user prototypes, offering a psychological lens for user segmentation. Fourth, our classification models—particularly Random Forest—achieved high predictive accuracy (85.1%) for Know_MBTI, confirming the feasibility of integrating cognitive profiling into adaptive recommendation systems.

By reframing personalization as a cognitively mediated process rather than a static demographic function, this research shifts the personalization paradigm toward cognition-aware system design. The proposed framework supports cold-start modeling, dynamic adjustment, and culturally sensitive recommendation strategies, with implications for more transparent, inclusive, and effective AI-user interactions.

Future research should expand this work in several directions: (1) refining the operationalization of personality awareness beyond binary MBTI knowledge; (2) conducting longitudinal studies to track the evolution of user cognitive states; and (3) validating the model across diverse cultural and platform contexts. Furthermore, applying this framework at scale will require the development of lightweight, perception-based assessment tools, alongside careful consideration of the ethical implications of cognitive-based user modeling.

In sum, this study contributes a theoretical model, empirical validation, and technical solution for integrating personality awareness into AI-driven personalization. It positions metacognitive insight as a key bridge between user psychology and algorithmic design—enabling the next generation of adaptive, user-sensitive recommendation systems.

Acknowledgments

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Appendix A

Detailed Measurement Items for Perception Dimensions

Cultural Content Definition

For the purpose of this study, "cultural content" in AI recommendations encompasses various forms of digitized cultural heritage and cultural knowledge, including but not limited to:

Historical and Heritage Content:

- Historical sites, monuments, and archaeological discoveries
- Traditional architecture and cultural landmarks
- Historical events, figures, and narratives
- Cultural artifacts and museum collections

Living Cultural Practices:

- Folk traditions, customs, and festivals
- Traditional arts, crafts, and performances
- Music, dance, and performing arts across cultures
- Culinary traditions and cultural practices

Intangible Cultural Heritage:

- Local legends, oral histories, and storytelling traditions
- Traditional knowledge systems and philosophies
- Religious and spiritual practices
- Language preservation and dialectal content

Contemporary Cultural Expression:

- Modern cultural movements and artistic expressions
- Cultural documentaries and educational content
- Cross-cultural dialogue and multicultural perspectives
- Cultural preservation and revitalization efforts

This broad definition acknowledges that cultural content in digital recommendation systems extends beyond traditional museum pieces to include diverse forms of cultural expression, preservation, and education that users might encounter on social media platforms and digital cultural platforms.

Measurement Items

Construct	Item Code	Questionnaire Item	Source Adaptation
Perceived Originality (PO)	PO1	AI recommendations introduce me to cultural content I wouldn't discover on my own	AMCA-FIL adapted
	PO2	The recommended cultural content expands my cultural horizons with novel perspectives	
	PO3	AI helps me explore diverse cultural topics beyond my usual interests	
Perceived Credibility (PC)	PC1	The cultural information in recommendations is factually accurate	AMCA-ETH adapted
	PC2	Recommended content comes from authoritative cultural sources	
	PC3	AI recommendations present balanced perspectives on cultural topics	
Perceived Personalization (PP)	PP1	Recommendations match my specific cultural learning interests	AMCA-ADM adapted
	PP2	The system improves understanding of my cultural preferences over time	
	PP3	AI recommendations are more relevant than my manual cultural content searches	

Note: All items measured on 5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree)

Adaptation Notes:

- PO items: Adapted from AMCA Content Filtering dimension (FIL1-FIL4), focusing on algorithmic discovery and content diversity
- PC items: Adapted from AMCA Ethical Considerations dimension (ETH1-ETH2), emphasizing content accuracy and bias awareness
- PP items: Adapted from AMCA Automated Decision-Making (ADM1, ADM3) and Human-Algorithm Interplay (HAI1-HAI2) dimensions, focusing on personalization effectiveness