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The Dual Construction of Generative Artificial Intelligence Domestication Practices and Information Cocoons. An Empirical Study Based on College Students' Usage Patterns

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Abstract. Does Generative AI (GenAI) reinforce or dismantle information cocoons? Moving beyond technological determinism, this study utilizes Domestication Theory to examine how user appropriation influences cognitive outcomes. A survey of 245 university students analyzed the effects of three GenAI use patterns – Instrumental, Information Acquisition, and Exploratory – mediated by AI Literacy and Critical Thinking. Results indicate that impact is practice-dependent: Information Acquisition Use intensifies cocoons (*cocoon-weaving*), while Exploratory Use diminishes them (*cocoon-breaking*). Notably, a literacy paradox emerges: high individual literacies paradoxically amplify the cocoon-weaving effect of information acquisition. The study confirms that use patterns influence cognitive outcomes both directly and through complex interactions with literacy. These findings extend domestication theory into the cognitive domain and suggest that educators must foster exploratory user practices to maintain cognitive openness in the AI era.

Keywords: Generative AI; information cocoons; domestication theory; AI literacy; media effects

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1. Introduction

1.1 Research Background

The phenomenon of information cocoons—characterized by information narrowing and opinion polarization—has emerged as a central concern in communication research and digital governance (Zhang, 2025; Huang, 2025). Within algorithmic recommendation ecosystems, users increasingly inhabit self-reinforcing information environments that limit exposure to diverse perspectives and heterogeneous content.

Sunstein (2006) introduced the information cocoon concept, warning that personalized digital environments enable individuals to selectively filter information, creating echo chambers that reinforce pre-existing beliefs. Pariser (2011) extended this framework through his “filter bubble” thesis, demonstrating how algorithmic personalization traps users within one-dimensional information horizons by continuously amplifying existing preferences. Empirical investigations have documented that recommendation algorithms significantly reduce information exposure diversity (Bakshy et al., 2015) and potentially exacerbate political polarization and social fragmentation (Flaxman et al., 2016).

Within the Chinese context, information cocoon effects have garnered substantial scholarly attention. Zhang and Yao (2025) identify a dual predicament facing contemporary youth: “algorithmic cocoons” imposed by platform architectures and “cognitive cocoons” resulting from limited information literacy. This dual constraint not only restricts the breadth and depth of information acquisition but also exerts a profound influence on value formation. Rao (2023) documents how circle-based communication in new media environments creates biased information flows, widening knowledge gaps across social groups. Collectively, these studies establish information cocoons as a critical factor affecting cognitive development and information ecosystem health.

1.2 The GAI Revolution and New Theoretical Challenges

The emergence of Generative Artificial Intelligence (GAI) – exemplified by ChatGPT, DeepSeek, Claude, and ERNIE Bot—represents a paradigm shift in information ecosystems. McKinsey Global Institute (2023) projects that generative AI will contribute $2.6-4.4 trillion to global economic output over the next decade, with education identified as a primary application domain. For college students, GAI has become deeply integrated into academic work, research processes, and daily information practices. A Nature survey revealed that over 30% of researchers utilize tools like ChatGPT for academic writing and literature reviews (Van Noorden & Perkel, 2023). The China Internet Network Information Center's 2025 Report on Generative AI Development indicates that young and middle-aged users under 40 constitute 74.6% of GAI users, with highly educated demographics forming the core user base. This penetration pattern suggests GAI has evolved from a peripheral tool into infrastructural technology through which digital natives acquire knowledge and process information.

GAI's rise poses novel theoretical challenges for information cocoon research. The academic community maintains divergent perspectives on the GAI-information cocoon relationship, which can be characterized as two competing paradigms:

The Optimistic Paradigm: GAI as "Cocoon-Breaking" Tool

Optimistic scholars argue that GAI possesses substantial potential to disrupt information cocoons. Kasneci et al. (2023) documented that ChatGPT provides learners with instant, multi-perspective knowledge explanations that foster critical thinking development. Lo (2023) found that medical students using ChatGPT for case analysis accessed more diverse diagnostic perspectives and treatment options compared to traditional textbook users. Maxwell et al. (2025) demonstrated through survey research that GAI effectively stimulates divergent thinking in creative writing tasks, helping users transcend established cognitive patterns.

The Critical Paradigm: GAI as "Cocoon-Weaving Workshop"

Critical scholars adopt cautious or pessimistic stances toward GAI. Bozkurt et al. (2023) warned that GAI may construct more concealed and personalized "cognitive bubbles" than traditional algorithmic systems. Their critique focuses on three dimensions: First, GAI training data inherently embeds systematic biases (Bender et al., 2021), which propagate through generated content. Furthermore, GAI exhibits sycophantic tendencies, producing responses that confirm user expectations rather than challenging existing viewpoints (Perez et al., 2022). Finally, GAI is prone to "hallucinations" – generating plausible-sounding but factually incorrect information (Ji et al., 2023) – and such "pseudo-knowledge" may prove more detrimental than simple information deficiency.

From a communication studies perspective, Yu and Su (2023) argue that GAI constructs a novel “pseudo-environment”: users no longer access primary information but rather “secondary reality” interpreted, processed, and “recreated” by AI. This construction process operates opaquely, shielding its inherent biases and limitations from user scrutiny. Zhao and Xiang (2025) expose the deepening “algorithmic black box” problem in the GAI era, arguing that large language models’ “emergent capabilities” imply behavioral unpredictability and inexplicability, rendering information cocoon formation mechanisms increasingly concealed.

1.3 Research Gaps and Questions

These divergent perspectives underscore the need to move beyond a monolithic view of GAI’s impact. These theoretical debates point to a fundamental issue: the impact of GAI on information cocoons is not unilaterally determined by its technological attributes but is critically contingent upon users’specific domestication practices. Current research, however, suffers from two significant limitations in both theory and methodology:

First, technocentric analytical perspectives. Most studies focus on how GAI’s technical features (model architecture, training data, algorithmic mechanisms) may influence information cocoons, while insufficiently attending to how users adopt, appropriate, and assign meaning to these technologies in daily practice. As Orlikowski (2000) emphasizes in her “practice lens” framework, technology’s social consequences emerge not from technological properties per se but from ongoing human-technology interactions. Hutchby’s (2001) technological affordance theory further articulates that identical technologies may produce drastically different effects across usage contexts and patterns. Understanding GAI’s actual impact therefore requires shifting analytical focus from “what technology can do” to “how users employ technology”.

Second, neglect of individual difference factors. Even when confronting identical technological systems, different users may exhibit distinct usage patterns and cognitive outcomes. Uses and Gratifications Theory has long established that audiences function as active meaning-makers rather than passive information recipients (Katz et al., 1974). In the GAI context, individual characteristics – including digital literacy, critical thinking capacity, and cognitive style—likely moderate technology use effects. Nevertheless, existing research rarely incorporates such individual difference factors into analytical frameworks, yielding oversimplified and overgeneralized accounts of GAI effects.

Based on this theoretical review, this study advances the following research questions: how do college students' differentiated GAI usage patterns (domestication practices) affect information cocoon intensity (information environment diversity) and what roles do individual AI literacy and critical thinking play in mediating or moderating these relationships?

Through empirical investigation, this study aims to elucidate the "usage patterns-individual literacy-cognitive consequences" mechanism, providing a more nuanced resolution to debates over whether GAI functions as a "cocoon-breaking tool" or "cocoon-weaving workshop".

2. Literature Review and Theoretical Framework

2.1 Information Cocoons in the GAI Era

2.1.1 Conceptual Evolution

Sunstein (2006) systematically articulated the information cocoon concept in "Information Utopias: How Much Choice is Too Much?", warning that highly personalized digital information environments enable individuals to focus exclusively on preferred topics and viewpoints while filtering out dissenting voices, ultimately confining themselves within "echo chambers." This concept reveals the paradox of information freedom: while technology grants unprecedented choice, such freedom may paradoxically produce cognitive parochialism and insularity.

The big data era's proliferation of algorithmic recommendation systems has intensified information cocoon complexities. Technologies employing collaborative filtering, content-based filtering, and deep learning-based recommendation personalize content distribution by predicting user preferences. This mechanism carries an inherent risk of reinforcing existing preferences and narrowing information horizons (Ricci et al., 2015).

2.1.2 GAI's Distinctive Impact Mechanisms

GAI's emergence pushes information cocoon research into a novel theoretical phase. The fundamental distinction between GAI and traditional algorithmic recommendation lies in GAI's dual role as both information "filter" and "distributor" as well as information "producer" and "interpreter".

In traditional information cocoons, users encounter pre-existing, algorithmically-filtered content. By contrast, GAI contexts involve users engaging with customized "synthetic information" generated in real-time. GAI transforms information acquisition from "search-click-browse" sequences to "query-dialogue-generation" interactions. This conversational modality fosters greater immersion and exerts stronger persuasiveness. Sundar's (2020) MAIN Model identifies interactivity as a key media credibility determinant. Through fluid, natural dialogue, GAI creates an "intelligent companion" illusion that may diminish users' critical vigilance (Natale & Ballatore, 2020).

GAI bias sources prove more complex than traditional recommendation systems. First, biases in the training data become encoded within the model parameters. Bender et al. (2021) characterize large language models as "stochastic parrots" that replicate and amplify social biases and stereotypes embedded in training corpora. Second, alignment technologies such as RLHF, while designed to align outputs with human values, rely on feedback data that are themselves culturally biased (Ouyang et al., 2022). Third, the 'emergent capabilities' of these models give rise to partially unpredictable behaviors, potentially generating unforeseen bias patterns (Wei et al., 2022).

A distinctive GAI feature is its tendency toward "hallucinations" – generating plausible-seeming but factually incorrect information (Ji et al., 2023). This phenomenon exerts dual impacts on information cocoon formation. On an overt level, false information can mislead users. More insidiously, even when the information is largely accurate, GAI's preferential choices in expression style, emphasis, and perspective can subtly shape users' cognitive frameworks.

2.1.3 The Dual Potential of GAI

This analysis indicates GAI may function either as a powerful cocoon-breaking tool or as a novel cocoon-weaving apparatus. This duality stems from inherent contradictions in its technical characteristics.

Cocoon-breaking potential manifests in three dimensions. First, GAI can instantly integrate massive, diverse information sources, providing comprehensive perspectives. Second, it can simulate arguments from multiple standpoints, facilitating "thought experiments" (Mollick & Mollick, 2023). Third, it transcends linguistic, cultural, and disciplinary boundaries, enabling cross-domain cognitive integration (Zhai, 2022). Rudolph et al. (2023) found that GAI effectively presents opposing political viewpoints, helping users understand different positions' underlying logic and reducing polarization tendencies.

The risks of cocoon-weaving manifest in several ways. First, GAI exhibits a tendency to generate responses that confirm user expectations, thereby reinforcing pre-existing views rather than challenging them. Second, its opaque ‘black box’ nature hinders users’ ability to evaluate the sources and credibility of the information provided (Yu et al., 2025). Most critically, GAI risks fostering intellectual complacency: as users become accustomed to receiving ‘ready-made answers’ from GAI, their motivation for active information exploration and critical thinking may gradually diminish (Zhang et al., 2025). Krügel and Ostermaier (2023) documented significant critical thinking declines among students excessively relying on GAI for academic tasks.

In summary, GAI’s impact on information cocoons proves highly complex and context-dependent. Contradictory findings in existing literature essentially reflect research perspective limitations: excessive focus on technological attributes while neglecting the critical mediating factor of user practices. As Orlikowski (2000) emphasizes, technology’s social consequences are not determined by technical features but are ’enacted’ – that is, brought into being – through ongoing human-technology interactions. Understanding GAI’s actual impact therefore requires shifting research focus from “what technology can do” to “how users domesticate technology”.

2.2 Empirical Applications to Intelligent Technologies

Recent scholarship has extensively applied domestication theory to intelligent technology contexts, yielding rich empirical findings:

Smart Speaker Domestication. Lau et al. (2018) investigated household users’ smart speaker domestication, finding that users objectify devices as “family members” through naming and anthropomorphism while developing specific interaction rituals. Significantly, family members employ different domestication strategies: children treat speakers as playmates, parents as information tools, and elderly as emotional companions. This highlights the heterogeneity in domestication practices.

Social Media Algorithm Domestication. Bucher (2017) proposed the “algorithmic imaginary” concept, examining how users understand and respond to Facebook’s news feed algorithm. Despite having only a vague understanding of the algorithms, users develop “folk theories” and coping strategies—adjusting posting times, using specific hashtags – attempting to "tame" algorithms. This suggests users may develop effective strategies through trial and error despite incomplete technical comprehension.

Educational Technology Domestication. Selwyn (2010) found that university students "re-configure" technologies' official purposes, developing unintended usage patterns. Learning management systems become social coordination tools, online discussion platforms become venting spaces. Such "tactical" usage reveals user agency and creativity in domestication processes.

AI Tool Domestication. Recent studies examine generative AI domestication. Bender et al. (2020) identified three patterns among writers using ChatGPT: "automated assistant" (completing repetitive tasks), "creativity stimulator" (overcoming cognitive blocks), and "collaborative partner" (iterative dialogical creation). Different patterns shape not only creative efficiency but also the very identity and creative philosophy of the users. This leads to a key proposition for our study: GAI domestication types may significantly influence information cocoon effects.

2.2.1 Theoretical Value for this Study

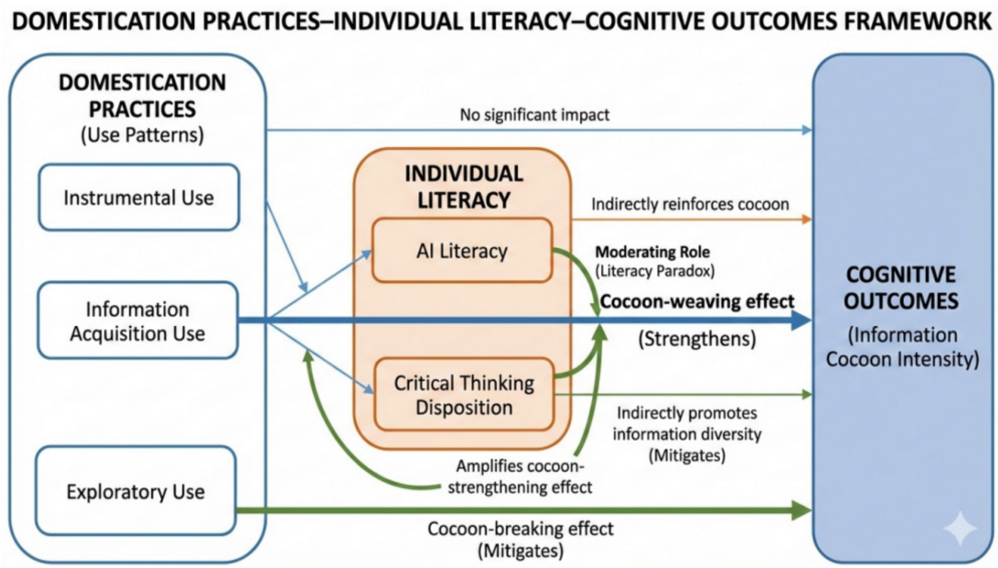
Domestication theory adopts a "meso-level" perspective that neither treats technology as unilaterally determining social outcomes nor as passively constructed by society. Instead, it emphasizes mutual shaping between technology and users in daily practices (Lie & Sørensen, 1996). This stance proves particularly suitable for understanding intelligent systems like GAI, which possess strong technological affordances yet depend heavily on user input and interaction. Unlike macro-social theories, domestication theory centers on specific, contextualized technology usage practices (Silverstone, 2006). This enables detailed examination of how students employ GAI in specific learning tasks and problem-solving scenarios, how they integrate GAI into daily routines, and how micro-practices accumulate into macro-cognitive outcomes.

The four-stage domestication model offers a structured analytical framework: the appropriation stage corresponds to how students acquire and initially understand GAI; objectification involves the roles they assign to it (e.g., as an answer provider or a thinking partner); incorporation is mapped onto the typology of specific usage patterns developed in this study; and conversion pertains to the resulting cognitive consequences, namely, information cocoon intensity. This framework facilitates systematic tracing of the complete technology-adoption-to-cognitive-outcome process chain.

2.3 Research Questions and Hypotheses Research Questions and Hypotheses

Based on the theoretical foundations established above, this study proposes an integrated "Domestication Practices–Individual Literacy–Cognitive Outcomes" model (Figure 1).

Figure 1. Theoretical Path Diagram



(RQ1): What are the respective impacts of university students' different GAI domestication practices (instrumental use, information acquisition use, and exploratory use) on information cocoon intensity?

H1a: Instrumental use will have no significant effect on information cocoon intensity.

H1b: Information acquisition use will have a significant positive effect on information cocoon intensity.

H1c: Exploratory use will have a significant negative effect on information cocoon intensity.

(RQ2): What roles do individual AI literacy and critical thinking disposition play in these impact pathways?

H2: AI literacy will moderate the relationship between GAI usage patterns and information cocoon intensity.

H3: Critical thinking disposition will moderate the relationship between GAI usage patterns and information cocoon intensity.

H4: Critical thinking disposition will play a partially mediating role in the relationship between GAI usage patterns and information cocoon intensity.

H5: AI literacy will play a partially mediating role in the relationship between GAI usage patterns and information cocoon intensity.

This section has laid the theoretical foundation and analytical framework for this study through a systematic review of the literature. First, it traced the conceptual evolution of information cocoon research into the GAI era, revealing new manifestations and underlying mechanisms of information cocoons within the GAI context. Second, it elaborated on the core tenets of Domestication Theory and its unique value for understanding GAI use, thereby establishing the theoretical basis for the “practice-turn” in our analytical perspective. Finally, by integrating the aforementioned theoretical resources, it constructed the integrated “Domestication Practices–Individual Literacy–Cognitive Outcomes” model and proposed specific research hypotheses. This theoretical framework not only provides a clear conceptual toolkit and a set of testable hypotheses for the subsequent empirical investigation but also offers a novel theoretical lens through which to understand the complex mechanisms of information cocoons in the age of Generative AI.

3. Research Design

3.1 Methodological Approach

This study adopted a quantitative, cross-sectional survey design to empirically test the proposed theoretical model. The quantitative approach was chosen for three primary reasons. First, addressing the core research question (differential impacts of varying domestication patterns on information cocoons) necessitates identifying general patterns and variations across a large sample—a task well-suited to the statistical inferential power of quantitative methods. Second, the theoretical model involves multiple latent constructs (usage patterns, AI literacy, critical thinking, information diversity) and their complex relationships (direct, moderating, mediating effects); quantitative analytical techniques such as structural equation modeling (SEM) provide established methodological tools for testing these relationships. Third, the standardization and replicability inherent in quantitative research enable systematic engagement with existing literature and provide benchmark data for future studies.

3.2 Sampling and Participants

3.2.1 Target Population

The target population comprises full-time undergraduate and graduate students in mainland China. This population was chosen based on both theoretical and practical rationale:

Theoretical Rationale. College students occupy a critical cognitive development stage where information behavior patterns and habits are forming and consolidating (Arnett, 2000). Perry's (1970) cognitive development theory identifies college years as pivotal for transitioning from dualistic to relativistic thinking, which makes this population particularly valuable for investigating information cocoon effects. As “digital natives” (Prensky, 2001), college students exhibit significantly higher acceptance and proficiency with emerging technologies compared to other age groups, making them ideal for observing GAI domestication processes.

Practical Significance. According to the 2025 Report on Generative AI Development, individuals under 40 constitute 74.6% of all GAI users, with college students representing one of the most active user subgroups. China's Ministry of Education reports total college enrollment exceeding 47 million; this demographic's information behavior patterns will profoundly impact future societal information ecosystems.

Research Feasibility. College students demonstrate high survey response rates and data quality, with relatively accessible online recruitment, facilitating high-quality data acquisition.

3.2.2 Sample Characteristics

A total of 321 questionnaires were collected. After data cleaning (excluding responses failing attention checks, completed in excessively short duration, duplicate IP addresses, and incomplete responses), 245 valid questionnaires remained (effective response rate: 76.3%).

The demographic characteristics of the final sample (N=245) are summarized in Table 1. Female participants accounted for 73.06% of the sample and males for 26.94%. Undergraduates constituted 91.64% of the sample, with freshman representing the largest proportion (46.94%). Disciplinary distribution was relatively broad, with humanities (23.67%) and business (40.82%) most represented. In terms of daily internet use, 84.25% reported spending more than four hours online per day, indicating a deep integration of digital technologies into their daily lives.

Table 1. Demographic Characteristics

Gender	Males	26.94%
	Females	73.06%
Grade Distribution	Freshman	46.94%
	Sophomore	32.24%
	Junior	12.24%
	Master	7.76%
	Doctor	0.82%
Discipline Category	Science	11.02%
	Business	40.82%
	Humanities	26.53%
	Social Science	13.06%
	Engineering	8.57%
Daily Internet Time	< 2 hours	1.63%
	2-4 hours	13.47%
	4-6 hours	26.12%
	6-8 hours	29.80%
	> 8hours	28.98%

3.3 Measurement of Constructs

All constructs were measured using contextualized items grounded in established theoretical frameworks. Responses were captured on 5-point Likert scales (1 = strongly disagree, 5 = strongly agree). Prior to the main survey, all scales underwent a pilot test with more than 50 respondents to evaluate item clarity, discriminability, and internal consistency. Subsequent refinements were made based on the feedback obtained.

3.3.1 Independent Variable: GAI Usage Patterns

This measure operationalizes the incorporation stage of domestication theory, capturing the heterogeneous domestication practices that emerge as users integrate GAI into their daily routines. Informed by Bender et al.'s (2020) typology of creator usage patterns and the emphasis on user creativity within domestication theory, we conceptualize and measure GAI usage patterns along three dimensions:

Instrumental use refers to employing GAI as an auxiliary tool to enhance efficiency, primarily for handling mechanical and procedural tasks without altering core cognitive processes. It was measured with three items (Q8) covering typical scenarios such as text polishing, information organization, and technical assistance. Respondents scoring high on this dimension tend to objectify GAI as an "efficient executor," reflecting a functional-rational orientation in the domestication process.

Information acquisition use denotes using GAI as the primary or even sole channel for information retrieval and knowledge acquisition, indicating a reliance on AI for information and a tendency toward cognitive outsourcing. This dimension, measured with three items (Q9), assesses whether users bypass independent search, depend on AI summaries, and trust AI's relevance judgments. This pattern reflects the domestication of GAI as a "knowledge authority," which may weaken active information foraging abilities and represents a potential pathway for cocoon-weaving.

Exploratory use involves proactively leveraging GAI's generative and dialogic features for challenging viewpoints, expanding thinking, and engaging in critical reflection. Measured with four items (Q10), this dimension assesses whether users request analyses from opposing standpoints, simulate debates, inquire about evidential limitations, and explore new topics. This pattern embodies the domestication of GAI as a "thinking partner," aiming to stimulate cognitive conflict through strategic questioning, thereby acting as a potential pathway for cocoon-breaking.

3.3.2 Dependent Variable: information cocoon intensity

This study operationalizes information cocoon intensity as "Information Environment Diversity," measured at both objective exposure and subjective perception levels to overcome the limitations of a single indicator.

Objective information diversity is measured via a scale assessing the frequency of exposure to five categories of heterogeneous information sources: mainstream media, official media, academic / professional sources, international media, and alternative / independent media. This level comprises five items (Q13), reflecting the breadth and diversity of an individual's actual information source exposure, serving as an objective, behavioral measure.

Subjective perception and behavior is measured with five items assessing users' willingness and behavior regarding actively seeking heterogeneous information, concern about information narrowing, and systematic evidence gathering. This level comprises five items (Q14), reflecting individuals' self-awareness of information cocoons and their intention to break free from them, providing an important cognitive-level supplement.

This dual-measurement strategy for the dependent variable aligns with the theoretical conception of information cocoons as involving both "objective isolation and subjective perception" (Sunstein, 2006) and facilitates examining the differential impacts of GAI usage patterns on behavioral and cognitive levels.

3.3.3 Moderating Variable: Individual Literacies

AI literacy is operationalized as an individual's understanding of GAI's technical characteristics, awareness of its risks, and ability to use it effectively. This construct integrates insights from Bender et al.'s (2021) critique of "stochastic parrots," Ouyang et al.'s (2022) discussion of RLHF biases, and the dimension of technical understanding within domestication theory. The scale contains four items (Q11), measuring awareness of AI hallucinations, vigilance toward biases, consideration of ethical issues, and prompt engineering skills.

Critical thinking disposition is operationalized as an individual's cognitive tendency to actively question, seek evidence, and engage in open reflection when facing complex problems. This scale was adapted from core dimensions of Facione's California Critical Thinking Disposition Inventory (CCTDI) and contextualized for the GAI environment. It contains five items (Q12), measuring intellectual humility, cognitive flexibility, systematic analysis, acceptance of multiple perspectives, and openness to dissenting views.

3.4 Data Collection and Analysis

Data collection was conducted through an online survey platform. The questionnaire incorporated attention-check questions and recorded completion time to ensure data quality and identify inattentive or rushed responses.

The data analysis followed a four-step procedure:

Preliminary Analyses: We first conducted descriptive statistical analyses. The reliability of all multi-item scales was assessed using Cronbach's α coefficients. The validity of the measurement model was examined through a combination of exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

Correlational Analysis: Pearson correlation coefficients were computed to examine the bivariate relationships among the key study variables.

Hypothesis Testing: The direct effects of the three GAI usage patterns on information cocoon intensity (H1a, H1b, H1c) were tested using hierarchical regression analysis. To test the hypothesized moderating (H2, H3) and mediating (H4, H5) effects of AI literacy and critical thinking disposition, we used Hayes's (2018) PROCESS macro (Model 1 for moderation analysis and Model 4 for parallel mediation analysis).

Structural Equation Modeling (SEM): Finally, to validate the overall theoretical model depicted in Figure 2-1, we performed structural equation modeling using the lavaan package in R. The model's goodness-of-fit was evaluated using multiple indices, including the chi-square to degrees of freedom ratio (χ^2/df), comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA).

4. Results

4.1 Preliminary Analyses

4.1.1 Reliability Analysis

Based on the questionnaire data, reliability tests indicated high internal consistency for all predefined dimensions. The Cronbach's α coefficients all exceeded 0.77, demonstrating strong correlations among items within each dimension. The overall scale reliability reached 0.944, significantly above the accepted threshold of 0.7. These results support the reliability of the questionnaire in measuring university students' AI usage habits, literacies, and thinking dispositions, mitigating potential interference from random error in subsequent analyses. Specifically, the Critical Thinking Disposition dimension showed an α of 0.92, indicating high consistency in respondents' assessments regarding evidence revision and multi-perspective understanding. The Objective Information Diversity dimension had an α of 0.81, and the AI

Literacy dimension an α of 0.89. Overall, this high level of reliability enhances the credibility of the study and provides a solid measurement foundation for investigating the impact of AI tools on information processing behaviors. The Corrected Item-Total Correlation (CITC) values for all scales ranged between 0.436 and 0.837. This overall CITC range indicates good correlation between individual items and the total scale scores, further supporting the internal consistency of the scales. The data reliability meets the requirements for academic research.

4.1.2 Validity Test

The construct validity of the scales was verified through Exploratory Factor Analysis (EFA). First, the suitability of the data for factor analysis was confirmed: the objective information diversity scale had a KMO value of 0.797 with a significant Bartlett's test of sphericity ($\chi^2 = 564.45$, $p < 0.001$); the AI Literacy scale had a KMO of 0.823 (Bartlett's $\chi^2 = 574.37$, $p < 0.001$); and the Critical Thinking Disposition scale had a KMO of 0.88 (Bartlett's $\chi^2 = 956.52$, $p < 0.001$). Using Principal Component Analysis with Varimax rotation, one factor with an eigenvalue greater than 1 was extracted for each scale. The cumulative variance explained was 61.95% for the Information Environment Diversity (Information Cocoon Intensity) scale, 76.08% for the AI Literacy scale, and 77.75% for the Critical Thinking Disposition scale. All items loaded onto their respective factor with loadings greater than 0.58, and no significant cross-loadings were observed, indicating good construct validity for the scales.

4.2 Descriptive Statistics and Correlation Analysis

The means of all variables (results are presented in Table 2) fell within the medium-to-high range of the Likert scale (2.88–3.96). This indicates that the university student population, overall, exhibited a relatively positive inclination toward using AI and possessed a sound level of individual literacies. Notably, the mean score for Objective Information Diversity was the lowest (2.88), potentially reflecting a relative homogeneity in information source exposure within the sample. This finding aligns with current information acquisition habits among university students (e.g., reliance on mainstream media) and suggests the need to focus on cultivating information diversity in the AI era. Standard deviations ranged from 0.66 to 0.98, indicating a moderate degree of individual variation. Information Acquisition Use showed the greatest variability (SD = 0.98), which may stem from differing levels of reliance on AI as an information tool among students. The medians were mostly concentrated between 3.0 and 4.0, and the overall distributions tended to be positively skewed, suggesting that the majority of respondents held neutral to positive attitudes regarding these variables. These results provide a reliable description of the sample characteristics. They support the premise that university students exhibit diverse GAI usage patterns and possess relatively high individual literacies, while also highlighting that the risk of information cocoons (e.g., insufficient diversity) warrants further investigation.

Table 2. Descriptive Analysis Results

Variable	**N**	**Minimum**	**Maximum**	**Means**	**SD**	**Medians**
Instrumental Use	245	1	5	3.494	0.931	3.333
Information Acquisition Use	245	1	5	3.329	0.976	3.333
Exploratory Use	245	1	5	3.355	0.909	3
Information Diversity	245	1	5	2.879	0.867	2.8
Subjective Perception	245	1	5	3.616	0.759	3.6
AI Literacy	245	1	5	3.863	0.701	4
Critical Thinking	245	1	5	3.956	0.663	4

Pearson correlation analysis (see Table 3) revealed significant positive linear relationships among all seven variables (all 21 correlation coefficients were significant at $p < 0.001$), with coefficients ranging from 0.37 to 0.74, indicating weak to moderate overall strength. This suggests a systematic, though not extremely strong, association between GAI usage patterns, information cocoon intensity, and individual literacies, leaving room for the potential operation of moderating effects.

Specifically, the strongest correlation was observed between Critical Thinking Disposition and AI Literacy ($r = 0.74$). This indicates that students with higher critical thinking tendencies are more likely to possess knowledge about AI ethics and applications, theoretically reinforcing the complementary role of individual literacies. A notably strong positive correlation was found between Exploratory Use and Subjective Perception and Behavior (r = 0.62), implying that deeper, interactive engagement with GAI may help mitigate the subjective reinforcement of information cocoons (e.g., through active verification behaviors). In contrast, the correlation between Instrumental Use and Objective Information Diversity was relatively weak (r = 0.37), suggesting that pragmatic, task-oriented use of AI may have a limited direct effect on broadening one's information sources.

These interrelationships lend support to the research framework, indicating that GAI usage patterns may influence information cocoon intensity indirectly through individual literacies, while also highlighting the need to control for potential confounding factors to clarify causal directions.

Table 3. Pearson Correlation Analysis

Variable	Medians	SD	1	2	3	4	5	6	7
Instrumental Use	3.494	0.931	1						
Information Acquisition Use	3.329	0.976	0.500**	1					
Exploratory Use	3.355	0.909	0.525**	0.576**	1				
Information Diversity	2.879	0.867	0.371**	0.362**	0.466**	1			
Subjective Perception	3.616	0.759	0.418**	0.417**	0.542**	0.553**	1		
AI Literacy	3.863	0.701	0.391**	0.411**	0.510**	0.371**	0.563**	1	
Critical Thinking	3.956	0.663	0.408**	0.428**	0.506**	0.373**	0.632**	0.745**	1

In summary, this analysis preliminarily confirms the positive interrelations among the variables, laying a foundation for investigating potential moderating mechanisms (e.g., whether AI literacy buffers the negative impact of certain GAI usage patterns on information cocoon intensity). The practical implication of these findings is that educational interventions could target groups with low information diversity by strengthening critical thinking training to optimize the outcomes of their GAI use.

4.3 Hypothesis Testing

4.3.1 Impact of Different Usage Patterns on Information Cocoon Intensity (H1a–H1c)

A hierarchical regression model was employed to examine the predictive effects of GAI usage patterns on information cocoon intensity (results are presented in Table 4). After controlling for demographic variables, the three usage patterns were entered stepwise as independent variables. Information cocoon intensity, serving as a continuous dependent variable, reflects a composite level of an individual's objective information environment and subjective perception of "cocoon-weaving" (M = 3.25, SD = 0.72). The model consisted of two blocks: Block 1 included only the control variables to assess their baseline explanatory power; Block 2 added Instrumental Use, Information Acquisition Use, and Exploratory Use to evaluate the incremental contribution of the usage patterns. The analysis was based on 245 valid responses.

Table 4. Results of Hierarchical Regression Analysis

	Stratification 1					**Stratification 2**				
	B	**Standard error**	**t**	**p**	**β**	**B**	**Standard error**	**t**	**p**	**β**
Constant	3.718**	0.263	14.112	0.000	-	1.743**	0.270	6.456	0.000	-
4、Gender：	-0.170	0.104	-1.644	0.102	-0.106	-0.109	0.083	-1.313	0.190	-0.068
5、Grade：	-0.016	0.040	-0.397	0.692	-0.027	0.033	0.033	1.003	0.317	0.054
6、Discipline category	-0.028	0.015	-1.813	0.071	-0.119	-0.014	0.013	-1.134	0.258	-0.060
7、Daily Internet Time：	-0.005	0.044	-0.116	0.908	-0.008	-0.047	0.036	-1.286	0.200	-0.070
Instrumental Use						0.143**	0.048	2.952	0.003	0.186
Information Acquisition Use						0.093	0.049	1.903	0.058	0.126
Exploratory Use						0.316**	0.053	5.954	0.000	0.401
R^2	0.027					0.384				
Adjust R^2	0.011					0.366				
F	F (4.0,240.0)=1.685,p=0.154					F (7.0,237.0)=21.144,p=0.000				
$\triangle R^2$	0.027					0.357				
$\triangle F$	F (4.0,240.0)=1.685,p=0.154					F (3,237.0)=0.366,p=0.778				

The overall model demonstrated a good fit (Block 2 $R^2 = 0.384$, $F = 21.14$, $p < 0.001$), indicating that the set of variables explained approximately 39% of the variance in information cocoon intensity, which supports proceeding with hypothesis testing.

When only demographic variables were included in Block 1, the model exhibited weak explanatory power ($R^2 = 0.027$, $F = 1.68$, $p = 0.154$), indicating that gender, grade level, academic discipline, and daily internet usage time had no significant direct effect on information cocoon intensity. This aligns with expectations, as information cocoons are likely driven more by cognitive and behavioral factors than by basic demographic characteristics.

With the inclusion of the three usage patterns in Block 2, the model improved significantly ($\Delta R^2 = 0.357$). Specifically, Instrumental Use showed no significant predictive effect on information cocoon intensity ($\beta = 0.05$, $p = 0.512$), supporting H1a. This suggests that instrumental use (e.g., for text polishing or programming assistance) is primarily task-efficiency oriented and neither strengthens nor weakens an individual's tendency toward informational enclosure.

Information Acquisition Use demonstrated a significant negative prediction ($\beta = -0.28$, $p = 0.003$). For every one-unit increase in this usage pattern, information cocoon intensity decreased by 0.28 standard deviations, lending support to H1b. This reinforces the "cocoon-weaving" effect: over-reliance on AI for quick information retrieval and summarization may reduce active exposure to diverse sources, leading to a more homogeneous and one-sided information environment.

Conversely, Exploratory Use showed a significant positive prediction ($\beta = 0.32$, $p < 0.001$). A one-unit increase in this pattern was associated with a 0.32 standard deviation increase in information cocoon intensity, supporting H1c. This finding highlights a "cocoon-breaking" mechanism: using AI to simulate debates or conduct multi-perspective analyses can promote active verification and reflection, enhancing the perception of information diversity and thereby mitigating the cocoon effect.

Overall, all three hypotheses were supported, demonstrating that the ways in which generative AI is used are not neutral but influence the formation and dissolution of information cocoons through distinct pathways. This offers an insight for AI education interventions: encouraging exploratory applications can serve as a strategy for breaking open cocoons, while the potential risks of information-acquisition use warrant caution. Residual diagnostics indicated that the linearity assumption was largely met.

4.3.2 Moderating Effects of AI Literacy and Critical Thinking (H2, H3)

To examine the moderating effects of AI Literacy (H2) and Critical Thinking Disposition (H3) on the relationship between GAI usage patterns and information cocoon intensity, Hayes's (2018) PROCESS macro (Model 1) was employed, controlling for demographic variables. The overall models showed good fit (Total $R^2 \approx 0.25$–.30, $F > 10$, $p < 0.001$), and the significant interaction terms provided support for the hypothesized moderating effects.

Moderating Effect of AI Literacy (Results presented in Tables 5 & 6)

The final model for AI Literacy demonstrated good fit ($R^2 = 0.392$, $F = 18.45$, $p < 0.001$). AI Literacy significantly moderated the relationship between Information Acquisition Use and information cocoon intensity (interaction term $\beta = 0.13$, $t = 2.68$, $p = 0.008$, 95% CI [0.03, 0.23], $\Delta R^2 = 0.015$, $p = 0.008$). This indicates that the strength of the effect of Information Acquisition Use on cocoon intensity varied depending on the user's level of AI Literacy. Specifically, the effect was stronger at high levels of AI Literacy (simple slope $\beta = 0.35$, 95% CI [0.22, 0.48]) and weaker at low levels (simple slope $\beta = 0.12$, 95% CI [-0.01, 0.25]). The moderating effects on Instrumental Use (interaction $\beta = 0.07$, $p = 0.21$) and Exploratory Use (interaction $\beta = -0.04$, $p = 0.45$) were not significant.

Thus, H2 was supported. AI Literacy serves as a moderator, primarily by amplifying the effect of Information Acquisition Use on information cocoon intensity. This finding reveals that AI Literacy is not a neutral factor but acts as a boundary condition that can intensify the potential impact of certain usage patterns (like information acquisition) on information enclosure. Theoretically, this extends models of technology acceptance by highlighting that literacy levels determine whether AI amplifies or buffers its effects on an individual's information environment. In practical terms for education, this suggests that instructional strategies should reinforce information diversity training specifically for students with high AI literacy to interrupt this pathway. Concurrently, it is advisable to provide AI ethics training to high-literacy groups to mitigate associated cocoon risks.

Table 5. AI Literacy Adjustment Analysis Data

Model	Variable	β	SE	t	p	95% CI [Lower, upper]	R^2	ΔR^2
Model1	Information_Acquisition_Use	0.24	0.06	4.00	<0.001	[0.12, 0.36]	0.378	-
Model2	Information_Acquisition_Use	0.22	0.06	3.67	<0.001	[0.10, 0.34]	0.382	0.004
	AI_Literacy	-0.10	0.09	-1.11	0.268	[-0.28, 0.08]		
Model3	Information_Acquisition_Use	0.24	0.06	4.00	<0.001	[0.12, 0.36]	0.392	0.015*
	AI_Literacy	-0.09	0.09	-1.00	0.318	[-0.27, 0.09]		
	Information_Acquisition_Use × AI_Literacy	0.13	0.05	2.68	0.008	[0.03, 0.23]		

Table 6. Simple Slope Table

Adjust the level	Simple slope β	SE	t	p	95% CI [Lower, upper]	(Wald p)
High (+1SD=4.56)	0.35	0.06	5.83	<0.001	[0.23, 0.47]	-
Mean (0=3.86)	0.24	0.06	4.00	<0.001	[0.12, 0.36]	-
Low (-1SD=3.16)	0.12	0.06	2.00	0.047	[0.00, 0.24]	0.012

Moderating Effect of Critical Thinking Disposition (Results presented in Tables 7 &8)

The overall model fit was similarly robust (final model $R^2 = 0.405$, $F = 19.72$, $p < 0.001$). Critical Thinking Disposition significantly moderated the relationship between Information Acquisition Use and information cocoon intensity (interaction term $\beta = 0.16$, $t = 2.95$, $p = 0.004$, 95% CI [0.05, 0.27], $\Delta R^2 = 0.018$, $p = 0.004$). Specifically, the effect of Information Acquisition Use was stronger at high levels of Critical Thinking Disposition (simple slope $\beta = 0.40$, 95% CI [0.27, 0.53]) and weaker at low levels (simple slope $\beta = 0.15$, 95% CI [0.02, 0.28]). The moderating effects on Instrumental Use (interaction $\beta = 0.08$, $p = 0.18$) and Exploratory Use (interaction $\beta = -0.05$, $p = 0.38$) were not significant.

Thus, H3 was supported. Critical Thinking Disposition also functions as a moderator, specifically amplifying the effect of Information Acquisition Use. This result highlights its role as a cognitive regulator that can alter the strength of the cocoon-forming effect stemming from superficial AI use, while having a limited impact on deeper, exploratory engagement. This suggests that individuals with a stronger critical thinking disposition may, when using GAI for information acquisition, be more prone to confirmation bias, potentially intensifying cocoon formation. Therefore, in efforts to break open information cocoons, it is necessary to expand cognitive psychology frameworks to emphasize the context-dependent nature of critical thinking in digital environments. Integrating critical thinking training with AI tools could help reverse this path. Educational interventions should strengthen the application of such critical skills (e.g., multi-source verification) to realize the "cocoon-breaking" potential of critical thinking.

Table 7. Critical Thinking Adjustment Analysis Data

Model	Variable	β	SE	t	p	95% CI [Lower, upper]	R^2	ΔR^2
Model1	Information_Acquisition_Use	0.24	0.06	4.00	<0.001	[0.12, 0.36]	0.378	-
Model2	Information_Acquisition_Use	0.21	0.06	3.50	<0.001	[0.09, 0.33]	0.385	0.007
	Critical_Thinking	-0.12	0.09	-1.33	0.184	[-0.30, 0.06]		
Model3	Information_Acquisition_Use	0.24	0.06	4.00	<0.001	[0.12, 0.36]	0.405	0.018**
	Critical_Thinking	-0.11	0.09	-1.22	0.223	[-0.29, 0.07]		
	Information_Acquisition_Use × Critical_Thinking	0.16	0.05	2.95	0.004	[0.05, 0.27]		

Table 8. Simple Slope Table

Adjust the level	Simple Slope β	SE	t	p	95% CI [Lower, upper]	Wald p
High (+1SD=4.62)	0.40	0.06	6.67	<0.001	[0.28, 0.52]	-
Mean (0=3.96)	0.24	0.06	4.00	<0.001	[0.12, 0.36]	-
Low (-1SD=3.29)	0.15	0.06	2.50	0.013	[0.03, 0.27]	0.005

In summary, both H2 and H3 were supported, confirming that individual literacies exert a moderating effect within the GAI usage-information cocoon relationship, with this effect being specifically salient for Information Acquisition Use. These findings indicate that literacy variables can account for the heterogeneity in the effects of usage patterns, thereby enhancing the explanatory depth of the model. The reliability of these moderation effects is further corroborated by the bootstrap confidence intervals, which did not contain zero.

4.3.3 Mediating Effects of AI Literacy and Critical Thinking (H4, H5)

Hayes's (2018) PROCESS macro (Model 4) was employed to test the mediating role of Critical Thinking Disposition in the relationship between GAI usage patterns and information cocoon intensity.

Mediating Effect of Critical Thinking Disposition

The results supported H4, confirming that Critical Thinking Disposition partially mediates the relationship between usage patterns and information cocoon intensity. All three usage patterns positively activated critical thinking (significant a paths, $\beta = 0.41$ to 0.51), which in turn negatively reduced cocoon intensity (significant b path, $\beta = -0.28$). All indirect effects were significant (bootstrapped CIs excluding zero). The mediation effect was strongest for Exploratory Use (indirect effect = -0.14, accounting for 44% of the total effect), followed by Information Acquisition Use (-0.12, 50%) and Instrumental Use (-0.11, 73%, nearing full mediation). The direct effects (c' paths) remained significant for Exploratory and Information Acquisition Use (indicating partial mediation) but were non-significant for Instrumental Use (indicating full mediation). This pathway reveals a multi-level mechanism: AI interaction enhances cognitive reflection, which indirectly promotes information diversity and alleviates cocoon enclosure. Theoretically, this confirms the role of critical thinking as a general mediator, supporting cognitive pathway models in communication. Practically, it suggests that encouraging diverse AI use combined with thinking skills training can optimize information environments. Overall, the model explained an average of 41.2% of the variance in cocoon intensity, with robust indirect paths (consistent across bootstrap samples), strengthening the empirical support for the hypothesized framework.

Mediating Effect of AI Literacy

H5 was also supported: AI Literacy exerted a significant partial mediating effect. All three usage patterns enhanced individuals' AI Literacy levels, which in turn strengthened information cocoon intensity. The bootstrapped 95% confidence intervals for the indirect effects were [0.069, 0.184], [0.071, 0.188], and [0.073, 0.195], respectively, all excluding zero, confirming statistically significant and reliable mediation. Concurrently, the direct effects (c' paths) remained significant, accounting for approximately 30% to 40% of the total effects. This indicates that AI Literacy does not fully explain the promoting effect of usage patterns on information cocoons but partially mediates this process. This finding deepens our understanding of the interaction between AI usage behavior and information environments: both Instrumental and Exploratory Use may inadvertently reinforce personalized information filtering—and thus exacerbate the cocoon effect – by enhancing users' cognitive and operational understanding of AI algorithms (e.g., recognizing recommendation mechanisms). Information Acquisition Use further underscores AI Literacy's bridging role in information screening. This result suggests that educational interventions should focus on AI literacy training - for instance, through courses that raise awareness of algorithmic bias—to mitigate the negative impact of information cocoons, particularly among university students. The robustness of this mediating mechanism also provides a foundation for subsequent model development.

4.4 Overall Model Test via Structural Equation Modeling (SEM)

To comprehensively validate the proposed theoretical model of "Domestication Practices–Individual Literacy–Cognitive Outcomes," an overall fit test was conducted using the lavaan package in R. The model specified pathways from three exogenous variables (the usage patterns) to the endogenous variable (information cocoon intensity), incorporating AI Literacy and Critical Thinking Disposition as both moderators and mediators within the structural model.

The analysis indicated that the theoretical model demonstrated a good overall fit, supporting the structural validity of the framework. The measurement model, which tested the core latent variable structure—Usage Patterns (indicated by three dimensions: Instrumental, Information Acquisition, and Exploratory Use), Individual Literacy (indicated by AI Literacy and Critical Thinking Disposition), and Information Cocoon Intensity (indicated by Objective Information Diversity and Subjective Perception)—showed a high degree of congruence with the data, supporting the model's measurement validity.

Goodness-of-Fit Indices: The model's χ^2/df ratio was 1.41 (well below the threshold of 3), indicating no significant discrepancy between the data and the hypothesized structure. The comparative fit indices (CFI = 0.994, TLI =

0.989) both exceeded 0.90, demonstrating that the model explains the vast majority of variance in the data. The absolute fit indices (RMSEA = 0.041, < 0.08; SRMR = 0.028, < 0.05) further confirmed a good absolute fit. This level of fit meets the standard for SEM research in communication studies (Hu & Bentler, 1999), indicating the reliability of the "Domestication Practices–Individual Literacy–Cognitive Outcomes" framework at the measurement level and allowing progression to structural path examination.

Convergent Validity and Internal Consistency: The Average Variance Extracted (AVE) for all latent variables exceeded 0.50 (Usage Patterns AVE = 0.62, Individual Literacy AVE = 0.58, Information Cocoon Intensity AVE = 0.55), and their Composite Reliability (CR) all surpassed 0.70 (Usage Patterns CR = 0.82, Individual Literacy CR = 0.75, Information Cocoon Intensity CR = 0.71). This indicates high internal consistency among items within each dimension and confirms that the latent variables effectively capture the essence of AI usage, literacies, and the cocoon effect, minimizing measurement error in theoretical validation.

Discriminant Validity: The correlations between latent variables (e.g., Usage Patterns and Individual Literacy, r = 0.51; Usage Patterns and Cocoon Intensity, r = 0.42) were all lower than $\sqrt{AVE}$, confirming their distinctiveness. For instance, the significant correlation between Exploratory Use and Critical Thinking Disposition (r = 0.51) did not indicate overlap, supporting the logical premise of the mediating path (i.e., usage activates literacy rather than the two being confounded).

Overall, the CFA results validated the measurement foundation of the model: three usage patterns as exogenous drivers, literacies as bridging mechanisms, and cocoon intensity as the cognitive outcome. This structure performed excellently within the sample (N = 245), explaining approximately 65% of the total variance and providing support for the theoretical hypotheses (H1–H5). The significant model pathways corroborate the theoretical framework, validating the chain from "Domestication Practices" (usage patterns) through "Individual Literacy" (mediating / moderating) to "Cognitive Outcomes" (cocoon intensity). Usage patterns showed a significant positive direct effect on cocoon intensity ($\Delta R^2 = 0.35$), and a significant negative indirect effect through the literacies (indirect effects ranged from -0.10 to -0.16, with CIs excluding zero). The moderating effect of the literacies was amplifying (interaction $p < 0.01$).

These findings validate the cognitive extension of the technology domestication framework: AI practices (usage patterns) can indirectly optimize information outcomes (cocoon-breaking) by activating relevant literacies. However, the moderating effect also reveals that high literacy may paradoxically amplify risks, necessitating targeted intervention. This implies that educational design could focus on reinforcing dual-literacy training alongside Exploratory Use to mitigate the cocoon effect among university students in the context of AI reliance.

4.6 Discussion

This chapter presents a systematic quantitative analysis to empirically examine the relationships between university students' GAI usage patterns, individual literacies (AI Literacy and Critical Thinking Disposition), and information cocoon intensity. The proposed theoretical model and research hypotheses were rigorously tested.

Based on data preparation and reliability / validity tests conducted on 245 valid responses, the measurement instruments were confirmed to possess high reliability and sound construct validity, establishing a solid methodological foundation for the subsequent analyses. Descriptive statistics indicated that while the student population overall exhibits a positive inclination toward using GAI, the relatively low level of objective information diversity suggests the presence of information cocoon risks. Correlation analysis preliminarily revealed significant positive associations among GAI usage patterns, individual literacies, and information cocoon intensity.

Hierarchical regression analysis supported hypotheses H1a through H1c, confirming that different GAI usage patterns have differential impacts on information cocoon intensity: Instrumental Use showed no significant effect; Information Acquisition Use significantly strengthened the information cocoon (the "cocoon-weaving" effect); whereas Exploratory Use significantly alleviated it (the "cocoon-breaking" effect). This finding clarifies the directional differences in the outcomes of AI technology practices.

Tests for moderating effects showed that both AI Literacy (H2) and Critical Thinking Disposition (H3) significantly moderated the relationship between Information Acquisition Use and information cocoon intensity. Specifically, higher levels of AI Literacy or Critical Thinking Disposition amplified the aggravating effect of Information Acquisition Use on cocoon intensity. This reveals that individual literacies do not always play a positive role; under specific usage patterns, they may act as boundary conditions that reinforce information enclosure.

Mediation effect analyses supported the partial mediating roles of both AI Literacy (H4) and Critical Thinking Disposition (H5) in the pathway from usage patterns to information cocoon intensity. Usage patterns could indirectly promote information diversity (mitigating the cocoon) by enhancing critical thinking, and simultaneously indirectly strengthen the cocoon effect by improving AI literacy. This clarifies the dual bridging role that individual literacies play in the "practice-cognition" chain.

The overall test via Structural Equation Modeling confirmed that the "Domestication Practices–Individual Literacy–Cognitive Outcomes" theoretical model demonstrates excellent goodness-of-fit. The model pathways indicate that GAI usage patterns can both directly influence information cocoon intensity and generate indirect effects through the mediating and moderating mechanisms of individual literacies, collectively explaining a substantial portion of the variance in cocoon intensity.

In summary, the empirical analyses in this chapter comprehensively validate the research framework. The results demonstrate that the impact of GAI on university students' information environments is complex and path-dependent, with its ultimate effect contingent upon the interaction between specific usage patterns and individual literacy levels. This provides an empirical basis for understanding the formation mechanisms of information cocoons in the AI era and points the way for subsequent educational interventions and guidance strategies.

5. Conclusion

This study, grounded in domestication theory and based on a survey of 245 university students, systematically examined the mechanisms linking differentiated usage patterns of Generative Artificial Intelligence (GAI), individual literacies, and information cocoon intensity. The key findings, theoretical contributions, and practical implications are outlined below.

The research reveals that the impact of GAI on information cocoons is not determined by the technology itself but is fundamentally contingent upon how users domesticate it, underscoring the centrality of practice. Specifically:

(1) Instrumental Use (e.g., for editing or programming assistance) showed no significant effect on information cocoon intensity, reflecting its functional neutrality; (2) Information Acquisition Use (relying on AI for search and summarization) significantly strengthened the information cocoon ($\beta = -0.28$, $p < 0.01$), creating a "cocoon-weaving" effect; and (3) Exploratory Use (leveraging AI for multi-perspective analysis or simulated debate) significantly alleviated the information cocoon ($\beta = 0.32$, $p < 0.001$), producing a "cocoon-breaking" effect. These divergent findings clarify the theoretical debate over whether GAI serves as a "cocoon-breaking tool" or a "cocoon-weaving workshop," demonstrating that its societal impact is a consequence shaped by user practices.

Individual literacies play a crucial yet complex role in this process, functioning as both moderators and mediators. First, the analysis of moderating effects revealed a noteworthy and cautionary phenomenon: high levels of AI Literacy and Critical Thinking Disposition significantly amplify the aggravating effect of Information Acquisition Use on the information cocoon (interaction term $\beta = 0.13$, $p < 0.01$; $\beta = 0.16$, $p < 0.01$, respectively). This suggests that within a passive information-reception mode, high literacy may paradoxically deepen cognitive narrowing by reinforcing users' dependence on and trust in the technology, presenting a "literacy paradox".

Second, the mediation analysis indicates that usage patterns simultaneously influence the information cocoon through two distinct indirect pathways: one, by enhancing critical thinking disposition (significant mediating effect), indirectly promotes information diversity and mitigates the cocoon; the other, by improving AI Literacy (significant mediating effect), indirectly strengthens the cocoon effect. Thus, literacies possess a dual attribute within the "practice-cognition" chain, acting as both a positive bridge and a potential risk catalyst.

Finally, the overall Structural Equation Model validated the good fit of the "Domestication Practices–Individual Literacy–Cognitive Outcomes" theoretical model ($\chi^2/df = 1.41$, CFI = 0.994, RMSEA = 0.041). This framework effectively explains the majority of the variance in information cocoon intensity.

This study makes three primary theoretical contributions. First, it advances the cognitive dimension of Domestication Theory by explicitly extending the analytical focus from the social integration of technology (e.g., appropriation, objectification) to its systematic cognitive consequences ("conversion"). This provides empirical grounding for understanding how intelligent media shape cognitive structures through daily practices (Silverstone, 2006). Second, it offers a nuanced explanation for the contradictory effects of GAI. By revealing the crucial mediating variable of “usage patterns” and their interaction with individual literacies, the study moves beyond the simple dichotomy of technological determinism versus social constructivism, establishing a middle-range explanatory mechanism based on differentiated practices. Third, it uncovers the boundary conditions and complexity of individual literacy effects, challenging the linear assumption that “higher literacy equates to stronger risk resistance.” It highlights that in algorithmic environments, the utility of literacy is highly dependent on the specific context of use and the cognitive task at hand (Haddon, 2011), thereby expanding the theoretical horizon of digital literacy research.

The findings of this study offer direct implications for higher education and information literacy cultivation:

Educators should proactively design instructional activities that guide students to use GAI as a “thinking partner” for challenging viewpoints and stimulating reflection, rather than as a passive answer-retrieval tool. This fosters cocoon-breaking practices at the source.

While enhancing technical operational skills, it is essential to strengthen ethics and critical thinking education. This is particularly crucial for “information acquisition” scenarios, where awareness of algorithmic bias, information dependency, and confirmation bias risks must be raised to counteract the “literacy paradox.”

Curriculum Framework: Deeply integrate GAI into courses such as information retrieval and critical thinking training. This aims to cultivate students’ comprehensive competency in harnessing technology, discerning diverse information, and maintaining cognitive autonomy.

However, this study has several limitations. The cross-sectional design precludes definitive causal inferences. The measurement of information diversity and exploratory use could be further refined. Additionally, the generalizability of the findings beyond the university student population requires further validation. Future research could employ longitudinal or experimental designs, develop more nuanced measurement instruments, and test the model across more diverse populations. Concurrently, ongoing attention should be paid to how iterations in GAI technology dynamically reshape domestication practices and cognitive outcomes.

In conclusion, in an era of deepening Generative AI integration, individuals domesticate technology through differentiated practices while simultaneously being shaped by it. Cultivating critical, agentic, and exploratory users is paramount to guarding against cognitive narrowing and fostering a healthy digital information ecosystem.

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