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How does information resource value of AI-generated content emerge? An exploratory study from the user evaluation perspective

Yu Zhu | **Chenyu Li** | **Jiyuan Ye**

School of Information Management, Nanjing University, Nanjing, China

Correspondence
Yu Zhu, School of Information Management, Nanjing University, Nanjing, China.
Email: zhu.yu@smail.nju.edu.cn

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Abstract

AI-generated content (AIGC), a novel information resource, has seen an irreversible growth trend in the information ecosystem. However, most prior AIGC studies focus on technological adoption and static evaluation, while little attention has been paid to the value emergence and value-added processes of AIGC at the information resource level. This study employed in-depth, semi-structured interviews with 22 experienced AIGC users and utilized content analysis to examine the factors influencing users' perceived value of AIGC, identify value-added processes, and explore the underlying mechanisms. Based on these findings, we propose the AIGC-Value-Added Framework, delineating four user-AIGC interaction phases: value exposure, value forming, value anchoring, and value realization, which collectively enhance the resource value of AIGC. This study introduces an integrative framework for understanding how value emerges and is added to AIGC as an information resource, thereby enriching the Library and Information Science literature on information value-adding practices in the AIGC context and offering stakeholders practical insights for optimizing AIGC leverage.

1 | INTRODUCTION

With the rapid development of generative AI (GenAI) models, content generated by GenAI, as known as AI-generated content (AIGC) is increasingly permeating everyday information environments, emerging as a significant information resource that users need to understand and engage with (Zhu et al., 2024). They are no longer merely experimental technological products but have become a key resource deeply integrated into scientific (Callaway, 2024; Grossmann et al., 2023), artistic (Our T2 Remake Team, 2024), and commercial processes (Maerten & Soydaner, 2024; Poireault, 2024). Accordingly, AIGC now plays an expanding role in the information ecosystem (Khan et al., 2025; Sun et al., 2025), with

Abbreviations: AI, artificial intelligence; FAE, framework of all-round evaluation; GAI, generative AI; IS, information systems & information science; LIS, library and information science; STEM, science, technology, engineering, and mathematics; TAM, technology acceptance model.

We employed ChatGPT for the following purposes: (1) translating parts of sections of the text into English, (2) proofreading and correcting grammatical errors. We evaluated the output by cross-referencing the translated and revised content with the original text to ensure accuracy, consistency, and alignment with the intended meaning. Additionally, we reviewed the final version to confirm that all technical terms and concepts were appropriately conveyed. The authors assume all responsibility for the content of this submission.

the potential to contribute value-added functions during information use and consumption. However, its high variability across systems and modalities (Liu, 2025), strong context dependence (Dorotic et al., 2024), and interactive co-creativity (Moruzzi & Margarido, 2024) challenge the traditional and static methods of evaluating information value. These features call for new theoretical perspectives to understand how the value of AIGC emerges and evolves through human–AI interactions.

Although current research has begun to address AIGC information evaluation to facilitate value realization, theoretical development remains scarce. First, existing discussions on AIGC information quality often adopt classical models from the information systems domain, like the Information Systems Success Model (DeLone & McLean, 1992), viewing AIGC as a by-product of human-system interaction. Consequently, most studies have focused on AIGC characteristics such as accuracy, completeness, and relevance as indicators of system performance (Choi et al., 2025), overlooking the resource-specific attributes of AIGC as a novel form of information resource. Second, current studies on users' evaluation strategies toward AIGC mostly remain at the level of static evaluation criteria—relatively fixed and predefined quality indicators—thereby positioning users as passive recipients rather than value co-creators (Fu et al., 2024). However, under the influence of AI, information quality has evolved beyond static system features (Shin, 2022), and the interaction between users and AI systems is increasingly viewed as a dynamic, co-creative process (Li et al., 2023). Therefore, existing evaluation frameworks are inadequate for capturing the participatory, dynamic, and contextually embedded features of AIGC value formation, making it difficult to systematically reveal the emergent mechanisms through which AIGC generates value. These instrumental paradigms, while capable of explaining users' functional adoption of GAI models, fall short of revealing the value emergence process as they function as information resource carriers. As information resource ecosystems evolve, a user-centered integrative framework is urgently needed to structure the knowledge of information use, uses, and users (Taylor, 1982) in the AIGC context.

To address these gaps, this study investigates the mechanisms through which AIGC's value as an information resource emerges from a user-centered perspective. Through in-depth, semi-structured interviews with 22 experienced AIGC users, we aimed to bridge the theoretical gap between static evaluation models and dynamic value-co-creation processes. Specifically, this study seeks to answer the following research questions:

- RQ1: What factors influence users' judgment of AIGC's value as an information resource?
- RQ2: How do user perceptions of AIGC values relate to their extent of transformation into tangible benefits during information practice?
- RQ3: What are the critical phases that AIGC must undergo in its transformation into an information resource of leverageable value?

By integrating user perspectives with an information-resource lens, this study developed the AIGC-Value-Added Framework, which systematically explains how AIGC's value is exposed, formed, anchored, and realized. This framework not only extends classical theories into a novel context but also highlights AIGC's distinctive role as a dynamic information resource, offering a coherent framework for understanding and guiding its construction, organization, and leveraging.

2 | LITERATURE REVIEW

2.1 | Dimensions of value evaluation

Evaluating the value of information has long been a core concern in LIS, approached through multiple theoretically grounded dimensions. Classical frameworks for information quality, such as Wang and Strong's (1996) model, identify four principal dimensions—intrinsic, contextual, representational, and accessibility—each operationalized via specific indicators to capture object-level properties. The fit-for-use perspective further emphasizes that value is contingent on the user context and purpose (Eppler & Wittig, 2000), highlighting the need for flexible evaluation frameworks across information types and user groups (Lee et al., 2002).

Because AIGC can be understood as a continuation of user-generated content (UGC) in the AI era, essentially a new modality of content creation enabled by intelligent tools (Zhu et al., 2025), research on UGC provides a direct theoretical bridge for analyzing how users evaluate AIGC. Prior studies of UGC have illustrated how content attributes, domain relevance, and social cues shape value evaluations. For instance, detail, readability, and objectivity influence judgments, while creator prominence and domain specificity affect perceived usefulness and engagement (Liang et al., 2020; Zhang et al., 2021; Zhuang et al., 2023). User-centered evaluation frameworks have also incorporated usability, authority, credibility, and comprehensibility, linking information characteristics to user behavior (Chuenchom, 2011; Tao et al., 2017). Recent studies evaluating GenAI-generated information reported that the opaque nature of GenAI algorithms and the absence of traditional cues signifying information quality complicate assessing AIGC's value

(Shin et al., 2025). Collectively, these findings underscore that value evaluation is multi-dimensional and complicated, encompassing content-centric, technology-influential, and context-dependent factors.

However, most existing studies have approached AIGC evaluation from the perspective of information systems that produce or deliver content (Yan et al., 2024), or integrated the assessment of content value with system value (Choi et al., 2025). In the current era, when users employ GenAI to create content, the trend toward separating the system from the content (Raban, 2007) has become more pronounced. Although the system and content may be complementary, it is theoretically meaningful to isolate the content-level value evaluation of AIGC from system-level assessments. Such a distinction allows for a more precise investigation of how users' information experiences shape the emergence of AIGC's value.

2.2 | Process of value perception

Information value is predominantly user-determined rather than inherent in the content, making value perception a subjective process shaped by personal and social influences (Raban, 2007; Rusho & Raban, 2020). Understanding how users perceive the value of AIGC requires reviewing both the cognitive mechanisms of value perception and the dynamic evolution of these perceptions through repeated interactions. Recent studies have examined users' perceptions of AI systems across diverse contexts including work practice (Wang et al., 2023), team collaboration (Dennis et al., 2023), e-commerce (Cheng et al., 2022; Jia et al., 2026), and healthcare (Jussupow et al., 2021) to investigate trust (Saffarizadeh et al., 2024; Wang et al., 2023), adoption (Ju et al., 2025; Yuniawan et al., 2025), satisfaction (Zhao, Li, et al., 2025), and continuous usage intention (Sikhondze et al., 2025; Zhou & Ma, 2025). While these technology-oriented investigations provide foundational insights, they focus on system acceptance rather than content evaluation, leaving open questions regarding how users perceive AIGC's value.

Regarding cognitive mechanisms, early studies demonstrated that users are boundedly rational (Simon, 1955) and tend to make intuitive decisions based on heuristics, such as representativeness, availability, and anchoring, especially under high uncertainty (Kahneman & Lovallo, 1993; Tversky & Kahneman, 1974). AIGC intensifies the reliance on heuristics. Unlike traditional sources, AIGC is generated using probabilistic models (Choi et al., 2025) without identifiable authorship, verifiable timestamps, or traceable provenance, while producing massive volumes of content that may contain fabrications (van Dis et al., 2023). These characteristics render systematic assessments unsustainable and transform heuristic evaluations from convenience to necessity (Shin et al., 2025).

Moreover, value perception is not a static judgment but a dynamic process that evolves over time and across repeated experiences (Raban, 2007; Rusho & Raban, 2020). Raban (2007) distinguished subjective value from experience value, demonstrating that experience value recursively feeds back into users' mindsets (or bias-sets), shaping future subjective values. Furthermore, experience increases value perception, particularly when users actively participate in production (Rusho & Raban, 2020). AIGC amplifies these dynamics in two ways. First, real-time generation accelerates the perception cycle, creating rapid iterations between expectations, feedback, and revised judgments, whereas output variance forces continuous recalibration. Second, AIGC blurs the distinction between consumers and producers. The value of AIGC emerges through co-constructive engagement, where users contribute contextual knowledge via prompts, exercise creative agency through iterative refinement, and integrate output into cognitive and practical workflows. Users can neither separate AI contributions from their intellectual inputs nor distinguish content values from process values. This transformation challenges frameworks conceptualizing users as "stand-by evaluators," suggesting the need for new perspectives on how AIGC's value emerges as a new type of information resource.

Taken together, existing studies provide a valuable foundation for understanding how users perceive information value. However, three critical limitations remain: (1) value is often treated as a set of static content attributes rather than an evolving construct; (2) assessments are predominantly system-oriented, overlooking AIGC's distinct informational dynamics; and (3) the temporal progression through which value emerges via user–AI interactions remains theoretically underexplored. To address these gaps, this study developed the AIGC-Value-Added Framework, a process-oriented model that delineates how informational, experiential, and social factors co-evolve through iterative user engagement. By tracing the sequential construction and addition of value, it moves beyond system-oriented and outcome-based evaluations toward a dynamic understanding of AIGC as a novel information resource.

3 | THEORETICAL BACKGROUND

Understanding users' information use, uses, and the mechanisms of value addition associated with AIGC

requires engagement with established theoretical frameworks. Various models have been developed to explain how individuals comprehend, evaluate, and utilize information in complex environments. We adopted Zhu's (2024) conceptualization of AIGC as "a carrier of meaningful and usable multimedia information collections generated by generative AI based on pretrained data." This definition highlights AIGC's essential attributes—its potential as an information resource with latent value—and conceptualizes it as a value-bearing and value-developing medium, not a mere technological output. Such a perspective provides a foundation for interpreting users' information-leveraging behaviors and situating our findings within broader discourses on human–AIGC interaction.

To further understand how users evaluate AIGC, this study draws upon dual-processing theories of information processing, including the Heuristic–Systematic Model (Chaiken, 1980) and Elaboration Likelihood Model (Cacioppo et al., 1986). Both posit that users' evaluations can follow two parallel routes: a heuristic route based on surface cues and a systematic route grounded in critical elaboration. These theories suggest that judgments of AIGC's information value are shaped not only by cognitive capacity and motivation but also by contextual cues such as interface design, source credibility, and perceived effort. Extending these models to the online information environment, Metzger's (2007) dual-processing model of credibility assessment emphasizes that users' evaluations depend on their motivation and ability to engage in critical assessments. When users perceive that inaccurate information may lead to meaningful consequences, they are motivated to engage in systematic evaluation. Conversely, when motivation or cognitive resources are limited, users tend to rely on heuristic cues. This dual-mode perspective provides a nuanced understanding of how context, motivation, and cognitive capacity jointly shape users' dynamic evaluations of AIGC's informational value.

Complementing these cognitive models, Ye's (2010) framework of all-round evaluation (FAE) provides an integrative analytical foundation. FAE conceptualizes evaluation as an act of value judgment consisting of three interrelated dimensions—form, content, and utility—through which users ascribe worth to an object. This tripartite framework underscores that evaluation is a meaning-making process that integrates representational characteristics, informational content, and pragmatic usefulness. Applying this lens to AIGC enables the systematic exploration of how users move from recognizing AIGC's attributes to assessing its instrumental or experiential utility, forming a structured pathway of value realization. Together, these theoretical foundations enable a comprehensive understanding of how users engage with AIGC cognitively and evaluatively, while offering a multi-level and process-oriented lens for analyzing the emergent processes of value addition and realization.

4 | METHODS

4.1 | Research design

Given that current research on the factors influencing user evaluation and utilization of AIGC, as well as the mechanisms underlying its value-added emergence, remains exploratory, we employed semi-structured interviews to collect perception-based descriptions from users with extensive AIGC experience. Through an in-depth, cross-modal, multi-case qualitative analysis (Miles et al., 2019), this study identifies the factors that shape users' value perceptions of AIGC and the mechanisms through which these factors exert their influence. The rationale for a cross-modal case study design lies in the observation that most existing studies draw conclusions from text-based samples (Ju & Stewart, 2024), whereas AIGC spans multiple modalities, including text, images, video, audio, and 3D models (Cao et al., 2023). Therefore, a multi-modal case approach is necessary to enable cross-validation among the different AIGC modalities. This method helps reduce potential biases arising from the characteristics of a single modality or the subjective interpretations of the researcher, which might otherwise influence the research outcomes. This also facilitates the discovery of deeper relationships obscured by complex phenomena, thereby enhancing the theoretical saturation and credibility of the findings. The interview protocol was designed with reference to the FAE. Questions are regarding participants' general AIGC usage background, value evaluation with the formal, content, and utility dimensions of AIGC, and forward looking for AIGC. Based on the usage background, participants were then guided to discuss their most frequent or impactful experiences with specific AIGC modalities. For participants with experiences across multiple modalities, we made efforts to encourage them to share insights on all the modalities they had interacted with, to gain a more comprehensive, multi-modal perspective.

To ensure the scientific rigor of the protocol, three participants were invited to a pilot interview and revisions were made based on their feedback.

4.2 | Participants

Following the principle of purposive sampling (Miles et al., 2019), all participants were required to be early adopters of GenAI technologies, ensuring they possessed

substantive, hands-on experience with AIGC, ensuring their ability to represent typical cases of the studied phenomenon. Recruitment was conducted via the researchers' professional and personal networks and the Chinese social media platform RedNote, and extended via snowball sampling. To reduce systematic bias, snowball recruitment was used to balance AIGC use cases and demographic characteristics. We sought heterogeneity in age, education, domain expertise, and primary AIGC use cases, and we cross-validated emergent themes across participants with varied profiles. While part of the sample consisted of technology enthusiasts or individuals with formal training in computer science or related fields, we deliberately ensured the inclusion of participants without STEM backgrounds, thereby capturing a wider range of perspectives and balancing technical with non-technical viewpoints. The sampling strategy aimed to maximize demographic diversity and deliberately seek individuals with specific experiences or expertise, which helped mitigate potential confounding factors from homogeneity in user characteristics, thereby enhancing the reliability of the findings (McIntosh & Morse, 2015). The sample size was determined based on theoretical saturation, a process in which recruitment and data analysis occur iteratively to identify when additional interviews no longer yield new themes or insights (Creswell & Creswell, 2017).

4.3 | Data collection

As reported in Table 1, we recruited 22 participants (data collection: December 2024 to April 2025). The process involved an initial set of 19 interviews, after which theoretical saturation was reached. To further validate this saturation, three additional interviews were conducted that produced no new themes, confirming that theoretical saturation had been achieved (Creswell & Creswell, 2017). Participants reported substantial AIGC experience (mean duration = 24.9 months) and a broad coverage of tools (see Table 1). Participants ranged in age from 15 to 45 years (mean = 27.5; male = 15; female = 7) and represented a spectrum of educational backgrounds and disciplinary affiliations. Furthermore, the participants reported active usage of a broad range of mainstream GAI tools, covering a variety of AIGC modalities, including text ($n = 22$, 42.3%), image ($n = 10$, 19.2%), code ($n = 10$, 19.2%), audio ($n = 5$, 9.6%), video ($n = 4$, 7.7%), and 3D models ($n = 1$, 1.9%). Interviews lasted 30–45 min on average. Before each interview, participants were informed of the research objectives and provided explicit consent to participate and to use their interview data for analysis. This study adhered to the principles of institutional ethical standards and received ethical approval from the Management Department of the School of Information Management at Nanjing University.

Except for one participant interviewed face-to-face, all other interviews were conducted via Tencent Meeting, an online videoconferencing platform that helped alleviate the pressure imposed by in-person interviews (Zhao, Wu, & Song, 2025). Notably, two participants contacted us voluntarily for a second round of interviews, during which they provided additional insights. All interview recordings were transcribed, manually reviewed, and corrected, resulting in a standardized qualitative dataset of over 250,000 Chinese characters, forming a solid empirical foundation for subsequent stages.

4.4 | Data analysis

The interview data were analyzed using a qualitative content analysis approach, supported by MAXQDA 2022 software. As the interview protocol was developed under the guidance of the FAE, it already had a certain structural orientation. To minimize the potential influence of this theoretical perspective on the exploratory coding process, we adopted an emergent data-driven coding strategy (Hsieh & Shannon, 2005). Rather than applying a predefined coding scheme, the coding categories were gradually constructed through an iterative process involving two researchers (Wei & Zhou, 2023). Using a card-sorting technique (Albert & Tullis, 2013), thematically similar codes were grouped and abstracted into higher-level categories, allowing the coding framework to take shape incrementally.

Triangular validation of the sample analysis process was employed to ensure the depth and credibility of the qualitative research. Data analysis involved three perspectives: users, developers, and relevant researchers. Additionally, AIGC experiences were cross-validated across multiple modalities, products, and use cases, enabling us to capture a broad range of viewpoints. This validation ensured our theoretical saturation process was comprehensive and rigorous, thus enhancing the credibility of our findings. Regular meetings were held to discuss emerging concepts and clarify coding rules, leading to continuous refinement of the coding scheme. In the final phase, intensive team meetings were conducted to resolve ambiguous codes. These meetings involved comparing tentative codes with existing categories, addressing discrepancies, and updating codebooks accordingly before the final version was consolidated.

TABLE 1 Participant characteristics.

ID	Age	Duration (month)	Gender	Education	Occupation	Major	Content type
ID_01	20	20	Male	Bachelor	Student	Information Systems	Text, code
ID_02	28	23	Male	Master	University Administrator	Art Studies	Text, image
ID_03	21	20	Male	Bachelor	Student	Clinical Medicine	Text, code, 3D model
ID_04	24	24	Male	Master	Student	Sociology	Text
ID_05	30	25	Female	Master	AI Product Development	Computer Science	Text
ID_06	31	25	Male	Bachelor	AI Product Development	Finance	Text, code, video, image
ID_07	25	24	Female	Master	Student	Information Sciences	Text, video, audio, image
ID_08	32	25	Male	PhD	AI Researcher	Library Science	Text, code, image
ID_09	21	14	Male	Bachelor	Student	Internet and New Media	Text, image
ID_10	45	30	Male	PhD	AI Product Development	Automation	Text
ID_11	35	18	Female	Bachelor	AI Technology Development	Computer Science	Text, image, audio
ID_12	29	24	Female	PhD	AI Researcher	Information Sciences	Text, code, image
ID_13	15	36	Female	Junior High School	Student	Science Student	Text, image
ID_14	27	24	Female	Master	AI Researcher	Management Science and Engineering	Text, code
ID_15	31	25	Male	Master	Foreign Trade and Social Media	Public Policy	Text, image, video, audio, code
ID_16	26	14	Male	Bachelor	Internet Operations	Computer Science	Text, video
ID_17	25	24	Male	Master	Student	Information Sciences	Text, code
ID_18	16	40	Male	High School	Student	Science Student	Text
ID_19	17	26	Male	High School	Student	Science Student	Text
ID_20	34	36	Male	Bachelor	AI Technology Development	Artificial Intelligence	Text, code
ID_21	36	26	Male	Master	AI Product Development	Digital Marketing	Text, code, video, audio, image
ID_22	37	24	Female	Master	AI Product Development	Journalism and Communication	Text

Note: Usage duration was self-reported by respondents and measured up to the time of the interview.

5 | FINDINGS

5.1 | Driving factors

The driving factors represent the initial phase that shapes users' value perceptions of AIGC. Comprising three dimensions—task category, social influence, and individual feature—these factors collectively establish users' initial expectations regarding AIGC's performance and continue to exert influence throughout subsequent processes of engagement.

5.1.1 | Task category

The task category reflects the users' purpose-driven variations in generating AIGC across different contexts, serving as a core external driver that triggers users to seek

value. Different task types guide users to focus on distinct attributes of information quality and shape divergent pathways of value perception.

- Task complexity: This refers to the clarity of the problem structure and determinacy of solutions. In low-complexity tasks, users tend to view AIGC as a direct content resource for problem solving, with evaluations focusing on accuracy and completeness. For example, ID_02 stated, "*Since I work in university administration and (need) documents like notifications, it [AIGC <Text>] can help me handle this completely fine*." In contrast, for high-complexity tasks, users place greater emphasis on AIGC's ability to inspire problem-solving ideas and act as a reference tool offering multi-perspective, process-oriented guidance.
- Task personalization: This influences how users evaluate the degree of alignment between AIGC and their specific task requirements, emphasizing that the AIGC should faithfully adapt to personal needs and the task contexts. In highly personalized tasks, users expect the generated content to accurately reflect their intentions and contextual backgrounds. For instance, ID_16 noted, "*We once needed a video of an American college student walking on campus, but we couldn't find anything suitable online. So, we used AI to generate a video of that specific scene (to meet our specific requirements) ...*"
- Task importance: This shapes users' tolerance for risks and the strictness of evaluation criteria. For low-importance tasks, users often adopt a delegation mode (Baird & Maruping, 2021), aiming to minimize human input. They will have high satisfaction as long as AIGC meets basic expectations and saves time. For example, ID_20 commented, "*During finals, using it [AIGC <Text>] for writing papers in some less important and demanding courses is extremely useful!*" By contrast, high-importance tasks lead users to expect AIGC to produce content that matches or exceeds standards they can achieve themselves.

In addition to these three dimensions, task-related attributes such as procedurality, certainty, urgency, repeatability, subjectivity, and concreteness also influence how users evaluate AIGC and form their expectations of its value.

5.1.2 | Social influence

Social influence drives user engagement with AIGC through cognitive framing and behavioral modeling. It serves as a major external impetus in that users' initial motivations and actions are shaped by their surrounding environment. During the early stages of AIGC adoption, social influence provides potential users with behavioral references that reduce their psychological barriers to use, thereby encouraging more individuals to experiment with AIGC. This influence operates through the following two aspects:

- Media outreach: Media outreach shapes the public's early engagement with AIGC by influencing their cognitive framework and formation of expectations. Reports on AI breakthroughs and trending applications raised public awareness, stimulating curiosity. As ID_01 remarked, "*My first exposure to AIGC <Text> probably came from the news. At the time, ChatGPT was introduced as a chatbot and featured in media reports. A lot of people were talking about it ... then everyone started sharing (their chat records with ChatGPT). So at that time, I felt it magical to generate such content*."
- Community influence: This facilitates the diffusion of AIGC adoption through strong-tie social networks. Observing the behavior of important referents plays a critical role in individuals' adoption decisions (Venkatesh & Davis, 2000). Several interviewees mentioned their decision to use AI tools for content generation was prompted by peer recommendations. Compared with general media promotion, behavior modeling within trusted social circles has proven more persuasive.

5.1.3 | Individual feature

In addition to external driving factors, individual features remain the intrinsic determinants of users' willingness to engage in active generation. This dimension refers to users' inherent and relatively stable personal characteristics.

- Ability: This refers to the users' level of competence in using AIGC to solve problems, which is primarily shaped by domain expertise and information literacy. Domain expertise reflects the depth and breadth of users' understanding in a given field, which influences their judgment of AIGC attributes like accuracy. For example, ID_02 noted, "*I use it [AI] to generate some code, and while the output is usable, I can't really tell if it's good or not—I just don't have the professional knowledge to evaluate it*." Information literacy refers to users' ability to access, evaluate, organize, and effectively utilize information. In AIGC contexts, users with higher levels of AI competence and information consciousness tend to exhibit stronger sensitivity to

technological development and were more likely to engage with AIGC early. As ID_08 commented: "*I first started using them [AIGC <Text and Image>] mainly because I do research in information management. I'm quite sensitive to the changes in content*."

- Personality: This dimension refers to relatively stable psychological traits, particularly those associated with technology acceptance such as openness to experience and risk. Users with higher openness are more receptive to technological innovation and demonstrate greater interest in exploring AIGC's creative uses. For instance, ID_06 stated, "*I tried them [AIGC <Text, Code, Video and Image>] basically out of curiosity. I saw this new technology (that could generate content), and I think I should keep up with it*."

5.2 | Attribute evaluation

Once activated by both internal and external driving factors, users often engage with AIGC and conduct multidimensional evaluations of the generated content. These evaluation practices can be categorized into horizontal evaluation and longitudinal evaluation. The former focuses on comparative assessments across multiple instances of AIGC, while the latter emphasizes the intrinsic quality of a single instance of generated information resource.

5.2.1 | Horizontal evaluation

Unlike UGC, a key characteristic of AIGC is users' ability to generate multiple outputs on the same topic quickly and to compare versions by switching across AI models. Therefore, AIGC is not treated as the single best answer but as part of an iterative process where users actively adjust and refine content. In this process, users typically rely on several key dimensions:

- Diversity: Users expect significant variations in logic, style, tone, and perspectives across AIGC. For instance, ID_11 remarked: "*When I use it [AIGC <Image>], I find it suffers from excessive homogeneity. My colleague and I gave it similar prompts, and the generated content showed barely any differences*." Users often attribute such homogeneity to repetitive structural and rhetorical patterns. As ID_04 noted: "*When I asked it [AI] about a personal dilemma, I could almost predict what it was going to say next—it [AIGC <Text>] would always begin with an objective analysis and end with something like 'Cheer up!'*"
- Adaptability: Users place increasing demands on AIGC's ability to adapt to specific task contexts. For example, ID_16 stated: "*I expect it [AIGC <Text>] to mimic the tone and formatting styles of different social media platforms, as well as their platform-specific language usage*."
- Exclusivity: In commercial settings, concerns regarding content exclusivity, legal compliance, and copyright infringement are critical to user evaluation. ID_16 further commented: "*I work in online marketing and need to use AIGC <Image and Video> for video platform promotions ... so I have to double-check the AI-generated characters and props to ensure there's no infringement risk that could get my content taken down*."

5.2.2 | Longitudinal evaluation

Similar to traditional information quality frameworks (Wang & Strong, 1996), users conduct comprehensive longitudinal evaluations of AIGC content. However, the evaluation of AIGC exhibits several emerging characteristics:

- Refinement: This captures user expectations of concise and well-crafted responses. Users often prefer AIGC which is compact, has high informational density, and is free of redundancy. For example, ID_22 commented: "*A lot of the examples or vocabulary used by AIGC <Text> feel like they're just piled on top, many of them are actually meaningless. Sometimes it uses overly ornate words to appear elegant, but it doesn't make sense (to me)*."
- Indexability: Compared to reference lists and index sections which were attached to the traditional information resources like academic books, users have broader requirements for AIGC's indexability, which emphasizes not only backward traceability but also the heuristic expansion of knowledge boundaries. This enhances transparency and helps users locate and verify supporting facts.
- Tone: A notable characteristic of AIGC is its use of emotionally expressive statements and stylistic language, which can influence user experience. On the one hand, some users find emotionally charged language valuable. For instance, ID_13 stated: "*Its [AIGC <Text>] emotional tone can really lift you from a state of low mood to a positive emotional state*." However, others may prefer instrumental tones. As ID_21 remarked: "*I don't really care about the emotional value it [AIGC <Text>] offers ... As long as it provides me with rational or functional assistance, that's enough*."

- Timeliness: Users are concerned about whether AIGC reflects up-to-date world knowledge, particularly in time-sensitive domains such as news, academic research, and product reviews.
- Scope: This refers to AIGC's breadth and depth of knowledge, as well as its ability to adapt to contextual and local linguistic nuances. Users expect AIGC to cover not only explicit, domain-specific knowledge but also tacit knowledge (Howard & Okan, 2025; Misyak et al., 2014), such as social norms. ID_05 observed: "*I hope it [AIGC <Text>] can cover more specialized domains. Much of that information is not publicly accessible. There are also certain social norms and unspoken rules that I wish it could understand*." In addition, users highlighted the need for localized language adaptation. For example, ID_07 noted: "*Its [AIGC <Text>] (Chinese) expression has a mechanical feel as if translated directly from English*."

In addition to these dimensions, users evaluate AIGC based on its explicitness, accuracy, correctness, and depth. They expected AIGC to avoid being overly formulaic, verbose, or fabricated, and instead be structured, meaningful, and trustworthy.

5.3 | Value perception

After completing a comprehensive quality evaluation of AIGC, users develop a value perception that often manifests as a state of flow experience. Critically, this perception differs from technology acceptance constructs (Davis, 1989) in that it evaluates AIGC as an independent information resource rather than as intrinsic system content representing GenAI's performance, and it captures post-generation assessment of specific outputs rather than anticipatory attitudes. In this phase, users become aware of the security, usability, and usefulness of AIGC, which directly influences their subsequent decisions on whether and how to further leverage the content.

5.3.1 | Security

Security refers to the users' holistic judgment of AIGC's credibility, compliance, and privacy as an information resource. This concerns the inherent risk of the content itself, instead of traditional IS security research focusing on system reliability.

- Credibility: This serves as a key criterion in user judgment of AIGC value (Wu et al., 2024). Users generally express concerns about whether AIGC is grounded in authoritative data sources, and whether there is a risk of false information (Choi et al., 2025). They are also concerned with the consistency of the content, particularly when the same query yields different or even contradictory results. For instance, ID_04 remarked: "*Maybe it's just my bias, but I always feel like it [AIGC <Text>] pulls bits and pieces from random places online like a secondhand dealer patching together a response*."
- Compliance: Whether AIGC complies with social norms, industry standards (Brundage et al., 2024), and AI regulatory frameworks, as well as whether the user's use is restricted by the platform's policies. For example, ID_19 expressed frustration: "*There are just too many banned words. I really hate the forbidden word list!*"
- Privacy: Given that GenAI providers frequently update their service terms and their models are in fierce competition, users are particularly sensitive to how their personal data are handled (Shin & Park, 2019). They express whether their inputs or registered personal information may be inadvertently revealed or regurgitated to other users through the generated content. As ID_21 emphasized: "*It [AIGC <Text>] must provide strong guarantees around my privacy and personal information. It shouldn't violate my privacy*."

5.3.2 | Usefulness

This refers to the extent to which AIGC serves as an effective knowledge-production factor. This diverges conceptually from TAM's perceived usefulness (Davis, 1993), which captures users' beliefs that using a system will improve job performance. Critically, AIGC usefulness is output-contingent rather than system-level, as the same GenAI system may produce outputs that users perceive as vastly different in usefulness. Two key aspects are involved.

- Human augmentation: This refers to AIGC's role in guiding and inspiring users, particularly in unfamiliar or cognitively demanding contexts. As ID_05 stated: "*At work, when dealing with areas that are cutting-edge or outside of my expertise, it [AIGC <Text>] walks me through them, it tells me which (information) is correct and which is not*."
- Production factor substitution: This aspect highlights AIGC's ability to substitute traditional inputs, such as human labor, time, and financial cost. Users recognize that AIGC enhances productivity through personalization and creative capability, and in many cases, reduces reliance on traditional information resources. For instance, ID_03 remarked, "*If we actually do*

experiments to capture an image of a protein structure, it's still quite expensive. But if we use AlphaFold [AI] (by inputting the protein's amino acid sequence to get a 3D protein model in advance), the cost can be significantly reduced. It [AIGC <3D Model>] can serve as a screening tool."

5.3.3 | Usability

Usability refers to user perceptions of the ease with which AIGC can be accessed, comprehended, and iteratively modified. This differs from TAM's perceived ease of use (Davis, 1989), which captures users' perceptions of effort required to operate a system. While TAM focuses on the system interface, AIGC usability concerns whether users can efficiently and conveniently engage with the generated outputs. For instance, an easy-to-use system may produce outputs that users find difficult to use because of a poor structure.

- Accessibility: Users expect few barriers to accessing AIGC, including minimal geographic or policy-based restrictions, short waiting times, low cognitive effort, and limited financial cost (Mosha, 2025).
- Modifiability: This denotes the extent to which the content can be precisely edited and iteratively refined to align with user needs. Unlike traditional information resources, which generally permit only passive consumption or manual adaptation, AIGC fosters the expectation that output can be dynamically modified through interactions. As ID_07 noted: "*... Compared to Suno, Tianyin gives me a lot more control to tweak the (AI-generated) music [AIGC <Audio>]. I can precisely edit things like the melody and lyrics ... This solved the problem of not being able to fine-tune the output precisely*."
- Comprehensibility: Although AIGC can handle highly complex information, users expect its external structure and internal logic to be clear and cognitively aligned with their understanding. Here, comprehensibility refers not to algorithmic transparency or explainability, but to the extent to which AIGC can be easily understood, absorbed, and internalized by users in ways that enhance their ability to further utilize the content. Evaluation includes factors such as hierarchical structure, degree of structural organization, avoidance of redundancy or incoherence, and the appropriateness of terminology for the target audience. As ID_21 remarked: "*It [AIGC <Text>] doesn't necessarily have to use bullet points or numbered lists, but overall it must be clear and the logic must make sense*."

5.4 | Expectation confirmation

5.4.1 | Fixed expectation confirmation

Fixed expectation confirmation refers to scenarios where users maintain initial expectations and do not adjust their evaluative thresholds. These users typically evaluate AIGC based on prior experience or pre-established standards, treating it as a tool that conforms to predefined criteria. They tend to apply static evaluation standards used for traditional information resources, expecting AIGC to meet these benchmarks without deviation. The degree of expectation confirmation aligns strictly with original expectations. For instance, ID_22 noted: "*I feel particularly satisfied to retrieve fixed information ... maybe because (the results) [from AIGC <Text>] are pretty accurate. But I get really dissatisfied when I search for something and AIGC <Text> is different from what I have had in mind*."

5.4.2 | Adaptive expectation confirmation

Adaptive expectation confirmation refers to the flexible adjustment of user expectations through iterative interactions with AIGC. Users with an adaptive conformation continually recalibrate their initial expectations during multiple rounds of content generation, forming a cyclical loop of expectation confirmation, standard adjustment, and re-confirmation. They dynamically perceive AIGC's capabilities and revise their expectations to align with its actual performance, resulting in a spiral, multi-level pattern of expectation confirmation. As ID_01 explained: "*... But honestly, I wasn't expecting much (from AIGC <Code>) at first, so when it doesn't do that well, I don't really think it's incompetent or anything*."

These two types of expectation confirmation were not mutually exclusive and may coexist within the same user depending on the task scenario. The three driving factors—task category, social influence, and individual features—jointly shape the confirmation mode a user is more likely to adopt. For instance, high-importance tasks are more likely to trigger fixed expectation confirmation, whereas highly personalized tasks tend to activate adaptive expectation confirmation.

5.5 | Resource leveraging

Resource leveraging refers to the stage in which users actively utilize, refine, and transform AIGC into value-added outcomes. This phase represents the practical implementation of users' prior evaluations and perceptions, marking a transition from value perception to

resource-leveraging processes, which form the direct foundation for value realization. Resource leveraging includes two distinct modes: immediate leveraging and sustained leveraging. These modes reflect different strategies users adopt when developing AIGC content into actionable or sustainable information assets.

5.5.1 | Immediate leveraging

Immediate leveraging refers to the process by which users rapidly refine and extract values from AIGC within a short period. This mode of leveraging primarily manifests in the following five behaviors:

- AIGC rejection: It refers to the active elimination of content that fails to meet individual standards. Rejection is not only a denial of the current content but also a starting point for regenerating AIGC. This behavior reflects the iterative nature of AIGC, whereby users do not passively accept content as they would with static information but actively participate in content re-production.
- AIGC verification: It involves parallel use of technical and human verification strategies. This compound validation approach demonstrates users' cautious attitudes toward AIGC credibility and functions as a self-protective mechanism against potential hallucinations.
- AIGC modification: It suggests that users treat AIGC as a malleable resource rather than a definitive one. The modification behavior reveals the processual nature of AIGC as an information resource and reflects users' dual roles as content co-creators and gatekeepers, emphasizing the central position of humans in content generation.
- AIGC adoption: It represents users' value judgment and serves as the final expression for expectation confirmation. Direct adoption indicates high alignment between AIGC and users' information needs, whereas selective adoption reflects users' capabilities to extract valuable content segments.
- AIGC sharing: It constitutes an external expression of individual evaluation and value perception, establishing a public discourse space for AIGC assessment and facilitating shared evaluative norms. Users may share AIGC for various reasons, including showcasing its usefulness (when outcomes are positive) or drawing attention to its flaws (when outcomes are problematic).

5.5.2 | Sustained leveraging

Sustained leveraging reflects the long-term realization of value from AIGC and is characterized by three deeper forms of engagement:

- AIGC hoarding: This indicates the users' recognition of the latent value of AIGC. Users may store content that appears useless without editing it, viewing it as a potentially valuable resource for future use. As ID_10 noted, "*I usually keep it [AIGC <Text>] stored there ([in Recent Chats)], but it's hard to say when I'll actually use it later. Anyway, I'm just not in the habit of deleting it or clearing it out*."
- AIGC instrumentalization: Refers to the transformation of one-time generated content into sustainable productivity resources. By constructing knowledge bases, users can integrate scattered AIGC into structured resources, making it a critical instrument for long-term learning and work support. For example, ID_03 stated, "*I saved the AI-generated deep learning model code in a folder. When I need it later, I just go into that folder, find it, tweak it a bit, and use it in my new code ... In deep learning models, a lot of functions-like the test function-basically stay the same, so I might just copy and paste them directly*."
- AIGC internalization: Represents the transformation of AIGC from external information to internal cognitive structures. This knowledge assimilation mechanism enables AIGC to transcend its role as a mere tool and become part of users' cognitive expansion, ultimately influencing their mental schemas and knowledge systems. It signifies the deepest level of impact, where AIGC reshapes how individuals learn, think, and express. As ID_05 stated, "*For the IELTS Task 1 essay, there are basically just a few set writing patterns. After generating expressions using AI multiple times, I compiled them [AIGC <Text>] together, and they [AIGC <Text>] gradually became my own (writing expressions)*."

5.6 | Value transformation

The value of AIGC is realized through its transformative impact on how users understand and transform the world.

5.6.1 | Understanding the world

When AIGC is embedded in users' daily work and interpersonal communication, it becomes a new form of informing knowledge that shapes how users understand the world. In this context, users are not simply exploiting AIGC but are engaged in dialogue with it, learning from interaction and dynamically adjusting their cognitive schemas (Shea & Wulf, 2005). As ID_04 noted: "*After using (contents generated by) GPT more frequently, I feel*

like I've been assimilated by it [AIGC <Text>]. For instance, in terms of language style and thinking patterns." This reflects deep, implicit cognitive interventions, similar to how books influence a reader's worldview (Chapman & Tunmer, 1997). AIGC also triggers emotional responses through its expressive use of language. When its content is natural and uplifting, users often experience surprise and delight. Conversely, when the content is vague, rigid, or overly polite, it may elicit feelings of aversion. For example, ID_01 remarked: "*You [AIGC <Text>] know me so well that even gives me that flattered feeling, like it's complimenting me*." Moreover, as a conduit for information and proto-knowledge (Zhu et al., 2024), AIGC enables users to access unfamiliar or abstract domains, expanding their cognitive boundaries. As ID_04 observed: "*What's great is that (AIGC <Text>) can disrupt ([expand)] the scope of your knowledge*." However, while AIGC can enhance user capabilities, it may also foster information dependency and diminish users' original creativity, critical thinking, and independent reasoning. As ID_05 warned: "*(After reading too much AIGC <Text>) I feel like my writing and thinking skills have seriously declined!*"

5.6.2 | Transforming the world

The value transformation of AIGC is further reflected in how users develop and apply it in concrete practice, ultimately serving the broader purpose of transforming the world.

- Problem solving: AIGC, such as outlines, images, or summaries, is rapidly integrated into user tasks involving writing, presentation, and communication. This content is immediately converted into resources for action. As ID_07 shared: "*I directly compare the answers [AIGC <Text>] to the literature (especially foreign language sources). It [AIGC <Text>] really boosts my reading efficiency*." In this sense, AIGC functions as an immediate value resource, participating in the value chain within a short time span and fulfilling practical functions.
- Action change: AIGC also operates as a kind of productive knowledge repository, the influence of which may extend beyond the user. It is often retained for long-term use and redistributed through indexing, sharing or citation. For example, ID_08 noted: "*This [AIGC <Code>] is something I'll use long term*," and "*I can convert some of the AI-generated interview guides into PDFs and share them with my collaborators so they can also review (and implement them)*." Once such content enters the networked archive ecosystem, it may persist as a form of durable content asset, shaping not only individual actions but also broader collective practices.

6 | DISCUSSION

6.1 | AIGC-value-added framework

The explosive growth of big data (Kitchin, 2014) and the democratization of information production by GenAI necessitate a re-evaluation of how AIGC should be assessed as an information resource, as well as a deeper understanding of its value-added (Benkler, 2007) realization pathways. Drawing from our qualitative findings and integrating insights from the dual-processing model (Metzger, 2007), value-added processes theory (Taylor, 1982; Taylor & Voigt, 1986), and information lifecycle theory (Marchand & Horton, 1986), we propose an AIGC-Value-Added Framework (Figure 1). Based on our cross-sectional interview data, the proposed framework identifies key phases of AIGC value emergence as experienced by users. While we present these phases in a structured manner, we acknowledge they may occur iteratively, simultaneously, or in varying sequences depending on specific user contexts.

Figure 1 shows the direct phases of user interaction and AIGC leveraging, comprising four distinct phases: value exposure, value formation, value anchoring, and value realization. These phases, presented sequentially for analytical clarity, should be understood as interconnected dimensions that emerged from participants' retrospective accounts. Each phase incorporates elements from traditional information lifecycle processes but reconceptualizes them within the context of user-driven value emergence.

Traditional information life cycle models have a well-defined information ecology consisting of information producers, transmitters, and consumers (Marchand & Horton, 1986). However, the anthropomorphic ease of use of GenAI chatbots has collapsed these traditionally separate roles into a fused structure. This fusion is associated with a state of information egalitarianism, in which users act simultaneously as initial producers, transmitters, and ultimate consumers of AIGC. Thus, they collectively constitute the generative and embedded structures of the information ecosystem.

Specifically, the value-exposure phase begins when users perceive a task-related context with a sense of inefficacy in achieving desired outcomes, associated with their intention to create, acquire, and use AIGC. This phase adds a pre-creation stage to the traditional information lifecycle (which usually starts at creation) where

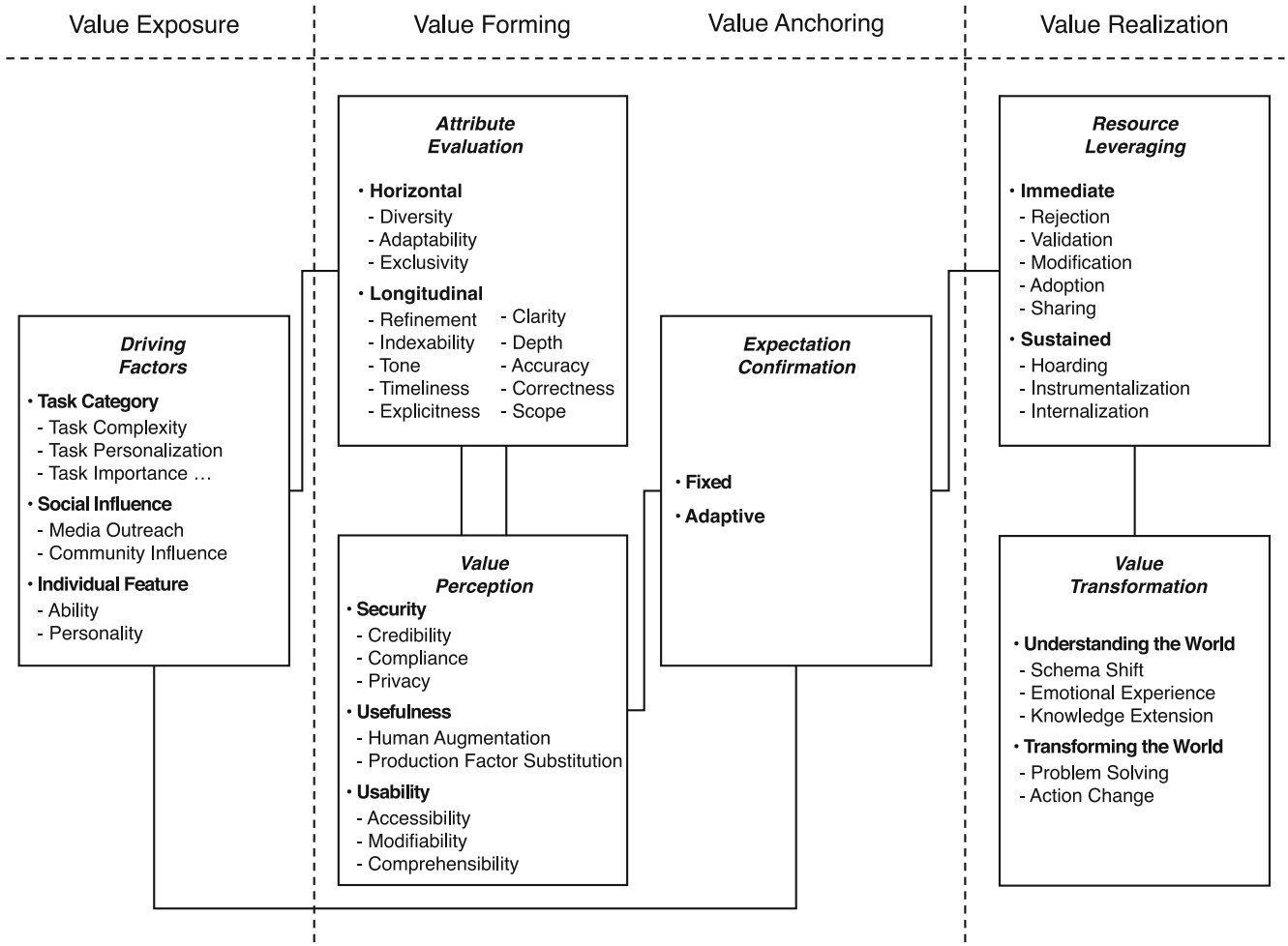

FIGURE 1 AI-generated content-Value-Added Framework. This framework represents theoretical relationships derived from qualitative analysis, rather than empirically validated causal paths.

users identify information needs and recognize potential solutions. In this sense, AIGC has emerged as an information resource designed to empower users to transform their understanding of the world or the world itself.

In the value-forming phase, users engage in attribute evaluation to assess the generated content. This phase integrates traditional information lifecycle processes of content creation and initial acquisition as users generate and simultaneously collect AIGC. The transformation from attribute evaluation to value perception involves a cognitive aggregation process whereby users synthesize multiple attribute-level assessments, weighting them by driving factors and context, personal priorities, and contextual factors, to form holistic judgments about the AIGC's adequacy. More specifically, at this phase users assess how well the current form of AIGC satisfies their own needs by drawing on its horizontal and longitudinal attributes—such as diversity, adaptability, and refinement—thereby perceiving the immediate value of AIGC in terms of security, usefulness, and usability.

The value-anchoring phase builds upon the initial value formation as users evaluate the information quality and perceived value of the AIGC they generate (Levitan, 1982). Whereas value-formation centers on evaluative cognition (users' immediate sense-making of generated outputs), value anchoring involves stabilizing cognition (integration into users' knowledge schemas). This phase incorporates elements of traditional information organization and storage as users mentally contextualize AIGC within their knowledge frameworks. This process involves a comparison between AIGC and users' fixed or adaptive expectations, which contributes to the confirmation and stabilization of value. This process is iterative and contextually mediated; emergent value perceptions may shape subsequent attention to specific attributes, creating a reciprocal feedback loop. Value anchoring is not influenced solely by AIGC's properties but is substantially shaped by the driving factors present during the value exposure phase (Taylor & Voigt, 1986). Moreover, because of the interactive nature of GenAI

tools, we emphasize that AIGC's value is not fixed but emerges through the user's continuous information experience (Rusho & Raban, 2020). Through this mechanism, users move from attribute assessments to coherent context-oriented value perceptions, bridging the gap between specific content characteristics and holistic informational value realization. As such, attribute evaluation and value perception may be mutually influential and bidirectional.

Last, in the value realization phase, which corresponds to the utilization stage in traditional models, we observe that AIGC's value encompasses both use value and exchange value. While use value is dominant (e.g., when AIGC serves directly in users' problem-solving or productivity tasks), exchange value becomes evident in sharing behaviors, where AIGC is distributed to third parties. These two types of values enable embedded co-creation between humans and AI (Vargo & Lusch, 2016), which we term embedded generative value (Foster & Clough, 2018). This value is endogenous to the iterative cycles of generative expectation (re)confirmation experienced by users (Rusho & Raban, 2020). However, the AIGC value ultimately depends on the usage context. Although some users may share their AIGC online or repurpose them as source material, our observations suggest that, unlike traditional web-based information resources, the co-creative experiences and values generated through AIGC do not appear prominently in social media spaces (Prahalad & Ramaswamy, 2004). Instead, they tend to be implicitly embedded in users' daily lives or absorbed into traditional information resources.

6.2 | Theoretical contributions

This study employs a bottom-up concept coding approach to construct the AIGC-Value-Added Framework, which integrates TAM (Davis, 1989), Expectation Confirmation Theory (ECT) (Oliver, 1980), and value-added processes (Taylor, 1982). The framework systematically delineates how AIGC engages with users through four phases: value exposure, formation, anchoring, and realization, thereby explicating the complete process of AIGC emergence. This framework reaffirms the applicability of existing theories and extends their explanatory power. First, drawing on TAM2 (Venkatesh & Davis, 2000), it retains the notion that social influence shapes perceived usefulness yet transcends TAM's static decision focus by extending it to a fine-grained, dynamic information perception framework. Second, it advances ECT by adapting it to the multistage, continuous nature of AIGC generation, unifying pre- and post-adoption expectations (Bhattacherjee, 2001), and emphasizing how users continually adjust their evaluations through ongoing interaction. Third, it broadens the applicability of value-added processes in human–machine collaboration by explaining how AIGC users incrementally enrich their initial AIGC and ultimately achieve both understanding and transformation of the world through continuous engagement (Taylor, 1982). This highlights the active role of users as producers in the AIGC value transformation process and reveals the central position of humans in AIGC value addition.

More importantly, we recognized the fundamental distinction between AIGC and traditional human-authored content. AIGC carries knowledge and satisfies users' information needs, conforming to the classical definition of information resources in LIS (Ray, 2025). However, unlike traditional resources, AIGC acquires dynamic technological properties due to its co-creation characteristics. AIGC content is generated in real time, is instantly responsive, and exhibits the features of a living information resource. This dynamism shifts the locus of value from being embedded in static content to emerging through ongoing interactions between users and the GenAI system. By integrating perspectives from information resource theory, technology acceptance, and value realization, our framework constructs a systematic knowledge structure that offers a comprehensive explanation of AIGC's value exposure, formation, anchoring, and realization. This significantly enriches our understanding of AIGC-related information practices in the fields of Information Science and Information System.

6.3 | Practical implications

AIGC is reshaping the mechanisms of information resource generation and utilization patterns, comparable to or even surpassing the rapid and profound transformation brought by web-based information resources in the 1980s and 1990s. As a discipline concerned with the development, organization, and utilization of information resources, LIS must respond to this paradigm shift. It is imperative to understand the value-added mechanisms of AIGC from the perspective of the emerging information resource lifecycle. The AIGC-Value-Added Framework we propose not only reveals how value emerges through user engagement but also provides a theoretical foundation and practical framework for future organization, retrieval, and use of AIGC-based resources. This perspective emphasizes that information systems should not focus solely on the technological question of how AIGC is generated, but also consider how it is used and value-added after generation.

Our findings offer the following practical insights for libraries, data centers, and other information service institutions.

- AIGC should be incorporated into a broader information resource system and managed accordingly. This calls for a paradigm shift in information resource management—from a traditional model of "static collection–structured organization–passive utilization" to a model characterized by "semantic reconstruction–dynamic generation–collaborative value creation."
- GenAI system design should integrate mechanisms that support the verifiability, indexability, and reusability of generative content to promote the sharing of high-quality AIGC and facilitate cumulative knowledge construction.
- Information literacy education should incorporate training in the recognition, evaluation, and responsible use of generative information resources, fostering users' capabilities to evaluate the quality and value of AIGC.
- In this era of normalized AIGC usage, institutions should proactively address governance issues related to content boundaries, accountability, data security, and privacy by formulating industry standards and ethical frameworks.

Looking ahead, computer science will continue to explore how to generate better results, and behavioral sciences will examine how to use it more effectively. However, the task of LIS is to answer a different yet critical question: "What has been generated, and how can this content meaningfully enrich our knowledge and transform the real world?" This study offers an inclusive pathway for the effective development of AIGC as a novel information resource and provides practical cognitive frameworks and strategic guidelines for stakeholders navigating the evolving information environment.

6.4 | Limitations and future work

This study has some limitations. First, although this framework provides a comprehensive conceptual structure for understanding AIGC value emergence based on our qualitative findings, we acknowledge that the temporal and causal relationships suggested here represent theoretical propositions rather than empirically validated sequences. Future longitudinal studies, experimental designs, and diary methods can further test and refine the dynamic aspects of these value phases, potentially revealing additional nuances in how users experience and realize value from AIGC across different temporal contexts and usage scenarios. Second, the proposed framework is primarily based on self-reported qualitative data from semi-structured interviews, which may be subject to recall bias or subjective interpretations. Although rigorous content analysis procedures were employed, cognitive discrepancies may still exist. Third, the analysis of AIGC as an information resource inevitably intersects with its technical foundations. During interviews, participants often conflated the performance of GenAI tools with the value of the content they produced. This observation highlights the need for the academic community to clearly distinguish the analytical boundaries between tools and resources when conducting in-depth discussions on AIGC's information resource value.

In the future, a critical research agenda would be to construct a generalizable and operationalizable evaluation framework for AIGC quality. Such a framework would not only facilitate the selection and leveraging of high-quality generative content but also support the management and service design of AIGC within broader information systems. Moreover, while this study offers an initial discussion of the confirmation mechanism in AIGC value realization, the underlying user cognitive models, expectation adjustment pathways, and resulting validation strategies require further theoretical and empirical investigation.

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DATA AVAILABILITY STATEMENT

The data are not publicly available due to privacy and ethical restrictions.

ORCID

Yu Zhu https://orcid.org/0000-0002-2548-828X
Chenyu Li https://orcid.org/0000-0003-3209-1130
Jiyuan Ye https://orcid.org/0000-0002-4232-8923

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