Scientific Reports

https://doi.org/10.1038/s41598-026-45101-3

Article in Press

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Received: 20 July 2025

Accepted: 17 March 2026

Published online: 21 March 2026

Cite this article as: Wang Q., Wang Y., Wei T. *et al.* Effects of AI-assisted review presentation formats on consumer decision-making efficiency from a cognitive load perspective. *Sci Rep* (2026). https://doi.org/10.1038/s41598-026-45101-3

Qi Wang, Yuwei Wang, Tianyu Wei & Si Fu

Effects of AI-Assisted Review Presentation Formats on Consumer Decision-Making Efficiency from a Cognitive Load Perspective

Qi Wang[1], Yuwei Wang[1], Tianyu Wei[1], Si Fu[2]
[1] School of Industrial Design, Hubei University of Technology, Wuhan 430068, China
[2] China-Korea Institute of New Media, Zhongnan University of Economics and Law, Wuhan 430073, China
Corresponding author: Si Fu (e-mail: z0004435@zuel.edu.cn).

Abstract
The value of experiential products, such as movies, is difficult to directly perceive, making online reviews a key factor in decision-making. The overwhelming volume of reviews exacerbates information overload, increasing the cognitive burden on consumers during decision-making. Therefore, the effective processing of information is crucial to the decision-making experience, and human-AI collaboration offers a new pathway in this regard. In this context, this study, based on cognitive load theory and cognitive fit theory, explores the impact mechanisms of AI-driven review presentation formats on consumer movie decisions, and the differences across various movie types. We classify movies into high cognitive demand (complex narrative, information-dense) and low cognitive demand (simple narrative, straightforward information), and design a 2 (review presentation format: bullet-point vs. paragraph) × 2 (movie type: low vs. high cognitive demand) experiment. The results reveal that, in high cognitive demand contexts, bullet-point reviews significantly reduce cognitive load by 11.8% (see the Results section for details), while in low cognitive demand contexts, no significant differences are found. Additionally, cognitive load plays a key mediating role in these effects, and the strength of this mediation is moderated by the cognitive demands of the task. This study uncovers the interaction between review presentation formats and task complexity, and how this interaction influences decision-making through cognitive load. Based on these findings, we propose contextualized and personalized information presentation design principles, offering new theoretical insights and practical frameworks for AI-driven information presentation research and platform review system optimization.

Keyword：AI-assisted review systems; Cognitive Fit Theory; Cognitive load; Decision difficulty; Review presentation format; User interface design.

1 Introduction

With the exponential growth of information, users increasingly struggle to quickly extract key insights relevant to decision-making [1]. While more information may superficially suggest greater comprehensiveness, the actual user experience often involves greater difficulty in making decisions—information not only fails to facilitate the process but also increases the burden of comprehension and choice. This phenomenon is fundamentally rooted in information overload [1]. When the available information exceeds an individual's cognitive capacity, users must expend more effort to filter, interpret, and integrate information. This not only depletes consumers’ limited cognitive resources but also prolongs decision-making time [1,2]. As cognitive resources become heavily occupied, the individual’s ability to evaluate, compare, and weigh alternatives diminishes, resulting in decision difficulty.

Decision difficulty is typically defined as the degree of difficulty experienced during the decision-making process [3], and its direct consequences include reduced decision quality, procrastination, and increased negative emotions. On a behavioral level, decision difficulty directly undermines decision effectiveness [2], such as procrastination in decision-making [4] and avoidance tendencies [5]. This effect is also significant in high pressure professional decision-making contexts. For example, when doctors perceive a decision as more "difficult," they are less likely to make an "appropriate" decision [6], revealing the direct impact of decision difficulty on the objective outcome of "decision quality." Research in moral psychology highlights the impact of decision difficulty on the decision-maker's subjective experience: in situations involving value conflicts, greater decision difficulty leads to more worry and regret [7]. These studies suggest that decision difficulty not only affects the decision outcome itself but also influences decision-making experiences and emotional states. Given this, addressing decision difficulty effectively becomes a key issue.

Cognitive Load Theory posits that the higher the demands of information processing, the greater the perceived decision difficulty [2,8]. In real world consumption contexts, users often experience cognitive burden when faced with large volumes of review information, which can affect the decision-making process [1]. As a result, an increasing number of platforms are leveraging AI to reduce information processing difficulty by extracting key information to assist consumer decision-making. For example, Ele.me platforms use AI summaries to help users capture core points without having to read lengthy texts (as shown in Figure 1). Academic research has primarily focused on the role of AI in information retrieval, filtering, and quality assessment [9-11], as well as the impact of generative AI on shaping consumer behavior through personalized and interactive experiences [12,13]. However, there is still relatively limited research on how AI can alleviate consumer decision difficulties by altering the way information is presented.

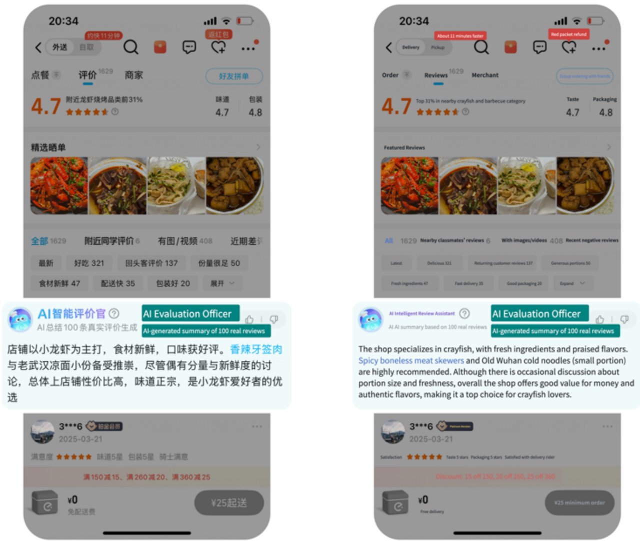

Figure 1. AI-generated review summary interface on the Ele.me platform (original Chinese interface and English-translated interface).

Currently, there are structural differences in review presentation formats. For example, Taobao adopts a structured tag based display, while Amazon predominantly uses paragraph text (as shown in Figures 2 and 3). Structured reviews are more helpful for users in quickly extracting key points, reducing cognitive load and decision complexity [14]. In contrast, unstructured paragraphs require users to invest more cognitive resources in information filtering, potentially exacerbating decision difficulties.

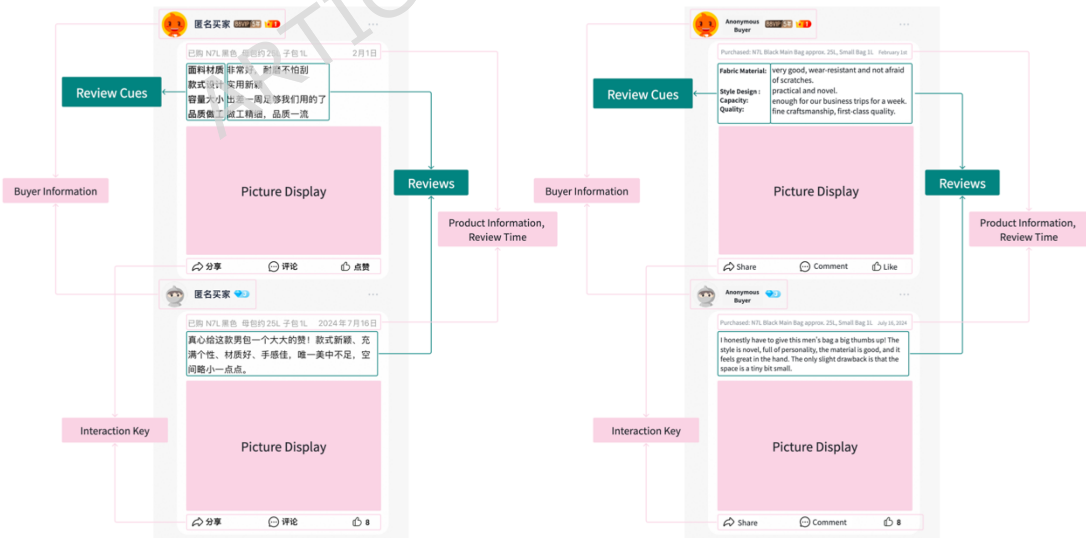

Figure 2. Bullet-point reviews on Taobao platform (original Chinese interface and English-translated interface).

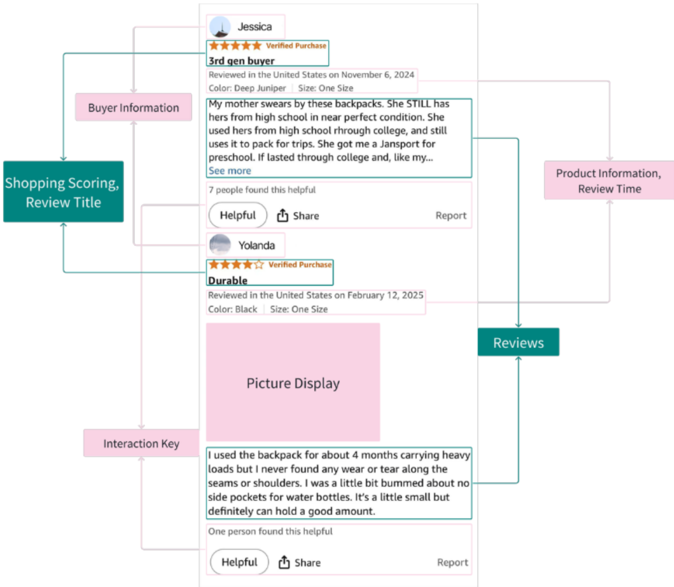

Figure 3. Paragraph reviews on Amazon platform.

In this context, the movie consumption scenario provides a typical setting for testing this mechanism. According to Nelson's (1970) product classification theory, movies are typical experiential products, distinct from utilitarian products, as their quality can only be fully perceived after consumption. Therefore, there is significant information asymmetry prior to consumption [15], and consumers often rely on movie reviews to reduce uncertainty [16]. However, although longer movie reviews provide ample information, they can easily exceed the capacity of short-term memory [17], and in the context of fragmented attention on mobile media, they are more likely to trigger information overload [1]. Therefore, this study selects movie consumption as the research context, focusing on the presentation and effectiveness of long movie reviews.

Cognitive Fit Theory emphasizes that the presentation of information should match the user's task requirements, which can significantly enhance information processing efficiency [18]. This suggests that the presentation of review information should not be uniform but rather dynamically adapted based on task complexity (e.g., movies with high/low cognitive demand). Based on Cognitive Load Theory and Cognitive Fit Theory, this study examines whether AI optimization of review presentation formats (such as bullet-point structuring) under different movie conditions (low vs. high cognitive demand) can alleviate users' cognitive load and improve their decision-making experience.

This study makes contributions at both the theoretical and design levels. At the theoretical level, the contributions are twofold: First, in the field of information and decision research, this study differs from previous research that focused on cognitive ability [19], information quality [20], psychological biases [21], or limited cognitive resources [22]. Instead, it focuses on the matching of complex information presentation with task complexity. By systematically examining the interaction between the two, this study reveals the moderating mechanism of AI-driven information presentation formats on consumer cognitive load and decision difficulty, providing new empirical evidence for understanding the psychological mechanisms behind AI-driven information presentation. Second, in the field of AI-enabled consumer decision-making, this study moves beyond the traditional focus on translation accuracy [9] or false information detection [10], and focuses on the often overlooked dimension of "information architecture." It also reveals the critical boundary of its impact—task complexity. At the design practice level, this study breaks away from the "one-size-fits-all" static review presentation formats by introducing "task complexity" as a key moderating variable. It proposes a new design principle for information presentation that dynamically adapts to users' cognitive tasks, providing conceptual guidance for building contextualized and personalized review systems on platforms.

2 Theory and hypothesis development

2.1 Decision difficulty and review presentation formats

The causes of decision difficulty can be explored from multiple perspectives. Simon (1956) argued that decision-makers' cognitive abilities, information availability, and time constraints prevent them from making fully rational optimal decisions, leading them to seek satisfactory decisions instead [19]. This view emphasizes that, in complex situations, cognitive load and external constraints are the primary reasons for decision difficulty. Iyengar and Lepper (2000) further demonstrated that when there are too many choices, the heavy information processing burden leads to decision difficulty and decision avoidance [2]. From a behavioral economics perspective, the "loss aversion" theory proposed by Kahneman and Tversky (1979) explains that decision conflicts arise when individuals are faced with choices involving gains and losses, as they tend to avoid losses, which increases decision complexity [21]. Vohs et al. (2018) pointed out that the decision-making process consumes limited cognitive resources, and prolonged decision-making reduces decision quality and weakens self-control [22]. Cognitive Load Theory (Sweller, 1988) offers a reasonable explanation for these phenomena: an individual's working memory capacity is limited [23]. When the amount of information is too large or the task structure is complex, the cognitive resources required for information processing exceed the capacity of working memory, leading to cognitive overload and exacerbating decision difficulty [8]. Therefore, the key to alleviating decision difficulty is not simply minimizing the amount of information or options, but rather utilizing cognitive resources more effectively [24]. In this context, Cognitive Load Theory further suggests that optimizing information presentation can improve cognitive resource allocation[25], providing theoretical support for empirical interventions.

In this study, “information presentation format” refers to the degree of textual structuring of reviews. Compared with charts or rankings, text better conveys the narrative and emotional aspects of reviews, and movie reviews are predominantly presented in textual form. Therefore, it becomes a core variable in movie consumption decisions.

When users face lengthy, ambiguous paragraph reviews (unstructured information), they are prone to information overload, which can trigger decision difficulty [1]. This occurs because a large volume of information increases the cognitive resources required for processing [25], thereby reducing the cognitive resources available for decision-making and exacerbating decision difficulty. Previous research has shown that textual structuring significantly affects users' comprehension difficulty [26]. This suggests that transforming unstructured paragraph text into a structured, bullet-point format may be a direct and effective way to utilize cognitive resources. Bullet-point reviews (structured information) pre-organize information, helping users more efficiently select and organize key points [27], thereby freeing cognitive resources for evaluating and comparing options and reducing decision difficulty.

In recent years, the development of generative AI has provided new tools for optimizing information presentation. For example, AI can condense complex data into concise, intuitive visual formats, enhancing users' pattern recognition and improving decision-making efficiency [28]; generate review summaries to improve the diagnosticity and usefulness of content [29]; and, through personalized and transparent recommendations, help users quickly identify the most relevant information, enhancing the perceived value of information and influencing behavior [30]. This suggests that when AI can integrate and simplify information, it has the potential to utilize users' cognitive resources more efficiently, thereby reducing decision difficulty.

Based on these theoretical and empirical insights, this study employs AI to present long review content in a standardized bullet-point format (e.g., plot, casting, production), which is expected to improve information clarity while optimizing the allocation of users' cognitive resources, allowing more resources to be devoted to decision-making and alleviating decision difficulty. It can be inferred that, compared with traditional paragraph reviews, bullet-point reviews are more likely to reduce consumers' decision difficulty. Therefore, we propose the following hypothesis:

H1: Compared with paragraph reviews, bullet-point reviews reduce consumers' decision difficulty.

2.2 Cognitive load and review presentation formats

Cognitive Load Theory posits that the human cognitive system consists of a limited-capacity working memory and a virtually unlimited long-term memory [31]. During information processing, extraneous cognitive load is primarily determined by the manner in which information is presented, and poor design can increase processing difficulty and cognitive burden [32,33]. In today's "attention economy," major platforms indiscriminately produce and present massive, disorganized UGC content, effectively transferring the cognitive burden of information identification and integration entirely to users, which has led to widespread digital fatigue and decision-making burnout.

Previous research has shown that improving information structure and enhancing information clarity can significantly reduce extraneous cognitive load, thereby improving information processing efficiency [34,35]. According to signaling theory, clear visual structures—such as hierarchical headings or cue words—can guide consumers to quickly locate key content, reducing the ineffective use of cognitive resources [27,36] and thus lowering extraneous cognitive load. This mechanism has received empirical support in multiple studies; for example, texts with signaling cues are processed more efficiently than unmarked texts [37], and Amazon's "Top Reviews" help consumers browse reviews more efficiently and assess review valence [38].

Existing research has confirmed the positive effect of information structuring (e.g., highlighting keywords) on reducing cognitive load. Zhou et al. (2022) found that emphasizing keywords in complex news reduces cognitive load, but overemphasis in simple news can be counterproductive [39], indicating that the effectiveness of information structuring depends on content characteristics and that a single intervention does not always reduce cognitive load. Luce et al. (1998) noted that information presented based on options typically requires more cognitive resources than information presented by attributes [5], suggesting that different organizational logics inherently entail distinct cognitive costs. Huang et al. (2018) found that in review-type information, complex fonts or low readability designs increase processing difficulty and reduce information impact [40], demonstrating that even micro-level presentation optimizations can significantly influence information processing efficiency. Most of these studies focus on the visual presentation of content itself, whereas the issue of inherently loose macro-level structure in user-generated content, such as reviews, remains largely unexplored. It is still unclear whether deeper structural interventions can alleviate cognitive load by reshaping the overall information architecture.

In the domain of user-generated content, such as online reviews, when review information is poorly organized and loosely structured, users must expend additional effort to filter and integrate information, consuming more cognitive resources and increasing extraneous cognitive load [41]. This study employs AI to convert reviews into a bullet-point structure. We propose that this structure provides clear visual cues through its bullet markers and reduces visual complexity via information chunking, enabling users to lower their information search costs and focus directly on key content, thereby alleviating extraneous cognitive load and driving an overall reduction in cognitive load. Based on this, we propose the following hypothesis:

H2: Compared with paragraph reviews, bullet-point reviews reduce consumers' cognitive load.

2.3 Cognitive load and decision difficulty

In online consumption contexts, A large volume of user-generated content and expert reviews serve as external information cues. While they provide additional references, they also increase information processing costs, leading to higher cognitive load [42]. Elevated cognitive load can result in a range of deteriorations in decision performance. Deck et al. (2015) found that higher cognitive load impairs individuals' basic judgment abilities and alters risk preferences [43]. Dijksterhuis and Van Olden (2006) showed that when task complexity exceeds an individual's processing capacity, decision quality declines significantly [44]. Haynes et al. (2009) reported that in scenarios with numerous options and limited decision time, information processing demands are more likely to exceed available cognitive resources, leading to decision difficulty [45]. Together, these findings indicate that cognitive load is a key psychological mechanism linking information presentation formats and decision outcomes.

Dual process theory posits that individuals employ two basic pathways in information processing: heuristic and systematic processing [46]. Heuristic processing relies on simple cues, requires low cognitive effort, and is suitable for resource constrained situations [47]. In contrast, systematic processing demands sufficient attention and cognitive resources, involving deeper reasoning and integration of information [46,48]. People tend to minimize effort in both cognition and behavior [47], and when cognitive resources are limited, they are more likely to rely on heuristic processing [47]. Conversely, when cognitive resources are ample and time permits, and when consumer motivation is sufficiently high, individuals are more inclined to engage in systematic processing to handle information.

Based on this, the present study posits that higher cognitive load consumes consumers' cognitive resources, making it difficult for them to process review content systematically. As a result, they rely more on rough judgments, increasing uncertainty and hesitation, which in turn heightens decision difficulty. Conversely, under lower cognitive load, consumers can engage in deeper information integration and reasoning, facilitating the formation of clear preferences and reducing decision difficulty. In the context of movie consumption, consumers' information processing capacity is limited [17] and long, unstructured reviews increase the burden of information filtering and integration, leading to higher cognitive load. We infer that the effect of review presentation format (bullet-point vs. paragraph) on decision difficulty is likely mediated by changes in consumers' cognitive load rather than a direct effect. Based on this, the study proposes the following hypotheses:

H3: The higher the perceived cognitive load, the greater the decision difficulty faced by consumers.

H4: Cognitive load mediates the relationship between review presentation format and decision difficulty.

2.4 Cognitive fit theory and movie type

Cognitive Fit Theory explains that the alignment between information presentation and task type affects decision performance [49]. High fit helps activate prior knowledge, form structured mental representations, and improve the efficiency and accuracy of information processing [18]. When information attributes align with existing expectations, the information is more easily integrated into prior knowledge structures [50], thereby reducing cognitive effort and enhancing processing efficiency [51]. Hong et al. (2014), using eye-tracking technology, demonstrated that matching task type with data presentation effectively reduces cognitive load [52]. Based on this, the present study applies this theory to the comprehension of movie reviews: when review presentation aligns with task demands, it facilitates audience understanding of content; when misaligned, it may create cognitive incongruence, increasing comprehension difficulties [53,54].

Task complexity reflects the extent to which task characteristics demand cognitive resources [55]. Cognitive demand refers to the level of cognitive resources required by a task [56]. High cognitive demand tasks consume more cognitive resources and are more likely to induce decision difficulty [2], whereas low cognitive demand tasks are easier to complete. According to Cognitive Fit Theory, when the structure of external information aligns with task attributes, it can facilitate mental representation and improve information processing efficiency [49,52,57].

In this study, a movie's "cognitive demand" represents the amount of cognitive resources consumers need to invest when making viewing decisions, reflecting the complexity of the decision task. Movies for which audiences must expend substantial cognitive resources to integrate information when evaluating whether they are worth watching are defined as high cognitive demand movies, corresponding to high cognitive demand tasks. Conversely, movies requiring relatively little cognitive resource investment are defined as low cognitive demand movies, corresponding to low cognitive demand tasks. Consumers often form mental expectations based on available cues [58], and movie-viewing decisions are no exception. High cognitive demand movies, characterized by complex narrative structures and high information density, present large volumes of information and intricate logical relationships. Consumers must integrate and reason over more information to form expectations, making the decision task more complex. Low cognitive demand movies, characterized by simple narratives and low information density, have straightforward plots and clear logic, allowing consumers to quickly integrate information and form mental expectations without complex reasoning, making the decision process relatively easy.

Based on this theoretical framework, we infer that for high cognitive demand movies, bullet-point reviews can chunk and present information logically, reducing integration difficulty, optimizing cognitive resource allocation, and lowering cognitive load. In contrast, for low cognitive demand movies, bullet-point reviews may disrupt semantic coherence, potentially increasing integration difficulty and cognitive load. Based on this reasoning, the study proposes the following hypothesis:

H5: Movie type moderates the relationship between review presentation format and cognitive load. For high cognitive demand movies, bullet-point reviews more effectively reduce consumers' cognitive load.

3 Method

3.1 Pretest

To select the movies for the main experiment, this study first screened six randomly selected films. A total of 61 volunteers aged 18–25, who had not previously watched any of these films, were recruited via the WeChat platform. Before rating, all participants read an operational definition of "cognitive demand," which clarified that it refers to "the extent to which making a viewing decision requires additional thinking, analysis, information integration, and judgment," to ensure rating consistency. Participants rated the cognitive demand of each film when making a viewing decision using a 7 point scale (1 = low cognitive demand, 7 = high cognitive demand). Based on the results, JONNY KEEP WALKING! ($M = 2.033$, $SD = 1.110$) was rated as a low cognitive demand movie, and Cliff Walkers ($M = 5.869$, $SD = 1.189$) was rated as a high cognitive demand movie, and were thus selected as representative samples for the main experiment. The full results of the pretest, including means, standard deviations, and inclusion decisions for all six films, are shown in Table S1. Since cognitive demand was assessed using a single item measure, reliability was not calculated.

3.2 Participants

The experiment was conducted at a public university in central China. This region provides a certain degree of social representativeness and facilitates access to university students with internet experience. Participants were recruited via the WeChat platform and had to meet the following criteria: (1) aged 18–25 years; (2) frequent users of smart devices for browsing movie reviews; and (3) had not previously watched the movies selected for the experiment. Using G*Power 3.1 ($\alpha = 0.05$, $1-\beta = 0.80$, $f^2 = 0.15$), the minimum required sample size was calculated to be $n = 77$. The study ultimately recruited 240 participants, exceeding this threshold. In total, 240 eligible students (121 males, 119 females) participated in the experiment. All participants provided informed consent and received monetary compensation.

3.3 Experiment conditions

To examine the interaction effect between review presentation format and movie type, this study employed a 2 (review presentation format: bullet-point vs. paragraph) × 2 (movie type: low vs. high cognitive demand) between-subjects experimental design.

Prior research has shown that when viewing movie trailers, consumers pay the most attention to elements such as cast, director, plot, soundtrack, and visual style [59], all of which collectively shape their cognitive responses. Building on this, the present study identified seven key movie elements as signaling dimensions for analysis: feelings, plot, characters, narrative, production, directing, and casting. Long-form user reviews were categorized based on these elements to enable clearer extraction and structured presentation of information. Specifically, emotions refer to the viewer's subjective feelings and interpretations of the movie content [60]. Plot includes the storyline and key events that drive the movie's narrative arc [61]. Characters represent the core of the movie, with their emotions and actions conveyed through audiovisual language [62]. Narrative denotes the method and structural features through which the story is told [63]. Production covers the movie's technical aspects, such as visual quality, music, and editing techniques [64]. Director refers to the director's artistic style and creative vision that shape the movie's overall tone and execution [65]. Finally, actors pertain to the cast's performance quality and their influence within the movie industry [66].

As no current movie platforms present consumer reviews in a bullet-point format, this study used AI-assisted structuring to process paragraph reviews. Using knowledge extraction techniques [67], the core semantic units within reviews were automatically identified and categorized according to the seven movie elements, without altering the original review content. Furthermore, online reviews containing keywords associated with positive or appreciative attitudes were classified as positive reviews, while those containing critical or negative language were categorized as negative reviews.

The experiment obtained the following four conditions:

(a) *Cliff Walkers* with bullet-point reviews;

(b) *Cliff Walkers* with paragraph reviews;

(c) *JONNY KEEP WALKING!* with bullet-point reviews;

(d) *JONNY KEEP WALKING!* with paragraph reviews.

Based on Miller's "7 ± 2" rule [17] and the interface characteristics of mobile review sections, this study presented six reviews for each movie, with each review controlled to 7–9 lines and approximately 21 characters per line. Figma was used to create 12 review pages (translated materials in Figure S1; comparability information in Table S2) as the stimulus materials. Each page consisted of two sections: (1) the movie poster and brief information, and (2) two consumer reviews related to the movie. During material preparation, the labels within each set of stimulus texts (e.g., "Feelings," "Plot," "Production") were strictly controlled to ensure that the frequency of each label was approximately equal across different conditions. The bullet-point and paragraph reviews were matched in terms of text length and information density, with systematic differences only in presentation format. This structural difference did not affect reading comprehension or evaluation tendency, ensuring comparability across experimental conditions.

For each movie, a pool of ten reviews—balanced between positive and negative—was assembled from Douban, Maoyan, WeChat public accounts, and related platforms. Some reviews were moderately modified to align with the experimental conditions. Within each experimental condition, six reviews (three positive, three negative) were randomly drawn from the pool and displayed in random order. Thus, in the high cognitive load × bullet-point condition, participants saw three bullet-point positive reviews and three bullet-point negative reviews.

3.4 Procedures

The study was conducted in a classroom equipped with multimedia facilities. Participants were seated randomly with adequate spacing to ensure a relatively independent, quiet, and focused environment for completing the experimental tasks. Before the experiment began, the experimenter informed participants that the study aimed to evaluate the functionality of an online movie platform. Participants then accessed the experiment page by scanning a QR code with their smartphones. The experimental procedure was implemented via the WeChat platform, which randomly assigned participants to one of four experimental conditions, ensuring randomness and balance across groups. To prevent mutual interference, participants were required to complete the tasks independently without communicating with others. The interface was designed to limit navigation and external distractions, and research assistants supervised the session throughout.

At the start of the experiment, participants first read an instructional guide asking them to imagine that they had sufficient free time and planned to go to the cinema to watch a movie. They were then directed to the main experimental page to browse the corresponding materials. After reading, participants completed a questionnaire measuring several key variables, including cognitive load, decision difficulty, and the manipulation of movie type (primary variables are shown in Table S3). The entire experiment lasted approximately 60 minutes. Upon completion, participants were thanked and debriefed regarding the study's true purpose.

3.5 Measures

3.5.1 Decision difficulty

This study employed three items to measure the level of decision difficulty, adapted from the work of Hu et al. (2019) [1]. A seven-point Likert scale was used (1 = strongly disagree, 7 = strongly agree). The specific items included (see Supplementary Table S3):

(1) I don't have an answer in my mind regarding this decision (whether to watch the specific movie presented in the experiment);

(2) For me, making this decision (whether to watch the specific movie presented in the experiment) is very difficult;

(3) I need more time to consider (whether to watch the specific movie presented in the experiment).

3.5.2 Cognitive load

Mental effort is defined as the amount of cognitive resources actually invested to meet task demands [68], and is commonly regarded as an indicator of cognitive load [69]. The scale used in this study was adapted from the research by Mirhoseini et al. (2021) [70]and includes five items. Participants reported their perceived level of mental effort on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree), thereby quantifying their subjective perception of effort.

The scale items were as follows (see Supplementary Table S3):

(1) I have invested a great deal of mental effort in this task (extracting information from the reviews);

(2) This task (extracting information from the reviews) requires intense mental effort;

(3) This task (extracting information from the reviews) requires high concentration;

(4) This task (extracting information from the reviews) does not require intense mental effort (reverse-coded);

(5) I had to think hard in this task (extracting information from the reviews).

3.6 Data analysis

The experimental data were analyzed using SPSS 29.0 and the PROCESS macro (version 4.2). First, descriptive statistical analyses were conducted for participants' perceived cognitive load and decision difficulty, followed by Pearson correlation analyses to examine the relationships among the key variables. Subsequently, Model 4 and 7 of the PROCESS macro was employed for hypothesis testing. In this model, review presentation format served as the independent variable, movie type as the moderator, cognitive load as the mediator, and decision difficulty as the dependent variable. Gender and age were included as covariates to control for potential demographic influences. To ensure the robustness of the findings, bootstrap resampling was performed with 5,000 iterations, and 95% bias-corrected confidence intervals were reported. All variables were mean-centered prior to analysis to reduce the risk of multicollinearity.

3.6.1 Descriptive statistics

Analysis of variance (ANOVA) was conducted using SPSS to compare the demographic characteristics across the four experimental groups. Tables 1 and 2 present the descriptive statistics for the key variables, respectively. The results indicated no significant differences among the four groups in terms of age distribution (mean age = 21.88 ± 1.974) or gender composition (121 males, 119 females), suggesting that the random assignment of participants was successful (p =0.62). Moreover, no demographic differences were observed between any two groups (p =0.78). Finally, Pearson correlation analysis revealed a significant positive relationship between participants' perceived cognitive load and their perceived decision difficulty (r = 0.45, p < 0.01).

Table 1. Descriptive statistics of covariables.

Group	Gender	Age
Group 1（N=60）	Male = 29	21.83 (±1.833)
Group 2（N=60）	Male = 34	22.02 (±1.979)
Group 3（N=60）	Male = 27	21.68 (±2.167)
Group 4（N=60）	Male = 31	21.98 (±1.935)
	X2=1.783, p =0.62	F (3,236) = 0.375, p =0.78

Table 2. Means and standard deviations of key variables in each group.

Variable	Group1(n=60)		Group2(n=60)		Group3(n=60)		Group4(n=60)	
	M	SD	M	SD	M	SD	M	SD
Cognitive Load	4.54	0.49	4.23	0.35	5.15	0.46	4.09	0.49
Decision Difficulty	5.24	0.59	4.43	0.62	5.82	0.50	4.50	0.57

This study strictly adhered to the ethical principles of the Declaration of Helsinki. All experimental protocols were approved by the Research Ethics and Technology Safety Committee of Hubei University of Technology (Approval No. HBUT20240009). All participants were fully informed of the study details, and written informed consent was obtained prior to the experiment.

4. Result

4.1 Manipulation checks

To verify the effectiveness of the movie type manipulation, an independent samples t-test was conducted. The results revealed a significant difference in ratings between high and low cognitive demand movie conditions (t [238] = 25.624, $p < 0.001$). Specifically, the low cognitive demand movie received a significantly lower rating (M = 2.350, SD = 1.058) compared to the high cognitive demand movie (M = 5.825, SD = 1.042), indicating that the manipulation was successful and the group assignment was effective.

4.2 Moderated mediation model

To examine the effects of review presentation format (bullet-point vs. paragraph) on consumers' decision-making and cognitive responses, and to investigate the moderating role of movie type (low vs. high cognitive demand), this study employed a 2 × 2 between-subjects experimental design and conducted a two-way analysis of variance (ANOVA).

The results of the two-way ANOVA with cognitive load as the dependent variable are presented in Table 3. The main effect of review presentation format was significant, $F(1, 236) = 16.26$，$p< 0.001$，$\eta p^2 = 0.06$. The main effect of movie type was also significant, $F(1, 236) = 138.19$，$p<0.001$，$\eta p^2 = 0.37$. Moreover, the interaction effect between presentation format and movie type was significant, $F(1, 236) = 40.68$，$p< 0.001$，$\eta p^2 = 0.15$, indicating that the effect of review presentation format on cognitive load differed significantly across movie types.

Table 3. Results of two-way analysis of variance.

Source	Sum of Squares	df	Mean Square (MS)	F	p	ηp²
Intercept	4869.00	3	4869.00	23899.11	< 0.001	0.99
Review Format	3.31	1	3.31	16.26	< 0.001	0.06
Movie Type	28.15	1	28.15	138.19	< 0.001	0.37
Review Format * Movie Type	8.29	1	8.29	40.68	< 0.001	0.15
Residual	48.08	236	0.20			

Note: R^2=0.453

Using PROCESS Model 4, we tested the mediating role of cognitive load (M) in the relationship between review presentation format (X; 0 = bullet-point, 1 = paragraph) and decision difficulty (Y), as shown in Table 4. Review presentation format had a significant positive direct effect on decision difficulty (B = 0.19, SE = 0.09, 95% CI = [0.002, 0.375]), supporting H1. Cognitive load exerted a significant positive effect on decision difficulty (B = 0.57, SE = 0.08, 95% CI = [0.415, 0.723]), supporting H3. Moreover, cognitive load partially mediated the relationship between review presentation format and decision difficulty, as indicated by a significant indirect effect (B = 0.13, SE = 0.05, 95% [0.047, 0.229]), providing support for H4.

Table 4. Mediation analysis of cognitive load (M) in the relationship between review presentation format (X) and decision difficulty (Y), and the moderating effect of movie type (W).

Effect Type	B(p)	SE	t	95% CI
Outcome Variable (M)				
X → M	0.24***	0.08	3.05	[0.083,0.387]
X → M (W=0)	-0.14	0.08	-1.66	[-0.299,0.026]
X → M (W=1)	0.61***	0.08	7.36	[0.444, 0.769]
W→ M	0.31***	0.08	3.80	[0.1510, 0.476]
X × W → M	0.74***	0.12	6.38	[0.514, 0.973]
Outcome Variable (Y)				
M → Y	0.57***	0.08	7.27	[0.415, 0.723]
X → Y（Total Effect）	0.32**	0.10	3.15	[0.121, 0.524]
X → Y（Direct Effect）	0.19*	0.09	1.99	[0.002, 0.375]
X → M → Y(Mediation Effect）	0.13	0.05	-	[0.047,0.232]
X → M → Y（(W=0)）	-0.08	0.05	-	[-0.170,0.007]
X → M → Y（(W=1)）	0.34***	0.06	-	[0.230,0.469]

Note: *p < 0.05, **p < 0.01, ***p < 0.001. All continuous variables were mean-centered.

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Using PROCESS Model 7, we further examined the moderated mediation effect, with movie type (W; 0 = low cognitive demand, 1 = high cognitive demand) as the moderator. Movie type significantly moderated the relationship between review presentation format and cognitive load (B = 0.74, SE = 0.12, t = 6.38, p < 0.001), as reported in Table 4 and illustrated in the full path model in Figure 4. A simple slope analysis (Figure 5) revealed that under conditions of high cognitive demand (W = 1), review presentation format significantly predicted cognitive load ($B = 0.61$, $SE = 0.08$, $t = 7.36$, 95% CI [0.444, 0.769]). In contrast, under conditions of low cognitive demand (W = 0), the effect of review presentation format on cognitive load was not significant (B = −0.14, SE = 0.08, t = −1.66, 95% CI [−0.299, 0.026]). To further compute the percentage change in cognitive load, under high cognitive demand condition, the mean cognitive load for bullet-point reviews is 4.543, whereas that for paragraph reviews is 5.150. The latter is 11.8% higher than the former, calculated as [(paragraph mean − bullet-point mean) / paragraph mean × 100]. These results indicate that review presentation format exerts a significant and positive effect on cognitive load only in high cognitive demand contexts. Accordingly, Hypothesis H2 was not supported, whereas Hypothesis H5 was supported. In addition, multicollinearity diagnostics for all regression models are reported in Table S4. The variance inflation factors (VIFs) for all predictors were below the threshold of 3.3, indicating no serious multicollinearity concerns [71].

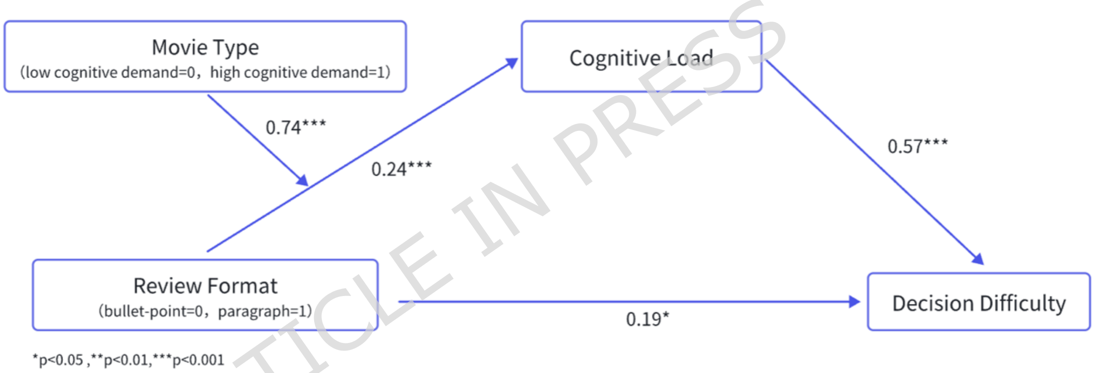

Figure 4. Moderated mediation mode.

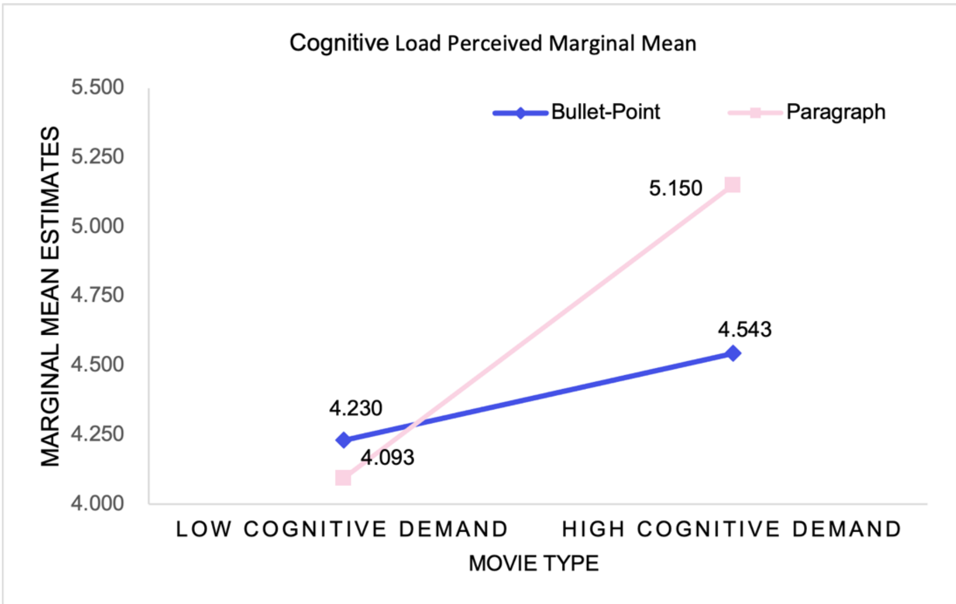

Figure 5. Interaction effect of review presentation format and movie type on perceived cognitive load.

5. Discussion

Grounded in cognitive load theory and cognitive fit theory, this study systematically examines how AI-assisted review presentation formats (bullet-point vs. paragraph) and movie type (high vs. low cognitive demand) jointly influence consumers' cognitive load and decision difficulty. Using a 2 × 2 between-subjects experimental design, the results indicate that AI-assisted bullet-point reviews, particularly for high cognitive demand movies, effectively reduce consumers' information-processing burden. This finding aligns with the signaling principle of cognitive load theory [27,35,72]. The attribute labels in structured reviews act as "cognitive signals," enhancing information organization and attentional allocation, reducing extraneous cognitive load, and improving information accessibility and decision efficiency [73,74].

Furthermore, movie type significantly moderated the relationship between review presentation format and cognitive load. Under high cognitive demand conditions, bullet-point reviews reduced processing difficulty through structured information, demonstrating the advantages of a structured format. In contrast, under low cognitive demand conditions, this structural advantage was not evident, as there was no significant difference in cognitive load between structured and unstructured formats. This may be because users' cognitive resources were sufficient under low-demand conditions, diminishing the additional benefit of structured information. These findings suggest that the effectiveness of information presentation depends on the cognitive demands of the task or context. The results are consistent with cognitive fit theory [49,52], which posits that information-processing efficiency is significantly enhanced only when the presentation format aligns with task complexity [51,57].

Further analysis revealed that cognitive load partially mediated the effect of review presentation format on decision difficulty, indicating that structural optimization does not directly improve decision experience but exerts its influence indirectly by affecting individuals' information-processing. This finding not only extends the application of cognitive load theory to the study of user reviews and interface design but also highlights the critical role of information presentation in shaping cognitive pathways.

Using online movie reviews as an example, this study explores how, in an era of information overload, intelligent algorithms can serve as cognitive aids by presenting structured information, thereby optimizing users' allocation of cognitive resources, enhancing information-processing efficiency, and improving decision effectiveness—achieving human–AI collaborative decision-making. Optimized information presentation not only reduces cognitive friction [75] but also alleviates information asymmetry, providing empirical support for improved platform interaction quality and user satisfaction. Moreover, this study introduces AI as a "cognitive enabler," advancing the empirical development of augmented intelligence theory and offering a scalable theoretical framework for the design of context-aware information systems.

For firms and platform managers, this study suggests that information presentation should be dynamically adjusted based on users' cognitive demands to optimize information delivery and enhance decision efficiency, positioning "optimal decision experience" as a core value proposition. In an environment of information overload, simply maximizing information and functionality—such as ratings, long or short reviews, bullet reviews, and tags—is not necessarily the best strategy. For high cognitive demand content, AI-assisted structured bullet-point presentation is recommended; for low cognitive demand content, traditional paragraph presentation may be retained.

For example, platforms can use AI-assisted structuring to annotate reviews along dimensions such as plot, characters, and production, reducing reading burden while granting reviewers greater freedom and promoting diverse expression (see Figure 6). Platforms can also guide users to write structured reviews (see Figure 7). This cognitively oriented strategy not only optimizes user experience but also helps firms build long-term competitive advantages in the era of information overload, facilitating a shift in management practice from "function-driven" to "user-experience-driven."

Although this study provides preliminary theoretical validation and design implications, several limitations should be noted. First, the sample primarily consisted of university students with higher education, who generally possess relatively high AI familiarity and media literacy. Therefore, the external validity of the findings needs to be further tested in broader populations. Second, the classification of movie type relied on a single-item measure; future research could combine user behavior data or richer movie features to empirically validate the categorization, enhancing its reliability and generalizability. Moreover, cognitive load theory treats cognitive load as a unidimensional construct of information processing, as in this study. However, the presentation of movie reviews and audience responses may be more complex. Factors such as viewers' emotional states, cultural backgrounds, and personal interests may interact with cognitive load, influencing the decision-making process. Thus, cognitive load theory may not fully capture the multidimensional cognitive demands involved in movie consumption.

This study focused on movies, a highly experiential product. Future research could extend the model to other experiential goods to examine its contextual applicability, or design experiments to specifically test moderation and mediation effects. At the same time, factors such as processing fluency, persuasiveness, or visual fluency may influence outcomes in different contexts. Future studies could incorporate user behavior metrics and neurophysiological measures to further examine how these factors affect cognitive and emotional responses, thereby deepening our understanding of decision-making outcomes.

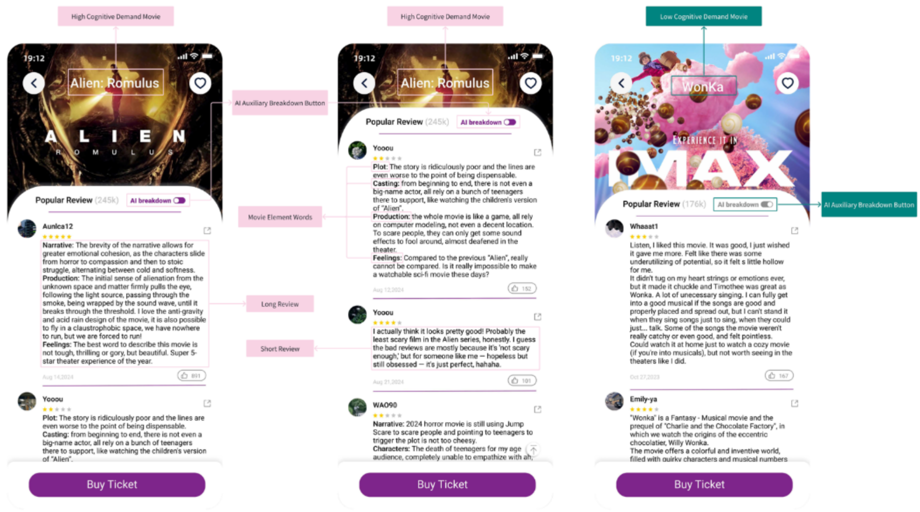

Figure 6. Design of movie platform review interface. (Poster image from *The Movie Database,*, https://www.themoviedb.org/; copyright belongs to the respective movie studios.

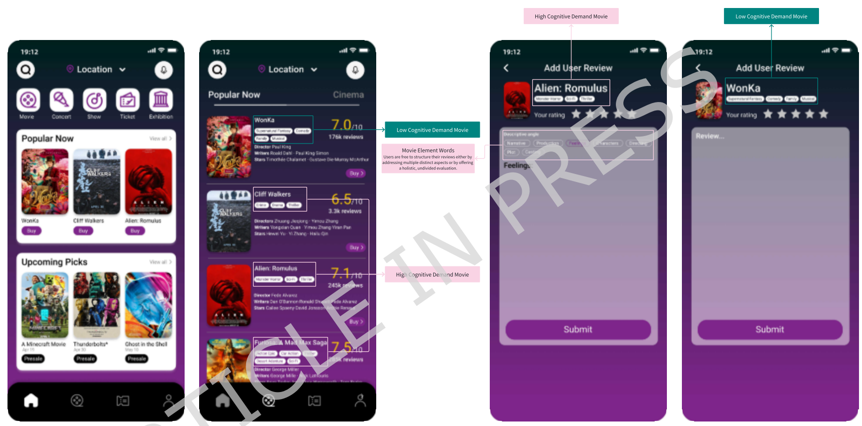

Figure 7. Design of review writing interface for movie platforms. (Poster image from *The Movie Database,*, https://www.themoviedb.org/; copyright belongs to the respective movie studios.

6. Conclusion

Grounded in cognitive load theory and cognitive fit theory, this study systematically examined how AI-driven review presentation formats (bullet-point vs. paragraph) and movie type (low vs. high cognitive demand) influence consumers' cognitive load and decision difficulty. The results showed that, compared with paragraph reviews, AI-assisted bullet-point reviews significantly reduced cognitive load for high cognitive demand movies. However, this advantage was not observed under low cognitive demand conditions, with no significant difference between the two formats. Further analysis indicated that cognitive load partially mediated the effect of review presentation format on decision difficulty, and this mediating pathway was moderated by movie type.

The study proposes a dynamic optimization strategy based on task complexity: AI-structured presentation for high complexity tasks and natural narrative for low complexity tasks. This approach could be extended to other experiential goods with high information asymmetry, such as books, games, and tourism services, to optimize information presentation and enhance decision-making efficiency.

Funding

This study was funded by the Humanities and Social Science Research Youth Fund Project of the Ministry of Education of the People's Republic of China " Research on the Reliability Evaluation and Optimization Mechanism of Online Film Reviews Based on Artificial Intelligence " (No. 21YJC760081).

Author contributions

Q.W: Conceptualization, Methodology, Data curation, Supervision, Funding acquisition; Y.W: Methodology, Data curation, Investigation, Formal analysis, Writing original draft. T.W: Methodology, Data curation, Investigation. S.F: Methodology, Data curation, Investigation, Writing-Reviewing and Editing, Supervision, Funding acquisition; All authors have read and agreed to the published version of the manuscript.

Competing interests

The authors declare no conflicts of interest.

Ethics statement

The present study was conducted in accordance with the ethical principles outlined in the 2013 Declaration of Helsinki and its subsequent amendments or equivalent ethical standards. This research obtained the ethical approval of the Research Ethics and Science and Technology Safety Committee of Hubei University of Technology (No. HBUT20240009).

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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