

Service Modeling for Decision-Making in Product Design Process Based on Knowledge Crystallization Theory: Postprint

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Abstract

[目的/意义] To serve problem-solution decision-making in the product design process, while satisfying the requirements for knowledge retrieval and reuse, and ensuring the sustainable development of products. [方法/过程] Based on the Knowledge Refinement Dual-Cycle Model, problems were identified in existing IBIS models and their improved variants. Therefore, the deliberation dialogue model and product design process were connected using the Knowledge Refinement Dual-Cycle Model to construct an IBIS representation supporting the product dual-cycle model. Traditional deliberation dialogue models employ max-min operators in fuzzy comprehensive decision-making judgments; since such operators may cause certain useful elements to become ineffective, the max-min operator is replaced with the Einstein operator. [结果/结论] The Einstein operator absorbs the concept of ignoring useless value data from the max-min operator, and performs high-level reduction of the data at both extremes. The IBIS representation supporting the product dual-cycle model provides a basic model framework for product design process decision service modeling, while the improved deliberation dialogue model provides reliable assurance for its core algorithm component.

Full Text

Decision Service Modeling of Product Design Process Based on Knowledge Crystallization Theory

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Abstract: [Purpose/significance] This study aims to serve decision-making for problem solutions in the product design process while meeting the needs of knowledge retrieval and reuse, thereby ensuring sustainable product development. [Method/process] Based on the knowledge crystallization double-cycle model, we identified problems in existing IBIS models and their improved variants. Therefore, we connected the discussion dialogue model with the product design process using the knowledge crystallization double-cycle model to construct an IBIS representation that supports the product double-cycle model. Traditional discussion dialogue models employ min/max operators in fuzzy comprehensive decision-making, which can render certain valuable elements ineffective. Consequently, we replaced these min/max operators with the Einstein operator. [Results/conclusions] The Einstein operator adopts the min/max operator's idea of ignoring useless value data while performing high-level reduction of data at both extremes. The IBIS representation supporting the product double-cycle model provides a basic framework for product design process decision service modeling, and the improved discussion dialogue model ensures reliable core algorithms.

Keywords: knowledge crystallization double-cycle model; product double-cycle model; IBIS representation; Einstein operator

The booming development of the internet industry has endowed information with characteristics of massive scale, dynamic change, and multi-source heterogeneity, necessitating fundamental improvements in how domain information is acquired, analyzed, disseminated, and influenced to support major decision-making [?]. V. H. Vroom et al. argue that descriptive and normative questions must be answered regarding the social processes used in organizational decision-making. Decision-making is a social process whose elements are proposed based on events occurring between people rather than within individuals, providing a foundation for elaborating how social interaction within organizations facilitates decision-making. The essence of knowledge crystallization corresponds directly to this perspective, beginning with a question that needs answering and requiring the participation of several people to form an elaboration [?]. R. Butler also believes that the decision-making process is more related to decision problems [?]. Therefore, knowledge crystallization theory has significant relevance to decision-making and can serve it. A. K. Churchland et al. validated from a neurobiological perspective that as task difficulty increases, the time and evidence required for decision-making increase [?]. Li Wu et al. argue that group decision-making research still lacks a relatively complete theoretical system, representing both a difficulty and a priority in research [?]. To concisely summarize the evidence needed for decision-making and reduce leaders' decision-making time, the knowledge crystallization double-cycle model systematically studies the transformation process of data, information, and knowledge to serve decision-making.

Many organizations only preserve final outcomes, leaving subsequent person-

nel confused about the causes and consequences. This often results in successors being unable to fully grasp the work, causing deviations or even counter-productive directions, which is detrimental to both individuals and collectives. Therefore, continuous knowledge accumulation and productization are crucial. Without accumulation, knowledge disappears with project completion and personnel turnover. Productizing accumulated knowledge demonstrates knowledge utilization [?].

Design rationale explains and records the product design process, including all background knowledge and information—such as what specific problems exist, how solutions are conceived, and what those ideas entail. Effectively representing design rationale in computers is fundamental to processing and reusing design knowledge [?]. A good representation model is essential for effective knowledge processing and reuse. The earliest implementation of such design rationale was the Issue-based Information System (IBIS) [?, ?]. The original IBIS evolved over time into an improved model supporting top-down product hierarchical models. Building on previous research, this study develops an innovative knowledge crystallization double-cycle model.

Prior domestic and international research on knowledge crystallization theory is most systematically and comprehensively represented by F. Sun and G. Cai's IBKC (issue-based knowledge crystallization) model [?]. However, their IBKC model only includes the evaporation-condensation process (i.e., removing useless information and retaining useful information for the problem at hand), lacks correlation between evaporation-condensation and evaluation-search processes, and involves only a single operation. In real-world contexts, besides evaporation-condensation, sublimation-deposition and melting-solidification processes also occur as products continuously upgrade. Hence, the knowledge crystallization double-cycle model emerges [?]. The crucial distinction of this model is its application of physical principles from the material world, fundamentally constructing an iceberg double-cycle model and mapping its elements to those of knowledge crystallization theory.

The model comprises two directions: positive and reverse cycles. The reverse cycle process includes five steps: (1) extracting all raw data for the problem to be solved; (2) screening relevant information from raw data; (3) selecting several people from different knowledge structures to read this information, with each person producing an elaboration of the solution; (4) having participants and experts jointly use a discussion dialogue model to select the most acceptable elaboration from all contributions, then refine it through additions, deletions, and modifications to form a solution refinement; and (5) understanding the knowledge structure and preferences of product users through interviews, surveys, and machine learning methods to personalize an easily understandable representation. When users receive the refinement, their comments become the sublimated or melted gaseous/liquid portions that constitute new raw data, generating a new round of changes in information blocks, elaborations, and refinements, thus forming the knowledge crystallization reverse cycle.

The positive cycle represents how users decide whether to use the solution refinement by evaluating and seeking information and raw data behind it. For researchers, tracing back to raw data reveals how raw data combines with solutions—this combination process is deposition or solidification, directly modifying the solution refinement and consequently changing related elaborations, information blocks, and raw data, forming the knowledge crystallization positive cycle [?].

Thus, knowledge does not change linearly from top to bottom, and top-down product hierarchical models have inherent limitations. Based on the knowledge crystallization double-cycle model and combined with product design processes, this study further constructs an IBIS representation supporting the product double-cycle model. The positive and reverse cycles complement each other, enabling continuous product upgrades while improving user experience and helping users with research backgrounds better fulfill their needs.

1 IBIS Research Status

The original IBIS model was proposed by W. Kunz et al. in 1970 [?]. The IBIS diagram is a classic model in design rationale (DR) expression. DR explains the reasons behind artifact design, where “artifact” broadly includes both hard products (manufactured goods) and soft products (language and various structural forms). DR facilitates design reasoning, evaluation, and reuse. The IBIS model includes three elements—issues, solutions, and arguments—plus directed relational edges between them, as shown in [Figure 1: see original paper] [?]. Solutions are ideas proposed in response to issues, while arguments are reasons supporting or opposing solutions.

K. C. B. Yakemovic et al. argue that software design for any large-scale system requires numerous decisions [?]. Most decision support tools have focused on helping users select existing solutions. IBIS provides a documentation framework that clarifies and represents the logic of analytical arguments and reasoning decisions in design and planning processes, applicable to complex designs with broad participation. IBIS’ s primary element is the issue, the organizational “atom” of IBIS. Issues may be of different types: deontic (Should X be this way?), factual-descriptive (Is Y this way?), factual-explanatory (Why is Z the case?), and factual-instrumental (How to achieve W?). Solutions differ accordingly: for deontic types, they can be “yes,” “maybe,” “unlikely,” or “no” ; for factual-descriptive, “yes,” “no,” or “yes, but…” ; for factual-explanatory, “if… then Z is this way” ; and for factual-instrumental, “if…then W can be achieved.” IBIS connects issues, solutions, and arguments into an interconnected network based on different relationship types. Arguments based on support and opposition indeed help identify which solutions were not considered and whether solutions are strong or weak. Therefore, IBIS can be considered a qualitative group decision-making system supporting decision tools, offering insights for hypertext, groupware, and technology-supported design processes [?].

After IBIS was proposed, many scholars adjusted it. Q. Cao et al. [?] argue that current architectural design processes are social activities with expanding participant scope, including not only architects, clients, and engineers but also various scientific and technical experts (e.g., health departments, technical specialists, scientists in special fields), bankers, lawyers, community representatives, environmentalists, government agencies, media, and the general public. With broad social participation, effective management (expression and communication) of information and knowledge in design and decision-making processes has become one of the most urgent tasks for modern design projects. To meet this challenge, academia and industry are developing more effective methods and tools, such as CAD (Computer-Aided Design) and CBR (Case-Based Reasoning). Although people seek breakthroughs in these methods, observation of design processes by many researchers (e.g., Schon, Akin) suggests that logical reasoning based on knowledge represented by rules (explicit and implicit) seems to be the most fundamental tool in designers' search for satisfactory designs. Some studies use fuzzy reasoning systems (FRS) to enhance IBIS, making design analysis more rational and decision thinking more meticulous [?].

E. Toktam et al. designed and developed an IBIS-based tool—IBISMod—that clients can access from anywhere using any platform [?]. The tool also supports synchronous collaborative decision-making processes, where participants can add, edit, delete, and drag nodes. Nodes can be edited or deleted by their creators. Synchronization is achieved by updating each participant's model when the database model changes. When the database model is modified, all users working on the same document receive a message indicating the original model has changed and are asked whether to update their model. The tool uses AJAX methods to improve system response time, which is beneficial when processing large IBIS charts requiring long response times [?].

Li Luye et al. combined requirement representation with the FBS (function-behavior-structure) model to propose an IBIS model supporting top-down product hierarchical models [?].

2 IBIS Representation Supporting Product Double-Cycle Model

[Figure 2: see original paper] shows the IBIS representation supporting product hierarchical models (a top-down representation) proposed by Li Luye et al. [?]. This representation improves the original IBIS model by dividing it into two layers: an upper decision layer and a lower structure layer. Issues in the upper layer are contained within product components in the lower layer. Several solutions responding to this upper-layer issue correspond to sub-components of the lower-layer product components, affecting sub-component structures. Sub-components may also contain new issues, whose solutions correspond to lower-level components, iterating until reaching the smallest parts and forming a complete product hierarchical model.

As the knowledge crystallization double-cycle model reveals, products do not become static after being built through a top-down process. Many products, such as today's smartphones, continuously upgrade, indicating that knowledge involves not only evaporation-condensation but also sublimation-deposition or melting-solidification processes. The specific representation of the product double-cycle model in IBIS is shown in [Figure 3: see original paper] (an extension based on the original IBIS diagram in [Figure 1: see original paper]). The topmost layer is the requirements layer, corresponding to "raw data" in the knowledge crystallization double-cycle model. The dashed box corresponds to the "exquisite knowledge crystal," with the entire process containing both forward and reverse cycles. Requirements include utility requirements (e.g., product components need to include certain sub-components, which may contain next-level sub-components) and non-utility requirements.

In the forward cycle process, utility requirements lead to issue generation, addressing the question of "when to consider issues." Product components contain these issues, while non-utility requirements form information blocks supporting arguments after reading and extraction. Arguments respond to solutions under the support of certain modal qualification values, and solutions respond to issues. Each solution determines the next-level sub-components of product components, which may also contain issues determining their structure. Corresponding solutions then determine the structure of the next-level components. Following this pattern, product design can be refined to the smallest unit—parts. During this process, new data may also be generated as raw data (i.e., requirements), forming the forward cycle.

The reverse cycle process begins inside the dashed box. The smallest unit parts can be traced back to sub-components, product components, arguments, solutions, issues, and requirements through searching and prompting. When returning to requirements (i.e., raw data), new or supplementary combination methods between requirements and the crystal structure within the dashed box may be discovered. The coexistence of forward and reverse cycles forms the IBIS representation supporting the product double-cycle model, which may generate new components or reconstruct original product components during this dual-cycle process.

The IBIS representation supporting the product double-cycle model offers two advantages: (1) Combined with the knowledge crystallization double-cycle model, it demonstrates the dynamic evolution process from coarse to fine and back, explicitly preserving the design process to avoid experience gaps caused by personnel turnover and benefiting knowledge reuse; and (2) Each issue in IBIS can be associated with a specific product hierarchy, effectively organizing originally fragmented IBIS information pieces through the double-cycle model. This allows viewing only hierarchy-related information among massive IBIS data, providing crucial filtering for IBIS information retrieval. Therefore, the IBIS representation supporting the product double-cycle model better supports knowledge retrieval and reuse, facilitating new knowledge generation and

original knowledge reconstruction.

3.1 Discussion Dialogue Model

After establishing the model architecture, we must consider the derivation processes and calculation methods between certain elements within the architecture, leading to the “discussion dialogue model.” When problems arise in product design processes, the discussion dialogue model provides services for their solution. The knowledge crystallization double-cycle model connects the discussion dialogue model with product design processes to construct the IBIS representation supporting the product double-cycle model. As environments change over time, this representation enables products to evolve accordingly, demonstrating the crucial role of the discussion dialogue model.

The discussion dialogue model employs fuzzy quantitative calculation, comparing results to identify the option with maximum acceptability as the group decision outcome. Group discussion information includes participants, organizers, discussion themes, processes, results, and speech information, with participants’ speech being most important. Discussion models primarily organize and manage various information generated in group discussions [?] and support viewpoint analysis and evaluation. Discussion information contains diverse knowledge and positions. In natural states, discussion speech involves large volumes and complex structures, requiring structured discussion models to avoid difficulties in viewpoint analysis and improve discussion efficiency. Discussion dialogue model research constitutes a theoretical foundation for decision-making research.

The argumentation portion involved in the “IBIS representation supporting the product double-cycle model” constitutes the discussion dialogue diagram shown in [Figure 4: see original paper]. The discussion dialogue diagram can be viewed as comprising multiple Issue-based Argumentation Graphs (IAGs). Each IAG includes only one issue node and, centered on it, describes the discussion dialogue activities conducted by the group regarding that issue, forming the basic unit of discussion analysis. The entire discussion dialogue diagram describes the group’s discussion activities on the overall major issue, with each IAG’s results integrated in real-time to form the overall issue result [?]. This study formally defines IAG as follows: Let P_i be the set of solutions connected to issue i , R_i be the set of argument relationships, S be the linguistic evaluation set, and δ be the modal qualification value representing the mapping from argument relationship set to linguistic evaluation set.

Next, we introduce the Toulmin inference model and explain the modal qualification value in the discussion dialogue model. The Toulmin inference model is S. E. Toulmin’s “six-element inference method” proposed in 1958, shown in [Figure 5: see original paper] [?]. Data, claim, and warrant are the three basic elements. Data derives the claim following the warrant. Backing is evidence for the warrant, which remains hypothetical before sufficient evidence is obtained. Backing makes the warrant tenable. The qualifier (corresponding to modal qual-

ification value δ in the discussion dialogue model) indicates claim strength, such as “very good,” “good,” “not good,” “poor,” etc. Inference does not hold beyond the qualifier’ s scope, a situation called rebuttal [?].

For example: “As a senior HR in a Fortune 500 company, based on his experience, he believes that people he recruits can better fulfill their job responsibilities.” Here, “people he recruits” is data, “he is a senior HR in a Fortune 500 company” is backing, “based on his experience” is warrant, “fulfill job responsibilities” is claim, and “better” is the qualifier (modal qualification value). That is, from data “people he recruits,” with backing “he is a senior HR in a Fortune 500 company” supporting warrant “based on his experience,” a claim “fulfill job responsibilities” is generated with qualifier “better.” However, in individual cases, people he recruits may fall far short of job expectations.

Let $S = \{S\alpha \mid \alpha = -t, \dots, -1, 0, 1, \dots, t\}$ be a predefined linguistic evaluation set [?], where we set $S = \{s_3 = \text{‘strongly object (SO)’}, s_2 = \text{‘object (O)’}, s_1 = \text{‘slightly object (LO)’}, s_0 = \text{‘inconclusive (I)’}, s_{-1} = \text{‘slightly support (LS)’}, s_{-2} = \text{‘support (S)’}, s_{-3} = \text{‘strongly support (SS)’}\}$. The modal qualification value δ in the discussion dialogue model can be any of these seven values: “ $s_3, s_2, s_1, s_0, s_{-1}, s_{-2}, s_{-3}$.”

To calculate a solution’ s acceptability, we must first compute argument nodes’ acceptability. Assume a discussion graph $P = A, R, \delta$, where $a \in A$. Let $R^-(a) = \{b \mid b \in A, (b, a) \in R\}$ be argument node a ’ s predecessor set, and $R^+(a) = \{b \mid b \in A, (a, b) \in R\}$ be node a ’ s successor set. If $R^-(a) = \emptyset$, then a is a leaf node. Set argument a ’ s acceptability as $H(a) = s_0$, indicating no support or opposition arguments for a .

If $R^-(a) = \{b_1, b_2, \dots, b_m\}$, then argument a ’ s acceptability is:

$$H(a) = \text{LWA}\{\delta(b_1, a), \delta(b_2, a), \dots, \delta(b_m, a)\} \quad (\text{Formula 1})$$

where LWA is the Linguistic Weighted Averaging operator. The weight w is related to node $H(b)$, calculated as:

$$w_i = \frac{f(H(b_i))}{\sum_{j=1}^n f(H(b_j))} \quad (\text{Formula 2})$$

where $f(H(b)) = I(H(b)) + t$, $I(s) = \alpha$, $2t = |S| - 1$, and $|S|$ represents the cardinality of linguistic term set S . $w \geq 0$ ($i = 1, 2, \dots, n$), and $\sum w = 1$.

Except for leaf nodes, all other argument nodes require reduction. The rule is: Let $\alpha \in A, c \in R^-(b) \neq \emptyset, b \in R^+(a) \neq \emptyset$. Given $\delta(c, a) = s$ and $\delta(a, b) = s$, node reduction rules are shown in [Figure 6: see original paper]:

1. In the discussion graph, remove directed edge (c, a) and add directed edge (c, b) , meaning b ’ s predecessors include a and c .
2. The modal qualification value of directed edge (c, b) is $\delta(c, b) = I^{-1}(\text{sgn}(\alpha) \cdot \text{sgn}(\beta) \cdot (|\alpha| \oplus |\beta|))$. Here, $I^{-1}(\alpha) = s$, $\text{sgn}()$ is the sign

function. This fuzzy comprehensive decision-making formula uses , the Einstein operator, which replaces the min/max operators chosen by some scholars. Since min/max operators are linear and have flaws—their results are determined by only one or several elements without fully incorporating all elements—the non-linear Einstein operator can fully utilize all information provided by raw data.

The Einstein operator () is defined as:

$$A \otimes_{\varepsilon} B = \frac{(1+u)^A - 1}{(1+u)^A + (1+u)^B - 1} \quad (\text{Formula 3})$$

where $w = (w_1, w_2, \dots, w_m)$ is the weight vector of δ ($i = 1, 2, \dots, m$).

Another form is:

$$A \oplus_{\varepsilon} B = \frac{(1+u)^A \cdot (1+u)^B - 1}{(1+u)^A \cdot (1+u)^B} \quad (\text{Formula 4})$$

3.2 Case Analysis of Discussion Dialogue Model Application

Assume a system refinement structure has two different schemes, with experts defining modal restriction values between arguments or between arguments and schemes. We calculate each scheme's acceptability to ultimately select the system refinement structure with highest acceptability. In this study, $|S| = 7$.

If using min/max operators, the reduction formula for [Figure 6: see original paper] would be $\delta(c, b) = I^{-1}(\text{sgn}(\alpha) \cdot \text{sgn}(\beta) \cdot (|\alpha| - |\beta|))$, where I is the min operator. Using the min operator to reduce [Figure 7: see original paper] yields [Figure 8: see original paper], while using the Einstein operator yields [Figure 9: see original paper].

In this example, from a local perspective, the difference in Scheme P_1 after reduction using both operators is $\delta(a_6, P_1)$. The min operator yields S_3 . Although $\delta(a_6, a_1) = S_3$ and $\delta(a_1, P_1) = S_3$ (meaning a_6 strongly supports a_1 while a_1 strongly opposes P_1), this does not imply a_6 strongly opposes P_1 , because $\delta(a_6, a_1)$ only represents a_6 's linguistic evaluation of a_1 , and $\delta(a_1, P_1)$ only represents a_1 's linguistic evaluation of P_1 . The Einstein operator calculates $\delta(a_6, P_1) = S_{1.8}$, which does not take one extreme like the min operator but completely ignores valuable information at the other end. Using operators containing addition, subtraction, multiplication, and division to calculate values from both ends yields more reliable results.

In Scheme P_2 , the difference is $\delta(a_8, P_2)$, where the Einstein operator calculates S_3 . Since one value is 1—the smallest absolute value among linguistic evaluation set elements, which can be ignored in fuzzy calculation—this absorbs the min operator's advantage. Thus, the Einstein operator adopts the min operator's strengths while avoiding its weaknesses.

In the entire discussion dialogue model, the algorithm is improved, yielding more accurate overall results. In this example, the min operator yields $H(P_1) = S_{1.4}$ and $H(P_2) = S_{0.097}$, while the Einstein operator yields $H(P_1) = S_{1.22}$ and $H(P_2) = S_{0.48}$. Since the Einstein operator produces more accurate results, we use its results for analysis, showing Scheme 2's acceptability exceeds Scheme 1's, thereby obtaining the group decision result.

4 Conclusion

Addressing needs for decision service, knowledge retrieval, and reuse, and recognizing limitations in IBIS representations supporting top-down product models, this study improved the IBIS model supporting product hierarchical models under the inspiration of the knowledge crystallization double-cycle model. We designed an IBIS representation supporting the product double-cycle model that displays the complete design process, effectively facilitating knowledge reuse and retrieval. This representation embodies the “double-cycle” connotation of the knowledge crystallization double-cycle model, visualizing the processes of knowledge sublimation, deposition, melting, and solidification (i.e., new knowledge generation and original knowledge reconstruction) and making these processes more effective.

The discussion dialogue model provides services for decision-making in product design processes, while the knowledge crystallization double-cycle model integrates the discussion dialogue model with product design processes to construct the IBIS representation supporting the product double-cycle model. This approach enables products to evolve with environmental changes for sustainable development.

In the argumentation phase, since traditional fuzzy comprehensive decision-making methods using linear min/max operators may have “rob Peter to pay Paul” defects, we replaced them with the non-linear Einstein operator. In the discussion dialogue model, the Einstein operator not only adopts the min/max operator's idea of ignoring relatively useless value data but also enables high-level reduction of valuable data at both extremes, improving calculation result rationality and providing modeling guarantees. The improved discussion dialogue algorithm enhances core algorithm reliability. Since operator calculations involve substantial data that cannot be handled manually alone, applying this method to existing tools and achieving broader application represent important next steps.

References

- [1] Wang Feiyue. Major transformation of knowledge production methods and science and technology decision support: big data and open information-oriented analysis and decision services for science and technology trends [J]. Bulletin of Chinese Academy of Sciences, 2012, 27(5): 527-537.

- [2] Vroom V H, Yetton P W. Leadership and decision-making [M]. Pittsburgh: University of Pittsburgh Press, 1973, 18(2): 3-9.
- [3] Butler R. Strategic decision [M]. Boston: Springer, 1998: 35-50.
- [4] Churchland A K, Kiani R, Shadlen M N. Decision-making with multiple alternatives [J]. Nature neuroscience, 2008, 11(6): 693-702.
- [5] Li Wu, Xi Youmin, Cheng Siwei. Review of group decision-making process organization research [J]. Journal of Management Sciences, 2002(2): 55-66.
- [6] Zou Yu. Thoughts on informatization of engineering consulting enterprises [J]. China Engineering Consulting, 2013(7): 16-20.
- [7] Qin Feiwei, Li Luye, Gao Shuming. Research progress on design rationale [J]. Journal of Computer-Aided Design & Computer Graphics, 2012, 24(10): 1283-1293.
- [8] Conklin J, Selvin A, Shum S B. Facilitated hypertext for collective sense-making: 15 years on from gIBIS [C]// LAP' 03: 8th international working conference on the language-action perspective on communication modelling. New York: ACM, 2003: 1-19.
- [9] Buckingham Shum S, Selvin A M, Sierhuis M, et al. Hypermedia support for argumentation-based rationale: 15 years on from gIBIS and QOC [M]// Dutoit A H, McCall R, Mistrik I, et al. Rationale management in software engineering. Berlin: Springer, 2006: 111-132.
- [10] Sun F, Cai G. Community issue review: crystallizing knowledge for encouraging civic engagement [C]// Proceedings of the 18th annual international conference on digital government research pages. New York: ACM, 2017: 260-269.
- [11] Wu Xiaofeng, Gao Feng, Cai Guorui. Integration development of positive and negative iceberg models and knowledge crystallization theory [J]. Library Theory and Practice, 2019(2): 37-42.
- [12] Kunz W, Rittel H. Issues as elements of information systems [R]. Berkeley: University of California, Center for Planning and Development Research, 1970.
- [13] Zhang Yingzhong, Luo Xiaofang, Chen Qian. Semantic expression of product design principles [J]. Journal of Mechanical Engineering, 2012, 48(17): 135-143.
- [14] Yakemovic K C B, Burgess Y E, Jeffrey C. Report on a development project use of an issue-based information system [C]// Proceedings of the conference on computer-supported cooperative work. Trier: DBLP, 1990: 307-312.
- [15] Quinsan C, Jean-Pierre P. Managing design information: issue-based information systems and fuzzy reasoning system [J]. Design studies, 1999, 20(4): 343-362.

- [16] Toktam E, Maryam P, Martin P. A collaborative Web-based issue based information system (IBIS) framework [EB/OL]. [2018-12-21]. Dunedin: University of Otago, 2009.
- [17] Li Luye, Qin Feiwei, Gao Shuming. Extended design rationale representation for effective support of design knowledge retrieval and reuse [J]. Journal of Computer-Aided Design & Computer Graphics, 2013, 25(10): 1514-1522.
- [18] Tan Junfeng, Zhang Pengzhu, Huang Lining. Discussion information organization model in hall for workshop of metasynthetic engineering [J]. Systems Engineering—Theory & Practice, 2005, 25(1): 86-92.
- [19] Chen Junliang, Chen Chao, Jiang Xin, et al. Group discussion model based on IBIS and Toulmin argumentation form [J]. Journal of Computer Applications, 2011, 31(9): 2526-2530.
- [20] Chen Ning. Application of Toulmin inference model in test validity argument [J]. China Examinations, 2012(4): 15-21.
- [21] Xu Z S. On generalized induced linguistic aggregation operators [J]. International journal of general system, 2006, 35(1): 17-28.

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