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Enhancing novel product iteration: An integrated framework for heuristic ideation via interpretable conceptual design knowledge graph

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ABSTRACT

Novel products emerge over time to survive the competitive landscape as no existing product can perpetually satisfy all evolving customer expectations. These products are often characterized by groundbreaking solutions previously unavailable on the market. However, the swift imitation of successful novel products by competitors underscores the need for sustained iteration and continuous improvement. Designers increasingly face challenges in keeping up to date with the growing volume and fragmented nature of design information from diverse sources. While knowledge graphs show promise in structuring and organizing complex design information, their effective application in the ideation process remains limited due to difficulties in automatic knowledge extraction and the lack of interpretability aligned well with designers' cognitive processes. This study proposes an integrated method to construct an interpretable conceptual design knowledge graph (I-CDKG) that features both inherent and acquired interpretability for heuristic product ideation. First, the schema layer models product design knowledge and governs the semantic connection of design information reinforced by design cognition principles to create a reasonable organizational framework to foster intuitive knowledge exploration. Second, the data layer mainly fulfills automatic and smooth design knowledge extraction for I-CDKG construction through the deep learning ERNIE-BiGRU-CRF model combined with BIESO labeling mode and triple-extracting algorithm. Third, the application layer empowers designers to visually delve into interpretable design knowledge to locate inspiration from cluster, relation, and nest levels and enable constant I-CDKG expansion as design schemes proliferate. A case study on the smart cat litter box demonstrates the feasibility of the proposed methodology. The evaluation results confirm the I-CDKG's advantages as a productive design tool for inspiring creative, practical, and cost-effective product ideations, thereby empowering the iterative development of competitive novel products.

1. Introduction

As the product industry continues to evolve, novel products are continually developed in response to the dynamic market demands, recognizing that traditional products may no longer adequately satisfy customer needs. It is undeniable that not every existing product can indefinitely fulfill ever-changing customer expectations. A *novel product* refers to a product that is newly introduced to the market and is characterized by its innovative features or solutions, offering enhancements to existing products in a way that hasn't been seen before. Typically, these products are in their early stages and have not yet undergone multiple iterations. Once a novel product succeeds, competitors hasten to imitate it, consequently necessitating rapid product iteration to bolster product competitiveness [1]. Despite its importance, the efficient

Abbreviations: AI, Artificial Intelligence; BiGRU, Bidirectional Gated Recurrent Unit; BiLSTM, Long Short-Term Memory; CRF, Conditional Random Field; CNN, Convolutional Neural Networks; DIKW pyramid, Data-Information-Knowledge-Wisdom pyramid; DKE, Design Knowledge Extraction; ERNIE, Enhanced Representation through Knowledge Integration with Explicit Semantics; I-CDKG, Interpretable Conceptual Design Knowledge Graph; KG, Knowledge Graph; LLMs, Large Language Models; ML, Machine Learning; NLP, Natural Language Processing; NPD, New Product Development; RKP, Rapid Knowledge Push.

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iteration of these newer, less-established novel products has been underexplored in the field of new product development (NPD).

One successful example of a novel product is the smart cat litter box, which spurred competition by incorporating technology that automates the cleaning process and monitors the cat's health. In comparison, mature products like air conditioners have existed for many years and have evolved numerous iterations, benefiting from a wealth of accumulated design information. However, while novel products require iteration to remain competitive in a volatile landscape, they often face a relative scarcity of existing design information to encourage updating, primarily due to their limited iteration history.

In this context, one of the most pressing challenges for novel products is the need for prompt collection of design information from diverse sources to help designers keep pace with the latest trends. Such information is vital for product development as it directly contributes to generating product ideas through knowledge reuse. It is widely recognized that in product iteration, designers typically rely on reusing existing knowledge rather than starting from scratch [2]. However, when new design problems arise that require reference to prior solutions, the process of knowledge reuse is significantly hampered if designers cannot quickly locate relevant knowledge scattered and disconnected across fragmented sources [3]. Furthermore, the competence of memorizing and analyzing all design schemes for one designer is limited, with more inspirational ones probably missing out [4].

In this regard, the progress in artificial intelligence (AI) and machine learning (ML), particularly in the form of knowledge graph (KG), offer promising solutions [5,6]. As the conceptual design stage determines approximately 75% of a product's life cycle cost [7], The primary focus of this study is to construct a conceptual design-level KG for knowledge organization and knowledge reuse to support the initial ideation for next-generation novel products. The widely recognized Data-Information-Knowledge-Wisdom (DIKW) pyramid in cognitive science and information science is commonly employed to explain the role of KG [8]. The DIKW pyramid and KG are closely intertwined, with KG acting as a tangible technological implementation of this hierarchical model [9]. According to Fig. 1, KG enables the storage of *design knowledge* extracted from multi-source *design information* such as design schemes, manuals, and patents. This structured approach supports the reuse of inspirational knowledge and facilitates the generation of *design wisdom* for product ideation.

While knowledge reuse ensures the efficient application of accumulated knowledge, knowledge organization forms the essential foundation for this process [10,11]. Specifically, KG possesses *inherent interpretability* represented through knowledge triple <head entity, relation, tail entity> which is the basic unit of each KG. It provides a human-readable and machine-interpretable way to express and preserve complex design knowledge, preventing knowledge loss [12]. Existing research has successfully advanced product design by utilizing KG's inherent interpretability in various contexts, such as product manufacturing [13], personalized customization [14], and performance evaluation [15]. Further, from the perspective of design cognition, the access and exploitation of prior knowledge plays a pivotal role in knowledge reuse and ultimately influence design outcomes [16]. This can be mapped onto the organizational architecture of knowledge triples within the KG, termed *acquired interpretability*. It is developed post hoc to allow more intuitive navigation to rapidly locate inspirational design knowledge, of which incorporating established design cognition principles to reinforce the KG architecture is a direct strategy. However, many existing design-oriented KGs ignore the optimization of acquired interpretability, falling short in adequately supporting designers in generating high-quality ideation.

Despite the potential of KG, its construction faces obstacles in design knowledge extraction (DKE) from unstructured documents [17]. Technically, constructing design-oriented KGs demands advancements in automating DKE processes, particularly through joint-based deep learning approaches that seamlessly integrate multiple tasks—such as entity recognition, relation extraction, and knowledge triple formulation—into a unified framework [18]. Such methods hold promise for efficiently transforming textual data into KG representations while preserving the complexity and specificity of design knowledge [19]. This remains an underexplored frontier, necessitating new method to bridge the gap between unstructured data and structured KG representations in the product design domain. Such method could eliminate the need for extensive retraining of deep learning models, allowing for broader applicability across diverse sources of design documents.

Motivated by these limitations, this study revolves around constructing and applying an interpretable conceptual design knowledge graph (I-CDKG). Compared with existing studies, the primary academic contributions can be outlined as follows.

(1) It is proposed to explore NPD from the perspective of newly launched novel products that stand out due to their innovative features or functionalities but have limited iteration histories. The necessity for knowledge reuse is emphasized to iterate on these products, highlighting the significance of accumulating up-to-date and disordered design information to foster innovative and cost-effective novel products.
(2) A hybrid method is proposed for automatic joint-based design knowledge extraction, combining the deep-learning ERNIE-BiGRU-CRF model, BIESO labeling mode, and triple-extracting algorithm. This novel method transforms unstructured design information into structured design knowledge, serving for the effective construction of I-CDKG.

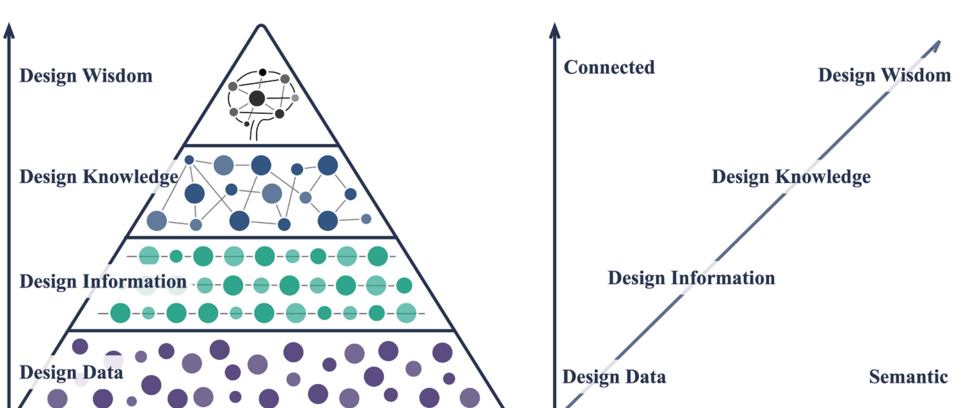


Fig. 1. DIKW pyramid in conceptual product design.

(3) The I-CDKG boasts both inherent and acquired interpretability. It employs a Cluster-Relation-Nest organizational strategy to create a tangible and designer-friendly architecture for storing knowledge triples. This approach explicitly embeds designers' information organization behaviors into KG architecture, enhancing the intuitive locating of design knowledge and generating high-quality heuristic product ideas.

The remainder of the paper is organized as follows. Section 2 outlines the related research background. Section 3 comprehensively illustrates the integrated framework for heuristic product ideation for novel products powered by I-CDKG. Section 4 presents a case study to validate the feasibility of the proposed method. Section 5 carries out evaluations and discusses the effectiveness and limitations regarding the results. Section 6 provides a conclusion, as well as future work.

2. Literature review

2.1. Conceptual product design ideation

Traditionally, designers often rely on brainstorming, mind mapping, or crowdsourcing to generate design ideas, supplementing their domain knowledge. To improve efficiency, the function-behavior-structure (FBS) model [20] and quality function deployment (QFD) [21] can be employed to develop and apply heuristic design principles. They offer structured methods for understanding and organizing design information, facilitating the creation of effective heuristics for solving design problems. TRIZ [22] is a heuristic design method that complements FBS and QFD by providing a systematic set of strategies for generating innovative solutions. Lee et al. [23] combined laddering theory, TRIZ, and QFD technique to realize effective design knowledge handling in innovation conceptualization. While these approaches are valuable for creating structured design heuristics, they often fall short in navigating the complex and open-ended design space. Usually, designers can only walk through a limited number of references or become "fixated" on limited ideas, where potential candidate ideas may be overlooked [24].

This gap has led to the exploration of ideation methods through the AI lens, which leverages computational power to process sheer volumes of data and alleviate designers' cognitive load. Unlike traditional design thinking or principles, AI-driven approaches represent a shift in how creativity and ideation are approached in product design [4]. AI techniques, particularly in computational creativity, focus on data-driven insights to develop creative tools that can aid designers in generating ideas more efficiently [25]. Zhang et al. [26] advocated a digital characterization and identification process model that enables intelligent design by digitally characterizing functional genes and rapidly identifying them with computer assistance. Chen et al. [25] introduced an integrated approach to enhance design ideation using AI and data mining techniques. This method included a semantic ideation network and a visual concepts combination model, inspiring both semantically and visually. Demirel et al. [27] presented a collaborative approach for quick-and-dirty concept creation and evaluation. It formulated a human-centered generative design framework that incorporates human factors early in the design process. In the context of AI-enhanced Smart Product-Service Systems (Smart PSS), Cong et al. [28] proposed an AI-assisted conceptual design method for Smart PSS that analyzes user-generated emotions and feelings. An interactive emotion board was introduced as a new design tool to organize these emotions, related design elements, and potential design points. Due to rapid changes in usage scenarios, Wang et al. [29] presented an AI-driven method that offers recommendations for selecting appropriate solution bundles by creating an adaptive, co-evolving value-co-creation system with active user participation throughout the product lifecycle.

Building on these advancements, recent breakthroughs in natural language processing (NLP) and ML have given rise to large language models (LLMs) that can produce creative outputs from textual prompts. While still a relatively new area in product design research, Bouschery et al. [30] investigated the potential of transformer-based language models to enhance human innovation teams in NPD. Their work demonstrated how these models can expand the exploration of problem and solution spaces, bringing forth improved innovation performance. Ma et al. [31] utilized LLMs to generate solutions for 12 design problems and compared these to a baseline of crowdsourced solutions. Their findings shed light on the quality of design solutions produced by LLMs and initiate an evaluation of prompt engineering techniques that practitioners could use to collaboratively generate higher-quality design solutions with LLMs.

Surveying the literature, an interesting yet overlooked phenomenon emerges: most research on design idea generation focuses on well-established products that benefit from rich iteration histories, leaving a gap in studies specifically targeting the novel products defined in this paper. This gap forms the foundation for the research presented here. For novel products that achieve early success, ideation becomes critical due to the intense competition they face. This competition drives shorter iteration cycles, limiting the time available for creative and inspirational exploration [24]. Additionally, these products differ from existing ones in that they inherently and relatively lack as much historical data and user feedback compared to long-established and mature products [1]. This tension between the need for rapid ideation and the limited time available serves as the driving force behind this paper's exploration of methods to enhance the efficient iteration of novel products. Specifically, the focus is on how to gather and utilize the growing and scattered design information from diverse resources in a timely manner.

2.2. Knowledge graph for product design

All of the references about KG for product design are listed in Table 1 for comparison.

2.2.1. KG application in product design

(1) Application of inherent interpretability

KG is not a completely new concept and can be traced back to Expert System [42], Ontology [43–46], and Semantic Network [33,47,48]. These predecessors laid the groundwork for today's KGs, which have shown significant promise in product design and are now recognized as a core element of next-generation industrial information systems [49]. Through the inherent interpretability formed by entities and their semantic relationships, KG has been extensively applied in the product design field.

Theoretically, employing KGs for product conceptualization is reasonable and well-founded. The use of KGs to support product design aligns closely with C-K design theory [50], which emphasizes the interaction between the concept space (C) and the knowledge space (K) to catalyze innovative product iteration. Within this framework, knowledge space (K) allows designers to create new design concepts, a process referred to in the theory as a K-C transformation or disjunction. Li et al. [18] expanded on this by integrating KG with the C-K model, significantly enhancing its practicality and productivity. They introduced an evolutionary design approach by developing two KGs and four KG-assisted C-K operators, facilitating the generation, validation, and optimization of design concepts.

Transitioning from theory to practice, TechNet[1] stands as a prominent example of a successful open-source engineering KG. In academic applications, Table 1 illustrates that most existing studies focus on leveraging KGs for product ideation. Shi et al. [34] created an engineering-specific ontology network by integrating text mining methods to construct unsupervised learning associations within design

[1] https://www.tech-net.org/.

Table 1
References comparison about KG for product design.

Reference, year	KG name	Key DKE technique	Joint-based DKE	Acquired interpretability	Case study	Design topic
Bharadwaj and Starly [32], 2022	PDKG	CNN	×	×	3D CAD model	3D model retrieving
Jing et al. [33], 2023	DKSN	BiLSTM-CRF	×	×	Pipeline inspection trolley	User preference mining
Han et al. [15], 2023	/	OWL language	×, manual	×	Bogie	Product performance evaluation
Liang et al. [16], 2024	PDI-KG	Latent semantic analysis	×	✓	Diaphragm parts	Process design
Shi et al. [34], 2017	/	NLP, item set association mining	×	×	Household water-purifier	
Li et al. [18], 2020	EKG, IKG	Stanford CoreNLP (BiLSTM-CRF)	✓	×	Smart nursing bed	
Jia et al. [35], 2021	DSKG	Tensor factorization	×, manual	×	Stamping die	
Zhang et al. [36], 2021	/	Semantic role labeling	×	✓	Fork	
Liu et al. [37], 2022	FSCN	Stanford Parser (BiLSTM)	✓	×	Drone	
Huang et al. [38], 2023	mKGCD	Stanford Parser (BiLSTM)	✓	×	Installation and handling equipment	Design ideation
Cheng et al. [39], 2024	MPDKG	BERT-BiLSTM	✓	×	New energy vehicle	
Jiang et al. [40], 2024	PKGADS	BERT-BiLSTM-CRF	×	×	In-pipe inspection robots	
Wang et al. [41], 2024	BIPD-KG	Annotation programs	×, manual	×	Coffee machine, water dispenser, and sofa	
Proposed framework	I-CDKG	ERNIE-BiGRU-CRF	✓	✓	Smart cat litter box	

contexts. In advancing data-driven design, Liu et al. [37] proposed the function-structure concept network, which boosts designers' creativity and idea generation by associating functional and structural information through sentence parsing and phrase extraction. From the perspective of tacit knowledge capture, Jia et al. [35] addressed capturing and reusing implicit design knowledge through relational learning for KG. Jiang et al. [40] expanded on this by establishing a patent KG that uncovers hidden relationships between design knowledge, providing novel insights that align with design preferences and stimulate creative solutions. To capture both explicit and tacit knowledge, Zhang et al. [36] developed an industrial KG that captures deep relational knowledge to support customization. With the rise of personalized customization, Cheng et al. [39] built a multi-domain product design KG, establishing cross-domain mappings to better adapt to evolving customer demands. Some studies integrate multiple KGs, Huang et al. [38] developed a multi-layer KG for conceptual design to mitigate the impact of conflicts on requirement-function-structure mapping. Other design topics drawing upon KG include 3D model retrieval [32], user preference mining [33], product performance evaluation [15], and process design intent [16].

Summarizing the above studies, they provide new methods that enhance design efficiency and innovation, underscoring KG's versatility in supporting different design stages [51]. The key strengths of KGs in conceptual product design are threefold. First, KGs provide greater flexibility and demonstrate stronger semantic parsing capabilities in knowledge re-utilization because of the arbitrary linkage among entities. Second, by deploying NLP techniques, KGs demand less time and manpower for evolutionary construction. Third, Designers can participate in the KG construction and updating, integrating their expertise and insights into it, enhancing designers' trust in the KG.

(2) Exploration of acquired interpretability

Unlike inherent interpretability, which is represented by knowledge triples by default, the acquired interpretability of a KG can be tailored to suit the specific needs of downstream tasks. While the inherent interpretability enables the accumulation of large amounts of design knowledge, design cognition suggests that success in design is not solely determined by the quantity of knowledge accumulated, but rather by how designers use that knowledge during the design process [52]. This underscores the necessity to explore ways to enhance the acquired interpretability of KGs. Inspired by this, one of the most effective strategies for customizing acquired interpretability is to leverage existing design cognition models, theories, or principles. This approach ensures that the KG aligns more closely with the cognitive processes and behaviors of designers, thus improving its utility in real-world design contexts.

It can be seen in Table 1 that only two studies have explored the concept of acquired interpretability. Zhang et al. [36] proposed a C-RFBS model which is derived from FBS model for the efficient reuse of interpretable design knowledge records across knowledge networks. Liang et al. [16] highlighted the challenge of capturing process design intent, which is tacit experiential knowledge embedded within process design but lacks a structured organizational framework and effective methods for representation. However, to the best of our knowledge, there remains a significant gap in research. Few studies have fully explored and applied cognitive theoretical frameworks to make KGs more intuitive and suitable for product designers, enabling them to better navigate and utilize design knowledge. This study aims to construct a KG that simultaneously possesses inherent and acquired interpretability to enhance designers' ability to generate high-quality heuristic product ideations.

2.2.2. Construction techniques for product design-oriented KG

Technically, the construction of product design-oriented KG often relies on text mining and ML tools to process raw design information from heterogeneous data sources, such as user-generated content, patents, design specifications, and design activities [53]. Entity recognition and relation extraction play a critical role in the identification of entities and relations from these sources. Collectively, these two processes are referred to as DKE, forming the backbone of the automatic construction of KG.

It is evident in Table 1 that several recent studies still rely on manual construction [15,35,41], which is time-consuming and labor-intensive. For automatic DKE, there is frequent adoption of NLP methods and toolkits. Advanced deep learning techniques, such as Convolutional Neural Networks (CNN) and Bi-directional Long Short Term Memory (BiLSTM), are used more frequently to perform DKE tasks from multi-disciplinary sources [49]. These mainstream DKE methods are typically categorized into pipeline-based and joint-based approaches. The pipeline-based approach treats entity recognition and relation extraction as separate subtasks, with relation extraction occurring after entity recognition. In contrast, the joint-based approach performs entity recognition and relation extraction simultaneously within the same model. Notably, as shown in Table 1, joint-based DKE methods [18,37–39] remain relatively underexplored. According to [13], it has been proven that joint-based methods presented stronger advantages than pipeline-based ones because of the enhanced relationship preservation, reduced error propagation, and improved efficiency and consistency. Therefore, further contributions are necessary to achieve efficient and automatic joint extraction of entities and relations, accelerating the construction of KG in the product design domain with the assistance of NLP techniques.

3. Methodology

Fig. 2 depicts a KG-based flow supporting novel product iteration in conceptual design. A small-scale KG for the novel product is established from the initial data foundation. In response to input design problems, product ideation is generated through knowledge push, which means the action of retrieving stored knowledge from KG to inspire the ideation of next-generation products [54]. During this process, two situations may arise: one where existing knowledge can be inferred and reused from the established KG (AI-supported), and another where designers need to be involved to create new knowledge if no knowledge can be reused (designer-supported). With the continual introduction of new design schemes, KG is expanding and refining to ensure timeliness and completeness. This study focuses on the journey from the input of "design problems" to the output of "heuristic product ideation." This approach places significant emphasis on creating a "space" conducive to sustaining innovation, with the KG serving as its core.

3.1. Overview of the integrated schema-data-application framework for heuristic product ideation via I-CDKG

An overview of the proposed framework is illustrated in Fig. 3. Based on the theory of KG [55], the detailed explanation of these three layers in I-CDKG is as follows:

(1) The schema layer establishes the overall and basic structure of I-CDKG, providing the semantic foundation for the data layer. It is typically static and infrequently altered.
(2) The data layer populates the structure defined in the schema layer to form and visualize I-CDKG, containing accumulated design knowledge. It is dynamic and evolves with time and scheme updates.
(3) The application layer applies the I-CDKG to practical design scenarios, supporting the generation of heuristic product ideation and dynamic knowledge expansion.

3.2. Schema layer

3.2.1. Interpretable architecture of I-CDKG based on design cognition

In essence, the I-CDKG is defined as a graph $G = \{E, R, T\}$, where E is a set of design element entities, and R is a set of relations that link two entities. T represents all knowledge triples. A knowledge triple is indeed the fundamental unit of the I-CDKG. In each triple $T_i = < E^i_{head}, R_i, E^i_{tail} >$, E^i_{head} is the head entity in triple T_i, E^i_{tail} is the tail entity, and R_i is the relation between E^i_{head} and E^i_{tail}.

Beyond these basic inherent elements, the I-CDKG is designed to build the acquired interpretability based on design cognition findings by Damen and Toh [52]. Their study identifies three key information organization strategies employed by experienced designers during the early phases of the design process: Clusters, Relations, and Nests. The Cluster-Relation-Nest organizational strategy improves information clarity, enhances the comprehensibility of the entire I-CDKG, and solidifies the foundation for subsequent knowledge exploration (Section 4.3.2). Each strategy represents an explicit approach to linking various types of design information, achieving a better explicit representation of the design cognitive process. The specific mapping mechanism of these strategies within the I-CDKG is as follows.

Clusters → Nodes: The cluster strategy refers to designers typically grouping design ideas with similar characteristics or purposes. When applied to the I-CDKG, a cluster contains various design elements with the same attributes, which can be stored as nodes in the KG. For instance, all nodes representing the components of the smart cat feeder (such as the cat bowl, control panel, and food reservoir) can be

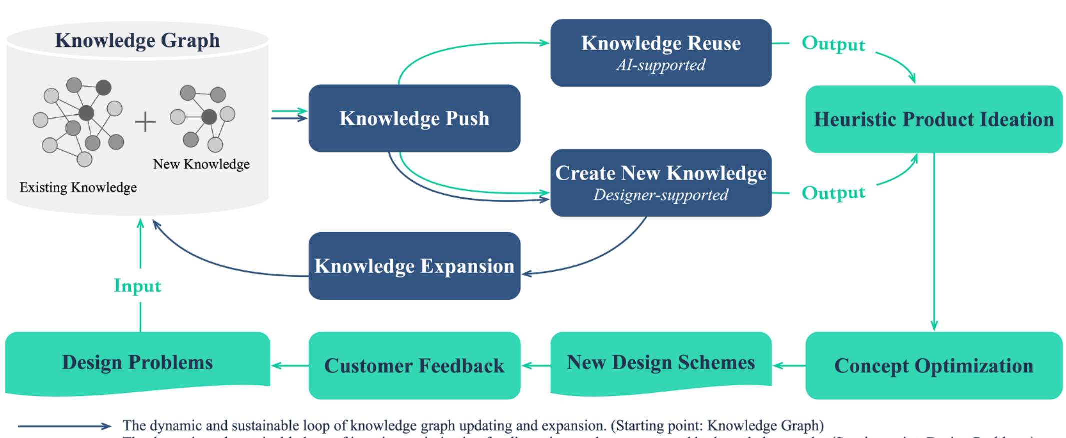


Fig. 2. A KG-based flow supporting novel product iteration in conceptual design.

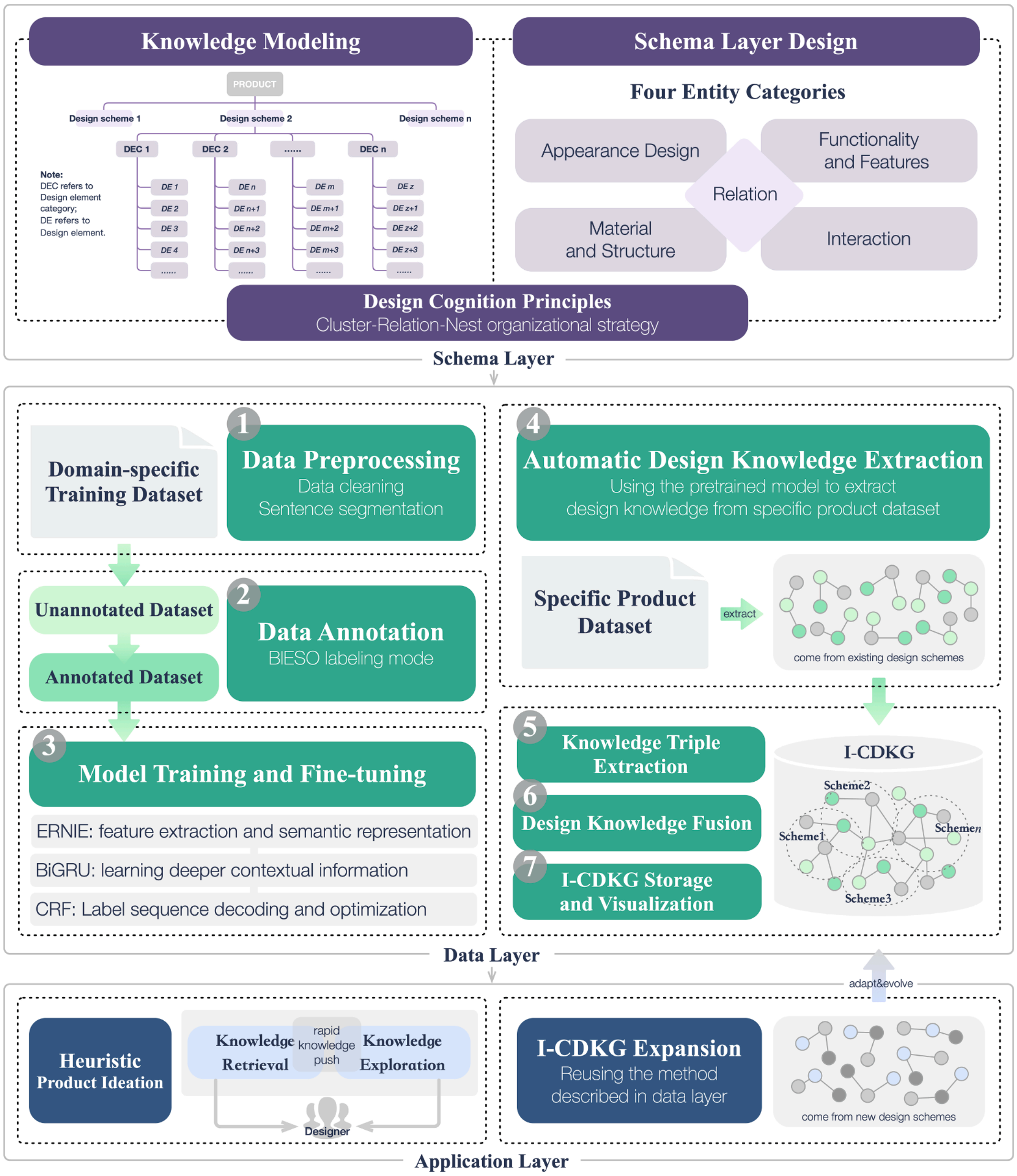


Fig. 3. Framework of the design heuristic generation for novel product iteration powered by I-CDKG.

considered as a cluster, collectively constituting the primary parts of the feeder.

Relations → Edges: The cluster strategy refers to designers focusing on the relationships or interactions between different design elements. Specifically, this involves combining multiple functions, technologies, or design features to create more complex and cohesive design concepts. In the I-CDKG, these relationships between design elements can be represented as edges in the KG. For example, the relation "Has_Material" indicates that the material used for the cat bowl is stainless steel.

Nests → Sub-KGs: The nest strategy refers to how designers combine multiple design features, functions, or concepts in a way that they support or enhance each other, resulting in a more complex and integrated design solution. All design information corresponding to a design scheme forms a nest, which can be transformed into a sub-KG. Each design scheme can be considered an initial node, with associated design elements seen as nodes directly or indirectly related to the initial node.

This architecture reduces the data granularity from the abstract level (in the designer's cognition) to the structured level (in the visual graph). Taking the simplest form of the I-CDKG, which consists of a single sub-KG, Fig. 4 showcases how the Cluster-Relation-Nest strategy maps onto the one sub-KG, guiding its acquired interpretability. Different sub-KGs are interconnected by shared nodes, ultimately forming the I-CDKG. Consequently, the I-CDKG can also be expressed as $G = \{E, R, T\} = \{subKG_1, subKG_2, \cdots, subKG_n\}$.

3.2.2. Design knowledge modeling

Since there are no existing knowledge models available for reuse, a knowledge modeling strategy for I-CDKG needs to be devised to support the interpretable architecture. The strategy involves following steps to ensure a thorough design knowledge model.

Step 1: Clearly define the target products, and then classify them based on their intended purposes. For example, smart cat products available in the market include smart feeders, smart water dispensers, smart litter boxes, smart drying boxes, portable monitoring cameras, etc. Within each product group, there exist numerous design schemes.

Step 2: Summarize the relevant knowledge about conceptual design, classified into four categories: appearance design (AD), functionality and feature (FF), material and structure (MS), and interaction (IR).

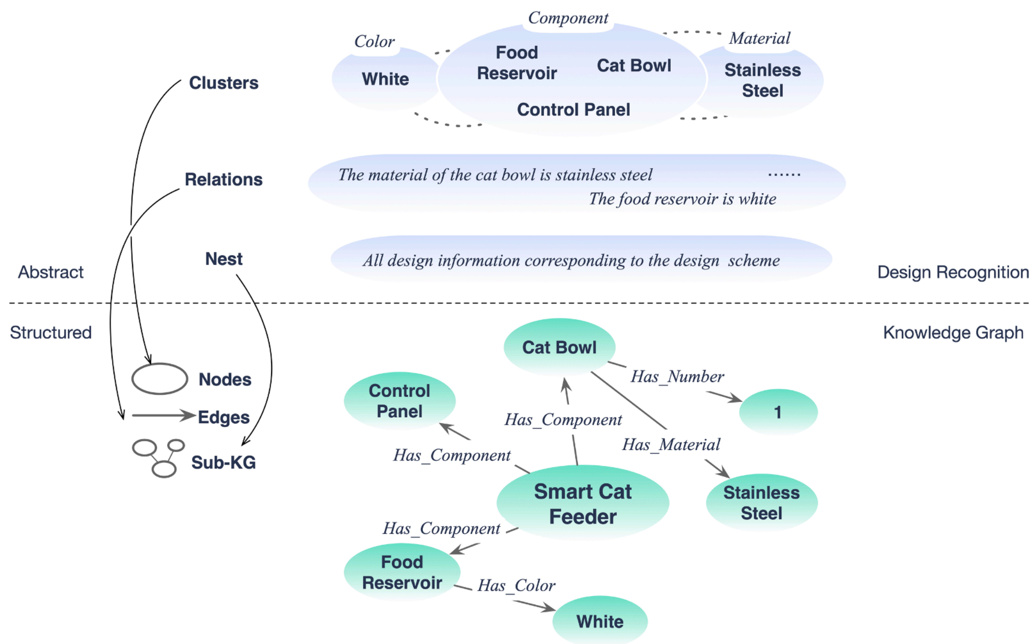


Fig. 4. Illustration of a simplified I-CDKG architecture grounded in Cluster-Relation-Nest organizational strategy.

Step 3: Define the specific design knowledge encompassed within each category mentioned above.

(1) AD refers to the external visual characteristics of a product, which includes elements such as shape, color, contour, style, etc.
(2) FF denotes the tasks that the product can perform as well as its unique attributes, which include the main functions, outstanding characteristics, supported technology, etc.
(3) MS describes the composition and arrangement of components within a product, which includes connection methods between components, structure of the component, materials, etc.
(4) IR emphasizes the interaction methods between the product and users, which includes interface design, interaction methods, basic equipped sensors, etc.

3.2.3. Schema layer design

Based on the well-structured knowledge model, entity types and relation types of design knowledge in the I-CDKG can be defined, known as the schema layer. The schema layer provides a unified data model and architecture. It specifies the organizational structure and attribute definitions of the data in the KG to ensure consistency and scalability.

The I-CDKG schema layer is expressed as $S_{CDKG} = \{T(E), T(R)\}$. $T(E)$ represents the same type of entity, such as $T(E_i)$ representing the color of different product components. $T(R)$ represents the same type of relation, such as $T(R_j)$ representing two components of the product having a certain type of connection method.

3.3. Data layer

3.3.1. Data preprocessing

In product design schemes, data are usually in different formats and intricate structures [13], posing challenges for direct utilization. Preprocessing steps are essential to prepare the data for meaningful analysis.

(1) Data cleaning: unstructured contents are transformed into natural language to ensure uniformity. Redundant words and irrelevant information are removed to enhance data relevance. Error correction is carried out to rectify inaccuracies within the dataset.
(2) Sentence segmentation: lengthy and complex sentences are disassembled into standardized and logically coherent units, making the data more digestible for subsequent analysis.

3.3.2. Integrated BIESO labeling mode

After preprocessing, the design data remains incomprehensible to machines. Semantic annotation is performed to enable knowledge extraction models (Section 3.3.3) to correctly understand and extract design knowledge. This paper introduces an integrated BIESO labeling mode [56] to support the entity-relation joint extraction task. The "O" tag denotes "Other," indicating that the word is independent of the extracted triples. Apart from the "O" tag, other labels consist of three components in the format of "X-YYY-Z":

(1) X: Word position in the entity is encoded by the signs in {B, I, E, S}, denoting {Begin, Inside, End, Single}.
(2) YYY: Relation identifiers are encoded according to the relation types defined in the established schema layer, such as {COL, MAT, LIN, CHA, …} corresponding to {Has_Color, Has_Material, Are_Linked, Has_Characteristics, …}.
(3) Z: Entity role is encoded by the signs in {1, 2}, representing {head entity, tail entity}.

Take the triple <落砂踏板 (litter tray step), COL, 白色 (white) > for example. The Chinese character "落" is the beginning word of the head entity "litter tray step" and is related to the "COL" relation. Therefore, "落" is labeled as "B-COL-1.".

3.3.3. Design knowledge extraction

Based on the labeling mode introduced in Section 3.3.2, DKE can be transformed into a sequence labeling problem using the ERNIE-BiGRU-CRF model [57]. As shown in Fig. 5, the model takes a text sequence as input and outputs every word's label.

(1) The ERNIE layer transforms the input design text sequence into semantically rich representations to enable subsequent layers to better understand the text meaning. Assuming the input design text sequence is $Z = \{z_1, z_2, z_3, \cdots, z_n\}$, where n represents the length of the sequence. The ERNIE layer processes Z to generate low-dimensional word embeddings E from three aspects: token,

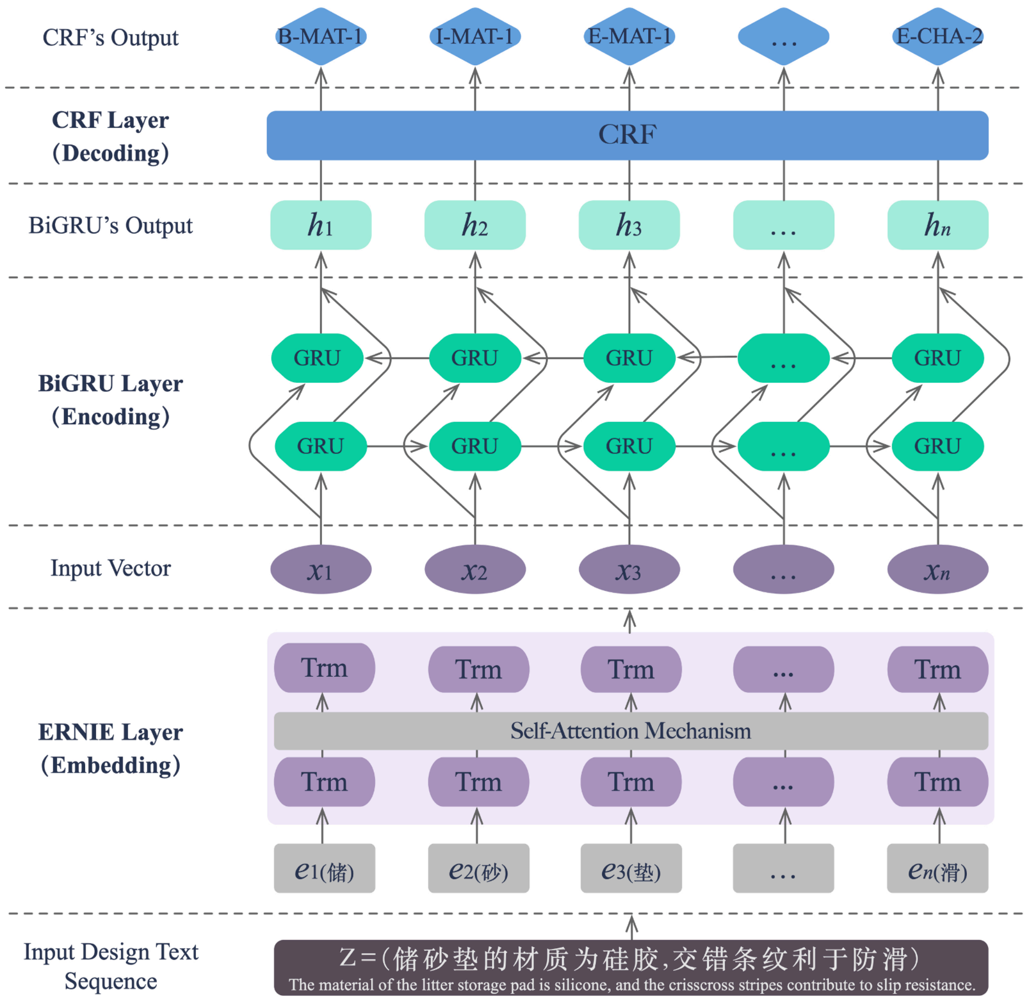


Fig. 5. Structural overview: ERNIE-BiGRU-CRF model for design knowledge extraction.

segment, and position. E serves as the input for the transformer encoder. Through a self-attention mechanism, the transformer captures semantic and syntactic features of Z, denoted as $X = \{x_1, x_2, x_3, \cdots, x_n\}$.

(2) The BiGRU layer is used to mine the deeper features and information from vector X. The specific operations are as follows.

Step 1: Input each x_i from vector $X = \{x_1, x_2, x_3, \cdots, x_n\}$ into each time step of the BiGRU network for bidirectional encoding.

Step 2: Obtain the forward feature vector $\overrightarrow{H}$ by employing the forward GRU, $\overrightarrow{H} = ForwardGRU(X) = \left\{\overrightarrow{h}_1, \overrightarrow{h}_2, \overrightarrow{h}_3, \cdots, \overrightarrow{h}_n\right\}$.

Step 3: Obtain the backward feature vector $\overleftarrow{H}$ by employing the backward GRU, $\overleftarrow{H} = BackwardGRU(X) = \left\{\overleftarrow{h}_1, \overleftarrow{h}_2, \overleftarrow{h}_3, \cdots, \overleftarrow{h}_n\right\}$.

Step 4: Concatenate the forward feature vector $\overrightarrow{H}$ with the backward feature vector $\overleftarrow{H}$ to obtain the complete feature vector sequence H, $H = \left[\overrightarrow{H}, \overleftarrow{H}\right] = \left\{\left[\overrightarrow{h}_1, \overleftarrow{h}_1\right], \left[\overrightarrow{h}_2, \overleftarrow{h}_2\right], \left[\overrightarrow{h}_3, \overleftarrow{h}_3\right], \cdots, \left[\overrightarrow{h}_n, \overleftarrow{h}_n\right]\right\} = \{h_1, h_2, h_3, \cdots, h_n\}$.

(3) The CRF layer models label sequences globally, enhancing the overall performance of the sequence labeling task. The output of BiGRU H serves as the input to the CRF layer. During inference, the model selects the label sequence with the highest total score as the final prediction.

3.3.4. Knowledge triple identification

After acquiring the labeled design text sequence, post-processing steps are needed to extract knowledge triples from the label sequences and corresponding text sequences. This process is necessary for knowledge fusion and supplements the ERNIE-BiGRU-CRF model. A set of triple-extracting algorithms are accordingly designed to extract knowledge triples in the form of <head entity, relation, tail entity> . The pseudocode is outlined in Appendix A. At this stage, the automatic joint-based DKE process is complete, achieved by integrating Section 3.3.2 to Section 3.3.4.

3.3.5. Knowledge fusion and storage

Discrepancies exist in the entity names across different data sources. To eliminate ambiguity and facilitate knowledge storage and management, it's essential to merge entities with similar meanings. For instance, both "储粮桶" and "粮桶" essentially refer to the same concept, which denotes a container for storing cat food. The unified term "储粮桶" can be specified to represent this concept.

In this study, Neo4j[2] is utilized to store knowledge triples. In Neo4j, the head and tail entities are stored as nodes, while the relations are stored as edges. Through Neo4j Browser, designers can interactively explore and comprehend the structure and content of I-CDKG.

[2] https://neo4j.com/.

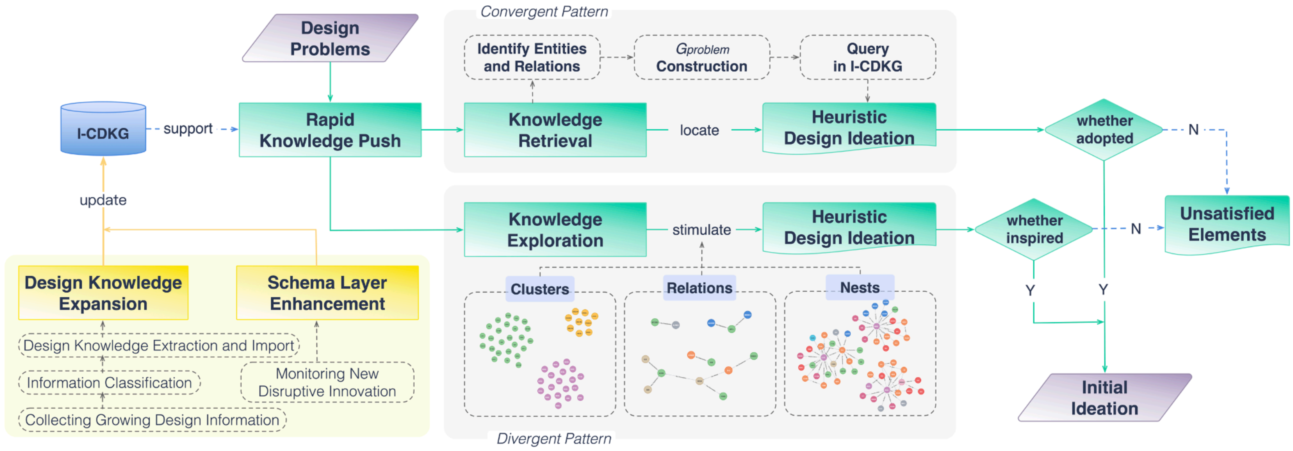


Fig. 6. The designer's involvement flow during the interaction with I-CDKG.

3.4. Application layer

The I-CDKG is envisioned as a tool to assist designers in 2 key aspects. Firstly, it supports designers in generating heuristic design ideas through rapid knowledge push (RKP) including knowledge retrieval and knowledge exploration. Secondly, it allows designers to dynamically enhance the schema layer and supplement newly emerging design information, ensuring the I-CDKG remains up-to-date. The interaction flow between designers and the I-CDKG is illustrated in Fig. 6.

3.4.1. Heuristic product ideation aided by I-CDKG

(1) Knowledge exploration: stimulating divergent thinking

Knowledge exploration can provide valuable references that foster divergent thinking in designers, promoting the generation of heterogeneous and innovative ideas. Grounded in design cognition principles, the I-CDKG architecture supports 3 distinct cases of knowledge exploration for finding potential inspiration.

Case 1: From the *Cluster-level* perspective, if a designer is interested in a particular design element, they can use Cypher queries to group together and analyze all relevant nodes that share common design elements.

Case 2: From the *Relation-level* perspective, based on the nodes identified in Case 1, designers can expand the edges of a node they wish to explore further to observe its relationships with other different types of nodes.

Case 3: From the *Nest-level* perspective, if a designer is interested in an entire design scheme, they can directly explore the corresponding sub-KG. This allows them to see all clusters (nodes) within the sub-KG and investigate the relations (edges) between different nodes.

(2) Knowledge retrieval: promoting convergent thinking

Knowledge retrieval can promote convergent thinking, helping designers narrow the research space and confine ideas more deeply. It filters through stored design knowledge and swiftly identifies design knowledge from the I-CDKG that matches a given design problem. Here are the detailed steps for locating heuristic ideas for specific design problems based on knowledge retrieval.

Step 1: Identify the entities and relations involved in the design problem according to the schema layer defined in Section 3.2.3.

Step 2: Use the Cypher language to write queries, constructing MATCH, WHERE, RETURN, and other statements to manipulate the graphical structure $G_{problem}$ related to design problems.

Step 3: Execute the Cypher query $G_{problem}$ against the I-CDKG to push relevant design knowledge and information to designers.

Step 4: Analyze the retrieved knowledge to generate heuristic ideas, incorporating insights and patterns identified from the query results into the initial design problem-solving process.

3.4.2. Dynamic I-CDKG expansion

(1) Design knowledge expansion

As novel products undergo continuous iteration and new revolutionary products emerge in the market, the volume of design information continues to grow. Scrapy is utilized to extract relevant product design documents and images from specified databases or web resources. When necessary, manual intervention is required to convert product design diagrams into natural language descriptions. After completing a new project, designers can add project-related design schemes to the I-CDKG. The collection of these new technological files depends on records provided by the designers. To enhance the efficiency of data preparation, ERNIE is utilized to automatically classify these newly collected design information files. The integrated method described in Section 3.3 can be repeatedly applied to automatically import all new design information into the established I-CDKG, ensuring that it remains sustainably updated over time.

(2) Schema layer enhancement

Although the schema layer does not change frequently, unexpected developments may occasionally occur for novel products. To adapt to new design needs and technological advancements, schema layer enhancement needs to be monitored and updated manually due to its design-specific nature.

4. Case study

The case study focuses on the burgeoning cat industry in China, which has witnessed a surge in the development of novel products for both cats and their owners. Among these innovations, the first Chinese-brand smart cat litter box was introduced to the market in July 2020 by the leading company PETKIT. Following this introduction, competitors began to imitate PETKIT's innovation. To showcase the applicability of the introduced methodology, the smart cat litter box is selected as the target product to construct a pilot I-CDKG.

4.1. Schema layer formation

According to Section 3.2.2, the design knowledge model of smart cat products is constructed following the introduced three steps, as illustrated in Fig. 7.

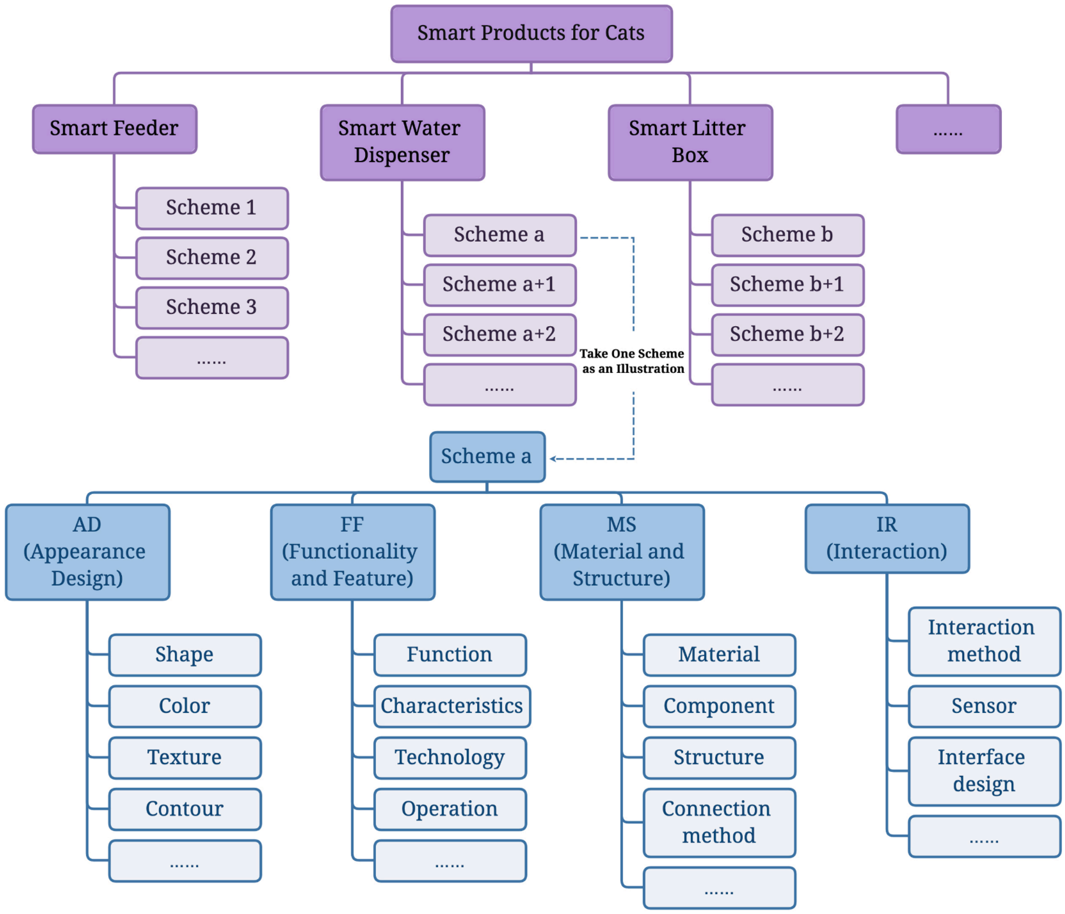


Fig. 7. The design knowledge model in the domain of smart products for cats.

According to Section 3.2.3, the entity types and relation types of design knowledge of smart cat products are defined, as shown in Table 2 and Table 3. Based on these defined entity and relation types, a label map comprising 101 labels is established, as listed in Appendix B.

4.2. *I-CDKG construction*

4.2.1. *Dataset collection*

According to Section 3.3.1 and Section 3.3.2, NLTK was utilized to remove redundant words and correct errors. Spacy is used for efficient sentence segmentation. Professionals are employed to label the dataset to ensure its quality. To avoid inconsistencies, a double annotation mechanism is implemented, where two annotators independently label the same dataset, and any discrepancies are resolved through third-party arbitration.

(1) Domain-specific training dataset

This dataset encompasses information from patent abstracts, various brands of smart cat products obtained through browsing official websites, and design manuals. The dataset comprises a total of 71,400 characters, consisting of 2804 entities. The number of entities in 17 categories is as follows: 138 (COL), 212 (OPE), 174 (DSS), 362 (CHA), 152 (TYP), 442 (FUN), 132 (TEC), 308 (COM), 248 (LIN), 124 (NUM), 206 (INT), 228 (MAT), 144 (SHA), 136 (CON), 226 (IRM), 164 (STR), and 130 (SEN). The labeled dataset was employed for training the ERNIE-BiGRU-CRF model to learn various features of smart cat products, thereby enhancing its generalization ability for domain-specific DKE tasks.

(2) Smart cat litter box dataset

This dataset comprises practical design schemes from different brands of smart cat litter boxes and some schemes extracted from patents as supplements. The collection period is from 2020.07 to 2022.12. A total of 196 design schemes are involved in it. This dataset is used to construct the pilot I-CDKG.

4.2.2. *Design knowledge extraction and I-CDKG visualization*

Utilizing the smart cat litter box dataset, the trained ERNIE-BiGRU-CRF model (Section 3.3.3) automates the joint-based DKE task. Every word is assigned a label, in which entity type and relation type are simultaneously contained. Subsequently, employing the method outlined in Section 3.3.4, design knowledge is extracted as triples. Fig. 8 illustrates labeling an input sequence using the integrated BIESO labeling mode and the extracted triples from the labeled sequence.

Afterward, all the triples are aggregated for knowledge fusion, and the outcomes of pre- and post-knowledge fusion are detailed in Table 4. In pre-knowledge fusion, various Chinese words or phrases that represent the same concept are listed, as different sources might use different terms to describe the same idea. To ensure consistency and clarity, a single representative and most commonly used word or term is selected to standardize the terminology across the KG, as shown in post-knowledge fusion. Fused knowledge triples are stored as a CSV file. Then, the file is transformed into I-CDKG in the Neo4j platform to fulfill the data layer population. Fig. 9 shows a part of the I-CDKG. The entire I-CDKG entails a total of 5036 knowledge triples.

4.2.3. *I-CDKG interpretability manifestation*

As discussed in Section 3.2.1, there are three types of knowledge

Table 2
The entity types in I-CDKG of smart cat products.

Entity Type	Example	Category
Product	It is the initial entity for each sub-KG, representing the name of each scheme.	/
Color	Pure white, light gray, bright yellow, etc.	
Shape	Rectangular ring, rectangular prism, spherical, etc.	
Contour	Smooth curved, minimalist angular, dynamic curved, etc.	AD
Style	Modern minimalist, traditional classic, technological futuristic, etc.	
Texture	Smooth surface, fine sandblasted, interlocking stripes, etc.	
Function	Cleaning litter, multi-cat recognition, weight monitoring, etc.	
Technology	Ultraviolet sterilization, intelligent sensing, ozone decomposition, etc.	FF
Characteristics	Easy disassembly, easy to clean, environmental friendliness, etc.	
Operation method	Push-pull, press, rotate, knob, etc.	
Material	Silicone, PP plastic, ABS plastic, PA plastic, etc.	
Component	Cat litter container, waste collection bin, main base, etc.	
Number	4 support legs, 2 cat bowls, 2 cat food bins, etc.	MS
Type	The type of litter container includes fully enclosed, semi-open, fully open, etc.	
Structure	Circular perforation, dual channel, convex-concave surface, etc.	
Interaction method	APP control, button control, voice control, etc.	
Sensor	Weight sensor, light sensor, magnetic sensor, etc.	IR
Interface design	Status indicator light, sound prompt, information display, etc.	

Table 3
The relation types between entities in I-CDKG of smart cat products.

Relation type	Explanation	Visual description	Abbr.
Has_Color	The color of Entity A is Entity B	A - Has_Color → B	COL
Design_Style	The design style of Entity A is Entity B	A - Design_Style → B	DSS
Has_Function	Entity B is the function of Entity B	A - Has_Function → B	FUN
Are_Linked	Entity A and Entity B are linked together	A - Are_Linked → B	LIN
Has_Component	Entity B is a component of Entity A	A - Has_Component → B	COM
Has_Marerial	The material of Entity A is Entity B	A - Has_Material → B	MAT
Has_Characteristics	Entity B is the characteristics of Entity A	A - Has_Characteristics → B	CHA
Has_Shape	The shape of Entity A is Entity B	A - Has_Shape → B	SHA
Has_Contour	The contour of Entity A is Entity B	A - Has_Contour → B	CON
Interaction_Method	Entity B is an interaction method of Entity A	A - Interaction_Method → B	IRM
Has_Number	The number of Entity A is Entity B	A - Has_Number → B	NUM
Has_Structure	The structure of Entity A is Entity B	A - Has_Structure → B	STR
Operation_Method	The operation method of Entity A is Entity B	A - Operation_Method → B	OPE
Has_Type	The type of Entity A is Entity B	A - Has_Type → B	TYP
Has_Sensor	Entity A has a sensor called Entity B	A - Has_Sensor → B	SEN
Interface_Design	Entity B constitutes the interface design in Entity A	A - Interface_Design → B	INT
Has_Technology	Entity A has a technology called Entity B	A - Has_Technology → B	TEC

organization designed to enhance interpretability within the I-CDKG, guided by the design cognition principles of Damen and Toh [52]. Consequently, as outlined in Section 3.4.1, these types of organization facilitate three distinct modes of knowledge exploration supported by the interpretability features of the I-CDKG.

To illustrate the *Cluster-level interpretability*, consider the “Type” categorization of a smart cat litter box, which is typically divided into three clusters: fully enclosed, semi-open, and fully open. Designers can group nodes corresponding to each cluster using Cypher queries, as depicted in Fig. 10(a). Within the established I-CDKG, three “semi-open” nodes are identified, suggesting the presence of three distinct design schemes that utilize this type.

When designers wish to delve deeper into the connections surrounding specific nodes within any given cluster, the *Relation-level interpretability* becomes relevant. By expanding a node, designers can observe its relationships with other nodes, as shown in Fig. 10(b). For instance, in step ①, the selected “semi-open” node is identified as having the characteristic of being “easy for observation,” which is directly linked to the “cat litter container” node. Expanding this component node in step ② allows designers to explore its surrounding relations. Relation-level knowledge exploration thus enables designers to analyze how different design elements contribute to the overall design scheme and how these connections influence functionality and usability.

From the perspective of *Nest-level interpretability*, each product design scheme is represented as a sub-KG. Using the real-life design scheme of the “Catlink smart cat litter box” as an example, its sub-KG visualization is illustrated in Fig. 10(c), encapsulating the comprehensive design elements and their interconnections. Importantly, sub-KGs are not isolated. As shown in Fig. 11, the sub-KGs of Scheme 1 and Scheme 2, both embodying minimalist design styles, are connected through the shared

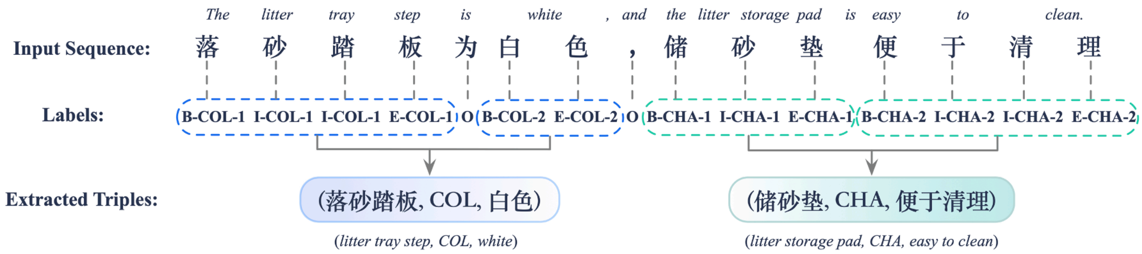


Fig. 8. Example of labeling a sentence and the extracted design knowledge triples.

Table 4
The results before and after design knowledge fusion.

Pre-knowledge fusion	Post-knowledge fusion
智能猫砂盆, 智能猫厕所	**智能猫砂盆** (Smart cat litter box)
噪音小, **噪声小**, 低噪音	**噪声小** (Low noise)
集便仓, 垃圾仓, 废物盒	**集便仓** (Waste collection bin)
方便清洗, 清洗方便, **易于清洁**	**易于清洁** (Easy to clean)
聚丙烯塑料, **PP塑料**, 聚丙烯	**PP塑料** (Polypropylene plastic)
……	……

entity “minimalism” (green paths). Additionally, components like the “cat litter container” in Scheme 1 and the “litter tray step” in Scheme 2 are linked by the common color “pure white,” establishing indirect connections between the two schemes (red paths). Through these linkages, initially independent sub-KGs can be interconnected, allowing designers to explore relationships between different design schemes and uncover new insights that may not be evident when examining each sub-KG in isolation.

4.3. Application scenarios of the I-CDKG

4.3.1. I-CDKG expansion

Here is a real scenario where an increasing number of design schemes emerge in the market after the initial collection of the smart cat litter box dataset. Data collection continues from January 2023 to January 2024, forming another latest smart cat litter box dataset. In particular, a revolutionary solution from the Tonepie brand entered the market in September 2023. It features an integrated silo design that prevents cats from getting stuck. Another innovation from the Neakasa brand was introduced for the first time in December 2023. It features an entirely open cat litter container to accommodate larger cats. Novel design schemes are promptly incorporated into the I-CDKG to ensure it remains up-to-date and robust. Ultimately, 2084 new knowledge triples are successfully added to the existing I-CDKG, allowing it to dynamically “grow,” as showcased in Fig. 12.

4.3.2. Interaction with I-CDKG for heuristic ideation

Here is a design problem-oriented scenario, in which a designer is tasked with designing a cat litter box that provides ample space for cats to use. Guided by Section 3.4.1, the following detailed steps in Table 5

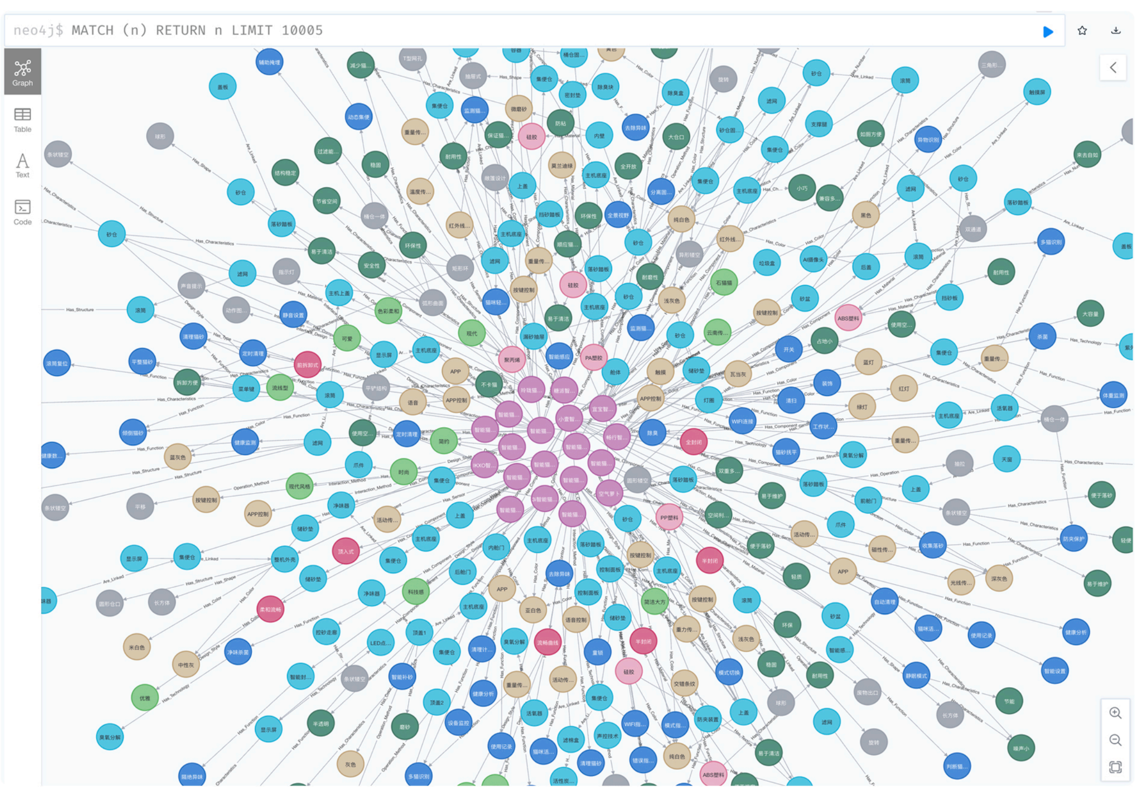
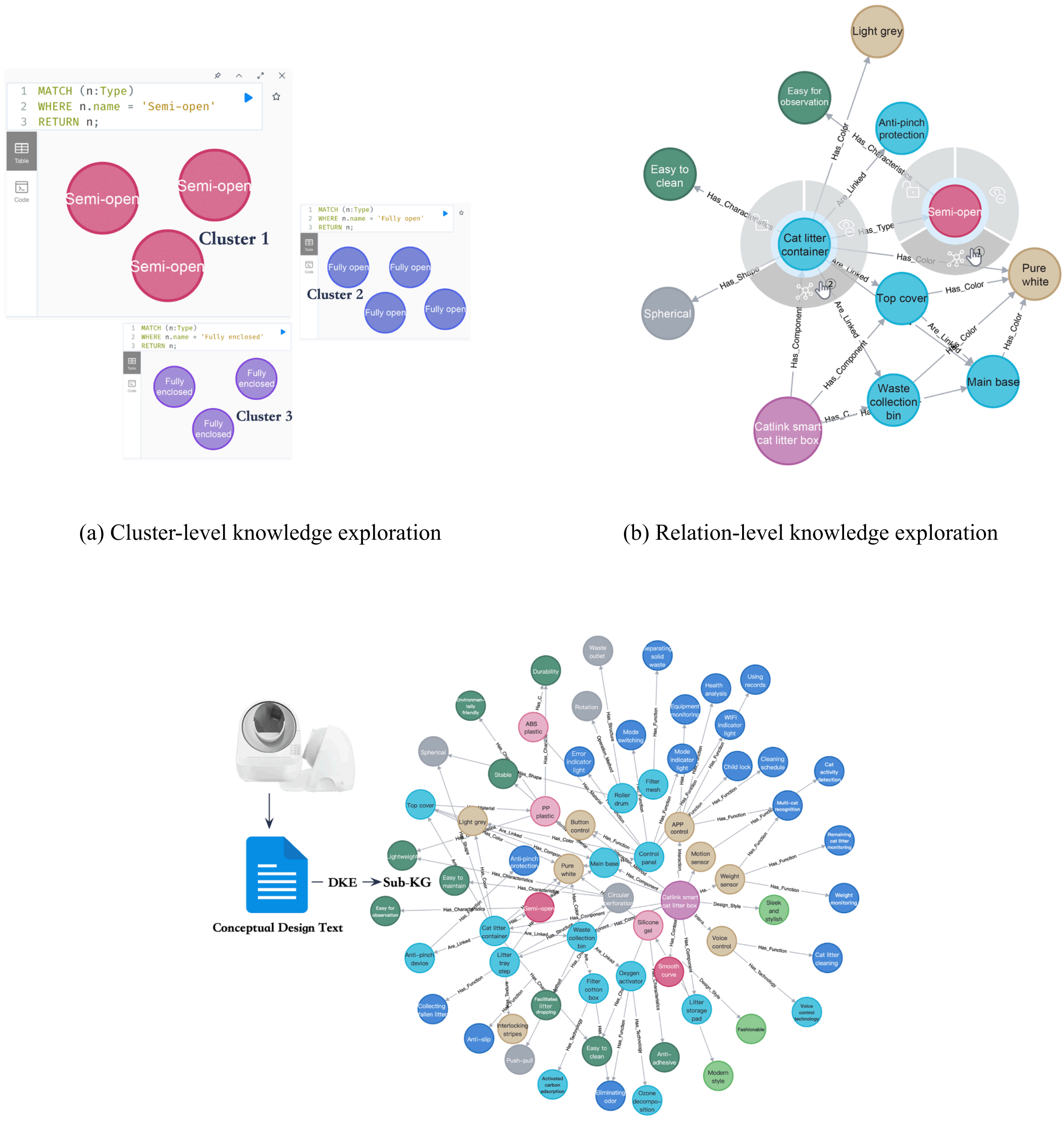


Fig. 9. The established I-CDKG for smart cat litter box. (Partial, in Chinese).



(a) Cluster-level knowledge exploration

(b) Relation-level knowledge exploration

(c) Nest-level knowledge exploration

Fig. 10. The manifestation of the interpretability of I-CDKG from three levels.

illustrate how the designer interacts with the I-CDKG and generates heuristic product ideas.

According to the RKP results in Fig. 13, design knowledge directly linked with the characteristic entity "ample space" is initially pushed to designers through knowledge retrieval. A preliminary observation reveals that both "double entry throughout" and "integrated silo" structures exhibit "ample space" characteristics. Subsequently, curiosity arises about what other entities are associated with these two types of structures. Therefore, through Relation-level knowledge exploration, related design knowledge is rapidly exhibited to designers. For the "integrated silo," it is observed that such a structure is integrated into Scheme B and additionally possesses characteristics of "small footprint," providing functions such as "isolating odor" and "anti-pinch protection." This resembles the divergent thinking of the human brain. In other words, when exploring design knowledge related to a cat litter box with ample space, other advantages of related product structures are also uncovered. Armed with all of these heuristic insights, designers generate some initial product ideas and inspirations to design a cat litter box with ample space for cats to use, which are summarized in Table 6.

It should be noted that the process of exploring inspiration for product design is endless. As shown in Fig. 13, designers can quickly identify that Schemes B and C are strongly correlated with the given design problem, enabling further observation of their design drawings to glean more inspiration. If designers want to seek more potential stimuli, they can interact with the I-CDKG to initiate Nest-level knowledge exploration and investigate the sub-KGs of Schemes B and C in detail.

Inspired by the initial product ideations in Table 6, a process of sketch development is undertaken using Midjourney to refine the

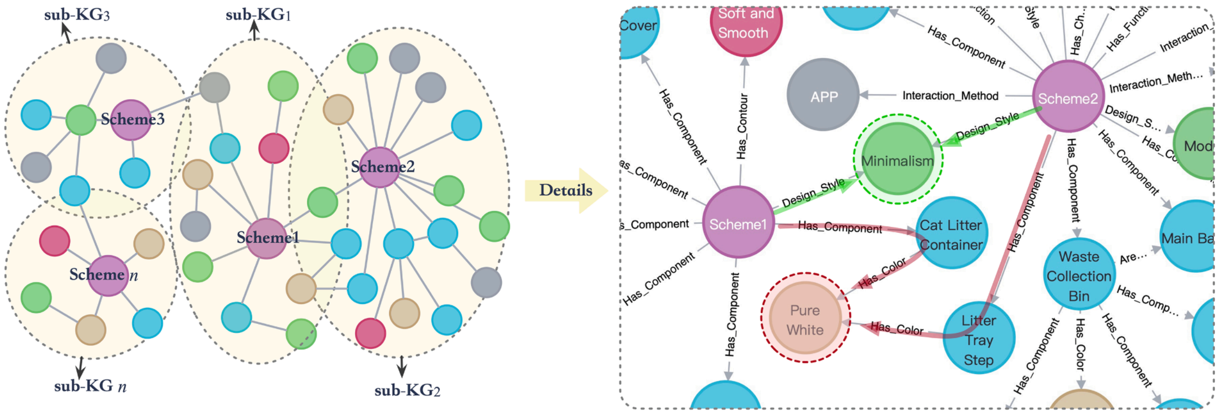


Fig. 11. An illustration of detailed interconnection between two sub-KGs.

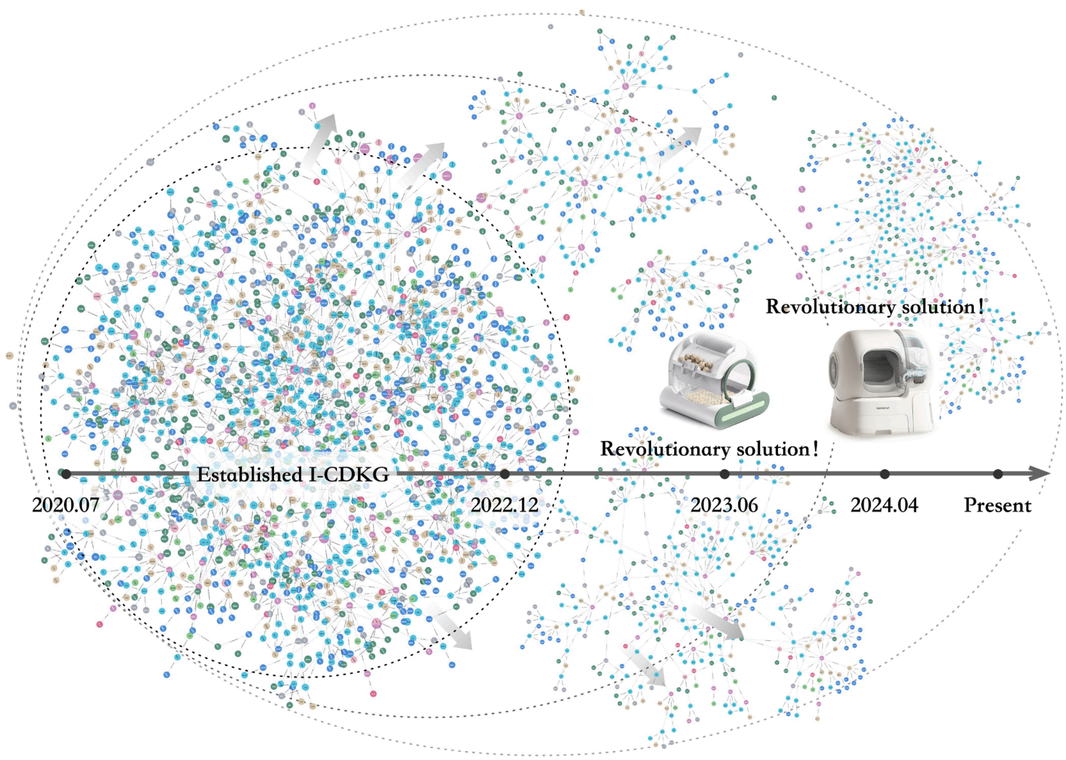


Fig. 12. Expansion of I-CDKG with the appearance of revolutionary solutions.

concepts. A 3D model of the selected final ideation is created using Rhino and the rendering is performed using Keyshot. The results are showcased in Fig. 14, where an extended entrance is added from the front to the top to increase the usable space. It should be noted that the prototype is intended to visually demonstrate the inspirational ideation, rather than serve as the final product.

Table 5
The action designer interacts with I-CDKG to locate heuristic product ideas.

	Designer action	Results
1	Identify entities and relations from the design problem	Entity: Product, Structure Relation: Has_Characteristics
2	$G_{problem}$ construction	MATCH (s:Structure)-[r1:Has_Characteristics]->(c:Characteristics {name: 'Ample Space'}) MATCH (p:Product)-[r2:Has_Characteristics]->(c) RETURN s, r1, c, p, r2;
3	Query in I-CDKG to locate corresponding knowledge	The interactive process of visual knowledge retrieval is shown in the green dashed box in Fig. 13.
4	Carry out Relation-based knowledge exploration mentioned in Section 3.4.1 (2)	The interactive process of two paths of visual knowledge exploration is shown in the blue and red dashed boxes, respectively, in Fig. 13.

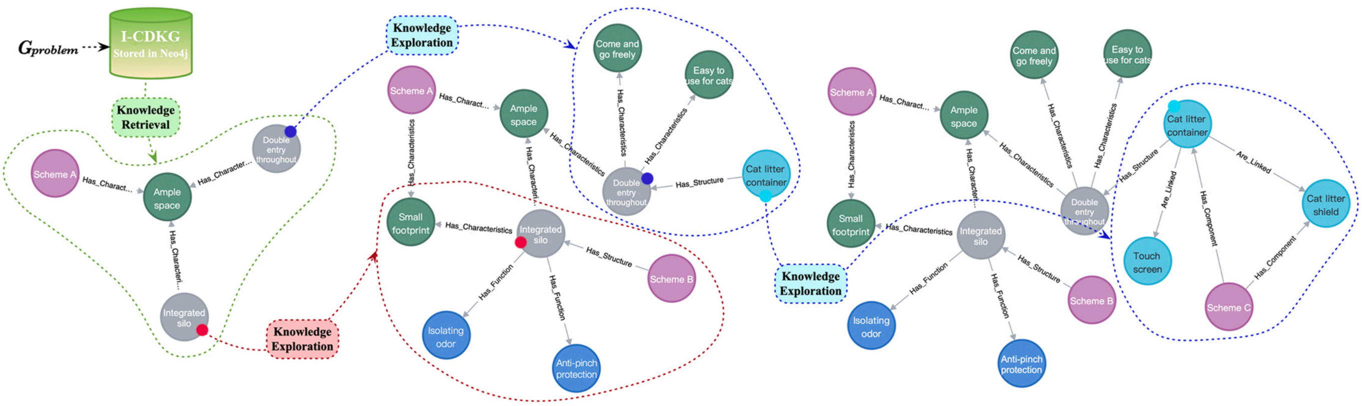


Fig. 13. The interactive process of visual knowledge retrieval and knowledge exploration in I-CDKG.

Table 6
Initial product ideations inspired by RKP results.

	Design Problem: How to design a cat litter box that provides ample space for cats to use?	
	Description in natural language	Reference
Heuristic ideation 1	Structures similar to "double entry throughout" found in Scheme C could be reused. It refers to the presence of two entry points, typically located on either side or at both ends of the litter box. This allows cats to enter or exit the litter box from multiple directions.	
Heuristic ideation 2	Structures similar to "integrated silo" found in Scheme B could be considered. It describes a design where the litter container and the box itself are combined into a single unit, rather than separate components. This aims to streamline the functionality and appearance of the litter box, saving more space for cats.	

Fig. 14. Sketch development and the computer simulation model of the selected ideation.

5. Results and discussion

5.1. Performance evaluation of I-CDKG as a design tool

The performance of the I-CDKG is evaluated from the designer's perspective utilizing two key criteria: *designer feedback* and *task completion*. The in-depth evaluation was conducted with eight industrial designers of similar education backgrounds, each having between 2 to 3 years of experience. They were trained to use the I-CDKG before the user study.

Designer feedback is employed to assess the usability of I-CDKG from both quantitative and qualitative perspectives. From the quantitative perspective, a simple and multi-dimension survey is conducted to garner designer feedback, comprising four questions reflecting interpretability,

Table 10
Performance evaluation results of I-CDKG.

Designer feedback	*Dimension*	*Average rating*	
Question 1	Interpretability	8.21	
Question 2	Learnability	7.32	
Question 3	Usefulness	7.67	
Question 4	Confidence	6.98	
Task completion	*Without*	*With*	*% Change*
1. Completion time			
Design problem 1	1.56	0.49	−68.59
Design problem 2	3.78	1.67	−55.82
Design problem 3	2.66	1.23	−53.76
2. Heuristic ideation quality			
Design problem 1	6.45	8.62	+33.73
Design problem 2	5.77	9.10	+57.68
Design problem 3	6.83	8.81	+29.01
3. Task completion rates	56.34	92.11	+35.97

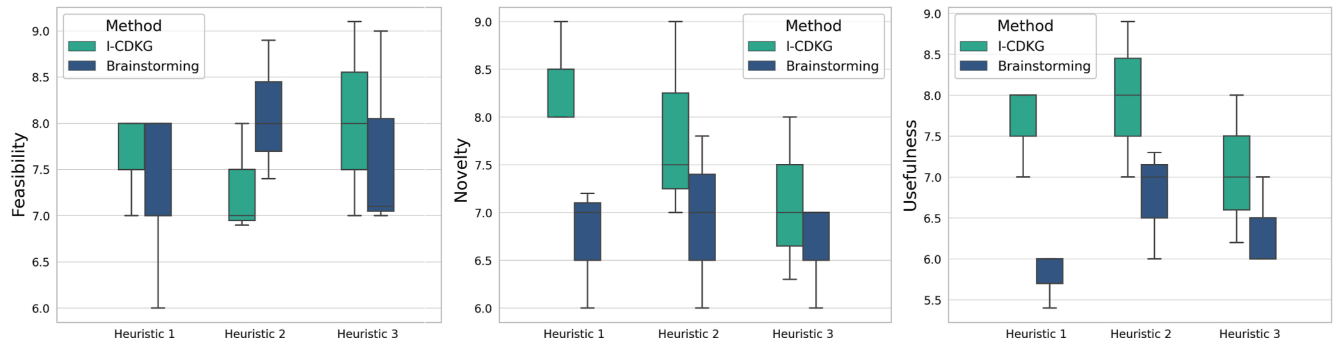


Fig. 15. The One-Way ANOVA analysis results between I-CDKG and brainstorming methods.

learnability, usefulness, and confidence, respectively. Questions asked to designers are specified in Appendix D1. Responses to these questions are quantified using a 0–10 rating scale, with the average rating computed to evaluate the overall feedback. From the qualitative perspective, aside from the four fixated questions, designers are encouraged to leave their comments if they have additional feedback. Outstanding feedback will be incorporated into the limitation section (Section 5.4).

Task completion is used to measure the effectiveness of solving design problems with and without the assistance of I-CDKG. In design practice, one task usually consists of several design problems. The design task designated for the user study is divided into three specific design problems. A detailed description is listed in Appendix C. The eight industrial designers are randomly divided into two groups assigned with the same design task. Task completion is further reflected by three aspects: completion time, heuristic ideation quality, and task completion rates. Definitions for these measures are listed in Appendix D2.

The performance evaluation results are summarized in Table 10. In terms of designer feedback, interpretability received the highest average rating of 8.21, which can be attributed to the acquired interpretability of the introduced I-CDKG. The interpretable architecture, detailed in Section 4.2.3, enables a more rational and efficient organization and management of design knowledge, allowing designers to easily and quickly explore conceptual design elements (such as style, materials, structure, etc.) and their interrelationships. As a result, usefulness scored 7.67, ranking second. The strong performance in both interpretability and usefulness significantly improved task completion. Specifically, the average completion time was reduced by approximately 42.72%, while the quality of heuristic ideation improved by an average of 40.14%. These findings suggest that when facing time-constrained engineering design tasks, the adoption of I-CDKG can assist designers in obtaining higher-quality ideation in a shorter period. This ultimately helps to shorten the overall development timeline and improve productivity, particularly during the conceptual design phase.

5.2. Expert evaluation of design heuristics generated by I-CDKG

Brainstorming is one of the most common and widely accepted methods for generating ideas in the design field. Its recognition makes it a standard reference method, helping to ensure the acceptability and credibility of experimental results. In this experiment, six designers with similar backgrounds and experience levels were randomly divided into

Fig. 16. Exploded-view drawing with cost estimation for the proposed product ideation.

Table 11
Market potential comparison.

Performance	Proposed Product	Existing Product 1	Existing Product 2	Existing Product 3
Relative size (with a 7.3kg cat inside)				
Roller volume	75L	70L	57L	106L
Entrance proportion	25%	10%	10%	12%
Total manufacturing cost	¥600	¥960	¥780	¥1250

two groups. Group A received training on the brainstorming method, while Group B was trained on using the I-CDKG. Both groups were required to execute the same design task within three hours to generate corresponding heuristic ideations.

An expert evaluation method proposed by the UCB co-design lab [31] was adopted to assess the design heuristics generated by I-CDKG. The evaluation focused on feasibility, novelty, and usefulness, with all criteria scored on a 0–10 rating scale. Two experts specializing in design theory and methodology were trained to perform the ratings. Finally, One-Way ANOVA was performed to test for statistical differences between I-CDKG-generated and brainstorming-generated heuristics.

While the evaluation results in Table 10 indicate that the I-CDKG facilitates higher-quality heuristic ideation, the expert evaluation results in Fig. 15 reveal the specific aspects in which I-CDKG outperforms, contributing to enhanced ideation quality. Specifically, the ANOVA test results of novelty (F-statistic of 6.997 with a p-value of 0.0176) and usefulness (F-statistic of 13.43 with a p-value of 0.0021) indicate statistically significant improvements. This implies that I-CDKG could encourage exploring unconventional ideas and help designers identify creative solutions that may not emerge through traditional brainstorming methods. It could be a robust tool for systematically exploring and applying design knowledge, making it particularly effective in solving engineering problems where creativity and practicality must align.

5.3. Cost analysis and market potential evaluation

To evaluate the economic feasibility and market potential of the product ideation generated in Section 4.3.2, a simplified and high-level manufacturing cost estimation was conducted. The cost analysis is based on the breakdown of major components [58], providing an overview of key cost drivers in the design. According to industry standards, the estimated total manufacturing cost is ¥600, as presented in the exploded-view drawing in Fig. 16.

To assess the proposed ideation's market potential, a comparison with a few best-selling products is presented in Table 11. Using a 7.3kg cat (typically considered a large cat weighing $\geq$ 6.5kg) as a reference, the Proposed Product offers the most flexible experience, minimizing spatial restriction. While Existing Product 3 achieves the largest roller volume, this comes at the expense of increased material usage and higher costs. In contrast, the Proposed Product addresses the same design problem by optimizing the entrance structure. This optimization saves material and reduces costs, with the entrance accounting for 25% of the device's total volume. This design will allow for competitive retail pricing while maintaining strong profit margins, making it a more affordable option for customers. Additionally, the product features fewer visible seams and a simpler mold structure, which will further shorten mold production time and lower manufacturing costs. In conclusion, the I-CDKG-based ideation method can enhance cost efficiency and improve product competitiveness for novel products by tackling engineering design problems right from the conceptual design phase.

5.4. Limitations

Despite the demonstrated advantages, several limitations should be acknowledged. (1) Design knowledge is extremely complex. The overlapping of knowledge triples is not completely avoided, potentially impacting the accuracy and usability of the I-CDKG. (2) The main focus of this study is attempting to construct a novel KG. Therefore, only RKP is showcased to demonstrate the application of the KG, while more sophisticated knowledge reasoning is not investigated. (3) While KGs assist heuristic product ideation, they do not address all design challenges. KGs often need to be complemented with other AI strategies and designers' strengths to achieve comprehensive and intelligent manufacturing systems.

6. Conclusion

To enhance product iteration following the successful launch of novel products, it is imperative to systematically accumulate and structure the growing volume of design information. This study constructed an innovative I-CDKG as a design tool specifically designed to support heuristic product ideation. The I-CDKG broadens the scope of knowledge provision and product iteration, offering a new approach to organizing and reusing design knowledge.

The theoretical contributions of this study are summarized in three key aspects. (1) It introduces a fresh perspective on novel product iteration, particularly for products that are entirely new to the market in recent years. (2) A novel hybrid method is adopted to expedite the construction of I-CDKG through automatic design knowledge extraction. This method combines the fine-tuned ERNIE-BiGRU-CRF model, BIESO labeling mode, and a triple-extraction algorithm to ensure effective entity-relation joint extraction. (3) Beyond its inherent interpretability, the I-CDKG architecture is optimized by adopting a Cluster-Relation-Nest organizational strategy to strengthen acquired interpretability, ensuring that design knowledge is not only accessible but also resonates with how designers instinctively organize information.

As for practical implications, the industrial applicability of the proposed method is demonstrated through two illustrative design scenarios involving smart cat litter boxes. In real-world engineering design challenges, particularly during the conceptualization phase, the I-CDKG effectively accelerates the design process while ensuring the generation of high-quality heuristic ideas. In cases where innovative solutions are critical to enhancing novel product competitiveness, the I-CDKG serves as a powerful tool to stimulate and inspire designers, enabling the creation of inventive and cost-effective solutions with significant market potential. Furthermore, it is anticipated that the I-CDKG could be integrated with other generative design tools or evaluation frameworks to holistically address engineering design problems.

Three potential directions will be pursued in future studies. (1) A combination of I-CDKG, semantic search, and generative AI could be considered to enhance the generation of heuristic ideation. (2) To foster the integration of machine-based and human-centric design methodologies, adaptive design techniques can be formulated. This initiative aims to effectively deploy dynamically evolving AI technologies in practical contexts, bridging the gap between machine thinking and design thinking. (3) The extension of the current framework will be explored to support not only incremental but also disruptive innovation, broadening its applicability in the NPD field. This would allow the I-CDKG to facilitate identifying groundbreaking products, making it a more versatile tool for product innovation.

CRediT authorship contribution statement

Yangfan Cong: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Suihuai Yu:** Supervision, Funding acquisition. **Jianjie Chu:** Supervision, Funding acquisition. **Yuexin Huang:** Validation, Data curation. **Ning Ding:** Investigation, Data curation. **Cong Fang:** Writing – review & editing, Formal analysis. **Stephen Jia Wang:** Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix A

The input of the algorithm is the output of ERNIE-BiGRU-CRF (i.e., text sequence labeled with the integrated BIESO labeling mode). Next, the code will traverse the label sequences and extract knowledge triples based on specific rules, storing them in the output. The extraction rules are detailed in Table A1 and Table A2.

Table A1
Calculation of triples set based on the label of each word in the input design text sequence.

Algorithm 1.

```
Input:   Labeled input design text sequence Sequence = {(word_1, label_1, (word_2, label_2)···, (word_i, label_i)};
Output:  Triples set Triples
for t = 1,2,···,i do
  if label_t's position label is S and the entity role is 1 then
    for j = t+1, t+2, ···, i do
      if label_j's relation type is the same as label_t's relation type and label_j's entity role is 2then
        if label_j's position label is S then
          Add the triple < word_t, label_t's corresponding relation type, word_j > to the triples set Triples;
        else
          Extract the complete entity set based on Algorithm 2 ;
          Add the triple < word_t, label_t's corresponding relation type, set > to the triples set Triples;
        end if
      end if
    end for
  if label_t's position label is B and the entity role is 1 then
    Extract the complete entity set_head based on Algorithm 2;
    for j = t+1, t+2, ···, i do
      if label_j's relation type is the same as label_t's relation type and label_j's entity role is 2then
        if label_j's position label is S then
          Add the triple < word_t, label_t's corresponding relation type, word_j > to the triples set Triples;
        else
          Extract the complete entity set_tail based on Algorithm 2;
          Add the triple < set_head, label_t's corresponding relation type, set_tail > to the triples set Triples;
        end if
      end if
    end for
  end if
end for
```

Table A2
Extracting complete entity words when the label's position label is B.

Algorithm 2.

Input: Labeled input design text sequence
$Sequence = \{(word_1, label_1, (word_2, label_2)\cdots, (word_i, label_i)\}$;
Output: Extracted complete entity *set*
Initialize the complete entity $set = \{\}$;
do
  $j = j + 1$;
  Add $word_j$ to the *set*;
while $label_j$'sposition label is E

Appendix B

Table B1
101 kinds of labels in this paper to carry out DKE experiments.

No.	Label	No.	Label	No.	Label	No.	Label	No.	Label
1	O	23	B-CHA-2	44	B-COM-1	66	B-MAT-1	84	B-IRM-1
2	B-COL-1	24	I-CHA-2	45	I-COM-1	67	I-MAT-1	85	I-IRM-1
3	I-COL-1	25	E-CHA-2	46	E-COM-1	68	E-MAT-1	86	E-IRM-1
4	E-COL-1	26	B-TYP-1	47	B-COM-2	69	B-MAT-2	87	B-IRM-2
5	B-COL-2	27	I-TYP-1	48	I-COM-2	70	I-MAT-2	88	I-IRM-2
6	I-COL-2	28	E-TYP-1	49	E-COM-2	71	E-MAT-2	89	E-IRM-2
7	E-COL-2	29	B-TYP-2	50	B-LIN-1	72	B-SHA-1	90	B-STR-1
8	B-OPE-1	30	I-TYP-2	51	I-LIN-1	73	I-SHA-1	91	I-STR-1
9	I-OPE-1	31	E-TYP-2	52	E-LIN-1	74	E-SHA-1	92	E-STR-1
10	E-OPE-1	32	B-FUN-1	53	B-LIN-2	75	B-SHA-2	93	B-STR-2
11	B-OPE-2	33	I-FUN-1	54	I-LIN-2	76	I-SHA-2	94	I-STR-2
12	I-OPE-2	34	E-FUN-1	55	E-LIN-2	77	E-SHA-2	95	E-STR-2
13	E-OPE-2	35	B-FUN-2	56	B-NUM-1	78	B-CON-1	96	B-SEN-1
14	B-DSS-1	36	I-FUN-2	57	I-NUM-1	79	I-CON-1	97	I-SEN-1
15	I-DSS-1	37	E-FUN-2	58	E-NUM-1	80	E-CON-1	98	E-SEN-1
16	E-DSS-1	38	B-TEC-1	59	S-NUM-2	81	B-CON-2	99	B-SEN-2
17	B-DSS-2	39	I-TEC-1	60	B-INT-1	82	I-CON-2	100	I-SEN-2
18	I-DSS-2	40	E-TEC-1	61	I-INT-1	83	E-CON-2	101	E-SEN-2
19	E-DSS-2	41	B-TEC-2	62	E-INT-1				
20	B-CHA-1	42	I-TEC-2	63	B-INT-2				
21	I-CHA-1	43	E-TEC-2	64	I-INT-2				
22	E-CHA-1			65	E-INT-2				

Appendix C

Table C1
Breakdown of the design task into three specific problems for user study.

Design task	Description
	To develop a smart cat litter box that provides a spacious and comfortable interior, features a modern and minimalist stylish appearance, and is equipped with an efficient and safe automatic cleaning system that ensures no harm to cats.
Design problem	**Description**
1	How to design the interior and exterior spaces of the litter box to provide a comfortable space for cats while maintaining overall compactness?
2	How to design the litter box's appearance to ensure it has a modern, stylish look and can integrate into various home decor styles?
3	How to design an efficient and safe automatic cleaning system that ensures cats will not get stuck during use?

Appendix D

Table D1
Four survey questions to acquire quantitative designer feedback.

Dimension	Survey question
Interpretability	How easy was it for you to interpret the design knowledge presented by I-CDKG?
Learnability	Did you find it easy to learn how to use I-CDKG to access design knowledge?
Usefulness	Did you find the heuristic insights provided by I-CDKG useful to apply in your design process?
Confidence	Do you agree that I-CDKG boosts your confidence in the design process?

Table D2
Definitions of the measures used for task completion.

Measure	Definition
Completion time	Time consumed for one design problem, measured in hours.
• without the assistance of I-CDKG	It is recorded through “design task assignment → design data and inspiration collection → ideation generation.”
• with the assistance of I-CDKG	It is recorded through “design task assignment → design heuristic and inspiration collection → ideation generation.”
Heuristic ideation quality	The quality of the ideas generated for one design problem, measured on a 0–10 rating scale.
Task completion rate	The proportion of design problems completed within a given timeframe of 3 h. Task completion rate=(number of completed design problems)/(total number of design problems)

Data availability

Research code can be found online at https://github.com/Anathan-lab/ERNIE-BiGRU-CRF.

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