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RESEARCH ARTICLE

A hybrid method for product low-end disruptive innovation

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ABSTRACT Product innovation is often a process for improving existing products. Low-end disruptive innovation (LDI) enables a product to meet the most price-sensitive customers in the low-end market. The existing LDI methods are mainly based on unnecessary characteristics of disruptive innovations. Thus, they cannot easily identify and respond to the LDI design needs. This study proposes a hybrid method for the product LDI in two levels of the product design based on the summarized definition and essential characteristics of LDI. Feasible areas of the product LDI are determined using a hybrid relational function model to identify the maturity of dominant technologies. The technologies are identified through the technical search and evaluation of the feasible area for innovation to form an initial LDI scheme. Then, the product function is optimized using the trimming concept of theory of inventive problem solving based on the characteristics of LDI. The final LDI scheme is formed and evaluated based on the essential characteristics of the product LDI. The feasibility of the proposed method is verified in the design of a new dropping pill machine.

KEYWORDS low-end disruptive innovation, product design, design improvement, theory of inventive problem solving, TRIZ, trimming

1 Introduction

Product innovation is vital for industries in competitive markets [1–4]. Low-end disruptive innovation (LDI) enables a product to meet the most price-sensitive customers in the low-end market [5]. Disruptive innovation has been applied in many fields of technology, product, and management [6,7]. New market disruptive innovation (NDI) products attract new customers by offering different functional combinations from the existing mainstream products [8]. LDI products offer lower cost and less functionality than the mainstream product [6,9–11].

An LDI product is decided based on its value and cost [8,12,13]. The existing research on product disruptive innovation is mainly focused on the study of product disruptive innovation opportunity generation, disruptive innovation product commercialization, and influencing factors. The study of product disruptive innovation design methods is lacking. Most of the existing studies are holistic studies of product disruptive innovation. However, NDI products and LDI products provide different functions [14] in different technological paths [15] and early adopters [16], which should be studied separately. LDI has inherent limitations in enterprise management [5] and applications [17,18]. The existing studies of LDI design methods are based on unnecessary characteristics, such as low cost, small size, simple system, and easy operation [19,20]. Thus, the LDI product design is prone to errors and limited in terms of the scope of operation. Moreover, the concept and characteristics of LDI remain ambiguous [21], resulting in a major obstacle to the study of product disruptive innovation design methods. In summary, a gap and an opportunity exist for researchers to develop a new design method for the application of design engineers in the industries based on the essential characteristics of LDI.

Therefore, this study proposes a prescriptive design method to guide the LDI product development. The concept and essential characteristics of product LDI are summarized through the study of the research literature. The generation of LDI products lies in two aspects: the change in the dominant subfunction technologies and the product optimization at the functional level. LDI starts from the conceptual design in a divergence–convergence

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process [22,23]. The design process of LDI products is mainly a process for improving the existing products [22]. Most of the existing redesign methods use a hierarchical function model [24,25] or component-function model [26] in problem-solving. A three-level product functional structure, including the models of solution-independent functions, solution-dependent functions, and technology- and solution-dependent functions, is defined to guide the process of product redesign by combining relational and hierarchical function models [27]. Functions are classified according to the solution information in different functional levels and boundaries. However, the details of function structure relations are lacking. In this study, product function layers are classified to fit the LDI product design process. LDI considers not only the applications of new dominant technologies but also the function optimization. Trimming can remove harmful function components and structures to improve the system value [28,29]. It also can be applied to reduce the product cost and simplify the product structure by using the resources in the system or supersystem [26,30]. The function optimization and trimming methods also improve the solution consistent with the product LDI.

The following parts of this paper are organized as follows. The related research on disruptive innovation and product LDI is introduced in Section 2. In Section 3, the five steps of the proposed method are introduced. A dropping pill machine is designed as an example to apply the proposed method for the product LDI in Section 4. Section 5 discusses the conclusions and future work.

2 Related research

2.1 Disruptive innovation

The academic interest in disruptive innovation theory rises rapidly [31]. The concept of disruptive innovation has been discussed in Refs. [12,21,32,33]. Although different methods of disruptive innovation exist in the field of management and technology, the number of publications on the theoretical research of disruptive innovation is limited [31]. The research has shifted from the concept to the application of disruptive innovation. Hierarchical models have been built to analyze different types of subversions systematically [34]. Disruptive innovation has different framework models for explaining and predicting disruptive innovation in terms of management cognition, company organization, company type, resource service, and energy conversion [32,35–37]. Research on disruptive innovation can be found in different industries, such as aerospace [38], energy [39], software [40], and financial services [41]. The impact of disruptive information technology innovation on cost was studied [42]. On the basis of the case analysis, the technological disruptive innovation process can improve the predictive ability of process-oriented industries, such as oil, natural gas, and minerals [43]. The impact of disruptive innovation on productivity was also discussed from a macro perspective [44]. Four nontechnical dimensions of disruptive innovation show its multidimensionality [45]. Researchers also compared disruptive innovation with frugal innovation [46,47] and disruptive innovation technology with emerging technology [48] to clarify further the concept, characteristics, and boundary of disruptive innovation. Current studies on product disruptive innovation can be divided into three areas: studies on product disruptive innovation opportunity generation, studies on disruptive innovation product commercialization and its influencing factors, and limited studies on the design process of product disruptive innovation.

Studies on product disruptive innovation opportunity generation mainly focus on predicting the disruptive innovation potential of hot technologies, such as augmented reality [49], 3D printing [50], pulsed light [51], LED [52], electric vehicles [53], and solar energy [54]. Different levels of disruptive innovation technology models were proposed [55]. Based on patent data and the susceptible, infectious, recovered and susceptible epidemic model, a process framework for predicting disruptive technologies was proposed [56]. A framework of the popular technology prediction was proposed based on the patent data and keyword network analysis to predict the emerging disruptive innovation technology for product development [57]. A patent development path of disruptive innovation was developed to identify possible future technologies using the *k*-core analysis and topic modeling [58]. The specific identification methods, impacts, and applications of disruptive innovation technologies were demonstrated in a case analysis [17]. An alternative historical method for disruptive innovation technology forecasting was proposed to accommodate the inherent uncertainty and nonlinearity of disruptive innovation technology paths [59]. Correlated functionality, technical standards, and ownership with the existing disruptive innovation theory were proposed in a three-step approach to identify and classify potential disruptive innovation technologies [14]. theory of inventive problem solving (TRIZ) was combined with life systems theory to form a canvas for nonexpert and expert users and anticipate the need for disruptive product innovation [60].

In studies on disruptive innovation product commercialization and its influencing factors, the impact of the external environment on the early stages of disruptive innovation product commercialization was analyzed from an institutional perspective, moreover, the strategies for disruptors and incumbents were developed to cope with this stage [61]. The requirements of disruptive innovation products from different perspectives were investigated [16,62–66]. A transformative innovation model was proposed to guide start-ups and small and medium-size enterprises in creating fundamentally unique, high-value new products [67]. Different maturity evaluation models were proposed for disruptive innovation [68,69]. Two business models were explored to determine the impact of disruptive technology capabilities on the development of blockchain-based disruptive innovation products [70]. Six major factors associated with achieving the commercialization of disruptive innovation products were identified in a three-stage model [71]. Four product pricing and positioning strategies and their corresponding optimal conditions were identified by analyzing the traditional and new attributes of a single product for emerging companies [72].

Disruptive innovation happens in the development of disruptive innovation products. Based on the case study, four strategies of research and development that use miniaturization, simplification augmentation, and application of technologies from other domains individually or in combination were identified to achieve product disruptive innovation [17]. A structured lean design approach was proposed for disruptive innovation by applying TRIZ tools to four components of new product development, namely, collection, deployment, reorganization, and transformation, to reduce ineffectiveness and maximize product value [20]. A systematic approach was proposed through functional differentiation to quantify NDI designs [8]. A function optimization method was proposed using general theory of powerful thinking to achieve the product LDI design by constructing contradictions [19]. In summary, the research on the design process of product disruptive innovation is limited. The existing product LDI design studies do not consider product characteristics, such as low cost, small size, simple system, and easy operation with limitations of the operability.

2.2 Low-end disruptive innovation

The emergence of LDI is caused by the cognitive barrier of the existing market, which makes identifying and responding to the design or service requirements for the product LDI difficult for industries [6,73]. When some industries move to the high-end market, rooms are left for new competitors to gain market share in the low-end market [5]. Unlike the NDI that produces a new value network by changing the core performance dimension of consumption and competitive products, LDI is rooted in the original mainstream performance dimension from bottom to top in the original value network [13,74]. These low-end user groups are sensitive to price because they cannot afford mainstream products with their limited purchasing capacity. As time moves, the LDI product is improved in the main dimension; finally, it attracts the mainstream customer who initially avoided it [12,15]. This LDI product began to emerge and eventually beat the mainstream product. As the LDI product's popularity rises, large companies also apply the LDI to maintain their market share from the high-end to low-end product markets [74,75].

Disruptive innovation is not a result but a process [21]. LDI considers not only technologies but also products and business models [6]. Product LDI mainly looks at overdesigned products whose functions and performances exceed customer requirements [9]. Combined with the evolution theory of technology systems in TRIZ, product disruptive innovation occurs in the mature stage of a product's mainstream technology [15]. Similarities exist between LDI and frugal innovation, which usually provides minimal functionality [46,76]. However, unlike frugal innovation, LDI does not defeat competitors by providing extreme cost constraints but focuses on improving the product system value [47,77,78]. Low-cost incremental innovation may also cause low costs and the high system value of a product in its original value dimension. However, the low-cost incremental innovation is a minor improvement in the original value trajectory, whereas the LDI causes a discontinuity in the original value trajectory. Therefore, an essential difference exists between them [79]. Although the system value of LDI products is high, their performance may be lower than that of the existing products. LDI products are much less expensive than the existing products; they also have unnecessary characteristics, such as simple functions, convenient operations, low cost, and environmentally friendly design [8,9,12,13].

Disruptive innovation is a relative term, which means that technology may be disruptive for one product type but sustainable for other products [14,80]. Technology has the potential for LDI if it can reduce the product cost through new technical standards or new forms of ownership [14]. Examples of the products in this scenario are Nucor's mini-mills, microcomputers, and inkjet printers. Compared with technologies, innovation is at a high level of system construction [1,32,48,81]. Product disruptive innovation is caused by the accumulation of many incremental innovations in the original technology [9,82]. Therefore, LDI products based on an incremental technology can also be vaguely radical in the technology [2,15]. Some enterprises with advanced technologies often achieve their LDI by optimizing the functions of existing products [74], such as the Celeron processor.

Therefore, from the perspective of product innovation, most LDI starts at the mature stage of the product's mainstream technology evolution curve. The mainstream function of this kind of innovative product is basically unchanged, and LDI does not pursue the improvement of product performance. However, LDI products have two essential characteristics, the low cost and high system value that can cause discontinuities in products' original value trajectory. They also have some unnecessary characteristics, such as the small size, simple system, and easy operation. Compared with the existing mainstream products, LDI products are generated in two aspects: One is the change of dominant subfunction technologies, and the other is the product optimization at the functional level.

3 Proposed method

Design models can be divided into a descriptive model and a prescriptive model [83,84]. Design theories describing the design content and/or design process are descriptive, whereas design methodologies indicating the ways of the design are prescriptive [85]. Different product design methods exist, but design methods for product LDI are lacking. The present research improves the existing design methods to accommodate product LDI aimed at practical applications for design engineers.

LDI discovers opportunities and solutions in a design process on the basis of the definition and characteristics of a product. The design process forms the functions of the product using available technologies to transform design requirements into the product structure. A method for the LDI product design is proposed in the following five processes.

3.1 Identification of product LDI opportunities

Discovering LDI opportunities is a primary task of the product LDI to decide the maturity of dominant technologies applied in the original product [15].

3.1.1 Hierarchical function modeling

For an original product S with n components, a hierarchical function model M_{H} of the original product can be established as follows to obtain a function set $\overset{\mathrm{H}}{F}$ with three levels of functions, including the technology-independent function, technology-related but component-independent function, and component-related function:

$$M_{\mathrm{H}} = \overset{\mathrm{H}}{K}(S), \tag{1}$$

where $\overset{\mathrm{H}}{K}$ is the knowledge required to build the hierarchical function model.

3.1.2 Maturity determination of the original product dominant subfunction technology

According to the function importance, subfunction set $\overset{\alpha}{F}$ can be divided into three categories: dominant subfunction set $\overset{\alpha}{F}_{\mathrm{a}}$, secondary subfunction set $\overset{\alpha}{F}_{\mathrm{b}}$, and equipped subfunction set $\overset{\alpha}{F}_{\mathrm{c}}$. If I_{Ra}, I_{Rb}, and I_{Rc} represent the functional role coefficients of dominant subfunctions, secondary subfunctions, and equipped subfunctions, respectively, then the relations of these three coefficients are $I_{\mathrm{Ra}} > I_{\mathrm{Rb}} > I_{\mathrm{Rc}}$, and the weighting values can be assigned as 0.5, 0.3, and 0.2, respectively [8]. According to the classification of functions used in this study, subfunctions belong to the technology-independent function on the boundary between technology-independent functions and technology-related but component-independent functions. Set $\overset{\Theta}{F}_{\mathrm{a}}$ belongs to the technology-related but component-independent function level. It corresponds directly to the dominant subfunction set $\overset{\alpha}{F}_{\mathrm{a}}$.

At present, the original product technology maturity is mainly decided in a subjective process. Technologies in the mature stage are targets for mining potential technological opportunities of LDI. The technology maturity identification reduces the analysis area of LDI opportunity in set $\overset{\Theta}{F}{}'_{\mathrm{a}}$. This process can be expressed as follows:

$$\overset{\Theta}{F}{}'_{\mathrm{a}} = \overset{\mathrm{N}}{K}(M_{\mathrm{H}}), \tag{2}$$

where $\overset{\mathrm{N}}{K}$ is the knowledge to decide the maturity of dominant technologies.

3.2 Hybrid relational function modeling

The function set $\overset{\mathrm{R}}{F}$ of a component-function model M_{R} includes useful function set $\overset{\mathrm{u}}{F}$ and component-function-related problem function set $\overset{\mathrm{p}}{F}$. The three types of problem functions include harmful function, insufficient function, and excess function. The useful function in the component-function model is the same as the component-related function in the hierarchical relational model. The importance of its components can be determined as follows by searching the level of each function in M_{R}:

$$M_{\mathrm{R}} = \overset{\mathrm{R}}{K}(S), \tag{3}$$

where $\overset{\mathrm{R}}{K}$ is the knowledge to build the component-function model.

A relational function model can be used to define problem functions at different levels. The basic function relationship of the hybrid relational function model is shown in Fig. 1 [27].

Component-function model M_{R} and hierarchical function model M_{H} are used to build a hybrid relational function model M_{M}. LDI potential function point set $\overset{\Theta}{F}{}'_{\mathrm{a}}$ can be expanded based on the hybrid relational function model to obtain the function area set $\overset{\Theta}{F}{}'_{\mathrm{a}}$ of potential LDI technologies. M_{M} shows not only the function area of potential LDI technologies but also the relationship of functions at different levels to reduce model complexity. The hybrid relational function model is shown in Fig. 2.

The hybrid relational function model is as follows:

$$M_{\mathrm{M}} = \overset{\mathrm{M}}{K}(M_{\mathrm{H}} \cup M_{\mathrm{R}}), \tag{4}$$

where $\overset{\mathrm{M}}{K}$ is the knowledge required to build the model.

3.3 Application of new dominant function technologies

New technologies can be searched using functions as keywords in function set F'_{a}. Then, they can be evaluated with the component-function model. If $F'_{\mathrm{a}j}$, $j > 0$ is the jth function of LDI potential technology function area set F'_{a}, then the sum of the performance indicators of its subfunctions is $\sum K^{\alpha}_{F'_{\mathrm{a}j}}$. The total cost of the replaced components is $\sum C'_{\mathrm{a}j}$. The local value of function $F'_{\mathrm{a}j}$ before the replacement by the new technology ($V'_{\mathrm{a}j}$) is as follows:

$$V'_{\mathrm{a}j} = \frac{\sum K^{\alpha}_{F'_{\mathrm{a}j}}}{\sum C'_{\mathrm{a}j}}. \tag{5}$$

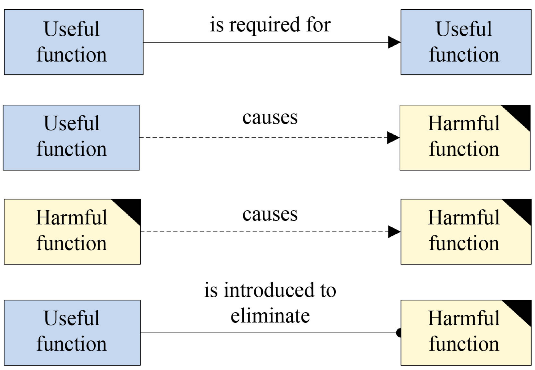


Fig. 1 Basic function relationship of the hybrid relational function model. Reproduced with permission from Ref. [27] from Elsevier.

The local value of function $F'_{\mathrm{a}j}$ after the new technology replacement ($V''_{\mathrm{a}j}$) can be obtained in the same way. According to the definition of product LDI, the local value of new technology should be higher than that of the original technology:

$$B_j = V''_{\mathrm{a}j} - V'_{\mathrm{a}j},\ B_j > 0, \tag{6}$$

where B_j represents the difference of the local value $V''_{\mathrm{a}j}$ of the $F'_{\mathrm{a}j}$ function after the technical replacement to the original local value $V'_{\mathrm{a}j}$. As the priority for the most valuable technology, B_j is arranged based on its value from large to small. After the application of new technology components, the relationship of other components in the system can be analyzed according to the hybrid relational function model to form a new component-function model. The initial scheme of the product LDI can be expressed as follows:

$$\overline{X} = \overset{\mathrm{S}}{K}\left(\overset{\Theta}{F'_{\mathrm{a}}} \cup M_{\mathrm{M}} \cup M_{\mathrm{R}}\right), \tag{7}$$

where $\overline{X}$ is an initial scheme of product LDI, and $\overset{\mathrm{S}}{K}$ is the knowledge to form the initial scheme.

3.4 Function optimization

Unlike the objects in the traditional trimming of products, the objects of LDI are mature products. Most of them do not have contradictions. Therefore, according to the characteristics of LDI products, the existing trimming rules and processes can be properly applied to LDI products at the functional level. The trimming rules for LDI products are shown in Table 1 [26,28].

For a component set S'' of the initial scheme with m components, the trimming sequence is decided based on

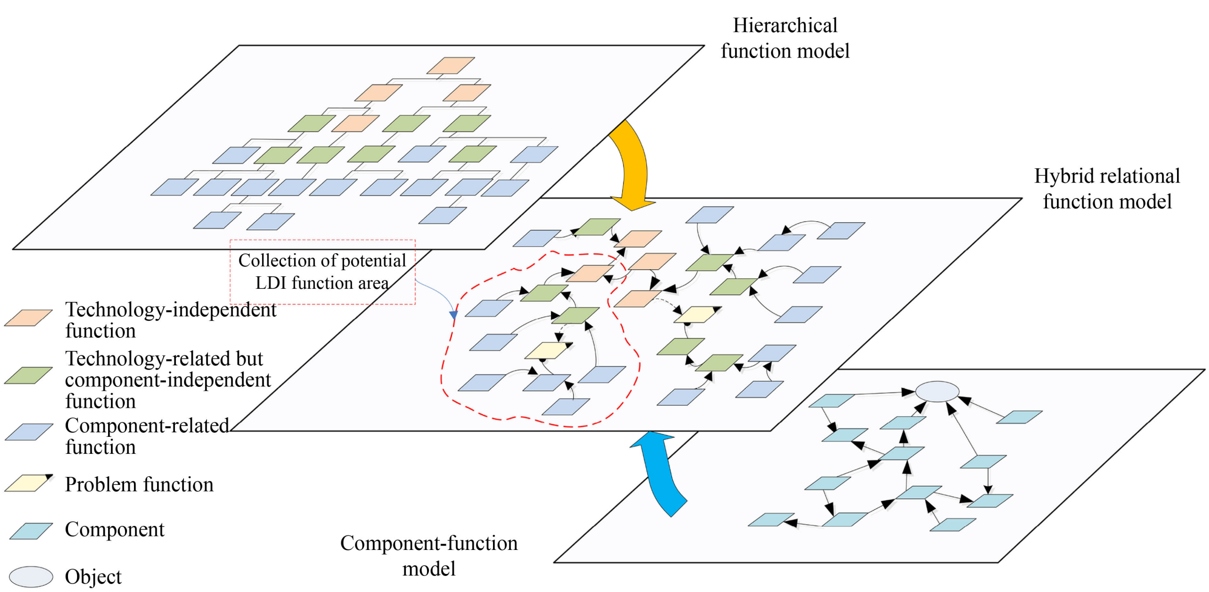
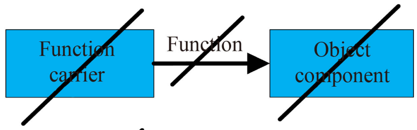
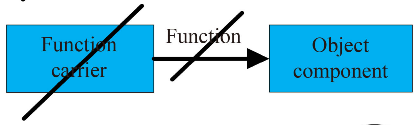
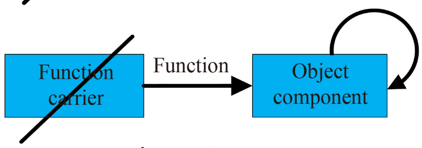
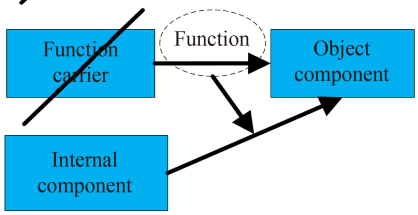
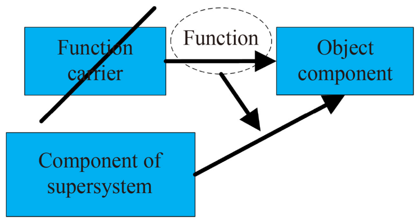


Fig. 2 Hybrid relational function model.

Table 1 Trimming rules for LDI products [26,28]

Trimming rules	Content of rules	Graphic	Source of system new function carrier
A	Trim it. When an object component of the function is not needed by the system, the function carrier is deleted.		No
X	Trim function is performed by the function carrier. If the function carried out by the function carrier is no longer needed, it is deleted, and then the function carrier is also deleted.		
B	The function performed by the function carrier is performed by the object component itself. If a system function can be executed by the target component, the original function carrier is trimmed.		Internal component of the system
C1	Function performed by the function carrier is performed by other components. If the system function can be executed by other components in the system, the original function carrier is trimmed, and the function is performed by other components in the system.		
C2	Function performed by the function carrier is performed by the supersystem component. If the system function can be executed by the supersystem, the function carrier is trimmed, and the function is executed by the supersystem.		Component of the supersystem

the complexity of the component-function interaction and the importance of function set $\overset{R}{F}$ corresponding to subfunction set $\overset{\alpha}{F}$. The complexity of the component-function interaction can be expressed by evaluation value $\sum \overset{R}{D}{}''$ in the system operation. The importance of subfunction set $\overset{R}{F}{}''$ corresponding to function set $\overset{\alpha}{F}{}''$ can be represented by functional role coefficients. Therefore, the importance degree P''_k of component S''_k can be expressed as follows:

$$P''_k = I_{\mathrm{Ra}} \times \sum \overset{R}{D}{}''_{\mathrm{a}k} + I_{\mathrm{Rb}} \times \sum \overset{R}{D}{}''_{\mathrm{b}k} + I_{\mathrm{Rc}} \times \sum \overset{R}{D}{}''_{\mathrm{c}k},\ 0 < k \leqslant m, \tag{8}$$

where $\sum \overset{R}{D}{}''_{\mathrm{a}k}$, $\sum \overset{R}{D}{}''_{\mathrm{b}k}$, and $\sum \overset{R}{D}{}''_{\mathrm{c}k}$ represent the evaluation values of the kth component functions associated with dominant subfunctions, secondary subfunctions, and equipped subfunctions, respectively. The order of components in the initial scheme is decided according to the importance degree P''_k, starting at the lowest important component. Based on the different classification of subfunctions, different trimming strategies can be determined as follows:

a) Trimming rule A is used to trim useless components after the application of new technologies.

b) According to the priority of trimming rules [26] and the classification of LDI product subfunctions, the model is trimmed as follows:

i) Function set $\overset{\alpha}{F}{}''_{\mathrm{c}}$ and its corresponding component set S''_{c} are deleted based on trimming rules according to their importance degrees. The priority order of trimming rules for function components is B-C1-C2-X, as shown in Table 1.

ii) The dominant- and secondary-subfunction-related function sets $(\overset{\alpha}{F}{}''_{\mathrm{a}} \cup \overset{\alpha}{F}{}''_{\mathrm{b}})$ and the corresponding component set $(S''_{\mathrm{a}} \cup S''_{\mathrm{b}})$ are formed.

According to the characteristics of LDI products, the dominant- and secondary-subfunction-related functions are unchanged, and retaining their functions is necessary. However, adjusting functional components after applying the new technology is also necessary. The priority order of trimming rules is B-C1.

The final design scheme is obtained after searching the function optimization X as follows:

$$X = \overset{T}{K}\left(\overline{X}\right), \tag{9}$$

where $\overset{T}{K}$ is the knowledge to optimize functions of the initial scheme $\overline{X}$.

Therefore, the final design scheme X can be written as follows:

$$X = \overset{\mathrm{T}}{K}\left(\overset{\mathrm{S}}{K}\left(\overset{\mathrm{N}}{K}\left(\overset{\mathrm{H}}{K}(S)\right) \cup \overset{\mathrm{M}}{K}\left(\overset{\mathrm{H}}{K}(S) \cup \overset{\mathrm{R}}{K}(S)\right) \cup \overset{\mathrm{R}}{K}(S)\right)\right). \quad (10)$$

3.5 Evaluation of the final scheme

The system value of an LDI product is very high, thus, its cost is much lower than the costs of existing products. The value formula of an original product is as follows:

$$V = \frac{I_{\mathrm{Ra}} \times \sum K_{F_{\mathrm{a}}}^{\alpha} + I_{\mathrm{Rb}} \times \sum K_{F_{\mathrm{b}}}^{\alpha} + I_{\mathrm{Rc}} \times \sum K_{F_{\mathrm{c}}}^{\alpha}}{\sum C}, \quad (11)$$

where V is the value of the original product, $\sum C$ is the total cost of the original product, and $\sum K_{F_{\mathrm{a}}}^{\alpha}$, $\sum K_{F_{\mathrm{b}}}^{\alpha}$, and $\sum K_{F_{\mathrm{c}}}^{\alpha}$ are the rank sum of the performance indicators of dominant, secondary, and equipment subfunctions, respectively. The value V''' of a product system after LDI can be obtained in the same way. While meeting the LDI, new products also have the following constraints:

$$L_1 = V'''/V,\ L_1 > 1, \quad (12)$$

and

$$L_2 = \sum C''' \Big/ \sum C,\ 0 < L_2 < 1, \quad (13)$$

where L_1 is the ratio of value V''' of the new product to value V of the original product, and L_2 is the cost ratio of a new product $\sum C'''$ to the original product $\sum C$. The final scheme should make L_1 larger than 1 and L_2 less than 1 as much as possible. The second low-end disruption process is conducted for the product with discontinuity of the product value.

3.6 Framework

In summary, the proposed method consists of the following five steps:

1) The technology maturity of the main subfunction is determined based on the technology-dependent function set $\overset{\Theta}{F}_{\mathrm{a}}$ and the dominant subfunction set $\overset{\alpha}{F}_{\mathrm{a}}$ of hybrid relational function model M_{H}. A set $\overset{\Theta}{F}{}'_{\mathrm{a}}$ of opportunists for LDI products is obtained.

2) Hybrid relational function model M_{M} is obtained by combining hierarchical function model M_{H} and component-function model M_{R}. In the hybrid relational function model, the set $\overset{\Theta}{F}{}'_{\mathrm{a}}$ of opportunities for LDI products is expanded to set F'_{a}.

3) Function set F'_{a} is searched from bottom to top for the corresponding new technologies by using functions as keywords. The local values before and after $V'_{\mathrm{a}j}$ are calculated to replace new technologies. The local value differences of the new and old technologies are compared to determine the replacement technologies and form the initial scheme.

4) Based on the TRIZ trimming rules of LDI and the importance degree P''_k of each component in the initial scheme, the product functions are optimized to form the final scheme X.

5) The low-end disruption can be decided for the final design scheme by comparing the value and cost of the original and LDI products for the final scheme to meet the requirements of LDI.

A framework for product LDI is shown in Fig. 3.

4 Application of the proposed method

This section chooses a dropping pill machine used for traditional Chinese medicine extraction to demonstrate the product LDI design process, verify the proposed method, and demonstrate its potential. The new design of the dropping pill machines is developed for applications in small firms. This new design is LDI compared with the design of the dropping pill machines used in middle-sized or large firms in China. The proposed method can be extended to a general model by abstracting the LDI design process for other applications.

Most of the existing machines in the market operate at a constant temperature and pressure for automatic production. The machine heats and melts the drug with the solid matrix to form a solution, suspension, or emulsion. Then, it drops the drug into a coolant that is immiscible with the drug matrix to cool it rapidly. The droplets shrink and condense to form a solid state of pellets. The existing machine structure is complex, and the cost is estimated at 3000 USD, which is not suitable for small and medium enterprises to use. This study develops a small-sized dropping pill machine with specifications shown in Table 2.

The product LDI is searched using the proposed method as follows.

4.1 Searching for LDI opportunities

According to Eq. (1), the hierarchical function model M_{H} of the dropping pill machine is built, as shown in Fig. 4.

Subfunctions are classified based on the function's importance. Dominant subfunctions include melting medicine, transporting liquid medicine, dropping liquid medicine, and cooling pills. Secondary subfunctions include storing medicine, collecting pills, and controlling the system. Equipped subfunction includes delivering pills. According to the patent analysis, patents related to dropping pill machines are mainly for improvement and dripper design. According to Eq. (2), the corresponding technologies of other dominant subfunctions are mature because of the long-time development.

4.2 Application of new technologies to the dropping pill machine

According to Eq. (3), a component-function model is

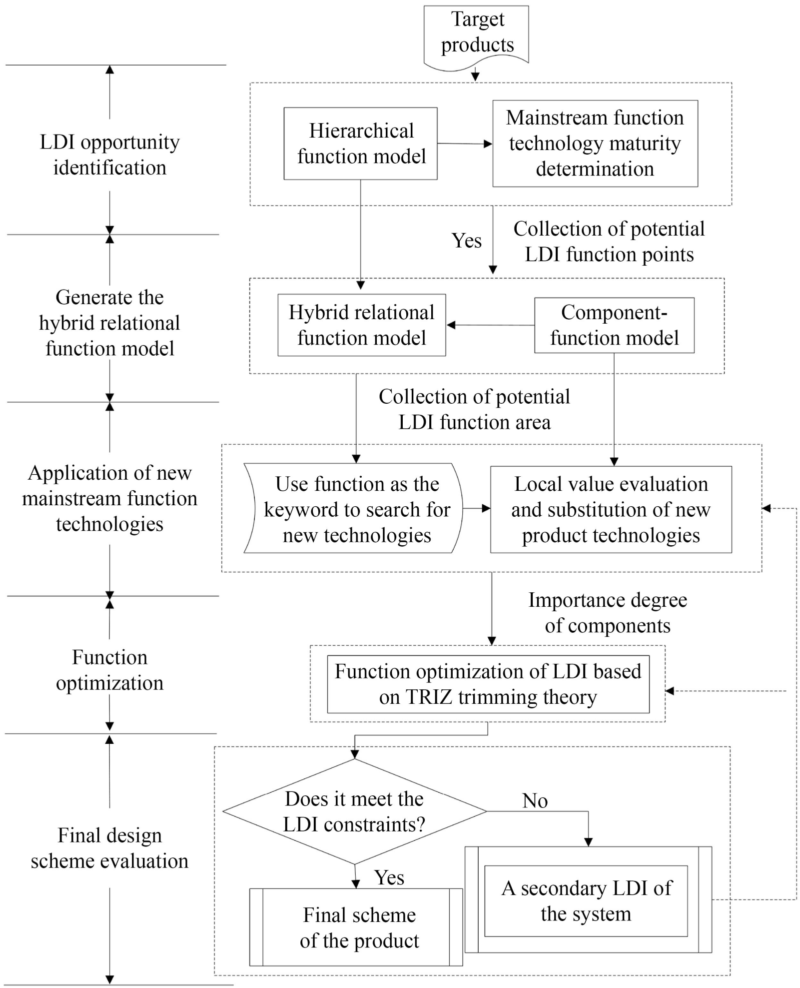


Fig. 3 Framework of product LDI.

Table 2 Dropping pill machine specifications

Working voltage	Power	Diameter of dropping pills	Yield	Contour size	Weight
380 V	1.8 kW	0.5–5 mm	10000 pills/h	950 mm × 850 mm × 1900 mm	500 kg

built for the dropping pill machine, as shown in Fig. 5, using the method in Refs. [26,28].

According to Eq. (4), hybrid relational function model M_M is built based on the component-function and hierarchical function models, as shown in Fig. 6. The red dotted line area is the collection of potential LDI function area set F'_a. Functions are used as keywords to search for new technologies from bottom to top in the area.

New technologies are searched using the function “divide liquid medicine” as keywords. The peristaltic pump is obtained. The component-function model in Fig. 5 indicates that the components that need to be replaced are the compressor, feeding pipe valve, and liquid storage tank. The cost is estimated at 1019.1 USD. The cost of the peristaltic pump is 186.2 USD. “Divide liquid medicine” corresponds to two dominant subfunctions of “transport liquid medicine” and “drop liquid medicine”. The performance indicators and expected performance rank are obtained, as shown in Table 3, through the group discussion of engineers and the method [8].

The local value difference for “divide liquid medicine” is $B > 0$. Therefore, the peristaltic pump can be used as a new technology for implementing product LDI for the machine. After the peristaltic pump is applied, the other components of the machine are optimized to meet the design requirements. The agitator and circulating heating oil pump are added to eliminate the harmful functions “medicine cannot evenly heated” and “heating oil cannot evenly heated” by analyzing the hybrid relational function model. “Stir the medicine in the medicine tank” and “drive the heating oil in the oil tank” become excess functions when the volumes of the medicine tank and oil tank are reduced according to design requirements. According to Eq. (7), an initial scheme model of the machine is built, as shown in Fig. 7.

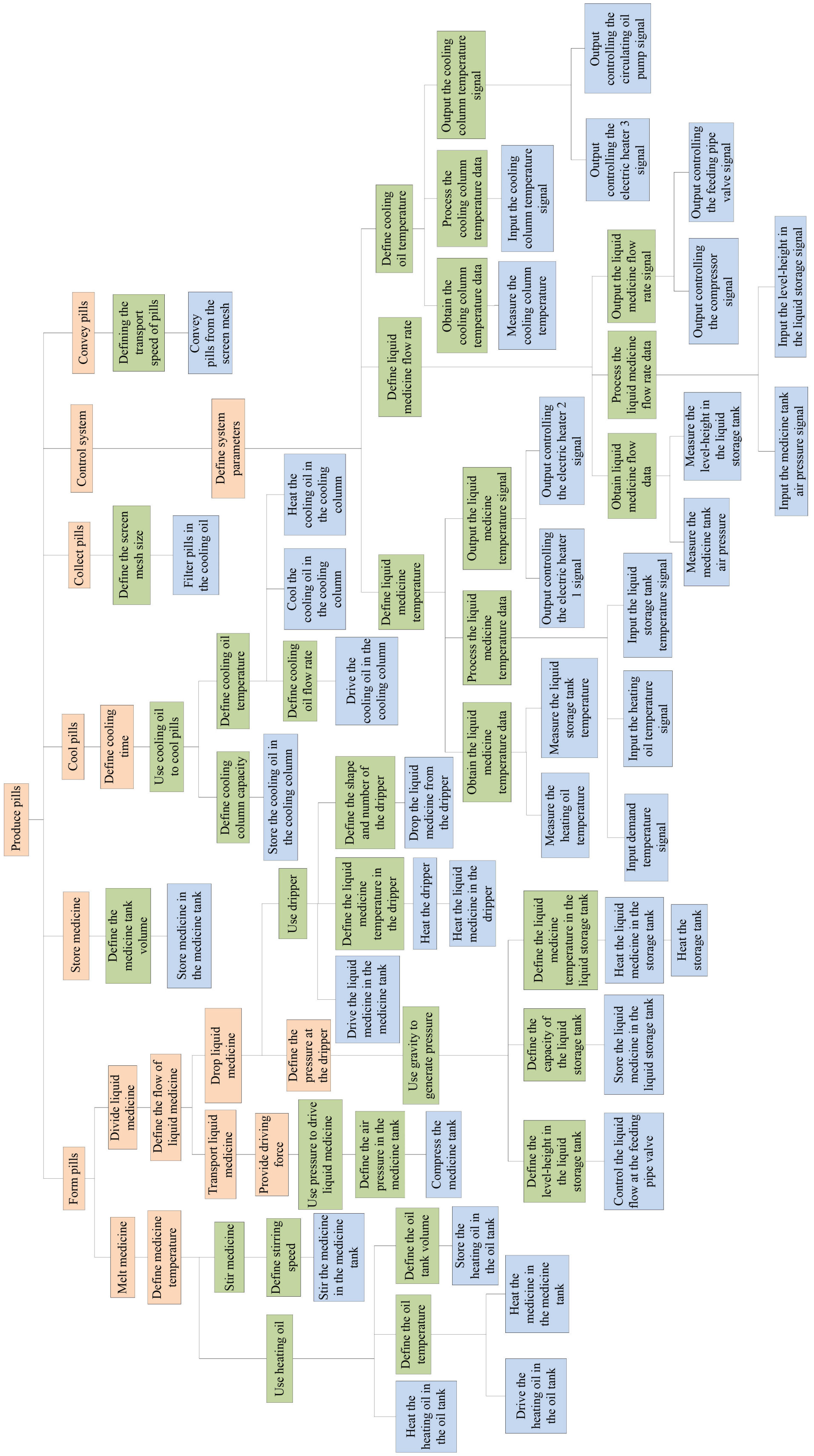


Fig. 4 Hierarchical function model of the dropping pill machine.

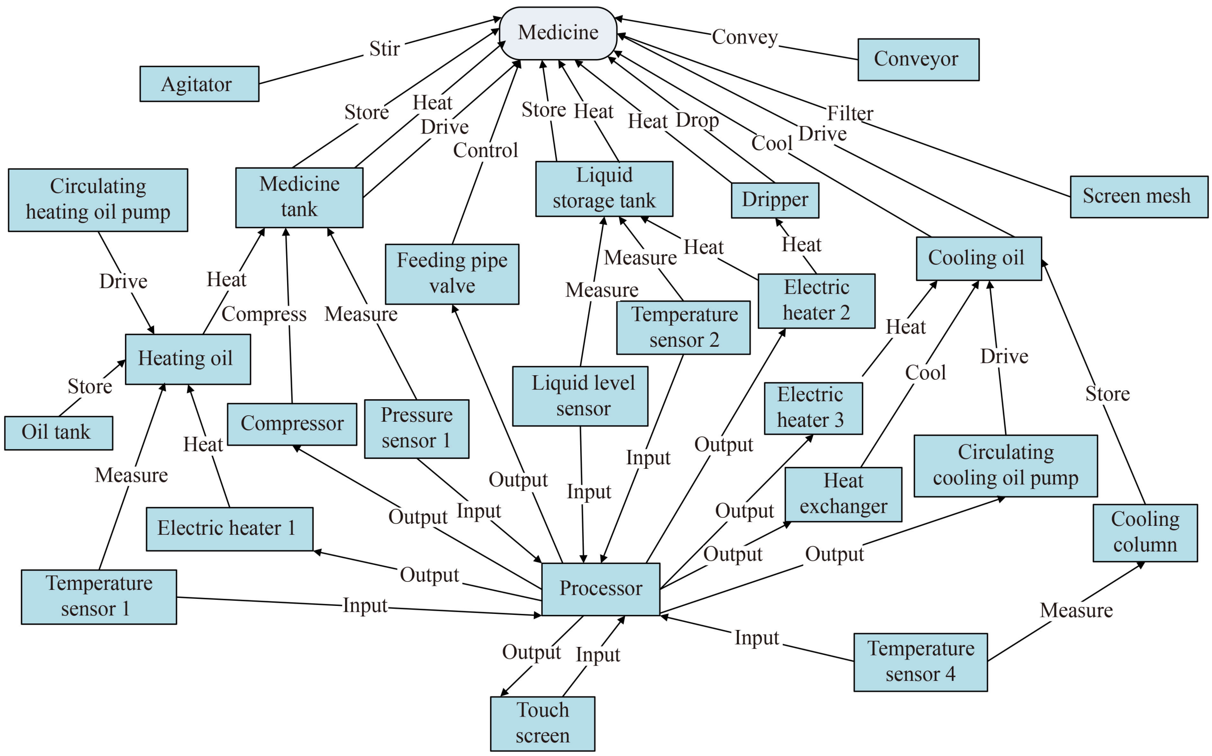


Fig. 5 Component-function model of the dropping pill machine.

4.3 Function optimization

The importance of each component in the initial scheme of the machine is decided as follows [86]:

(1) The function level of functions of the component is decided based on the distance between the component and object. In the component-function model, the function directly acting on the object has the highest function level, which is recorded as A_0. i represents the functional level of the component being acted on, $i > 1$. If the component acts on the component with function level A_i, its function level is A_{i+1}. The rules for evaluating component function levels are as follows:

Rule 1: The lowest functional level is 1;

Rule 2: Rank (A_{i-1}) = Rank $(A_i) + 1$;

Rule 3: Rank (A_0) = Rank $(A_1) + 2$;

Rule 4: When a component performs multiple functions, its function level is the sum of each function level;

Rule 5: The functional level of the component to the supersystem is A_1.

After the function level is calculated, the highest function-level value is adjusted to 10, and the other function levels are adjusted according to this proportion.

(2) The function level of the problem function is decided by the designer according to the actual situation. The value range is −10 to 0.

Therefore, the function level in the initial scheme of the dropping pill machine is shown in Fig. 8.

According to Fig. 8, the importance degree of components in the initial scheme in Eq. (8) under Section 3.4 is used to obtain the importance degree of components in the initial scheme of the machine, as shown in Table 4.

According to the component importance shown in Table 4, the following trimming operations are performed on the component-function model:

1) Agitator: It is a dominant function corresponding component. The function performed by the agitator can be performed by the medicine itself. Therefore, the agitator can be trimmed by trimming rule B.

2) Circulating heating oil pump: It is a dominant function corresponding component. The function performed by the pump can be performed by the heating oil itself. Therefore, the pump can be trimmed by trimming rule B.

3) Trimming rule A is used to trim the useless components, pressure sensor 1, and liquid level sensor after the application of the new technology.

4) Conveyor: It is the equipped function corresponding component. The function performed by the conveyor can be performed by the supersystem component. Therefore, the conveyor can be trimmed by trimming rule C2.

According to Eq. (9), the final scheme design model is formed, as shown in Fig. 9.

4.4 Evaluation of the final design scheme

The estimated cost of the final scheme is $1053.1. The expected performance ranking of the dropping pill machine is shown in Table 5 based on the method in Ref. [8].

According to the value of the product in Eq. (11) in

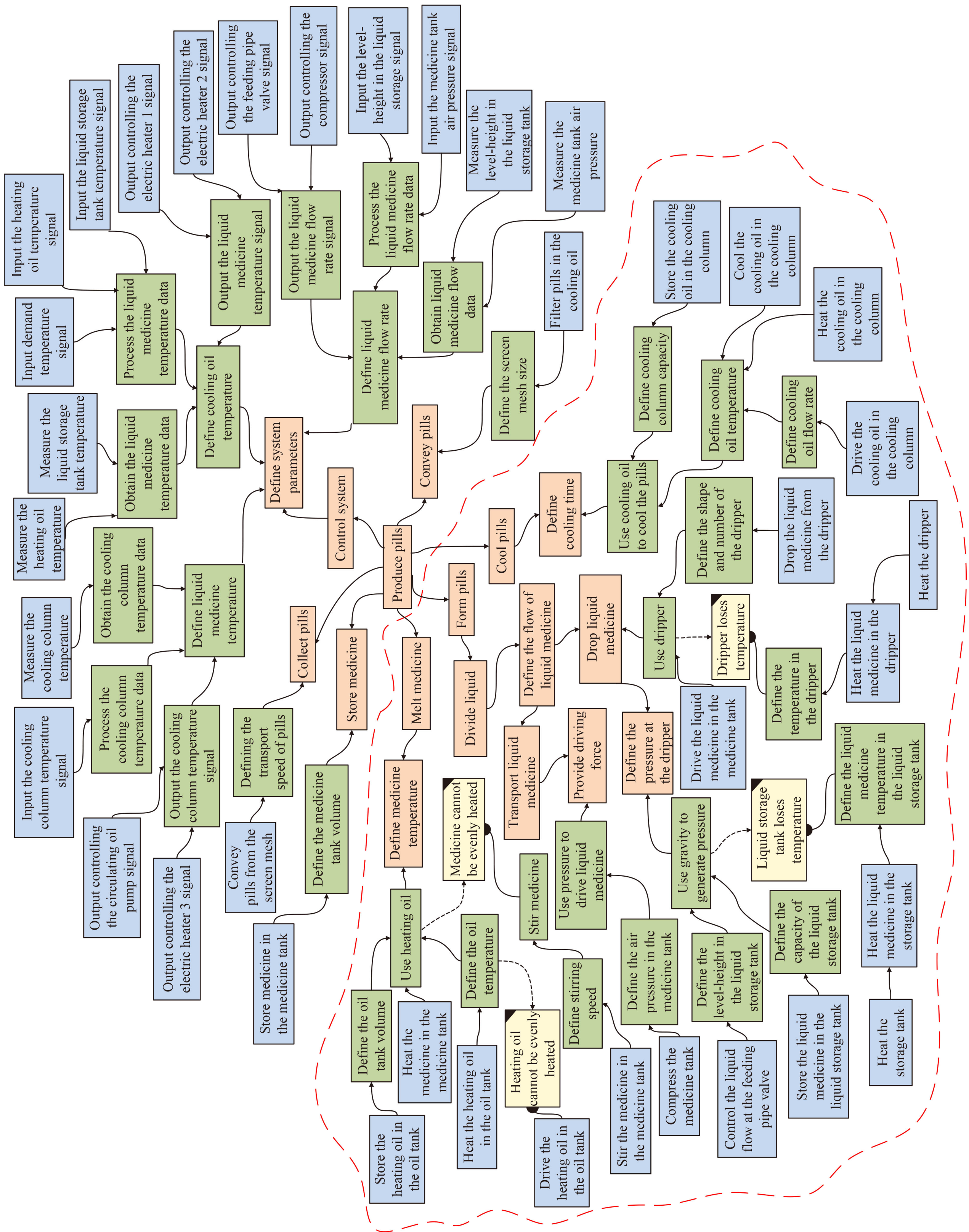


Fig. 6 Hybrid relational function model of the dropping pill machine.

Section 3.5, the calculation result is $L_1 > 1$ and $0 < L_2 < 1$. After the solution evaluation, a discontinuity of the product value exists. The scheme fully meets the requirements of LDI. Compared with the original system, the improved dropping pill machine has the advantages of simple operation and a simplified system structure that meets design requirements. It reduces the cost, improves the system value, and realizes the product LDI. The layout and prototype of the dropping pill machine after LDI is shown in Figs. 10 and 11.

5 Discussion and conclusions

This study proposes a new design method for developing LDI products. According to the definition and characteristics of LDI, the product LDI is proposed as a divergent–convergent process, including the technology substitution, function optimization, and design constraints of the product. The method is introduced based on a hybrid relational model by decomposing product functions. It combines the reengineering method in the product concept design phase and the TRIZ-based trimming method. The area of potential LDI technologies is determined by analyzing the maturity of domain subfunction technologies. The initial scheme of LDI is formed by searching and replacing the function-based keywords in the function area of potential LDI technologies. A TRIZ-based trimming method for product LDI is proposed to optimize product functions. The combined application of the two methods is an attempt to obtain the optimal design scheme for product LDI. The design scheme is evaluated under the design constraint of product LDI. It is presented at each stage of product LDI. The value evaluation method combines the product evaluation method at the concept design phase and the TRIZ-based trimming evaluation method, thereby making the evaluation method compatible. The method provides a feasible path for the design of LDI products. The method is applied in the design of a new dripping pill machine. The major contributions of this study include two aspects: theory and practice.

In terms of theory contribution, a definition for the design of the product LDI and two essential characteristics of LDI products, namely, low cost and high system value that can cause discontinuity in products' original value trajectory, are summarized by reviewing various perspectives. The combination of these two characteristics is a sufficient and necessary condition for product LDI. We also find that the changes in LDI products come

Table 3 Expectant performance ranking after the persistent pump is replaced

Subfunction list	Performance indicators	Expectant performance rank
Transport liquid medicine	Rate of flow	0.1
	Reliability	0.8
Drop liquid medicine	Rate of flow	0.1
	Reliability	0.8

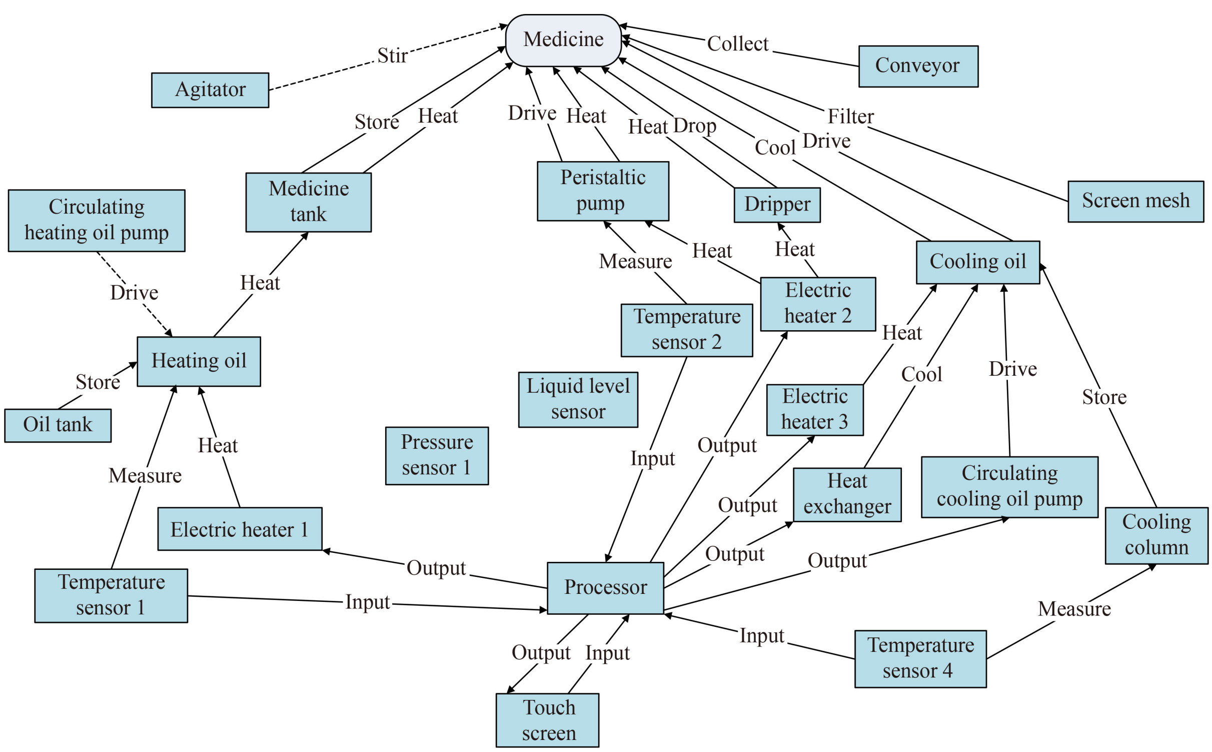


Fig. 7 Initial scheme model of the dropping pill machine.

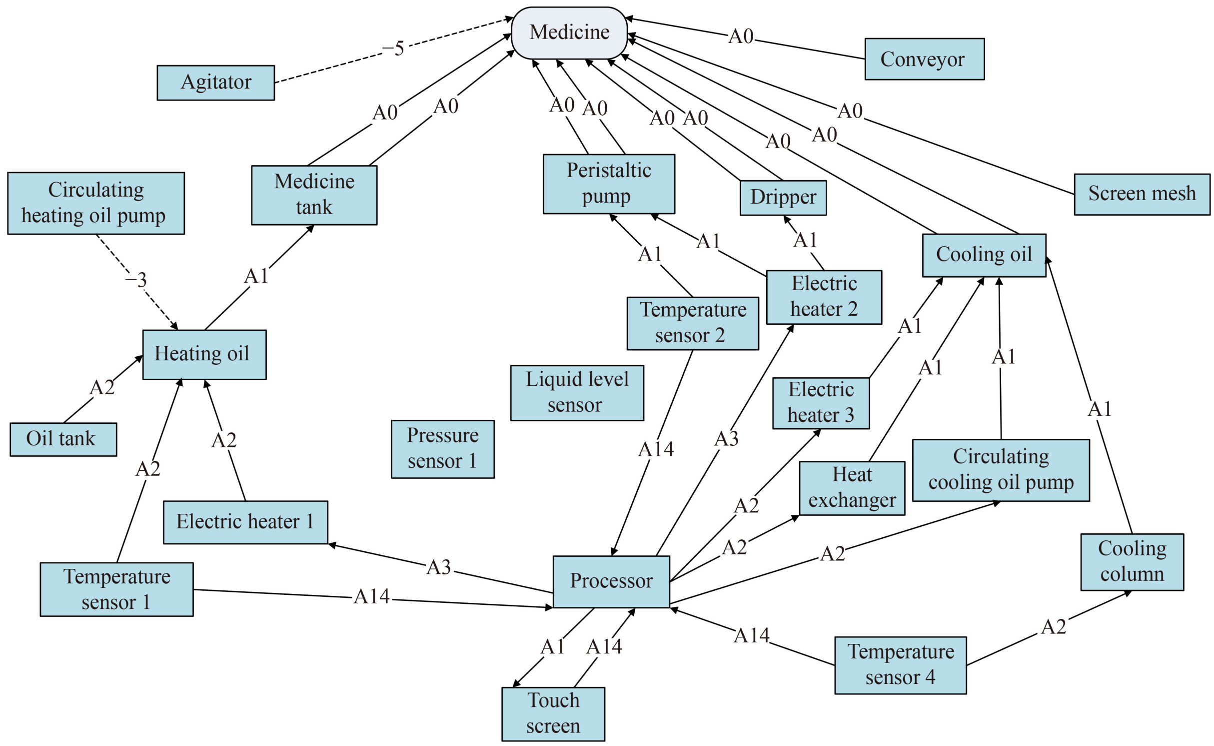


Fig. 8 Function levels in the initial scheme of the dropping pill machine.

Table 4 Importance degree of components in the initial scheme of the dropping pill machine

Component	Component importance
Agitator	−5.00
Medicine tank	8.00
Oil tank	4.06
Heating oil	4.37
Electric heater 1	4.06
Temperature sensor 1	2.63
Pressure sensor 1	0.00
Touch screen	0.19
Conveyor	2.00
Screen mesh	3.00
Temperature sensor 2	2.81
Circulating heating oil pump	−3.00
Liquid level sensor	0.00
Peristaltic pump	10.00
Processor	20.50
Dripper	10.00
Electric heater 2	8.75
Cooling oil	10.00
Circulating cooling oil pump	4.38
Temperature sensor 4	2.62
Cooling column	4.38
Electric heater 3	4.38
Heat exchanger	4.38

from two aspects: the dominant subfunctional technology and product optimization at the functional level. These summaries and findings signify that we have addressed the major theoretical obstacles affecting the study of product LDI methods. In the present research, the hybrid relational model is improved, and the trimming principle is reordered to suit the product LDI. Compared with the existing LDI design methods based on unnecessary characteristics, such as low cost, small size, simple system, and easy operation, the method in the present study incorporates the characteristics of the increased system value and low cost throughout the product LDI design, thereby improving the accuracy of the product LDI design results. For researchers, the present study's review of disruptive innovation reveals that research on product disruptive innovation methods is still in its infancy and these methods remain a research topic for disruptive innovation research. According to the product LDI characteristics and definitions in the specific situation of different industries and regions, specific design methods will be required for the product LDI in the future.

In terms of practice, unlike the existing studies that apply new technologies to different fields, the present study provides a product LDI design method from an enterprise perspective for a successful application in the design of a new dripping pill machine. The method can be used easily by enterprise engineers to access product LDI solutions. The two changes in the LDI products summarized in the present study also reveal the pervasiveness of product LDI for enterprises at all stages

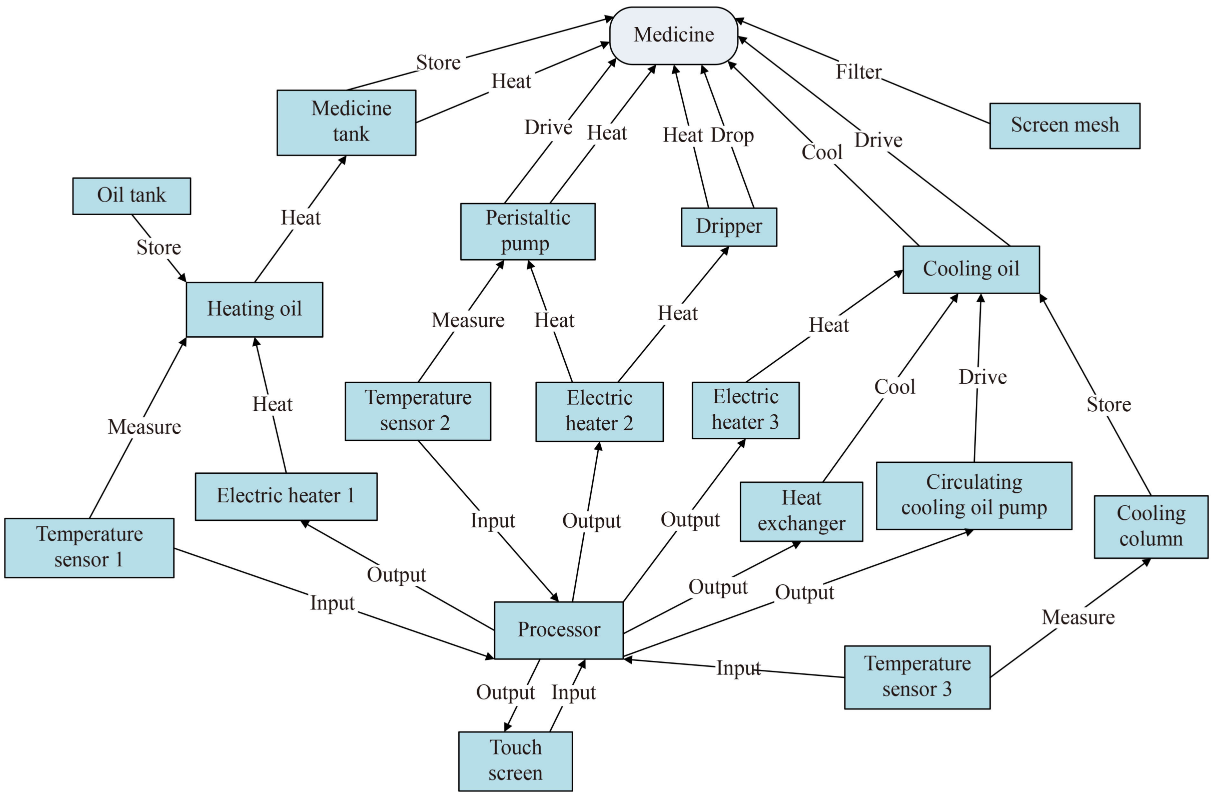


Fig. 9 Final scheme model of the dropping pill machine.

Table 5 Assignment of the expectant performance ranking of the dropping pill machine

Subfunctions	Functional role coefficient	Subfunction list	Performance indicators	Expectant performance rank
Dominant subfunctions	$I_{Ra} = 0.5$	Melt medicine	Heating time	0.6
	–	–	Reliability	0.5
	–	Transport liquid medicine	Rate of flow	0.1
	–	–	Reliability	0.8
	–	Drop liquid medicine	Rate of flow	0.1
	–	–	Reliability	0.8
	–	Cool pills	Cooling time	0.5
	–	–	Reliability	0.5
Secondary subfunctions	$I_{Rb} = 0.3$	Store medicine	Capacity	0.1
	–	Collect pills	Capacity	0.1
	–	Control system	Reliability	0.5

of product development. The proposed method can help managers identify the specific product LDI strategies based on their industry position, thereby allowing them to capture the market and maximize profits in the competition.

Given the limitations of the present study, the model content of the LDI must be presented in detail, particularly for the opportunity of LDI products. The search method for new mainstream technologies and the evaluation method for the final design scheme will be improved to reduce the dependence on subjective factors. The evaluation method of this study for product LDI is qualitative. Future research will further quantitatively evaluate the extent of product LDI. Future research will be useful for companies in evaluating the product LDI schemes. Substantial LDI case data will be obtained as the present method is applied. They will be used for further optimization of the method. The process of product LDI can become extremely cumbersome for complex product systems. The design method in the present study is expressed in mathematical language, and a framework for a computer-aided system is initially developed. The use of intelligent decision-making methods will also be a part of our future work.

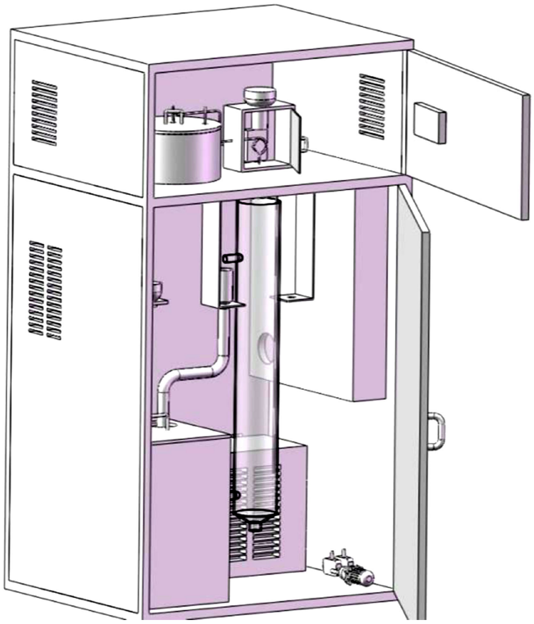


Fig. 10 Layout of the new dropping pill machine.

Fig. 11 Prototype of the dropping pill machine.

Nomenclature

Variables

A_i	ith function level of the component-function model of the initial scheme
B_j	Local value difference of the jth local value
$\overset{\mathrm{H}}{F}$	Function set of the hierarchical function model of the original product
$\overset{\mathrm{p}}{F}$	Component-function-related problem function set of the original product
$\overset{\mathrm{R}}{F}$	Function set of the component-function model of the original product
$\overset{\mathrm{u}}{F}$	Useful function or component-related function set of the original product
$\overset{\alpha}{F}$	Subfunction set of the original product
$\overset{\mathrm{R}}{F}''$	Function set of the component-function model of the initial scheme
$\overset{\alpha}{F}''$	Subfunction set of the initial scheme
$\overset{\alpha}{F}_{\mathrm{a}}$, $\overset{\alpha}{F}_{\mathrm{b}}$, $\overset{\alpha}{F}_{\mathrm{c}}$	Dominant, secondary, and equipped subfunction sets of the original product, respectively
$\overset{\Theta}{F}_{\mathrm{a}}$	Technology-related but component-independent function set
F'_{a}	Function area set of potential LDI technologies
$F'_{\mathrm{a}j}$	jth function of LDI potential technology function area set
$\overset{\Theta}{F}{}'_{\mathrm{a}}$	Function point set of potential LDI technologies
$\overset{\alpha}{F}{}''_{\mathrm{a}}$, $\overset{\alpha}{F}{}''_{\mathrm{b}}$, $\overset{\alpha}{F}{}''_{\mathrm{c}}$	Dominant, secondary, and equipped subfunction sets of the initial scheme, respectively
I_{Ra}, I_{Rb}, I_{Rc}	Functional role coefficient of dominant, secondary, and equipped subfunctions, respectively
$\overset{\mathrm{H}}{K}$, $\overset{\mathrm{M}}{K}$	Knowledges required to build the hierarchical and hybrid relational function models, respectively
$\overset{\mathrm{N}}{K}$	Knowledge to decide the maturity of dominant technologies
$\overset{\mathrm{R}}{K}$	Knowledge to build the component-function model
$\overset{\mathrm{S}}{K}$	Knowledge to form the initial scheme
$\overset{\mathrm{T}}{K}$	Knowledge to optimize functions of the initial scheme
L_1, L_2	Value and cost ratios of the original to the new product, respectively
m	Number of the initial scheme components
M_{H}, M_{M}	Hierarchical and hybrid relational function models of the original product, respectively
M_{R}	Component-function model of the original product
n	Number of the original product components
P''_k	Importance degree of the kth component in the initial scheme
S, S''	Component sets of the original product and initial scheme, respectively

$S''_{\mathrm{a}}, S''_{\mathrm{b}}, S''_{\mathrm{c}}$	Component sets of the dominant, secondary, and equipped subfunctions in the initial scheme, respectively
V	Value of the original product
$V'_{\mathrm{a}j}, V''_{\mathrm{a}j}$	Local values of the jth function before and after the new technology replacement, respectively
V'''	Value of the final design scheme
X	Final design scheme of product LDI
$\overline{X}$	Initial scheme of product LDI
$\sum C$	Total cost of the original product
$\sum C'_{\mathrm{a}j}$	Total cost of dominant subfunctions associated with the jth function before the new technology replacement
$\sum C'''$	Total cost of the new product
$\sum \overset{\mathrm{R}}{D''}$	Evaluation value of component functions
$\sum \overset{\mathrm{R}}{D''}_{\mathrm{a}k}, \sum \overset{\mathrm{R}}{D''}_{\mathrm{b}k}, \sum \overset{\mathrm{R}}{D''}_{\mathrm{c}k}$	Evaluation values of the kth component functions associated with dominant, secondary, and equipped subfunctions, respectively
$\sum K_{F_{\mathrm{a}}}^{\alpha}, \sum K_{F_{\mathrm{b}}}^{\alpha}, \sum K_{F_{\mathrm{c}}}^{\alpha}$	Rank sums of performance indicators of dominant, secondary, and equipped subfunctions, respectively
$\sum K_{F'_{\mathrm{a}j}}^{\alpha}$	Rank sum of performance indicators of dominant subfunctions associated with the jth function before the new technology replacement

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