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Inspirational Stimuli to Support Creative Ideation for the Design of AI-powered Products

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Abstract

Artificial Intelligence (AI) has the potential to revolutionize product design, and designers need to know how to best leverage its capabilities. Based on the concept–knowledge (C-K) theory, a set of inspirational stimuli (IS) for the design of AI-powered products (ISfAI) has been developed to contribute to the conceptual design stage. We extracted 40 ISs from 1,755 granted AI patents using a five-step process and validated their feasibility through a controlled experiment using three design aids: brainstorming, ISfAI Sheet, and ISfAI Cards. Results suggest that the ISfAI Cards can serve as a creative tool to enabling practitioners to generate a greater range of high-quality AI-powered ideas, particularly in terms of Novelty, Creativity, Elaboration and Flexibility. This study has practical implications for developing AI-powered products and services.

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1 Introduction

Research thoroughly supports the critical role of new product development (NPD) and innovation in ensuring long-term firm success [1]. Artificial intelligence (AI) has captured significant interest across various industry sectors [2] as it significantly enhances product intelligence, responsiveness, and alignment with the dynamic needs and expectations of consumers [3]. The term "AI products" refers to products or product features that leverage AI capabilities to enhance and influence the human experience [4]. "AI-powered" refers to technology or systems that incorporate AI capabilities to perform tasks or make decisions typically requiring human intelligence. "AI-powered products" means products (physical or digital) that incorporate AI capabilities. Examples of AI-powered products include the iRobot Roomba, a robotic vacuum cleaner that uses AI to map spaces, plan cleaning routes, and avoid obstacles; and Netflix, which employs AI to analyze users' past behaviors and preferences to personalize content recommendations [2]. Designers are leveraging AI's unique features for enhanced functionality in their designs [5, 6]. However, research indicates that practitioners, including designers and product managers without a background in AI or data science, struggle to grasp AI's potential and create innovative solutions for targeted design issues, limiting their effective involvement in AI product development [5, 7].

In order to assist practitioners, a range of AI design tools [8], methods [9-11] and guidelines [12-14] have been developed. However, these methods mainly focus on supporting the later phases of the design process, particularly the evaluation phase. Limited research has been conducted to explore strategies for practitioners to generate a larger variety of innovative and diverse concepts for the early ideation phase in the AI domain. The process of generating multiple, diverse solutions to a problem, which can result in innovative outcomes, is commonly known as concept generation or ideation [15]. Ideation plays a fundamental role in shaping the design direction and significantly contributes to the generation of novel concepts and the potential for business success [16]. However, generating a diverse range of ideas can be challenging for designers due to fixation, where their attention becomes fixated on a single past example or a single new idea [17, 18]. Studies have demonstrated that product design practitioners encounter challenges related to design fixation when generating AI-powered product ideas [6].

In an attempt to increase concept generation for AI-powered product ideas, our research question is: *How might practitioners be supported in understanding the capabilities of AI to generate novel and diverse AI-powered ideas in the early conceptual design phase?*

Based on the concept–knowledge (C-K) theory, the generation of innovative design concepts relies on expanding the concept and knowledge space by introducing knowledge from external domains [19]. Thus, this paper aims to develop "creative tools" that leverage knowledge from the AI domain to facilitate the generation of AI-powered ideas. The use of creative tools is

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essential to assist designers in generating a greater number of innovative ideas within limited timeframes [16]. This study seeks to methodically analyze AI-related applications and technologies based on granted patent documents and propose a set of inspirational stimuli for AI-powered concept generation (ISfAI). Drawing on the CK theory, which posits that innovative design concepts arise by expanding concept and knowledge spaces via the integration of external domain knowledge, this paper introduces the development of an Inspirational Stimuli tool for the design of AI-powered products (ISfAI). This tool is designed to offer medium stimuli, eschewing both near and far stimuli, to focus on building the knowledge space and improving knowledge reasoning processes. Consequently, it will enable practitioners to access broader design spaces and generate a more diverse range of AI-powered product ideas.

This research makes two primary contributions: 1) developing two types of design stimuli tools (i.e. ISfAI Sheet and ISfAI Cards) for AI-powered product concept generation; 2) advancing understanding of the practicality and effectiveness of ISfAI in the context of making AI more explainable and supportive of design ideation.

2 Literature review

This section will review what are the challenges for generating AI-powered product ideas and what aids are already available. It will also review the role of stimuli in ideation.

2.1 Challenges for Generating AI-Powered Product Ideas

Technology typically undergoes a transition from being a specialized tool to becoming a widely used mainstream resource, and AI is currently experiencing a similar transformation [20]. In the user experience design domain, AI has emerged as a new design material [5, 6]. This shift allows people to reconsider the value of technology from a human-centered perspective, thereby refining products that possess true competitiveness. However, practitioners faced challenges for designing AI-powered ideas. One of the primary challenges in designing AI systems has been the difficulty in defining the extent of their capabilities, that is, understanding what AI can and cannot do [7]. Furthermore, designers may face challenges in effectively leveraging AI for the specific design problem, as their knowledge and understanding of AI may be limited [5]. This limited understanding can hinder designers' ability to generate diverse AI-powered concepts, as they may become fixated on particular ideas [17, 18]. For example, practitioners encounter design fixation challenges when trying to generate AI-powered ideas beyond automation, recommenders, and reminders [6]. Consequently, the domain of AI product design has historically been guided by AI scientists and engineers possessing an intricate comprehension of AI technology. Nevertheless, this cohort frequently falls short in grasping the essential user requirements and insights vital for

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producing valuable products or services [4, 21]. These various factors contribute to over 85% of AI innovation projects facing failure [22].

2.2 Existing Design Aids for Generating AI Product Ideas

In the realm of psychology, scholars utilize the network model of memory to explain the origins of design fixation. Within this network model, each node represents a concept. When an instance stimulus activates a concept node, the probability of activating nodes directly associated with the initial idea is higher [23]. A method to mitigate design fixation involves offering designers abundant and diverse external information resources and stimuli. Consequently, the development of tools and aids to support AI design has gained significant attention in recent years. Amershi, et al. [14] developed a set of 18 guidelines for Human-AI Interaction. Additionally, major tech companies such as Google and Microsoft have also created their own sets of AI/Machine Learning (ML) guidelines for practitioners [12, 13]. Feng and Mcdonald [24] developed an Interactive Machine Learning Approach for Designing ML Applications. Researchers have explored the extraction of AI capabilities from HCI literature [25]. A recent study proposed a tangible AI capability toolkit to support design students in learning and ideation [26]. Greer, et al. [27] states: "The format used to present the product evolution design guidelines is the *imperative* form from English grammar." Buxton [28] noted that practitioners commonly recognize guidelines as predominantly contributing to prototyping and refinement stages, ensuring precision in execution. In comparison to AI guidelines, practitioners express a desire for enhanced assistance in the ideation phase and problem formulation, aiming to avoid failures in AI product development [4]. In the early conceptual design phase, where practitioners encounter challenges in understanding AI capabilities and envisioning innovative AI solutions for specific design problems [7], there is a dearth of tools to facilitate AI-powered product innovation. Ideation plays a crucial role in shaping the type of design and is instrumental in generating novel concepts and achieving business success [16]. However, limited research has been conducted to assist practitioners in generating novel and diverse AI-powered concepts during this critical stage.

2.3 Impact of Stimuli on Ideation

In design research, the term "stimuli" encompasses informational inputs that facilitate the ideation phase for designers by supplying potential inspirations [29]. The spectrum of potential inspiration sources spans various categories by its origin (internal or external), analogical proximity (near or far), and medium (textual, visual, or other) [30]. Inspirational stimuli, defined as closely related to the problem space, were found to activate distinct brain regions that facilitate memory retrieval and problem-solving through insight rather than analytical processes [31]. Gonçalves, et al. [32] classified stimuli into "close", "distant", and "too distant". They discovered that participants

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experienced "peak inspiration" when exposed to stimuli at a moderate distance, identified as "distant". Various empirical research indicates that distant stimuli positively affect creativity. For instance, Chan, et al. [33] reported that far-field and uncommon examples enhance the novelty and variability in the quality of solution concepts. Similarly, Chiu and Shu [34] identified that designers utilizing word stimuli that are oppositely related generated more innovative concepts. Goucher-Lambert and Cagan [35] found that stimuli closely related to the task enhanced the utility and feasibility of design solutions, while stimuli from a greater distance increased the novelty of these solutions. However, several studies challenge the assumption that distant stimuli foster creativity. An engineering design study reported that patents with a moderate level of dissimilarity served as more effective sources of analogical inspiration [36]. Wang and Nickerson [37] discovered through a Wikipedia-based approach that stimuli with remote connections enhance the novelty of ideas, while closely related stimuli increase the quantity and practicality of ideas. Furthermore, a detailed examination of various design concepts on an online platform tracking inspirational sources revealed that conceptually closer sources provided more substantial benefits for creativity compared to more distant ones [38]. A key limitation of using distant stimuli is their tendency to be perceived as irrelevant [36]. Therefore, an ideal degree of stimulus relatedness likely exists, maximizing benefits when the stimuli are neither overly close nor excessively distant [39].

Research has explored the efficacy of different stimulus representations. Visual stimuli are linked positively with the innovative outcomes of participants [40]. Goldschmidt and Sever [41] argue that textual stimuli are vital both as part of the design workflow and as an educational tool within design studios. However, these stimuli require more interpretation than visual forms, which can negatively affect the generation of ideas. Borgianni, et al. [42] point out the advantages of developing design tools that integrate various types of stimuli to facilitate idea generation. Additionally, scholars stress the importance of delivering stimuli effectively during the design process to significantly improve designers' performance [30].

3 Developing ISfAI

The literature review has identified a gap for aids focusing on the early conceptual design stage, which can be designed to offer medium stimuli to build the knowledge space and improving knowledge reasoning processes. This section will introduce the development of the Inspirational Stimuli (IS) for AI-powered product ideation (ISfAI).

3.1 Extraction Method

To develop ISfAI, the five-step extraction process was adopted (Fig. 1).

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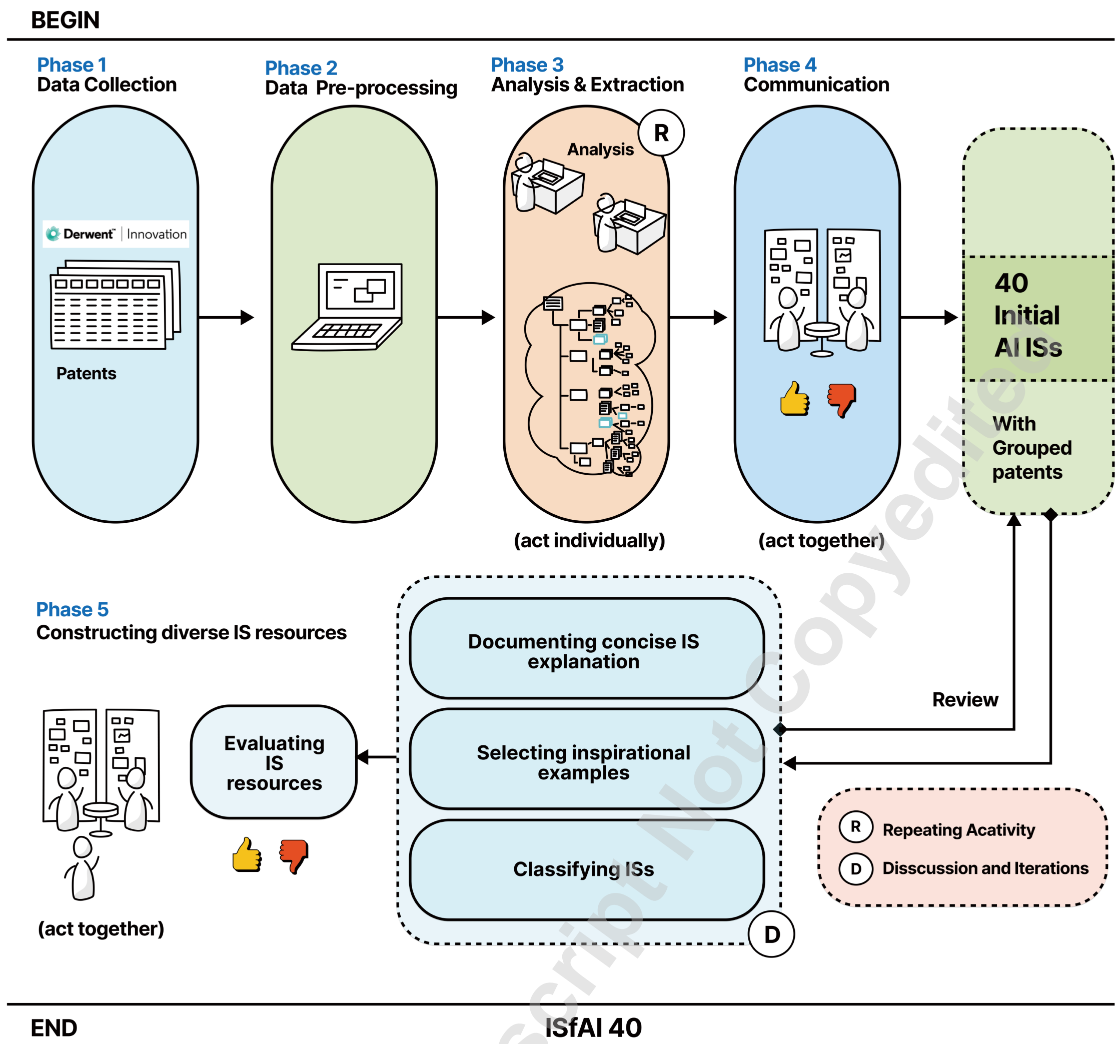

Fig. 1 The framework of developing ISfAI

3.1.1 Phase 1: Data collection

Patent documents are highly valuable for accessing both technological and commercial information, making them a valuable resource for comprehensive research [43]. TRIZ [44], a widely recognized stimuli for engineering innovation, also relies on the analysis of patent abstracts. This inspired us to explore existing AI patents available in both English and Chinese languages. Analyzing invention data from patents offers three main advantages: 1) fewer interfering factors, as patent documents provide concise and accurate descriptions in their titles and abstracts, allowing researchers to more effectively and efficiently extract IS; 2) a broader dataset coverage, as study has indicated that 70-90% of technical information is exclusively disclosed in patents [45]; and 3) patents serve as a reliable and extensive source of engineering design knowledge, having undergone rigorous examination to ensure their sufficiency in defining the invention, novelty, and usefulness [46].

To obtain a selection of representative patent samples, we implemented a systematic and precisely defined methodology, outlined as follows:

1) **Search Databases.** We utilized Derwent World Patents Index (DWPI) (https://www.derwentinnovation.com) patent databases to retrieve patent datasets, which is considered the most comprehensive database for enhanced patent information globally.

2) **Search Terms and Criteria.** We provided the detailed search strategy (see Table 1), including the specific search terms, databases used, inclusion/exclusion criteria, Specifically, 1) this study used 'Artificial Intelligence' as the keyword in searching the patent title and abstract of all patent datasets from DWPI. These terms were designed to encompass a broad spectrum of patents related to our research topic. 2) Patents from the United States, China and the Europe were included, as these countries and regions lead AI in technology and marketing, and English and Chinese were accessible languages for the authors. 3) The patent type only included the granted invention patents, and other types were excluded such as Utility Model and Pending Patents. 4) The publication dates included the period from 1st January 2008 to 1st January 2020. A total of 2,062 AI-related patent data were initially collected, and subsequent filtering was applied to eliminate "dead" and "indeterminate" patents, resulting in a final dataset of 1,755 patents. In the context of DWPI, "dead" patents are those that have reached the end of their patent term or have been abandoned by the patent holder before the expiration date, which means they hold low value. "Indeterminate" patents are patents for which the status is uncertain or unknown. These patents are neither definitively "live" (still in force) nor "dead" (expired or abandoned). The data were exported to Microsoft Excel files for further analysis, including Patent Name, Patent Title, Abstract, and Assignee/Applicant. The abstract provides a brief summary of the main invention or design, highlighting its key features and functions. It also includes technical information about the design, such as technologies used, and processes involved.

Table 1 Search Strategy

Search Strategy	Patent Collections
TAB=(artificial intelligence) AND DP>=(20080101) AND DP<=(20200101)	Collection: CN Grant, EP Grant,US Grant (Applications and Utility Models are excluded)
Record(s) found out	2,062
Filtering the Alive patents (Dead and Indeterminate are excluded)	1,755 (Application Language: EN, ZH) EN=English, ZH=Chinese

Note: TAB=Title/Abstract; DP=Publication Date; CN=China, EP=Europe, US=United States

3.1.2 Phase 2: Data pre-processing

Derwent Innovation's translation of patent data titles and abstracts into English ensured the

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uniformity of the "word" as a consistent measure for both English and Chinese content. We used QSR NVivo 12® [47, 48] to analyze word frequency in patent titles and then exported the results to Microsoft Word for detailed examination.

3.1.3 Phase 3: Analysis and extraction

The purpose of this phase was to analyze the key functions and features of the collected AI-related patents and extract common AI IS from their functions and features. Two research experts in AI product design were involved in the IS extraction process. They both understood English and Chinese and could read the US, CN, and EP's patent documents. They each analyzed and extracted the AI IS individually. The description of this extraction procedure is described below and illustrated in Fig. 2.

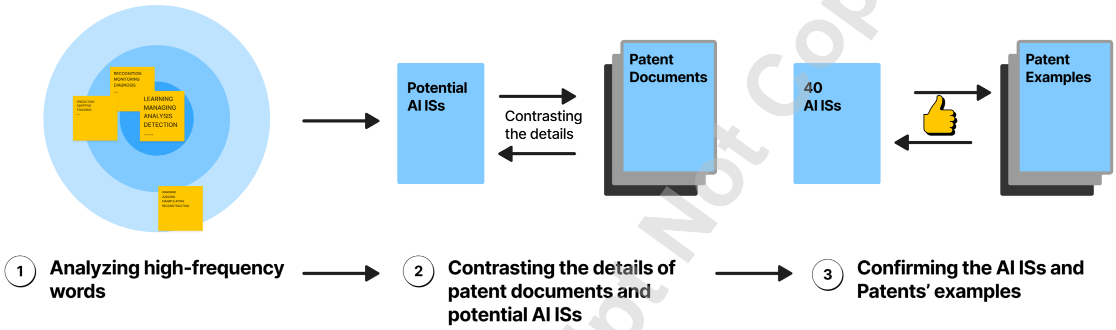

Fig. 2 Potential AI IS extraction procedures

1) **Analyzing high-frequency words (act individually)**. High-frequency words in patent titles serve as indicators of the key functions and features of a technology because they represent concise and standardized terms that highlight the most critical aspects of the invention [49]. The researchers performed a manual review of the identified high-frequency words to ensure that they were directly related to our research objectives in extracting useful ISfAI. Specifically, each researcher individually reviewed *high-frequency words* that appeared in more than three patent titles. They selected these words relating to AI features and functions, and highlighted them in Microsoft Word. A total of 46 words were identified.

2) **Contrasting the details of patents and potential IS (act individually).**

The researchers utilized QSR NVivo 12 to create 46 potential nodes. Each node served as a keyword to track patent titles for further analysis. The researchers individually examined the titles of each tracked patent to determine their relevance to the node. If a patent's title was highly relevant, it would be added to the corresponding node. When the researchers could not ascertain whether a patent was AI-related by its title, they reviewed the abstract and patent documents.

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3) **Confirming the initial IDS based on the patents' examples (act individually).** To maximize the inclusion of diverse IDSs and avoid overlooking unique ones, we established a threshold (i.e., three times) to confirm the IS, which aligns with the commonly accepted standard in previous studies [50, 51]. The researchers individually examined whether there were at least three AI-related patent examples that shared common key functions and features. Based on these groups of nodes, the design stimuli were confirmed. Fig. 3 shows an example of how an IS was extracted from relevant patents. 'Evaluation' was extracted as six granted patents' titles commonly share the key function and feature in evaluation.

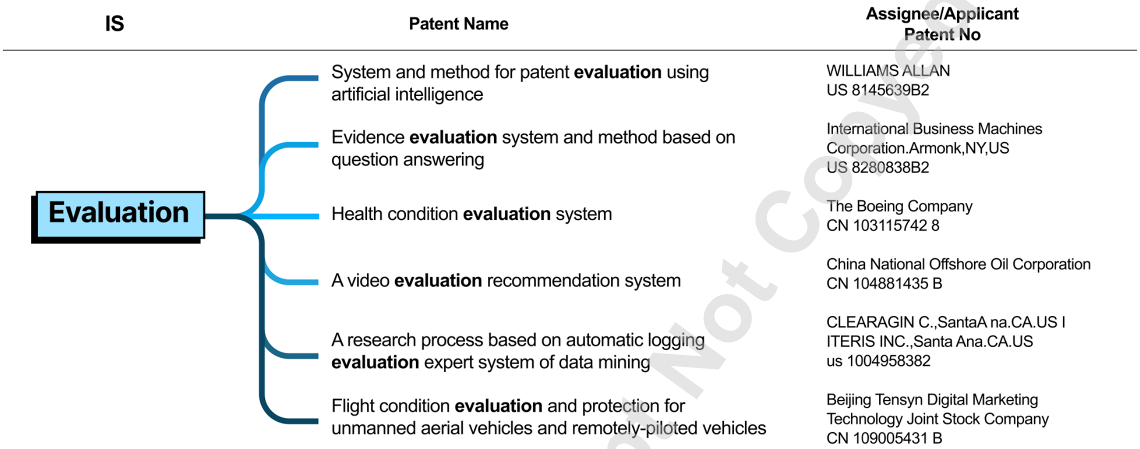

Fig. 3 An inspirational design stimulus extraction example

3.1.4 Phase 4: Communication

This phase is to combine all initial ISs together. First, the two researchers shared extracted ISfAI and evidences of patent examples. To assess the reliability of the extraction process, Cohen's Kappa consistency test was employed, resulting in a Cohen's Kappa coefficient of .863, indicative of strong reliability. Second, they consolidated overlapping ISs with a meticulous review process to merge similar ISs to avoid redundancy (e.g., analyzing and analysis, decision and determining, identification and recognition), while also ensuring that no ISs were overlooked. The goal was to reduce redundancy and streamline the list. Third, the researchers evaluated the initial list through collaborative discussions, aiming to reach a consensus.

3.1.5 Phase 5: Constructing resources

1) **Documenting concise explanation.** Each stimulus was described in a concise explanation including key characteristics of AI capabilities, benefits, and application (see Fig. 4). This process involved the collaboration of three domain experts (i.e., in addition to the two experts in AI product design initially engaged in the extraction of the IS, an additional expert in AI/Machine Learning was enlisted to contribute to the development of the IS explanation).

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They undertook a comprehensive analysis of patent clusters, focusing on shared capability features such as "recognition" and "forecasting". Special attention was given to the "Abstract" and "Claims" sections of the patent documents to gain an in-depth understanding of the AI designs and their unique features. The aim of this analysis was to discover fundamental ISs by identifying patterns and strategies common to these patent clusters across various AI applications. The characteristics were systematically extracted from patent examples within specific IS Groups. For example, our descriptions incorporate key characteristics (e.g., #22 Autonomous: *The ability to operate and make decisions independently*, *without direct human intervention* or control, *to achieve its intended objectives or tasks)*. The majority of ISs emphasize the principal benefits of AI capabilities. For example, #17 Interaction: *This can enhance the user experience and add playfulness." Similarly*, #38 Monitoring: [this AI capability] *can reduce human intervention in processes*. To ensure broader accessibility and practicality, complex technical jargon in the descriptions was replaced with plain phrases to facilitate comprehension and application. Similar ISs were clarified, e.g., "*Personalization* often involves dynamic, data-driven adaptation, while *customization* relies on predefined options and user choices."

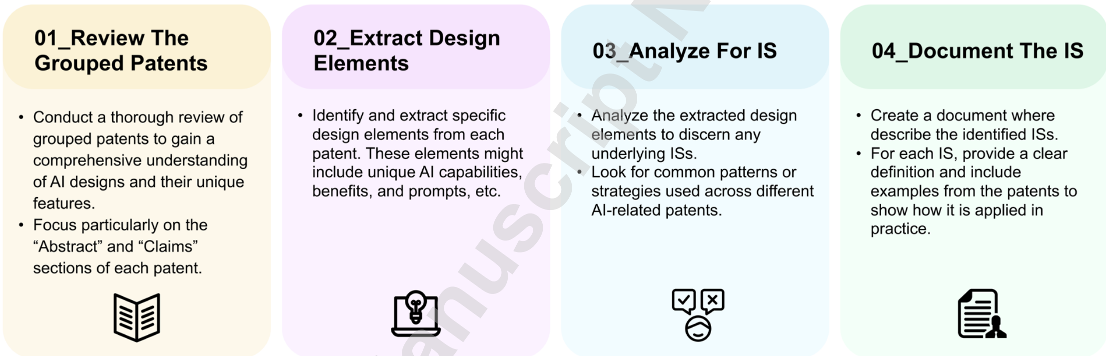

Fig. 4 Procedures for IS extraction

2) **Selecting inspirational examples.** Examples can facilitate user understanding of the IS in particular contexts; they are a valuable approach for ideation or problem-solving. However, example designs may constrain creativity and limit the exploration of a broader spectrum of alternatives [52]. Furthermore, the fixation effect becomes more pronounced with familiar stimuli compared to novel ones [53]. Thus, offering a variety of inspirational examples can aid in ideation. The researchers selected these examples based on two criteria: 1) easy to understand and 2) inspirational and novel AI applications.

3) **Classification.** The absence of adequate organization and classification within IS may impact productivity when employing these tools. Domain-specific design heuristic sets (DHS) (e.g., DHS for Additive Manufacturing [54] and DHS for Limited Hand Mobility [50]) have applied the classification for boosting the applied productivity. To elaborate, we categorized 40 ISs into four distinct groups: *A. Decision Making, B. Personalization, C. Productivity, and D.*

Security. This categorization aims to facilitate understanding and improve the memorability of the ISs.

4) **Evaluating IS resources.** Experts independent of the initial ISfAI list extraction process were tasked with the review. They were two industrial design professors, an AI specialist, and a digital transformation expert; they assessed the ISfAI for understandability, memorability, and usability. After their assessment and feedback, our research team undertook detailed discussion to reach consensus and refine the tool.

This evaluation aligns with a similar approach used in a previous study [51]. The success of the process is dependent on several factors, including the independent examination by multiple coders, inter-rater reliability testing, and collaborative discussions to address discrepancies. These steps enhance the credibility and accuracy of the extracted IS. Specifically, to ensure the reliability and validity of the process, two additional coders, both with Masters degrees in industrial design, independently examined whether the extracted ISs were evident within the grouped patent examples. The inter-rater reliability test between the two coders yielded a result of 98%, indicating a high level of agreement. Any discrepancies that arose during the assessment were resolved through discussions involving the two researchers and the two coders, ultimately achieving a consensus of 100%.

The comprehensive list of 40 ISfAI, organized thematically, is presented in Appendix Table 1. These are considered instrumental in assisting designers or design teams in generating solution concepts for the development of AI-powered products.

3.2 Designing Multimodal Delivery Format for the ISfAI

This section explores strategies for structuring the format of presenting ISfAI to design practitoners.

3.2.1 ISfAI Cards

Card-based design tools have been extensively utilized, offering numerous advantages. They “serve as a physical reference during design discussion, facilitating communication and shared understanding” (p. 696) [55]; they are more effective as handy tools than electronic ones [56]. The researchers utilized cards as a medium to present the ISfAI tool, making them accessible and designer-friendly. The researchers also reviewed Design Heuristics cards, referencing research by scholars [50, 57-60]. Furthermore, the researchers explored card-based design tools [55, 61, 62]. Subsequently, aligning with our review and objectives, the researchers developed a set of ISfAI cards. Fig. 5(A) and (B) present two examples of the cards for illustrative purposes.

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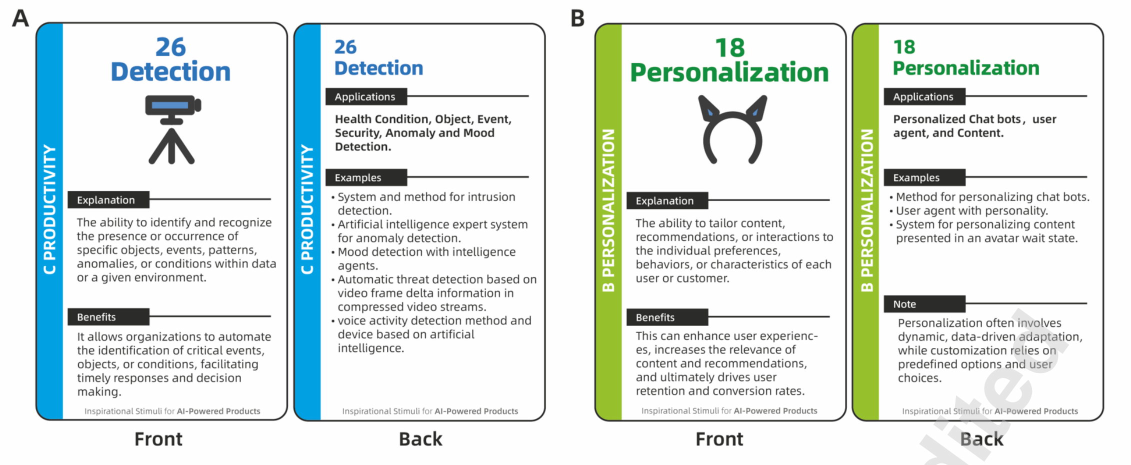

Fig. 5 (A)The ISfAI card #26 Detection and (B) The ISfAI card #18 Personalization

The card dimensions precisely match those of a standard credit card (i.e., 85.60 millimeters by 53.98 millimeters). It is large enough to handle easily, yet small enough not to be cumbersome. The size offers enough surface area to accommodate essential contents. Concurrently, these cards are designed to enable users to conveniently arrange multiple cards within a constrained table space, thereby creating a composite stimulus. The card layout is inspired by that of the 77 DHs Cards [58], DH for Additive Manufacturing (DHfAM) [57], and industrial design taxonomic classification card [61]. The front side of the ISfAI card (see Fig. 6-A) features six components: (1) number, (2) title, (3) abstract icon, (4) category (color-coded), (5) explanation, and (6) benefits. The reverse side (Fig. 6-B) added applications and examples, and sometimes additional notes. The following section outlines strategies for developing the ISfAI cards.

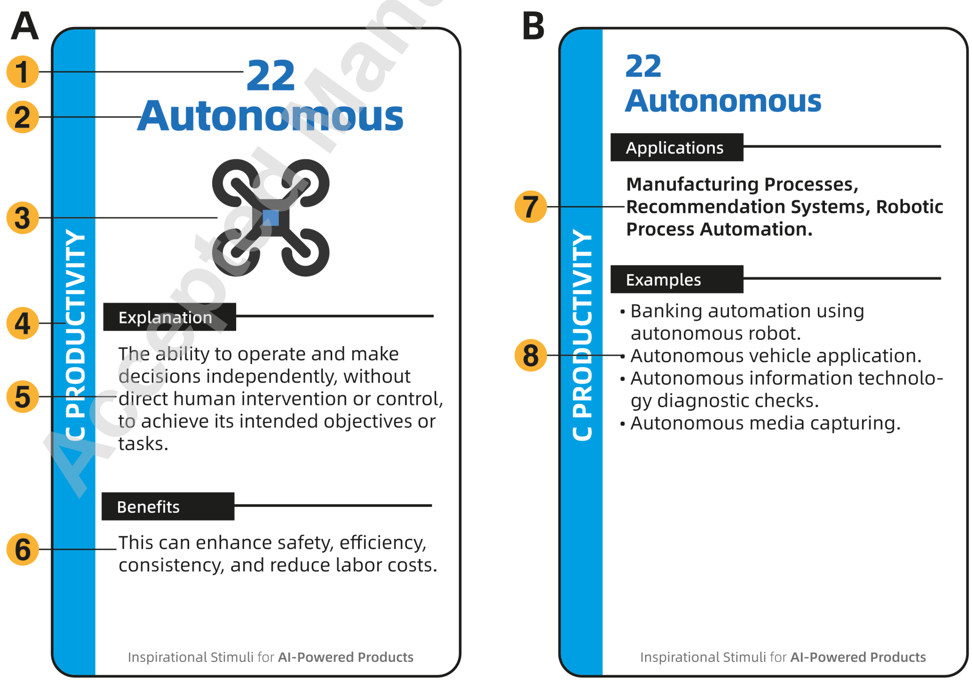

Fig. 6 (A) Front side of ISfAI Card;(B) Back side of ISfAI Card

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1) **Layout.** The abstract content, which includes the "*title*", the "*explanation*" and "*benefits*" presented on the front of the cards, is designed to prevent users from becoming overly focused on specific examples. (Examples are provided on the reverse side).
2) **Classification.** Color-coding was implemented to bolster visual differentiation (see Fig. 7). This approach is designed to enhance users' ability to identify inspirational features while browsing, thereby improving the clarity of categorization and promoting productivity when employing the tool.

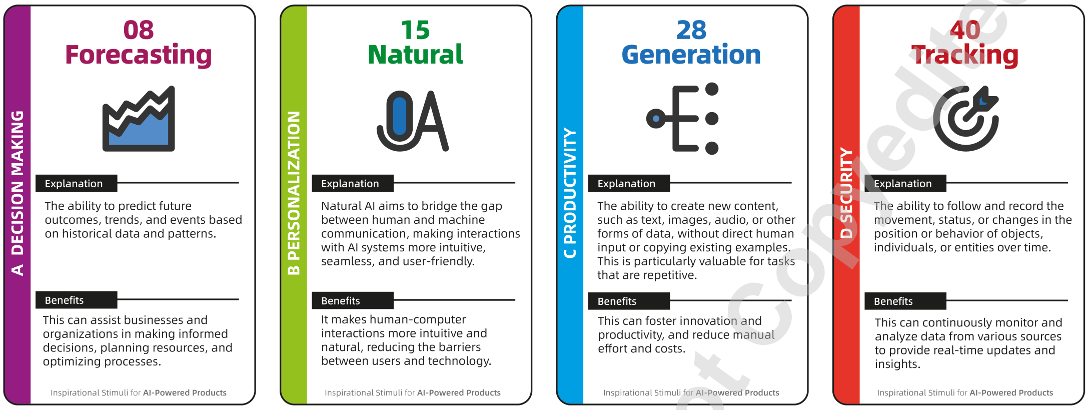

Fig. 7 Color-coding scheme

3) **Icons.** The majority of design stimuli utilize figures of product examples to facilitate the enhancement of creativity among designers [50, 57-60]. However, these sets are primarily focused on tangible product design. While such examples can inspire designers, they also risk confining their creative process to the specifics of these examples, potentially hindering exploratory creativity [63]. This study focuses on the development of technology-oriented IS, wherein technological capabilities often possess a higher level of abstraction than tangible examples. Effectively conveying these abstract technological aspects through real-life examples poses a significant challenge. With our focus on deepening the understanding of AI capabilities rather than just providing inspiration, we have favored the use of abstract icons over specific image examples. Abstract icons offer several advantages: 1) they have universal meanings, transcending cultural and linguistic boundaries; 2) they enable clear and concise depiction of complex concepts, facilitating immediate comprehension; 3) they foster creative thought by encouraging designers to engage in higher-level imaginative processes. However, abstract icons may require additional context or elucidation to ensure the correct interpretation of their intended meaning. Therefore, we have incorporated descriptions and patent examples as practical aids to mitigate these drawbacks. This combination allows designers to explore varied sources of inspiration while maintaining a clear understanding of the foundational concepts. We have selected dark blue and gray for the icons, as these hues are deemed most effective for conveying scientific or technological information [64].

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Fig. 8 presents a stimuli sheet for function-oriented analogies in AI applications, including abstract icons and titles. This sheet provides an abstract representation of the IS, allowing designers to leverage their imagination and creativity without being overly constrained by excessive details [65].

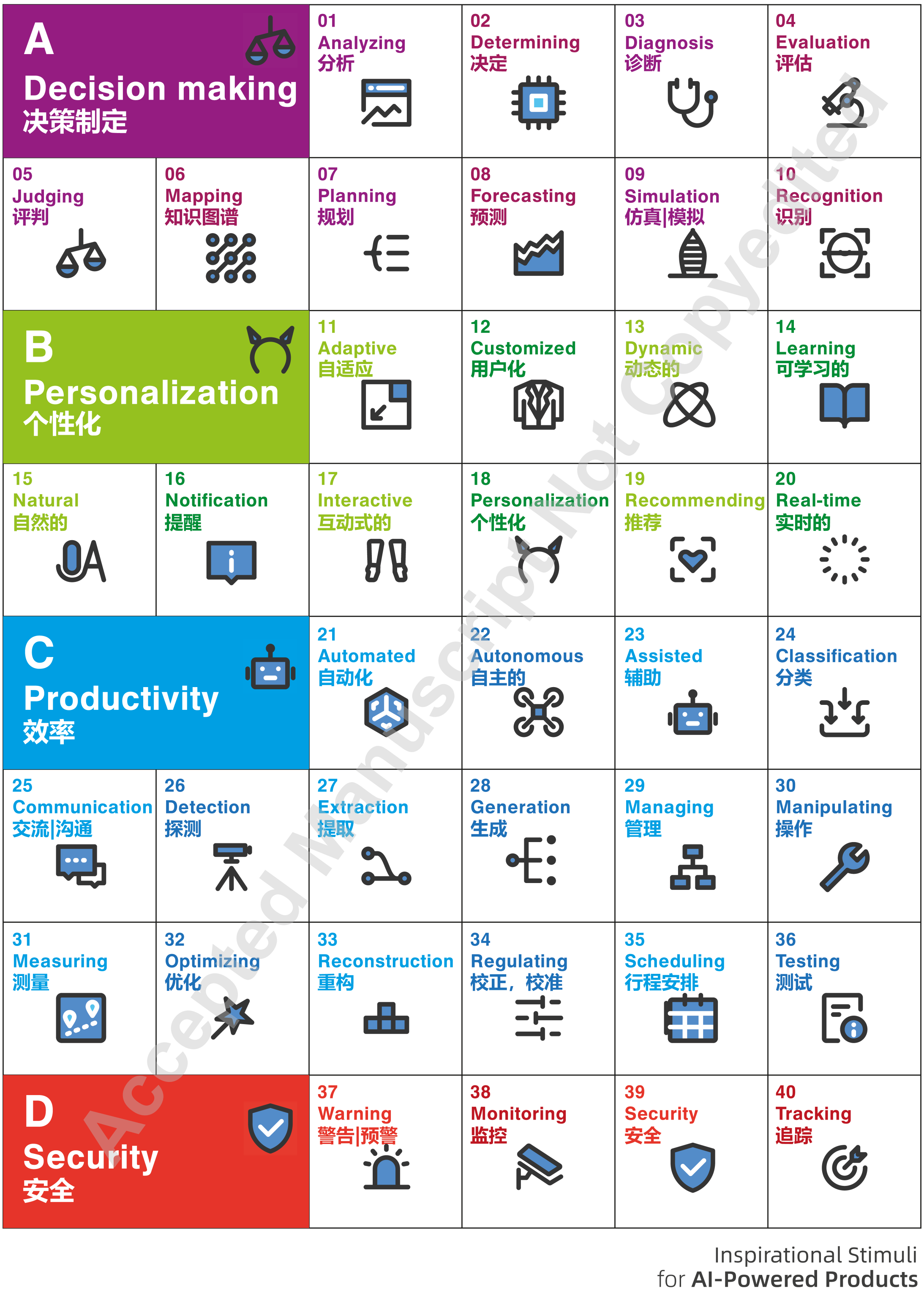

Fig. 8 A stimuli sheet for function-oriented analogical ISfAI

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4 Evaluation Study

The primary aim of this study was to investigate the utilization of different formats of ISfAI (i.e., as a set of cards – Fig. 5, and as a single sheet – Fig. 8) by users and evaluate its effectiveness during the conceptual ideation phase.

4.1 Hypotheses

Building upon literature [50, 66, 67], we list four research hypotheses, as follows:

H1. Designers will show evidence of integrating ISfAI into their concept development processes.

H2. The utilization of ISfAI will lead to the generation of a greater number of AI-powered ideas compared to Function-oriented Analogical Stimuli and Brainstorming Techniques.

H3. The utilization of ISfAI cards will result in the production of AI-powered ideas that are more novel, useful, and creative than those generated by ISfAI Sheet (function-oriented, analogical) and Brainstorming Techniques.

H4. The utilization of ISfAI cards will result in the production of AI-powered ideas that are more elaborate, flexible, and practical than those generated by ISfAI Sheet and Brainstorming Techniques.

We conducted an empirical study by comparing the ideation outcomes of participants using three different design aids: Individual Brainstorming (IB), Function-oriented Analogical Stimuli, and ISfAI.

4.2 Participants

The study sample consisted of second-year industrial design students from a research-intensive university, who were enrolled in a course on new product development. The research protocol was approved by the university's ethics committee. The students were briefed on the educational benefits of participating in the study. A total of 68 students voluntarily participated, with no compensation offered and no impact on their academic evaluations for opting out. The participants were randomly divided into three groups: Experimental Group A, which used the function-oriented analogical sheet (Fig. 8) for brief) (n = 23); Experimental Group B, which employed the ISfAI cards for detail (n = 22); and a Control Group that engaged in Individual Brainstorming (n = 23).

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4.3 Design Task

The main criterion was to create a novel task that would not be influenced by existing solutions. Additionally, the problem needed to be an open-ended design challenge with multiple potential solutions that could be tackled within a brief design session and did not require complex technical knowledge. Therefore, the design brief was selected as follows:

'*In today's world, society has become ever more fast-paced, with less time to slow down and relax. And in the hustle and* bustle *of life, people have become spiritually drained and less motivated to deal with household chores. Thus, there is more attention on finding convenient household appliances to decrease time spent on chores and increase time for family, hobbies, and other interests*. Your task: *Design a helpful smart household appliance that makes life at home more convenient. Optimize or innovate on a traditional approach. Give the user a totally new living experience*.'

The brief was taken from the iF Talent Award, Haier Design Prize 2019 [68]. The brief was chosen for three reasons: 1) It concerned product innovation; 2) It was neither abstract nor narrow; 3) It removed the potential bias of experience.

4.4 Procedure

Table 2 presents a detailed outline of the experimental procedure, which encompassed the following stages: (1) A 10-minute lecture on smart product design, attended by all students; (2) Specific instructions on employing IS tools, provided for the two IS groups. Given that all students had previous exposure to brainstorming techniques through a course project, no further instructional session was deemed necessary. For the Control Group, a brief refresher on Individual Brainstorming (IB) guidelines was provided; (3) The distribution of experimental materials, which included ISfAI cards, ISfAI sheet (see Fig. 8), IB guidance, design brief, sketching sheets, and an information sheet with a consent form; (4) Assigning students the task of generating multiple design concepts using various ideation methods (i.e., ISfAI sheet, ISfAI cards, and Brainstorming) within a 60-minute period, with periodic reminders to use the full allotted time; (5) A 20-minute session for all students to complete their sketching sheets and design descriptions; (6) An additional 10 minutes for students in both experimental groups to identify the specific IS they utilized. To ensure individuality in the process, the students worked alone to avoid discussion or mutual influence. Upon completion, they submitted their work and consent forms electronically.

Table 2 Experimental procedure

Order of activities	Groups		
	Control Group IB (n = 23)	Experiment A Group with Sheet (n = 23)	Experiment B Group with Cards (n = 22)
1. Lecture on smart product design (10 min)	X	X	X
2. Instructional session on How to use the tools (10 min)		X	X
3. Receive design aids		X Sheet	X Cards
4. Complete design task (60 min)	X	X	X
5. Complete design description (20 min)	X	X	X
6. Identify which IDS(s) were used (10 min)		X	X

Note: Number of participants in each group indicated by *n*.

4.5 Metrics and Data Analyses

To maintain consistency in time allocation among participants, concept sheets submitted after the designated time limit were not included in the analysis. One late submission was not included. Among the qualified submissions, 23 used the IB technique, 23 used the Sheet (Fig. 8), and 21 used the ISfAI cards. A total of 214 concepts were generated, with students producing between 1 and 8 concepts each. Seven ideation metrics were selected to assess the study's outcomes: (1) Quantity, (2) Novelty, (3) Usefulness, (4) Creativity, (5) Elaboration, (6) Flexibility, and (7) Practicality. These metrics were used as they have been widely employed to assess the quality of design ideation outcomes [50, 66, 69-72].

a) *Quantity.* Generating more ideas increases the chance of better ideas [71, 73]. Quantity is defined as the total of all generated ideas (Q_{Total}) [71].
b) *Novelty and Usefulness.* Novelty and Usefulness represent the two core dimensions of the current scientific definition of creativity [74]. *Novelty* refers to the degree of uniqueness or unpredictability of an idea when contrasted with others [71]. According to Sarkar and Chakrabarti [75], the overall *Usefulness* of a product can be evaluated based on three equally significant factors: the significance of its use, the extent of its popularity (i.e., the number of people who use it), and the frequency or duration of the benefits it provides [75].
c) *Creativity* is defined as ideas that are both novel and useful [74], contribute the most value to the design process [76].

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d) *Elaboration and Flexibility*. Elaboration and flexibility were included as they represent historically significant methods for assessing the creativity of responses in both the Torrance Tests of Creative Thinking [77] as well as in Guilford's SOI model [78]. Elaboration plays a crucial role in fostering creativity as it contributes to the development and refinement of ideas [79]. This criterion refers to the degree of detail or complexity in a design solution [80, 81]. Flexibility refers to a design's ability to accomplish the design task using various AI means, key indicators such as stimuli and unique AI capabilities are assessed at the group level. Designs that incorporate broader stimuli or functions are deemed more flexible as they use AI in various ways, thereby increasing their chances of attaining feasible AI in the final selection process.

e) *Practicality.* Practicality refers to whether or not the technologies needed for the realization of a proposed idea are currently available [40]. High practicality indicates a design solution that is more feasible and economical to implement, whereas low practicality indicates a design solution that may be too costly, time-consuming, or difficult to implement in practice.

All metrics' measures besides quantity (i.e., Novelty, Usefulness, Elaboration, Flexibility, Practicality) were measured using Amabile's (1982) Consensual Assessment Technique (CAT) [82]. Consistent with Consensual Assessment Technique (CAT), 1) each assessor evaluated the design concepts in a different random order, and the metrics were assessed in varying random sequences, such as assessing all designs for *Flexibility* first, followed by *Usefulness*, and so forth; 2) prior to assessment, the assessors were required to comprehensively familiarize themselves with all works under evaluation and subsequently gauge the ratings in accordance with the relative quality of these works; 3) all assessors were tasked with the subjective and independent evaluation of individual ideas. The assessors were furnished with the *Novelty* assessment framework articulated by Sarkar and Chakrabarti [75]. The assessors were informed that aesthetic appeal and diversity level were not included in *Novelty* evaluation, and limitations in sketching skills should not influence their assessment. The assessors were recruited to spend 3 days judging the 214 designs across multiple metrics; they were asked to utilize a 5-point Likert Scale to rate each idea [83], with 1 representing the lowest and 5 the highest. Fig. 9 presents examples of low and high-scoring cases. Throughout the rating process, scheduled breaks were incorporated to mitigate the potential impact of fatigue. Subsequent to the acquisition of assessments, an assessment of inter-assessor reliability was conducted for each metrics. The intraclass correlation coefficient (ICC) test was employed [84, 85]. The ICC was computed using *SPSS* V24 for this assessment. The results indicate that the ICC values for *Novelty, Usefulness, Elaboration, Flexibility,* and *Practicality* are .766, .623, .856, .904, and .628, respectively. It is worth noting that all values exceeding .60 are typically considered acceptable in estimating interrater agreement [86].

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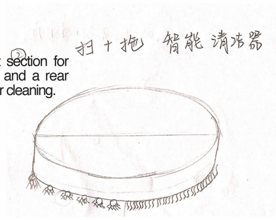
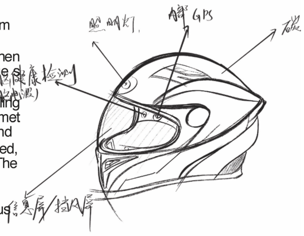
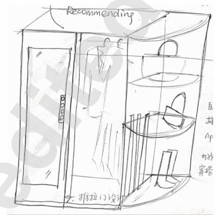
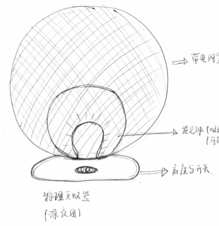
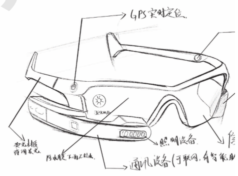
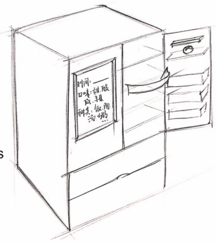
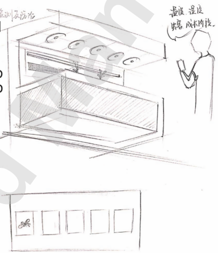
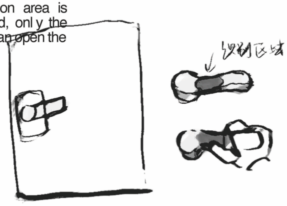
Metrics	Low Scoring Case		High Scoring Case	
Novelty	**Smart Cleaner** Featuring a front section for debris collection and a rear mop brush for floor cleaning.		**Smart Motorcycle Helmet** Crafted entirely from carbon fiber, this helmet boasts an integrated GPS locator and a brain health monitoring system. When the wearer becomes fatigued, it issues alerts. The built-in intelligent voice system is linked to the internet, enabling voice-controlled access to various helmet functions such as top helmet control and information display (time, weather, speed, etc.), sunshade adjustment, and more. The exterior of the helmet is equipped with a vehicle detector, which scans passing vehicles to assess the user's safety status and issues warnings if a vehicle gets too close.	
Usefulness	**Broadcast Clock** This is a broadcast clock that can connect to your phone and remind you of your schedule.		**Smart Wardrobe Mirror System** This is a smart wardrobe mirror. Its main functions include recording what clothes you have, and the system automatically recommends outfits based on your existing clothes, the weather, and your personal style. It can also record your outfits through the mirror, helping those who struggle with outfit choices to eliminate their worries.	
Elaboration	**Automatic Mosquito Killer** This is an automatic mosquito killer. It attracts mosquitoes with light and eliminates them with an external electric grid. It attracts mosquitoes at night and kills them. Additionally, it can be used as a night light.		**Smart Glasses for Cyclists** The frame of these glasses incorporates luminescent material for enhanced visibility in dark environments. A left-side device provides road condition updates by sharing satellite-sourced road information. If conditions are hazardous, congested, or vehicles are in proximity, warnings are issued. The lens acts as an information display, projecting data such as speed, wind speed, weather, and time without obstructing vision. The right side holds communication equipment with bone-conduction audio, enabling networking and voice-controlled operations. Additionally, the frame features GPS tracking and brainwave monitoring to assess the rider's health.	
Flexibility	**Portable Clothes Dryer** This portable clothes dryer box is perfect for traveling, ensuring your clothes stay dry. Not only does it dry your clothes, but it also disinfects and sterilizes them.		**Smart Refrigerator** Through a mobile app or a small program, this refrigerator: 1) Records food information, including dates and nutritional content, offering storage recommendations. 2) Uses food details and user preferences (such as fitness, weight loss, muscle gain) to suggest meal plans and recipes, ensuring food is consumed before expiration and reminding users to discard expired items. 3) Offers cooking timers, event reminders, and voice control. 4) Uses methods beyond appearance to determine freshness and recommended consumption dates for unpackaged food. 5) Categorizes and displays detailed information for all items.	
Practicality	**Intelligent Plant Disease and Pest Control Device** This device scans plants and soil, with an app displaying temperature, humidity, growth stage, and more. If no issues are detected, the app displays "healthy". If diseases or pests are identified, corresponding treatments are sprayed. If the soil lacks essential nutrients, relevant nutrients are added.		**Smart Door Lock** A fingerprint and palmprint recognition area is placed on the handle. When locked, only the homeowner's twisting of the handle can open the door.	

Fig. 9 Assessment of Low and High Scoring Cases for Evaluation Metrics

To assess whether designers demonstrated evidence of utilizing IS in their concepts, two trained coders with bachelor's and master's degrees in industrial design were involved. The coders examined concept sketches, written descriptions, and the participants' claims of using ISfAI. The claims of IS(s) usage by each participant were initially recorded in an Excel spreadsheet and then verified. Four possibilities for each concept were considered [87]: (1) IS(s) evident and claimed; (2) IS(s) evident but un-claimed; (3) IS(s) not evident but claimed, and (4) IS(s) not evident and un-claimed. Each coder independently identified any incorrectly identified IDS(s) and added the appropriate number of IS(s) if their usage was observed. Discussions were conducted to reach a consensus whenever necessary. Furthermore, this study also aimed to

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explore whether students could generate ideas using common stimuli without the assistance of the ISfAI tool. To examine the use of IS in the Individual Brainstorming (IB) group, two coders reviewed concept sketches and written descriptions. Each coder independently recorded the identified IS, and discussions were held when necessary.

4.6 Results

The average rating scores for each participant were calculated, and statistical analyses were performed using *SPSS* V24. The results were reported following the guidelines outlined by the American Psychological Association (APA) [88]. The normality of the data was assessed and confirmed using Anderson-Darling's Normality Test.

4.6.1 Inspirational Stimuli Use

Fig. 10 presents the visual comparison of IS usage data among the three groups. In the concepts generated by Group A, only 7 concepts (1.7%) did not utilize any IS. In total, 40 concepts were identified using more than two ISs which represents 61.5% of all the concepts generated. Among the concepts generated by Group B, only 3 concepts (4.1%) did not utilize any stimulus. In total, 59 concepts were identified using more than two ISs which represents 80.8% of all the concepts generated.

This study also revealed that the majority of students utilized ISfAI, which supports the **H1**. In the Experiment Group A, #17 Interaction was the most frequently used IS (15 times), followed by #21 Automation. However, six ISs (i.e., #4 Evaluation, #15 Natural, #27 Extraction, #33 Reconstructing, #34 Regulating, and #36 Testing) were not used by any student. In the Experiment Group B, #23 Assisting was the most frequently used IS(s) (17 times), followed by #16 Notification. Nevertheless, three ISs (i.e., #30 Manipulating, #13 Dynamic, and #33 Reconstructing) were not used by any student.

The Control Group demonstrated a focus on the utilization of certain specific ISs, such as Automation (27 times), Notification (#16) (9 times), Recognition (#10) (5 times). Nonetheless, 25 ISs were not employed within the IB group, including #17 Interaction, the most utilised in Group A.

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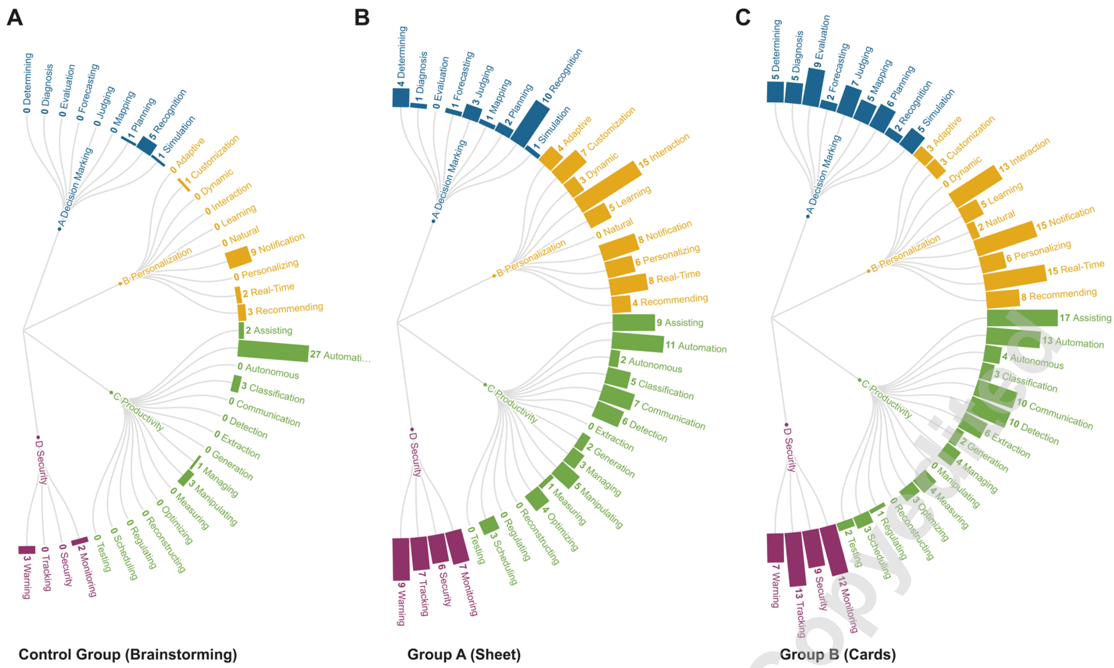

Fig. 10 The frequency of Stimuli used. (a) Group IB; (b) Group A (Sheet); (c) Group B(Cards)

4.6.2 Quantity

The Control Group (n = 23) generated 76 ideas, the Experiment Group A (n = 23) generated 65 ideas, and the Experiment Group B (n = 21) generated 73 ideas. The average number of ideas for every participant was compared across the three groups by employing the *ANOVA test*. The *ANOVA test* results show the mean difference was not significant: F (2, 64) = .934, p = .398, η^2 =.028, which did not support the H2.

4.6.3 Novelty and Usefulness

Through expert ratings, we compared the average *Novelty* and *Usefulness* scores of the Control Group, Experiment A, and Experiment B groups. The results revealed highly significant statistical differences in *Novelty* among the three groups (F(2, 211) = 20.435, p < .001, η^2 = .162) (see Table 3). Similarly, the average practicality differences were also significant within the three groups (F(2, 211) = 4.633, p = .011, η^2 = .042). Post hoc tests (Tukey HSD) further showed statistically significant differences in *Novelty* scores, with students using Sheet (M = 3.3, SD = .728) and Cards (M = 3.5, SD = .669) achieving higher *Novelty* scores compared to students using Brainstorming (M = 2.8, SD = .777) (see Table 4). Additionally, post hoc tests revealed statistically significant differences in *Usefulness* scores, with students using Sheet (M = 3, SD = .496) and Cards (M = 3.2, SD = .555) achieving higher *Usefulness* scores compared to students using Brainstorming (M = 2.9, SD = .442) (see Table 4). These results partly support the H3.

Table 3 Results of One-Way Analysis of Variance (ANOVA) on Ideation Performance

Metrics	*Groups* Group A (Sheet) M (SD)	Group B (Cards) M (SD)	Control Group (Brainstorming) M (SD)	*F*	*p*-value	*Eta Squared*
Novelty	3.3 (.728)	3.5 (.669)	2.8 (.777)	20.435	< .001***	.162
Usefulness	3.0 (.496)	3.2 (.555)	2.9 (.442)	4.633	.011**	.042
Creativity	3.2 (.521)	3.3 (.531)	2.8 (.471)	17.767	< .001***	.144
Elaboration	3.0 (.744)	3.4 (.891)	2.7 (.661)	15.310	< .001***	.127
Flexibility	2.3 (.913)	2.8 (.886)	1.9 (.785)	22.725	< .001***	.177
Practicality	3.2 (.508)	3.1 (.498)	3.5 (.548)	11.003	< .001***	.094

Notes: *** $p < .001$(2-tailed).

Table 4 Tukey's HSD Post hoc Test Results for Novelty and Usefulness

Groups		*Mean Difference*	*Standard Error*	*Sig.*
Exploring Novelty: Multiple Comparisons				
Group A	Group B	-.2008	.1239	.239
	Control Group	**.5357***	**.1228**	**.000**
Group B	Group A	.2008	.1239	.239
	Control Group	**.7366***	**.1191**	**.000**
Control Group	**Group A**	**-.5357***	**.1228**	**.000**
	Group B	**-.7366***	**.1191**	**.000**
Exploring Usefulness: Multiple Comparisons				
Group A	Group B	-.17039	.08515	.114
	Control Group	.07348	.08435	.659
Group B	Group A	.17039	.08515	.114
	Control Group	**.24387***	**.08182**	**.009**
Control Group	Group A	-.07348	.08435	.659
	Group B	**-.24387***	**.08182**	**.009**

*Note: * indicates significant mean differences at the .05 level.*

4.6.4 Creativity

Creativity were determined by taking the average of the *Novelty* and *Usefulness* scores [40]. There was a highly significant difference in *Creativity* among the three groups ($F(2, 211) = 17.767$, $p < .001$, $\eta^2 = .144$) (see Table 3). Post hoc tests (*Tukey HSD*) revealed a statistically significant difference in Creativity scores, with students using Sheet ($M = 3.2$, $SD = .521$) and Cards ($M = 3.3$, $SD = .531$) obtaining higher *Creativity* scores compared to students using IB ($M = 2.8$, $SD = .471$) (see Fig. 1-A and Table 5). There was no significant difference between students using Sheet and Cards.

Table 5 Tukey's HSD Post hoc Test Results for Creativity

Groups		*Mean Difference*	*Standard Error*	*Sig.*
Group A	Group B	-.185616	.086472	.083
	Control Group	**.304605***	**.085664**	**.001**
Group B	Group A	.185616	.086472	.083
	Control Group	**.490222***	**.083095**	**.000**
Control Group	**Group A**	**-.304605***	**.085664**	**.001**
	Group B	**-.490222***	**.083095**	**.000**

*Note: * indicates significant mean differences at the .05 level.*

High Creativity (HC) concepts are defined as ideas with *Novelty* and *Usefulness* scores of 3 or higher. The HC ideas were identified in the Control Group (n = 7), Group A (n = 12) and Group B (n = 25). The proportion of HC concepts in the Group A was .185, whereas the Control Group was .092. A *Chi-square test* showed no significant difference between the two groups: χ^2 (1, n = 19) = 2.572, p = .109. In contrast, the proportion of HC concepts in the Group B was .342, while in the Control Group, it was only .092. A *Chi-square test* indicated a highly significant difference between the two groups: χ^2 (1, n = 32) = 13.839, $p < .001$, indicating that the Group B generated more HC concepts than the Control Group (see Fig. 12). Furthermore, the proportion of HC concepts in the Group B was .342, while in the Group A, it was .185. A *Chi-square* test revealed a highly significant difference between the two groups: χ^2(1, n = 37) = 4.366, $p < .037$, indicating that the Group B generated more HC concepts than the Group A (see Fig. 12). These results support the H3.

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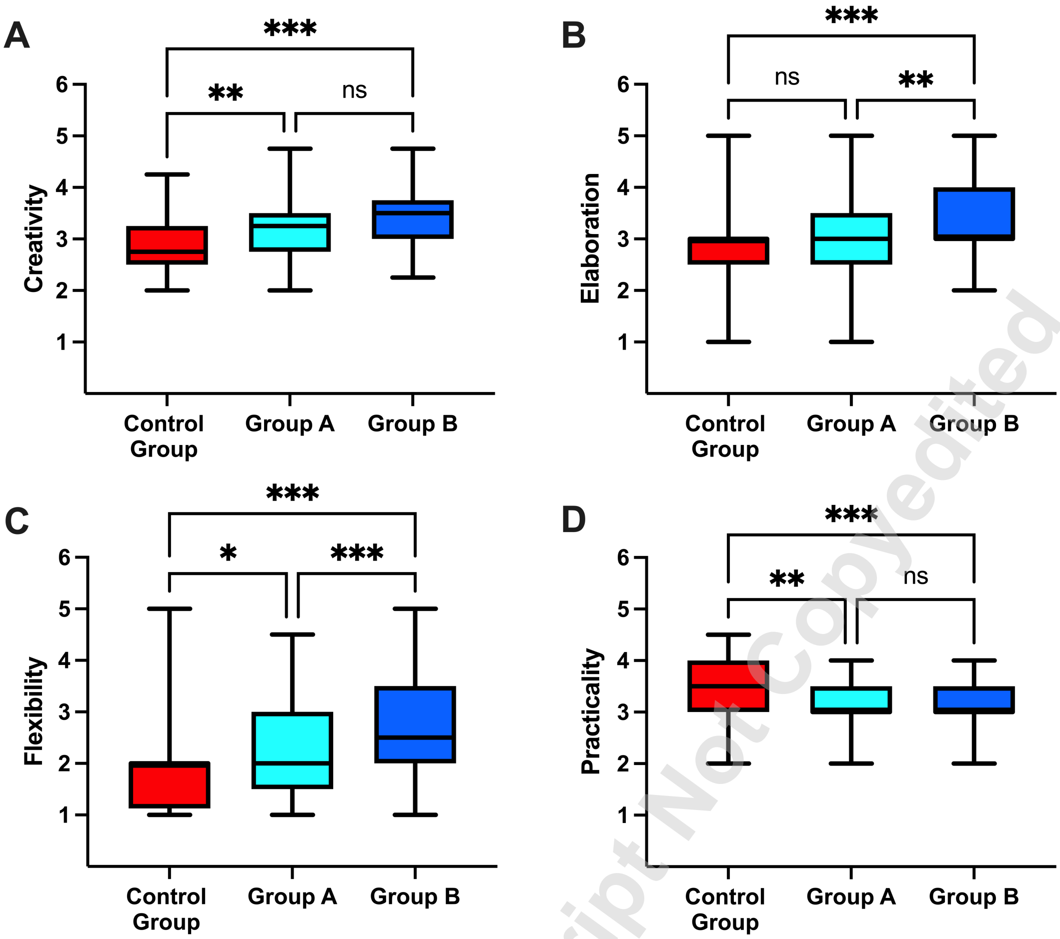

*Fig. 11 (A) Box chart of Creativity scores; (B) Box chart of Elaboration score; (C) Box chart of Flexibility score; (D) Box chart of Flexibility score. (note: ***p < .001, **p < .01, *p < .05, ns denotes no significant)*

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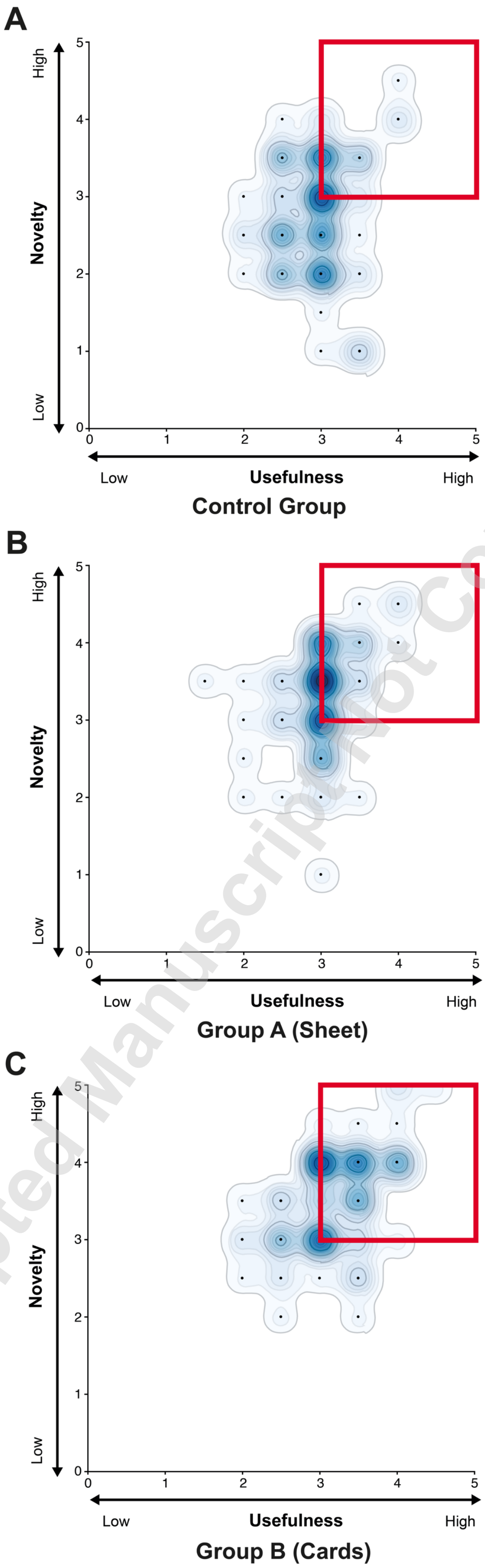

Fig. 12 (A)Idea distributions of Control Group in the novelty–usefulness space; (B)Idea distributions of Group A (Sheet) in the novelty–usefulness space; (C)Idea distributions of Group

B (Cards) in the novelty–usefulness space. (Note: the red square illustrates the high creative ideas (novelty and usefulness score > 3))

4.6.5 Elaboration, Flexibility and Practicality

There was a highly significant statistical difference in Elaboration among the three groups ($F(2, 211) = 15.310$, $p < .001$, $\eta^2 = .127$) (see Table 3). *Post hoc tests (Tukey HSD)* revealed statistically significant differences in the average elaboration scores. Students using Cards ($M = 3.4$, $SD = .891$) scored higher than both Sheet ($M = 3.0$, $SD = .744$) and Brainstorming (M = 2.7, $SD = .661$) groups (see Fig. 11-B). Additionally, there was no significant difference between students using Sheet and Brainstorming. The result supports the H4.

There was a highly significant statistical difference in *Flexibility* among the three groups ($F(2, 211) = 22.725$, $p < .001$, $\eta^2 = .177$) (see Table 3). Post hoc tests (*Tukey HSD*) revealed statistically significant differences in the average flexibility scores. Students using Cards ($M = 2.8$, $SD = .886$) scored higher than both Sheet ($M = 2.3$, $SD = .913$) and Brainstorming (M = 1.9, $SD = .785$) groups (see Fig. 11-C). Additionally, students using Sheet ($M = 2.3$, $SD = .913$) scored higher than the Brainstorming group ($M = 1.9$, $SD = .785$) (see Fig. 11-C). The result supports the H4.

There was a highly significant statistical difference in *Practicality* among the three groups ($F(2, 211) = 11.003$, $p < .001$, $\eta^2 = .094$) (see Table 3). *Post hoc tests (Tukey HSD)* revealed statistically significant differences in the average practicality scores. Students using brainstorming ($M = 3.5$, $SD = .548$) scored higher than both Group A – using Sheet ($M = 3.2$, $SD = .508$) and Group B – using Cards ($M = 3.5$, $SD = .548$) (see Fig. 11-D). However, there was no significant difference between students using Sheet and Cards (see Fig. 11-D). The result did not support the H4.

4.6.6 Correlation Analysis

Fig. 13 presents the correlation matrix between the quantity of IS usage and the metrics of *Novelty*, *Usefulness*, *Creativity, Elaboration, Flexibility, and Practicality*.

In the Group A (using Sheet), the quantity of IS usage showed a slight positive correlation with *Novelty* scores ($r = .319$, $p = .01$), a slight positive correlation with *Usefulness* scores ($r = .301$, $p = .015$), a slight positive correlation with *Creativity* scores ($r = .366$, $p < .001$), a moderate positive correlation with *Elaboration* scores ($r = .569$, $p < .001$), a moderate positive correlation with *Flexibility* scores ($r = .550$, $p < .001$), and no correlation with *Practicality* scores ($r = -.093$, $p = .463$).

In the Group B (using Cards), the quantity of IS usage showed a slight positive correlation with *Novelty* scores ($r = .302$, $p = .009$), a slight positive correlation with *Usefulness* scores (r

= .274, p = .019), a slight positive correlation with *Creativity* scores (r = .334, p = .004), a slight positive correlation with *Elaboration* scores (r = .394, p = .001), a moderate positive correlation with *Flexibility* scores (r = .550, p < .001), and no correlation with *Practicality* scores (r = - .008, p = .943).

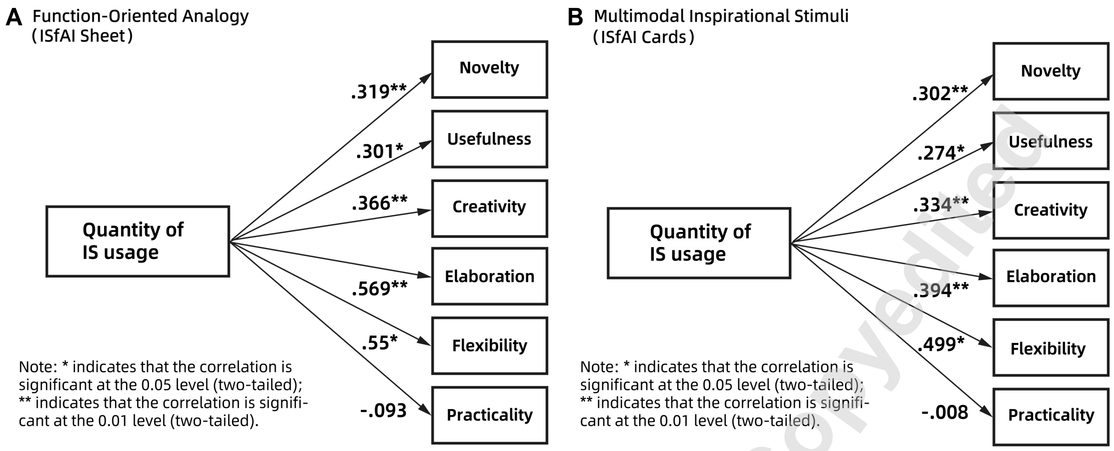

Fig. 13 Summary of Correlations Among IS Indices (Note: The displayed numbers represent Pearson correlation coefficients, R values.)

5 Discussion

This section will summarise the main findings in comparison to published work, and discuss the contribution, significance and limitation of the study, with directions for further study.

5.1 Main findings

The study found that the evidence of ISfAI use was ubiquitous, with almost all design concepts produced by industrial design students displaying such use. Furthermore, the research revealed that a significant number of design concepts were inspired by more than one IS, which was similar to previous studies [54, 67]. However, limited use of IS was observed in the Control Group which demonstrated a significant difference in the richness of ideas when compared to the Groups using ISfAI. The ISfAI tools (Sheet and Cards) assisted student designers in generating design concepts with rich and unique AI capabilities. This finding supported **H1.**

The Control Group mainly used Automation (27 times) and Notification – comparable to reminders (9 times). To our knowledge, this study represents the first empirical investigation to support previous research indicating that practitioners encounter challenges with design fixation when generating ideas for AI capabilities beyond automation, recommendation, and reminders [6].

Second, this study also investigated whether designers were observed to generate a higher number of concepts when utilizing ISfAI. However, the results indicated no significant difference

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in the average number of ideas generated by the participants in the Control and Experiment groups. **H2** was not supported. This finding contradicts the results reported by Daly, et al. [66], who found that Control Group (using Brainstorming) generated more ideas than Experiment Group (using Stimuli) in a 25-minute session. It is imperative to highlight the extended duration (i.e., 60-minutes) during which our study was conducted, as this factor may have exerted an influence on the observed variance in the quantity of generated ideas. For example, The Control Group students, drawing upon their prior experiences, may have initially generated a greater number of ideas within a short timeframe. Nonetheless, as the allotted time increased, they could have encountered challenges in exploring a more expansive design space. Further studies could explore the impact of longer time (e.g., 90 minutes or 120 minutes) on the quantities of the ideas by the Experiment and Control Groups.

Third, this study explored whether utilization of ISfAI by designers would result in the generation of concepts that are more novel, useful, creative. The findings largely supported **H3**, indicating that the utilization of ISfAI facilitates the generation of ideas that are more novel and creative. The study also revealed that function-oriented analogical words (as presented on the Sheet – Fig. 8) proved beneficial in enhancing the ideation performance in *Novelty* and *Creativity* in comparison with the Control Group. Overall, by using readily accessible ISfAI (i.e., Sheet or Cards), the student designers were observed to have enhanced their divergent thinking. The ISfAI employed analogical terms, which positively influenced ideation performance. This aligns with previous studies demonstrating how analogical terms can stimulate the generation of additional solutions with desirable characteristics [89-91]. The 40 inspirational stimuli offered by ISfAI were closely aligned with the design task and provided a diverse range of solutions for designing AI-powered products. This facilitated designers in exploring a broader solution space and generating innovative concepts. Besides, ISfAI offers comprehensive explanations of AI capabilities, accompanied by examples selected from an extensive collection of granted patents. Notably, patents stand as a robust and extensive reservoir of engineering design insights, having undergone rigorous scrutiny to validate their ability to define the invention, novelty and usefulness [46]. Therefore, these patent-based examples hold the potential to boost practitioners' ideation procedure, fostering the generation of novel and useful AI-enabled concepts. Working memory (WM) is also seen as an element of search leads, and these elements are the activation sources for the long-term memory (LTM) [37]. Therefore, providing a large number of external clues (e.g., stimuli, and examples) can be beneficial to expand a wider design space. This study emphasized the advantages of developing design tools that integrate various types of stimuli to facilitate idea generation, aligning with the results of a previous study [42].

Fourth, this study explored whether utilization of ISfAI by designers would result in the generation of concepts that are more elaborate, flexible, and practical. The results largely support **H4**. We found that the concepts generated by Group B (using the ISfAI cards) exhibited

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significantly higher levels of Flexibility and Elaboration, not only surpassing those of Control Group but also notably exceeding those of Group A (using the ISfAI sheet). Our study finds that within Group B, only two types of function stimuli (i.e., Reconstructing and Dynamic) were not utilized, whereas in Group A, six types of function stimuli (i.e., Reconstructing, Regulating, Testing, Natural, Evaluation, and Extraction) were not utilized (see Fig. 10). This suggests that the detailed explanations and specific examples provided in the ISfAI cards significantly enhanced students' comprehension and cognitive engagement, deepening their understanding of AI, and clarifying the links between the function-oriented analogical words and AI technology. Empirically, the study demonstrates that enhanced accessibility to design knowledge may potentially augment productivity in ideation. It has been observed that designers are capable of swiftly integrating domain-specific knowledge into design briefs, thereby effectively addressing design challenges. This integration not only enhances flexibility but also promotes more elaborate concept generation. We found that students in the control group attained higher *Practicality* scores compared to those in both experimental groups. This can be attributed to the fact that most design ideas in the control group were derived from real-life products, leading to their high practicality. On the other hand, the experimental groups using ISfAI achieved higher creativity scores and utilized more complex and diverse AI capabilities, posing a greater challenge in terms of *Practicality*.

Overall, the findings indicate that ISfAI is a valuable tool in the ideation process, particularly for promoting *Novelty, Creativity, Elaboration, and Flexibility* in conceptual design.

5.2 Contribution, Significance and implications

In the rapidly evolving technological landscape, designers need to acquire new knowledge and skills to effectively leverage emerging technologies and foster the development of innovative products [92]. In this study, we developed two aids for AI-powered product design. The first tool, ISfAI Sheet, is designed to provide abstract AI capabilities based on the function-oriented analogical words, particularly in mapping AI's design space, thereby boosting practitioners' ability to rapidly generate initial AI-powered ideas. Conversely, the ISfAI cards, the second tool, provide designers with valuable domain-specific knowledge and inspirational design resources in the field of AI. These tools bridge knowledge and experience gaps, overcoming design fixation challenges associated with generating AI-powered product concepts. This study demonstrated that domain-specific IS can act as a potential medium-level stimulus source, maximizing benefits and positively influencing design outcomes. We encourage educators to integrate ISfAI tools into creative activities through the design of exercises that encourage students to participate in supported exercises.

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Developing IS typically requires a substantial investment of time and effort, which can hinder designers and researchers from promptly accessing valuable knowledge to support early ideation. To foster the generation of innovative product design ideas, designers must master or understand the latest technologies, enabling multidisciplinary integration and interdisciplinary collaboration. This study introduces a novel framework for extracting technology-oriented design stimuli from patent datasets, which has demonstrated effectiveness. This framework offers three key advantages: 1) it leverages the vast text data available in the current big data era and advocates for utilizing patent databases to efficiently gather domain-specific datasets; 2) the framework utilizes *word frequency* as a method for computer-aided extraction, along with qualitative analysis software, to rigorously and efficiently extract potential stimuli from the acquired large unstructured textual dataset; 3) the framework is user-friendly and does not require advanced computer skills, making it a valuable approach for students to enhance their understanding of new technologies and to generate innovative ideas. The framework and strategy also serve as methodological guidance and references for future development of more automated extraction methods or systems for developing design aids.

When designers lack external stimuli, they must heavily rely on Working Memory (WM) [93] to store all the information generated during the ideation process. This includes problem statements, retrieving idea seeds from long-term memory (LTM), and intermediate ideation results [94]. However, the restricted capacity of WM [93] implies that some information may be lost and remain unrecoverable, thereby adversely affecting concept generation [94]. For this reason, the ISfAI sheet (see Fig. 8) facilitates analogical reasoning by aiding in the retrieval of effective and novel analogies stored in designers' long-term memory, allowing them to explore fresh possibilities through the application of functional similarities between various objects, systems, or concepts. Our ISfAI cards (Fig. 5) can serve as a structured prompt tool to enhance WM tasks, particularly in the context of generating AI-powered product design ideas. In essence, ISfAI empowers designers to seek inspiration in unexpected sources and devise innovative solutions that mitigate the impacts of *design fixation*.

Given the diversity of ideation techniques, designers and educators frequently encounter ambiguity when choosing suitable methods for idea generation. This study conducted empirical research to compare the differences among three ideation techniques: *Individual Brainstorming* (IB), ISfAI Sheet, and ISfAI Cards. The empirical study demonstrates that during the early stages of concept generation, these ISfAI tools can assist designers in expanding design possibilities and generating a greater number of high-quality ideas. This serves to address the challenges posed by the trends of digital transformation [95, 96] and the problem of designers becoming "fixed" in their approaches [17, 18]. The research findings present a valuable collection of design strategies capable of aiding design practitioners, educators, and students in the selection of suitable ideation techniques to boost creativity. For example, when facing time constraints, choosing the ISfAI

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Sheet tool can offer advantages due to its direct approach to ideation support, which involves employing analogy words to explore long-term memory and harnessing the power of divergent thinking. Conversely, when sufficient time is available, choosing ISfAI Cards holds the potential to yield ideas that are more creative, elaborate, and flexible. Given the frequent emphasis on enhancing the likelihood of designers' success, incorporating a metric or dimension that gauges the probability of success when utilizing design methods would hold significant value [97].

This paper proposes a novel approach for extracting IS specifically tailored for emerging technologies, with ISfAI serving as a case study. Our method is adaptable for extracting other technology-oriented IS for X, such as IS for Internet of Things (IoT) and IS for Metaverse. When the current tools are insufficient, professionals can also extract other domain-specific IS from "world knowledge (big data)". This process addresses design fixations and knowledge barriers, enhancing interdisciplinary knowledge and design experience, stimulating idea generation, and ultimately leading to a large number of highly creative concepts. This stage corresponds to the K→C (Disjunction) in the C-K theory [98]. This method may help solve design innovation problems related to solving ill-defined [99] or wicked problems [100, 101] and complex sociotechnical systems [102].

Our work parallels the AI capability framework outlined in [103] which presents informative slides categorizing AI capabilities into eight distinct groups (Estimate, Forecast, Compare, Detect, Identify, Discover, Generate, Act). The significance of the ISfAI extraction methodology and the tools is that they not only support opportunistic Design for AI but also provide more systematic and precise guidance for the conceptual design phase. In contrast to the approach in [103], which analyzes 40 AI examples across 14 domains from existing products and services, our ISfAI is informed by a broader spectrum of sources. It incorporates insights from 1,755 granted AI-related invention patents, covering a wide range of industries and enterprises, thus offering a more comprehensive perspective.

5.3 Limitations and future work

By utilizing the ISfAI, practitioners can effectively expand their design space by generating more creative AI-powered product design ideas through the use of one or multiple IS(s) simultaneously. However, it is crucial to acknowledge that during the later stages of the design process, these concepts may necessitate further discussion with AI algorithm scientists/engineers to assess their technical feasibility or refer to AI design guidelines for evaluation [14].

Although patents are often used in extracting IS, and the 1,755 patents constitutes a substantial and thoughtfully curated dataset intended to capture a meaningful cross-section of the patent landscape, we are aware that focusing on the patent titles and "word frequency count" has its limitations in identifying the common functions across actions related to AI. The 40 stimuli identified are quite generic. In addition, the extracted ISfAI in this study are based on the current state of AI, which is a fast-developing technology. It is important to acknowledge that different application scenarios may arise over time, leading to new innovations and needs for new tools.

In future studies, we plan to explore alternative methods for achieving a more representative sample. Future studies ought to delve deeper into the modalities and optimal timings for integrating ISfAI to enhance the efficacy of the ideation process.

6 Conclusion

This study referenced the concept–knowledge (C-K) theory and proposes ISfAI for supporting concept generation for AI-powered product design ideas. We developed a universal and efficient framework for extracting domain-specific stimuli. We extracted 40 stimuli by analyzing 1,755 granted AI patents, and tested them with design students using a design brief for a 'smart household appliance'. The results indicate that ISfAI is effective in assisting student designers to generate creative ideas during the early stages of concept design, facilitating the generation of more novel, creative, elaborate, and flexible ideas. It was observed that a more comprehensive presentation of ISfAI, encompassing extensive descriptions and examples, is effective as an ideal level of stimulus tool (neither far nor near). Overall, ISfAI can serve as an ideation tool to support design students and potential practitioners in generating more creative, elaborate, and flexible concepts, while mitigating the impact of design fixations and providing support for exploring a broader design space to generate AI-powered product design ideas.

This study contributes to the expanding research on the intersection of AI and design, offering original, and practical tools for the development of AI-powered products, and delivering a rigorous approach to, and valuable insights into, the formulation of effective technology-oriented inspirational stimuli for design. The study also identified that timing (duration of the use of the design aids) plays a potentially critical role in the assessment of the effective of design aids. This is a direction for further exploration.

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Figure Captions List

Table Caption List

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Appendix

Table 1 IS for AI

No.	IS	Descriptions
A	DECISION MAKING	
1	Analyzing	The ability to examine and interpret data, information, or content to derive insights, patterns, trends, or meaningful conclusions. It empowers organizations and individuals to make informed decisions, uncover hidden insights, and extract valuable knowledge from the vast amount of data available in today's digital age. Applications: Data Science, Business Intelligence, Health Information, Emotion, User Behavior, and Scientific Research.
2	Determining	The ability to make decisions or reach conclusions based on data, information, rules, or criteria. Determination involves evaluating available evidence, analyzing factors, and arriving at a judgment or decision, often to solve a problem, answer a question, or achieve a specific goal. This can maximize profit, minimize costs, or achieve efficiency. Applications: Risk Assessment, Medical Diagnosis, Quality Control.
3	Diagnosis	AI's diagnosis capabilities involve analyzing data, recognizing patterns, and drawing conclusions about specific conditions or issues. This leads to quicker and more accurate diagnoses. Applications: Healthcare, Manufacturing, and Fault Detection.
4	Evaluation	The process of assessing the performance, effectiveness, or quality of systems, models, or algorithms. It helps determine their readiness for practical use and identifies areas for improvement. Applications: Evidence, Health, Patent, Video, Flight Condition Evaluation.
5	Judging	The ability to make evaluations, assessments, or determinations based on predefined criteria or rules. This can enhance consistency and objectivity in evaluations while reducing the reliance on manual judgment, particularly in situations where large volumes of data or assessments are involved. Applications: User-Generated Content, Quality of Products or Services.
6	Mapping	Generating visual representations of data by utilizing spatial relationships in the graphics to represent the relationships within the data. This can enhance the simplicity of analysis. Applications: Feature Representation, Knowledge Processing.
7	Planning	The ability to make decisions and develop strategies to achieve specific goals or objectives in a structured and efficient manner. This can utilize with maximum efficiency the available time/resources and reduce risks. Applications: Logistics and Supply Chain, Manufacturing Process, Route, Power System, Treatment Panning.
8	Forecasting	The ability to predict future outcomes, trends, and events based on historical data and patterns. This can assist businesses and organizations in making informed decisions, planning resources, and optimizing processes. Applications: Traffic, Clinical, Patent, Weather, Sales, Performance, Manufacturing Process, and Demands Forecasting.
9	Simulation	The ability to model and replicate real-world processes, systems, or environments in a digital or virtual space. This can provide a cost-effective and efficient way to analyze and understand real-world scenarios, leading to better decision-making, design improvements, and risk mitigation. Applications: Manufacturing Process, Traffic, Actor, Flight, and Epidemiological Simulations.
10	Recognition	The ability to identify, categorize, or acknowledge specific patterns, objects, features, or concepts within data or sensory input. This can perceive and understand the world or data it interacts with. Applications: Disease, Document, Image, Emotion, Gesture, Text, Object, and Face Recognition.
B	PERSONALIZATION	
11	Adaptive	The ability to learn from experience and adjust its behavior or performance based on new data, feedback, or changing conditions. This can dynamically update its internal representations, models, or strategies to improve its performance and adapt to evolving situations. Applications: Traffic System, User interfaces, Conversational System
12	Customization	The ability to adapt and personalize their responses, recommendations, or behavior based on individual user preferences, needs, or historical interactions. Customization allows AI to provide tailored experiences and solutions to different users, enhancing user satisfaction and engagement. Applications: Adaptive Interfaces, Product Customization, Learning Adaptation, and Content Personalization.
13	Dynamic	The ability to adapt, respond, or change their behavior in real-time or based on changing circumstances, inputs, or requirements. This can enhance user experiences, improve system efficiency, and address complex problems in dynamic and evolving environments. Applications: Dynamic Emoticon, Avatar, Navigation, Prediction and Library.
14	Learning	The ability to acquire new understanding, knowledge, behaviours, skills, values, attitudes and preferences based on experience, data, and feedback. It allows systems to improve and adapt without explicit programming. Applications: Chinese characters writing learning, Image Recognition, Autonomous Driving, and Reward System.
15	Natural	Natural AI aims to bridge the gap between human and machine communication, making interactions with AI systems more intuitive, seamless, and user-friendly. It makes human-computer interactions more intuitive and natural, reducing the barriers between users and technology. Applications: Natural Language Interaction, Natural Interactive User Interface, Conversational AI.
16	Notification	The ability to send alerts, messages, or updates to users or other systems to convey important information, events, or changes in real-time or near-real-time. This can keep users informed, enhancing user engagement, and ensuring that important information is not missed. Applications: Healthcare Reminders, Weather and Traffic Updates Notification, Security Alerts.
17	Interaction	The ability to engage in meaningful and dynamic exchanges with humans or other systems. Interaction capabilities are essential for creating user-friendly AI systems that can assist, inform, or entertain users effectively. This can enhance the user experience and add playfulness. Applications: Customer Service, Education, Entertainment and Healthcare.
18	Personalizing	The ability to tailor content, recommendations, or interactions to the individual preferences, behaviors, or characteristics of each user or customer. This can enhance user experiences, increases the relevance of content and recommendations, and ultimately drives user retention and conversion rates. Note: Personalization often involves dynamic, data-driven adaptation, while customization relies on predefined options and user choices. Applications: Personalized Chat bots, User agent, and Content.
19	Recommending	The ability to suggest or propose items, actions, or options to users based on their preferences, behavior, or context. This can enhance user engagement, increases user satisfaction, and drives user interactions in various domains. Applications: Product, Video, Film, Personalized Ads，Resolution Action Recommendations.
20	Real-Time	The ability to process and respond to data or events with minimal delay, typically within a very short and predictable timeframe. This can enable faster decision-making, enhance user experiences, and improve the efficiency and effectiveness of various processes and applications. Applications: Financial Trading, Health Condition, Network Security, Industrial Automation, and Chatbots and Virtual Assistants.

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C	PRODUCTIVITY	
21	Automation	The ability to perform tasks, processes, or actions without direct human intervention. This can streamline operations, increase efficiency, and free up human resources for more complex and creative tasks. Applications: Industrial Automation, Process Automation, Assistants
22	Autonomous	The ability to operate and make decisions independently, without direct human intervention or control, to achieve its intended objectives or tasks. This can enhance safety, efficiency, consistency, and reduce labor costs. Applications: Medical Diagnosis, Industrial Automation, Process Automation.
23	Assisting	To augment human capabilities rather than replacing human involvement entirely. AI systems with assisting capabilities are designed to work alongside humans, complementing their skills and abilities, and enhancing their productivity and decision-making. Applications: Process Optimization, Creative Assistance, Exercise, Medical Diagnosis.
24	Classification	The ability to categorize or assign data, objects, or entities into predefined classes or categories based on their characteristics, features, or attributes. It helps automate decision-making processes by categorizing and organizing data, making it easier for businesses and organizations to extract insights and take actions based on categorized information. Applications: Documents, Content, Activity Classification.
25	Communication	The ability to understand and generate human language in a manner that allows for effective interaction and exchange of information between the AI system and users. This can engage in human-like conversations, providing users with valuable information, assisting with tasks, answering questions, and more. Applications: Virtual Assistants, Chatbots, Language Translation Tools, Customer Support Systems.
26	Detection	The ability to identify and recognize the presence or occurrence of specific objects, events, patterns, anomalies, or conditions within data or a given environment. It allows organizations to automate the identification of critical events, objects, or conditions, facilitating timely responses and decision-making. Applications: Health Condition, Object, Event, Security, Anomaly and Mood Detection.
27	Extraction	The process of identifying and retrieving specific pieces of information or data from unstructured or semi-structured sources, such as text, images, or documents. This is valuable for automating data collection and data processing tasks, reducing manual effort, and accelerating data-driven decision-making. Applications: Document Summarization, Feature Extraction, Data Extraction, Knowledge Extraction.
28	Generation	The ability to create new content, such as text, images, audio, or other forms of data, without direct human input or copying existing examples. This is particularly valuable for tasks that are repetitive or time-consuming. This can foster innovation and productivity, and reduce manual effort and costs. Applications: Artistic Creations, Agent Avatar, Questions and Answers, and Homepage Generation.
29	Managing	The ability to handle and oversee complex tasks, processes, or systems with minimal human intervention. This can efficiently organize, optimize, and control various aspects of a given process or system, leading to improved performance and outcomes. Applications: project management, energy management, group reward, medical care and retail management.
30	Manipulating	The ability to change, transform, or alter data or other information based on predefined rules, learned patterns, or user instructions. This can process and modify data to achieve specific objectives, solve problems, or generate new outputs. Applications: Virtual environment, Avatar Manipulation.
31	Measuring	The ability to assess, quantify, and evaluate various aspects of data, performance, level of difficulty or processes. Specifically, it can analyze data and provide meaningful metrics, scores, or evaluations to aid decision-making, optimize performance, or monitor progress. Applications: Measure Health Data, Product Quality, Difficulty, Performance.
32	Optimizing	The ability to improve and enhance the performance, efficiency, or effectiveness of a process, task, or system by making adjustments or refinements. This can lead to cost savings, improved performance, and better resource utilization across a wide range of applications. Applications: Route, Energy Efficiency, Decisions, Robust Optimization.
33	Reconstructing	The ability to analyze and rebuild information, data, or objects from incomplete, degraded, or fragmented sources. This can improve the usability and interpretability of the data, images, or content, leading to better decision-making and understanding in fields like healthcare, image processing, and data analysis. Applications: 3D, image and system reconstruction.
34	Regulating	The ability to enforce rules, policies, or constraints to ensure that it operates within specified bounds, adheres to ethical and legal standards, and behaves responsibly. This can prevent harmful consequences, and build trust in AI technologies. Applications: User experience, external systems or environments regulation.
35	Scheduling	The ability to plan and organize activities, tasks, resources, or events in an efficient and time-optimized manner. This improves resource utilization, reduces operational costs, and enhances overall efficiency in various domains. Applications: Project Management, Production Scheduling, and Transportation and Logistics.
36	Testing	The ability to the process of evaluating, assessing, and validating AI systems or software to ensure their functionality, performance, reliability, and security meet specified criteria and standards. This can automate various testing processes, making them more efficient and effective. Applications: Software Applications, Semiconductor, User Interface, and Security Testing.
D	SECURITY	
37	Warning	The ability to detect and issue alerts or notifications about potential risks, threats, or critical situations to users or relevant stakeholders. This can help organizations and individuals take proactive measures to mitigate risks, prevent adverse outcomes, and ensure the safety and well-being of people and assets. Applications: Network Threat Monitoring, Dangerous Driving, Quality Control, and Departure Warning.
38	Monitoring	The ability to continuously observe, track, and gather data or information from various sources, processes, or systems in real-time. This can improve decision-making, risk management, and overall performance. Applications: User Activity, System, Network, Health, Financial Market, Structure Stability, Application Performance, Computing Resource and Social Media Monitoring.
39	Security	The ability to protect and safeguard data, systems, networks, and digital assets from unauthorized access, breaches, threats, and vulnerabilities. This can assist in identifying, mitigating, and responding to security risks and incidents. Applications: Network Information Security, Cyber Threat Intelligence.
40	Tracking	The ability to follow and record the movement, status, or changes in the position or behavior of objects, individuals, or entities over time. This can continuously monitor and analyze data from various sources to provide real-time updates and insights. Applications: Asset, Users, Target, Body Language, Motion, and Gesture Tracking.