Idea Generation with Technology Semantic Network

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ABSTRACT

There are growing efforts to mine public and common-sense semantic network databases for engineering design ideation stimuli. However, there is still a lack of design ideation aids based on semantic network databases that are specialized in engineering or technology-based knowledge. In this study, we present a new methodology of using the Technology Semantic Network (TechNet) to stimulate idea generation in engineering design. The core of the methodology is to guide the inference of new technical concepts in the white space surrounding a focal design domain according to their semantic distance in the large technology semantic network, for potential syntheses into new design ideas. We demonstrate the effectiveness in general, use strategies and ideation outcome implications of the methodology via a case study of flying car design idea generation.

Keywords: Technology semantic network; semantic distance, data-driven design; idea generation, flying car

1. INTRODUCTION

Engineering design idea generation for innovation traditionally relies on intuition, expertise and cognitive capabilities, and subjects to high uncertainty. The uncertainty is even greater for inexperienced engineering designers and emerging technologies, such as 5G telecommunications, autonomous vehicles, and flying cars (Sun et al., 2014). To inspire design ideation, various data-driven methods and software tools have been introduced to explore and retrieve design precedents (patents, documents, etc.) and utilize them as design stimuli (Murphy et al., 2014; Song et al., 2017a). In general, the design stimuli have been retrieved as documents within a limited scope of specific domains. This study focuses on retrieving design information in a more granular level (i.e., words or phrases) in the total technology and engineering knowledge base to provide more nuanced, systematic, and rapid design inspiration.

Specifically, we present a methodology that leverages a technology semantic network to infer generic and specific technical concepts beyond a focal design domain for potential syntheses into new design ideas with regards to the focal domain. The core of the methodology is the Technology Semantic Network (TechNet) (Sarica et al., 2020), a large-scale network of technical terms that are retrieved from patent texts in all technology domains and associated according to pairwise semantic distances among them. In TechNet, the terms represent generic components, functions, structures, configurations, working principles, mechanisms, etc. in engineering and technology. Their semantic distances indicate the technical relevance of the technical concepts that the terms represent, and thus guides the inferences across concepts. This study contributes to the growing literature on methods and tools for data-driven design.

In this study, we employ the TechNet-based methodology to generate new flying car design ideas. Flying cars has attracted growing public attention in the past two decades (*Hype Cycle for Emerging Technologies*, 2018). Nonetheless, the existing flying car designs are still immature and far from the convergence to a dominant design (Suarez & Utterback, 1995). The uncertainty and vast open design possibilities of flying cars present a suitable and interesting case for the application of our methodology for data-driven design. Furthermore, the research team also presents extensive background and experiences in automotive engineering.

In the next sections, the methodology is introduced after a review of the related literature. Then, the case application of our methodology to flying car design idea generation is presented, and followed by a discussion on its limitations and future research directions.

2. RELATED WORK

Our research is inspired by the prior literature on the data-driven design aids and intends to operationalize the comprehensive TechNet as an infrastructure for providing design inspiration. Thus, we review the related prior work on data-driven design aids and semantic networks.

2.1. Data-driven design aids

Various data-driven methods and tools have been introduced to support engineering design ideation. For instance, FuncSion (Chakrabarti & Tang, 1996) generates solutions for a specific set of functional requirements, using its database of functional elements and their relations. VISUALIZEIT (English et al., 2010) uses a database of component flow graphs, which are created by applying graph grammar rules to functional graph models, to support concept generation. AskNature (Deldin & Schuknecht, 2014) is a web-based database of biological systems, which are organized by their biomimicry taxonomy, for the interest of biologically-inspired designs. IDEA-INSPIRE (Chakrabarti et al., 2006) represents both natural and artificial systems based on the SAPPhIRE (State-Action-Part- Phenomenon-Input-oRgan-Effect) ontology to support the search for natural or artificial solutions to a given design problem.

A growing stream of research has proposed methods to represent and retrieve patent documents as potential sources of design inspiration. In particular, function-related representations have attracted the greatest attention. For instance, Russo et al. (2012) adopted the Function-Behavior-Structure ontology (Qian & Gero, 1996) to construct systematic queries to retrieve state-of-art patents for a specific design problem using Subject-Action-Object (SAO) structures. Fu et al. (Fu et al., 2013a) used latent semantic analysis (LSA) of function verbs in patent texts to associate patents in a Bayesian network to guide the selection of patents as design stimuli. Murphy et al. (2014) represented functional aspects of designs in patents using the Bag-of-Words approach and mapped them with a vector space model to aid the search for functionally analogical patents to a specific query. Likewise, Liu et al. (2020a) proposed a framework of representing patents with a bag-of-words approach using functional categories and classifying them with respect to the topmost hierarchy of the functional-basis (Stone & Wood, 2000).

Some other methods and tools represent patents beyond functions. Mukherjea et al. (2005) introduced the BioMedical Patent Semantic Web by extracting the biological terminology in patent abstracts in the biomedical field and then associating patents by utilizing the knowledge from biomedical ontologies. Berduygina and Cavallucci (2020) mined the dependency structures between individual patent claims and linguistic features in claim jargon to support the use of the theory of inventive problem solving (TRIZ) (Altshuller & Altov, 1996). Lee et al. (2015) constructed a morphological matrix for a specific technology based on patent metadata and keywords to identify novel patents for uses in technology opportunity analysis. Song et al. (2017b) focused on the classification labels of patents in the Japanese Patent Classification System to discern patents for technology opportunity discovery. InnoGPS (Luo et al., 2019) uses a technology domain network map based on the international patent classification system from information science research (Alstott et al., 2017; Yan & Luo, 2017a) to guide the search and retrieval of design documents and concepts across domains to inspire creative design concept generation via design analogy and synthesis.

A growing number of design ideation methods and tools have utilized large public semantic networks, such as WordNet and ConceptNet, rather than patent databases, as the backend knowledge base. WordNet (Miller et al., 1990) has been the most popularly utilized. For instance, WordTree (Linsey et al., 2012) uses brainstorming sessions and the WordNet's hierarchical structure to populate a tree structure, in which functional aspects of the design problem are represented with new additional verbs, to further guide the search for analogical solutions. Yoon et al. (2015) proposed a method to discover patents according to their function similarity assessed by leveraging WordNet's hierarchical structure. Georgiev & Georgiev (2018) developed WordNet-based metrics to measure divergence, polysemy, and creativity of the ideas from concept generation sessions. Nomaguchi et al. (2019) proposed to evaluate the novelty of function combinations in design ideas based on semantic similarities in WordNet, a word2vec model trained on Wikipedia, and these two metrics together, and reported a negative correlation between the human evaluations of novelty and the semantic similarity of the combined functions.

Other than WordNet that was collectively built via direct human efforts, a few other free online knowledge bases have also been employed in new design ideation methods or tools. For example, Chen & Krishnamurthy (2020) proposed an interactive procedure to retrieve words and terms in ConceptNet to inspire designers. ConceptNet (Speer et al., 2017) is a large public knowledge graph automatically extracted from Wikipedia, built and maintained at MIT Media Lab. Han et al. (2020a) also proposed to evaluate new ideas by measuring the semantic similarity between design concepts using ConceptNet. Camburn et al. (2020) proposed a set of new metrics for automatic evaluation of the natural language descriptions of a large number of crowdsourced design ideas, and their evaluation was based on the Freebase (Bollacker et al., 2008), another large public structured knowledge database managed by Google.

The growing uses of such public semantic network databases in the development of design ideation support tools have inspired the development of semantic networks based on engineering data. For instance, Shi et al. (2017) and Liu et al. (2020b) proposed the use of semantic networks mined from scientific papers as sources of inspiration for design concept generation. Chen et al. (2019) utilized the semantic concept network from Shi et al. (2017) to retrieve implicit and explicit design stimulation at the semantic level and supported these stimuli with image synthesis to stimulate designers in ideation sessions.

On the other hand, a few recent studies employed the whole patent database instead of focusing on a specific domain and generated network maps to resemble technology space where all patent classes in the existing patent classification system are operationalized as nodes

(Alstott et al., 2017; Yan & Luo, 2017b). However, these studies are limited by the structure of patent classification systems and patent metadata; thus, they can only support high-level inspirations (Luo et al., 2018). Furthermore, the studies on providing semantic level design stimulation and evaluation generally rely on common-sense knowledge bases, such as WordNet and ConceptNet, or language models not trained specifically for engineering. In fact, the engineers' perception of technical terms is biased and represented better by knowledge bases that are specifically trained on technological knowledge (Sarica et al., 2020).

2.2. Semantic networks

We intend to use a semantic network of technical terms, which covers generic engineering design concepts in all domains of technology, to support technical design inferences for idea generation. The past two decades, but especially the last decade, witnessed great progress in natural language processing (NLP) that allows researchers to introduce a few large-scale semantic networks based on generic human knowledge. For instance, WordNet (Miller et al., 1990), ConceptNet (Speer et al., 2017), never ending language learning (NeLL) (Mitchell et al., 1998) and Yago (Rebele et al., 2016) are available for public uses and have enabled various applications, such as information retrieval, semantic analysis, knowledge exploration and discovery, artificial intelligence (AI), etc., in many different fields. These knowledge databases are often generated by linguistically and statistically learning the information in knowledge repositories such as Wiktionary and Wikipedia, and merging the knowledge entities, and relations based on readily available or collaboratively created ontologies.

Despite these efforts on creating large-scale semantic networks for generic uses, only a few engineering researchers have carried out the same task in the context of engineering. For instance, Shi et al. (2017) mined and analyzed 20 years of publications, nearly one million engineering papers, from ScienceDirect and one thousand design posts from blogs and design websites to extract technical terms and construct a large-scale semantic network. Despite the great amount of data collected, it is unclear if their data of different types can resemble comprehensive engineering knowledge in all domains. Liu et al. (2020b) proposed a method to create a concept network by mining the concepts from the technical documents related to a specific design problem and associating them via the vector representations of these concepts by utilizing a word-embedding algorithm and synset relations of the WordNet. For the same purpose of creating a large-scale semantic network in the context of engineering and technology, we directed our attention to the patent data that provide more comprehensive coverage of the engineering knowledge base.

Patents are reliable and rich sources of engineering design knowledge (World Intellectual Property Organization, 2004; Asche, 2017) since they have been examined rigorously to ensure their adequateness on defining the invention, their novelty, and usefulness. These characteristics of the patent examination process assure the quality of the patent data and avoid redundant designs to be documented in the patent database. Particularly, United States Patent and Trademark Office (USPTO) patent database is one of the largest patent databases, publicly available, organized in systematic catalogues of the inventions, and continuously evolving as inventors file patent applications and new technologies emerge.

In our recent work (Sarica et al., 2020), we have constructed a technology semantic network (i.e., TechNet) that consists of more than 4 million technology-related terms, which represent technical concepts in all domains of technology, and their semantic distance. The complete digitalized USPTO patent database from 1976 to October 2017 was utilized to construct TechNet. The utilization of the complete patent database was aimed to ensure the comprehensiveness of TechNet and the balanced coverage of knowledge in all domains of technology. In a benchmark comparison with other existing semantic network databases including WordNet, ConceptNet, and B-link (Shi et al., 2017), TechNet presented superior performances in term retrieval and inference tasks in the specific context of technology and engineering (Sarica et al., 2020). TechNet has been utilized to augment patent search (Sarica et al., 2019a), technology forecasting (Sarica et al., 2019b), and idea evaluation (Han et al., 2020).

To construct TechNet, we first mined the raw patent texts to exact the terms (words and phrases) that represent meaningful engineering concepts (e.g., functions, components, configurations, working principles), using NLP techniques for phrasing, denoising, lemmatization, and so on. On this basis, word-embedding models were trained (also in the total database) to project the terms to vectors and form a unified vector space that would represent the total engineering knowledge space. Then, a large technology semantic network can be forged by associating the technical terms by pairwise vector cosine similarity. The TechNet construction procedure was data-driven and unsupervised and summarized in Fig. 1. Interested readers can refer to our prior publication (Sarica et al., 2020) for further details.

FIGURE 1 ABOUT HERE

Fig. 1: A summary of TechNet construction process (Sarica et al., 2020)

In the present paper, we introduce a methodology that utilizes the Technology Semantic Network (TechNet) as a backend infrastructure to support idea generation. In contrast, prior studies have either used comprehensive common-sense knowledge databases or field-limited datasets to provide semantic-level aids for engineering design ideation generation. The novelty of the study is in the use of a comprehensive technology-focused semantic network trained from the technical patent database to aid in technical idea generation.

3. METHODOLOGY

The spirit of our methodology is to infer new technical concepts from those already used in prior designs of a domain according to the term-to-term semantic distance in TechNet. Fig. 2 depicts the methodology that includes 3 main steps: 1) retrieve used concepts within a focal design domain (or design object or interest), 2) infer new concepts beyond the domain (i.e., the white space concepts), and 3) relate and synthesize the white space concepts with the original design domain to generate new ideas. The following subsections describe the details of these steps.

FIGURE 2 ABOUT HERE

Fig. 2 The overall methodology.

Step 1: Concept retrieval in a focal design domain

The first step is to use TechNet[2] to retrieve the terms in the technical documents representing the prior designs in a domain (i.e., identify the terms that are in both the technical

[2] Accessible at http://www.tech-net.org/[2]. One can also use the public API to access TechNet. API definitions can be found at https://github.com/SerhadS/TechNet.

documents and TechNet). These terms represent the technical concepts (e.g., functions, components, structures, working principles) that have *already* been used in the designs of the focal domain to date. These prior documents need to be identified and curated first and have complete coverage of the prior designs of the domain. While we mine patent documents only in the case study of the present paper, other types of design documents (e.g., technical reports, engineering paper publications) may also be useful for the same purpose.

These concepts can be assessed according to their importance with regards to the focal design domain. For this purpose, we propose the following *term-domain importance* metric (tdi_t) by considering both a term's occurrence frequency in the focal domain and its specificity to the domain:

$$tdi_t = tf_{t,D} * ts_{t,D} \tag{1}$$

$$tf_{t,D} = \frac{|\{d \in D: t \in d\}|}{|\{d: d \in D\}|} \tag{2}$$

$$ts_{t,D} = \frac{\sum_{d \in D} count(t, d)}{\sum_{d \in P} count(t, d)} \tag{3}$$

where *t* refers to a single term, *d* refers to a patent document, *P* stands for the set of patents in the whole patent database, and *D* refers to the set of patents in a design domain. This metric favors the terms that are more common in the domain but not as common in the entire patent database.

Term-domain frequency ($tf_{t,D}$) (0,1] is measured as the number of patents in the domain that contain the term relative to the total number of patents in the domain. It indicates how commonly a concept is used in the prior designs of the domain of interest. However, a commonly occurring concept in a domain might be a general one for all domains. Thus, we also incorporate the *term specificity* ($ts_{t,D}$) (0,1] metric, which is measured as the count of the term in the patents in the domain relative to the total count of the term in the total database. High term specificity indicates that a concept is specific to the design domain and may contain domain-specific characteristic design information.[3]

Step 2: Concept inferences beyond the domain

The second step is to infer, according to the term-to-term semantic similarity information in TechNet, from the terms in the prior design documents of the focal domain to additional technical terms that have not appeared in the prior design documents of the focal domain. The total of these additional terms forms the total *white space* to the focal design domain. Hereafter we call those terms outside the focal domain the *white space terms* and the concepts they represent the *white-space concepts*. The white space concepts have varying latent relevance to those already used in the original design domain.

To measure such a technical relevance (R_i), we assess the semantic relevance of the white space terms to those in the documents of the focal domain and calculate it as a potential white space term's weighted average semantic relevance to the terms in the focal domain:

$$R_i = \frac{1}{n}\sum_{t=1}^{n} w_{i,t} td i_t \tag{4}$$

$$w_{i,t} = \frac{\sum_{j=1}^{n} v_{i,j} v_{t,j}}{\sqrt{\sum_{j=1}^{n} {v_{i,j}}^2}\sqrt{\sum_{j=1}^{n} {v_{t,j}}^2}} \tag{5}$$

[3] To measure a term's specificity to a domain, one can also use the inverse of a term's general popularity metric. One example is the total number of patents that contain the term in the total database divided by the total number of patents in the database. Based on the data of our later case study, we found this metric and the *ts* metric we use in the main text is highly correlated and interchangeable.

where *n* is the number of unique terms in the focal domain; $w_{i,t}$ is the semantic similarity between the i^{th} new term and the t^{th} domain term; v_i is the vector representation of term i; and tdi_t is the weighting factor, term-domain importance, defined by Equation (1) above.

On this basis, we further standardize the *R* metric by the *z*-score formulation as follows,

$$ZR_i = \frac{R_i - \mu_R}{\sigma_R} \tag{6}$$

where μ_R is the mean and σ_R is the standard deviation of the *relevance scores* (*R*) of white space concepts. A negative *ZR* score of a concept implies it is more distant to the focal design domain than average white space concepts; *vice versa*.

Step 3: Idea generation

Then it comes to the third step, in which the designers make attempts to relate the previously unused white space concepts with the original design domain to generate new design ideas. Since the white space concepts, by definition, have not been previously used in the designs of the focal domain, new ideas that relate and synthesize them with the focal domain naturally derive novelty. Therefore, our proposed procedure in principle ensures the novelty of new ideas when they are generated. In particular, the relevance score (*R*) or its normalized form (*ZR*) may further guide the search and retrieval of the white space concepts to relate to the focal design domain for potential syntheses into new design ideas.

According to the extensive design creativity literature (Gentner & Markman, 1997; Ward, 1998; Christensen & Schunn, 2007; Tseng et al., 2008; Chan et al., 2011, 2015; Fu et al., 2013b; Chan & Schunn, 2015; Song et al., 2017a; Srinivasan et al., 2018), near stimuli to the target design domain can stimulate more ideas and more feasible ideas (Gick & Holyoak, 1980; Weisberg, 2006; Fu et al., 2013b; Chan et al., 2015; Keshwani & Chakrabarti, 2017; Srinivasan et al., 2018), whereas far stimuli may stimulate fewer ideas and ideas with high infeasibility and abstractness, but give rise to the novelty of the generated ideas (Gentner & Markman, 1997; Ward, 1998; Tseng et al., 2008; Srinivasan et al., 2018). Therefore, when searching and choosing white-space concepts as potential design stimuli, one may focus on the near-field concepts with high *R* values (e.g., $ZR>0$) for ideation productivity, but anticipate common and non-surprising ideas. Alternatively, one may focus on the far-field concepts with low *R* values (e.g., $ZR<0$) for the interest of generating novel ideas, but expect a lower chance of idea generation success and infeasible or vague ideas. Likewise, newly generated ideas can be instantly evaluated and compared in terms of novelty and feasibility according to how distant the adopted white space concepts are from the original domain, following the theories.

In particular, TechNet serves as the knowledge base and digital infrastructure for the methodology and workflow above. TechNet used in this study has 4,038,924 technology-related terms and roughly 8×10^{12} undirected quantified semantic relevance values between each possible pair of terms and is larger than WordNet of 155,236 entities and 647,964 relations and ConceptNet of 516,782 entities and 1.3×10^{11} relations. To the best of our knowledge, it is the largest technology-related semantic network to date. TechNet terms cover all domains of engineering defined in the Cooperative Patent Classification system. In particular, the distribution of terms is highly correlated with the distribution of patents across different technology domains, suggesting proportional and balanced coverage of relatively large or small domains (Sarica et al., 2020).

Thus, for a specialized design domain, TechNet enables the exploration in a sufficiently wide engineering knowledge space beyond the focal domain itself for the discovery of white space concepts for creative synthesis with those within the domain. Now we apply the TechNet-based methodology to generating flying car design ideas.

4. CASE STUDY: FLYING CAR DESIGN IDEA GENERATION

A flying car/roadable aircraft is a hybrid of an automobile and an aircraft, which merges the advantage of an automobile for door-to-door transportation with less temporal and spatial restrictions and higher accessibility, and the advantage of an aircraft for faster transportation without bounding by road and traffic conditions, and geographical limitations (Crow, 1997; Kim et al., 2013). The worsening traffic jam problems in megacities, complex and rapid emergency rescue needs, as well as growing public support on sustainability (lower carbon emissions) steer the public interest in designing flying cars for dual-medium (road-air) transportation (Follmann & da Cunha, 1997). The prospective advantages of flying cars have attracted the attention of several companies and motivated them to design, prototype, and test flying cars, even in the city environment[4]. Fundamentally, there are two main technical paths to design a flying car: designing an aircraft that is roadable or designing an automobile that is flyable. These paths are adopted by aircraft companies and the automobile manufacturers respectively, prioritizing the fly mode and the drive mode, respectively.

Even though public interest just increased recently, the flying car designs date back to 1917. Glenn Curtiss designed and prototyped the first flying car that could only hover ("Glenn

[4] Media coverage about unmanned logistics flights of EHANG.

Curtiss Sees a Vision of Aviation's Future," 1927). This was followed by several attempts of specialized inventors such as Taylor Aerocar (Jensen, 1971) and Fulton Airphibian (Ziesloff, 1957), automobile manufacturers such as Carrozzeria Colli (Bridgman, 1952) and Chrysler (Harding, 1998), and aircraft manufacturers such as Curtiss-Wright (Harding, 1998). These attempts resulted in several working prototypes, but none of them proceeded to mass production. On the other hand, the past two decades witnessed increasing public interest in flying cars, followed by the entrance of several companies into the domain, such as AeroMobil in Slovakia, Airbus in France, MetroSkyways in Israel, PAL-V in the Netherlands, Terrafugia in the US (Singh, 2017). Fig. 3 presents two prototypes of PAL-V and Aeromobil, taking two different approaches for shifting between the drive mode and the fly mode, vertical take-off and landing (VTOL), or short take-off and landing (STOL) respectively.

FIGURE 3 AROUND HERE

Fig. 3: Examples of flying cars: (a) VTOL designed by PAL-V[5], (b) STOL designed by Aeromobil[6]

4.1 Retrieving used concepts in prior flying car designs

We conducted an exhaustive search for flying car patents in the USPTO patent database that resulted in a set of 164 flying car patents between 1974 and 2018. The exhaustive search process combined patent text mining, citation analysis, inventor, and classification relationships to retrieve relevant patents. In particular, the set of relevant patents was expanded by employing an iterative process involving heuristic learning from patents retrieved in each iteration. Each iteration involves validity checks and expands query keywords, the citation

[5] Image retrieved from https://www.pal-v.com/en/ (access date: 31/01/2020)
[6] Image retrieved from https://www.aeromobil.com/ (access date: 31/01/2020)

network, and the set of inventors until convergence to a fixed set of patents. Hence the whole process ensures the completeness and accuracy of the retrieved patent set (Song & Luo, 2017).

2,396 unique technical terms in TechNet are retrieved from the titles and abstracts of the flying car patents. These retrieved terms cover various types of engineering concepts, such as working principles, main functions, sub-functions, structures, configurations, physical subsystems, modules, and components of prior flying car designs. Table 1 reports the top 30 terms with respect to tdi scores based on Equation (1).

TABLE 1 AROUND HERE

Some of these terms are synonymous notions of the flying car such as “aerocar” and “roadable aircraft”, which directly indicate inventors’ design tendencies, e.g., a car that can fly or a plane that can be driven on roads. A subset of terms refers to specific concepts that define the working principles of flying cars in both air and road environments, such as “upward lift force”, “variable-environment”, “ground propulsion”. Such terms as “center of gravity”, “telescopic wing”, “nose-height” and “directional flight propulsion” point out the problem or solution foci of designers. The “center of gravity” of the vehicle becomes a challenging issue for dual-mode operations. “Nose height” is an important parameter in airplane docking systems, which will be also an issue for flying cars. “Directional flight propulsion” is a concept used in both VTOL and hovering. Moreover, many terms in the list refer to physical components (e.g., “payload clamp”, “multiple ducted fan”, “ground module”) and desired functional performances (e.g., “lowered energy consumption”, “larger lift”, “powerful suction”, “faster flight”, “advanced vertical agility”, “easily-convertible”).

In brief, these terms allow us to develop a quick understanding of frequently used technical concepts in the existing designs of flying cars.[7] In other words, these terms succinctly describe a domain-specific concept space of prior flying car designs. They serve as the starting and reference point for the inferences to and selection and evaluation of other white space concepts beyond prior flying car designs for new flying car design ideation.

4.2. Retrieve white-space concepts

There are more than 4 million technical concepts in TechNet, whereas 2,396 of them have already been used in prior flying car designs. Thus, there still exist enormous design opportunities via the synthesis of white-space concepts with flying cars. In the meantime, the large size of the white space also demands structured guidance for the search and retrieval of concepts. Here we focus on semantic distance as the guiding variable to retrieve white space concepts from the near field to far-field to prior flying car designs as potential ideation stimuli and make attempts to relate and synthesize them with flying cars as the way to generate new design ideas. Based on design creativity theories, white-space concepts with relatively high latent relevance to flying car designs are more likely to stimulate ideas and more feasible ideas, whereas the far-field concepts are anticipated to be less effective in stimulating new ideas but may contribute to greater novelty of the new ideas once they are generated.

We first retrieve the top 100 most relevant white space terms to each of the 2,396 terms in the flying car patent set. The total set consists of 107,529 unique terms.[8] The *ZR* scores

[7] In a comparison test, we found that these technical concepts are more representative and specific to flying cars, than those general terms identified simply based on term occurrence in the domain (i.e., wing, fuselage, aircraft, rotor, propeller, air, body, drive, ground, fly, control, duct, mount, wheel, connect, form, longitudinal axis, pair, flight, configure, frame, lift, road, extend, engine, land, generate, side, attach, located).

[8] Meaning that more than half of the returned terms from the previous step either appear in focal 2,396 terms or are repeating.

of these terms lie in the range of [-4.449, 7.565] where 89% of them have *ZR>0*. The *ZR* score of each term is calculated, based on Equation (6), against a random sample of 100,000 white space terms with a mean ($\mu_R = 0.2646$) and standard deviation ($\sigma_R = 0.0660$) in the distribution of their R_i scores defined in Equation (4). We consider this set of concepts approximate a relatively large and diverse but still confined "near field" to the focal flying car design domain in the total TechNet. Note that, alternative white space term discovery methods can be adopted for this step as well.[9] Table 2 lists the top 30 white space concepts according to their *ZR* scores, which fall in the range of [6.460, 7.565]. We will use this set of concepts as the nearest stimuli for idea generation later.

TABLE 2 AROUND HERE

Next, we divide the total set of 107,529 terms into 10 equal-size quantiles from high to low *ZR*, and randomly sampled 10 terms in each quantile. This results in a set of 100 randomly selected near-field concepts in Table A1 in Appendix. This second set of white space concepts may provide a balanced coverage of a large and diverse near field surrounding existing flying car designs. Their *ZR* scores lie in [-0.812, 5.964] and all are below the *ZR* scores of the nearest 30 concepts in the first stimuli set (Table 2).

On this basis, we further randomly sample 100 concepts from the total TechNet regardless of their semantic distance to the flying car domain, in Table A2 in Appendix. Their *ZR*

[9] If required computational resources are available, one can directly calculate the relative relevance of each of about 4 million unused terms to the prior terms in TechNet and rank them to identify the most relevant ones. Alternatively, we retrieve a certain number of new terms to each prior term, pool them together, and rank them. Even though in the main case we focused on 100 new terms for each prior term, one can implement a higher or lower number to adjust the scope of exploration. One can also implement a threshold value of the semantic relevance between potential new terms to a prior term to determine which and how many new terms to retrieve for pooling and ranking.

scores range in [-1.673, 4.311]. Fig. 4 compares the distributions of these two randomly sampled sets of 100 white-space concepts by *ZR* scores. The mean *ZR* score of the 100 near-field random concepts is 1.6 and greater than 0, whereas the totally random concept set exhibits a nearly symmetrical distribution with a mean *ZR* of -0.04.

FIGURE 4 ABOUT HERE

Fig. 4: Distributions of the stimuli by semantic distance to existing flying car designs, including A) 100 concepts randomly selected from the nearest 107,529 concepts (red) and the 100 concepts randomly selected from the entire TechNet (black).

In brief, the first two sets of white-space concepts are retrieved by preferring technical concepts near those already used in existing flying cars, and many of them are from either car or aircraft domains (based on Table 2 and Table A1 in Appendix). In contrast, the third set of white space concepts are retrieved without any constraint with regard to their semantic distance to flying cars and may come from any domain in the total technology space. Although the second set is also randomly sampled, the random draws were within a confined near-field. Fig. 5 summarizes the relations of the three sets of white space concepts resulting from different retrieval strategies.

FIGURE 5 ABOUT HERE

Fig. 5: The three stimuli sets

4.3. Idea generation with white space concepts as stimuli

Then these three sets of 30, 100, and 100 white space concepts are used as inspirational stimuli for generating new flying car design ideas. Three of the four co-authors of the paper, with basic engineering knowledge of flying cars, went through each concept in the three stimuli sets one by one and made attempts to apply the ideation heuristic of relating and synthesizing each white space concept with flying cars to generate new design ideas. We spent 30 to 45 minutes on each set of stimuli to generate ideas individually.

A) Ideation with the nearest white-space stimuli (30 concepts)

As reported in Table 2, we were able to generate new ideas that relate and synthesize 16 out of the 30 nearest stimuli with flying cars. For instance, the nearest white-space concept “payload mount adapter assembly” (*ZR*=7.565) is a normal one for aircraft operation and can be transferred to flying car designs for payload management. “Ordnance ejector systems” (*ZR*=7.318) are used in military aircraft and can also be used in flying cars for easy delivery of small cargos. “Deicer control system” (*ZR*=7.18) can be employed for a flying car to enable continuous operation. “Inverted airfoil” (*ZR*=7.176) designs that are common in aircraft can be adopted to enhance the flight performance of flying cars as well. A flying car may also include a “wing tip docking system” (*ZR*=6.995) that is common in aircrafts, for demanding operations, higher thrust, or larger loads.

The designs of current flying cars are generally more similar to airplane designs than car designs since the air drag issue in the fly mode is more challenging for fuel efficiency, travel range enhancements, and safety. But, to make the flying cars a real alternative in the current transportation system, the drive mode should also be considered fairly. For this purpose, some of the nearest concepts may provide inspiration. For instance, such concepts as “virtual-wheeled” (*ZR*=6.874) using transformable wheels to enable continuous motion in rough terrain conditions, “front underfloor structure” (*ZR*=6.888) that were developed to reduce the air resistance of land vehicles, and “lane mark recognition” (*ZR*=6.924) which is a basic function in autonomous vehicles, are all potentially applicable and valuable to flying car designs.

In addition, “retractable lifting blade” (*ZR*=6.864) designs can be used to achieve a more compact drive-mode operation. “Torque split gearbox” (*ZR*=6.802) is used in rotary-wing aircraft to enable dual counter-rotating rotor operation, and can also be used to introduce new propulsion solutions for flying cars. “Rolling motion stability control” (*ZR*=6.802) is a cruise stability system that senses the possible rolling motion of a land vehicle and corrects it using break and acceleration controls. If flying cars are to become practical, industry standards such as stability control for automobiles will be eventually integrated into flying cars. Moreover, “solar battery mounting structure” (*ZR*=6.972) suggests the adoption of solar power as a primary or secondary power source in flying cars, and “vehicle battery diagnosis system” (*ZR*=6.868) can be adopted for flying car battery management.

In principle, as long as an idea is generated via the synthesis of a white space concept with flying cars, its novelty is ensured. However, the novelty is a matter of degree and may correspond to the semantic distance of the specific stimulating concept from the white space to the original design domain. Particularly, most of the nearest white space concepts in Table 2 are from existing designs of either aircraft or automobiles and suggest straightforward flying car design opportunities by simply adopting them into flying cars. The ease to conceive these design ideas and the high feasibility to implement them is enabled by the high latent relevance of the stimuli to prior flying car designs. But the novelty of such ideas is also naturally limited.

B) Ideation with random stimuli in a wider near field (107,529 concepts)

To generate more novel design ideas, we explore more distant stimuli in the white-space by focusing on the 100 randomly selected concepts in the near-field set. Since these concepts are among the nearest 100 concepts for some of the prior flying concepts, they define a large but still rather confined near field to flying cars. With these 100 stimuli, the three engineers in our team generated 21, 30, and 34 ideas respectively in 30 to 45 minutes. Some of these ideas overlap and the integration of them leads to a set of 59 unique ideas, with inspiration from 46 white space concepts out of the set of 100, as reported in Table A1 in Appendix. The efficacy of this set of 100 concepts to inspire idea generation (46 of 100) is slightly lower than that of the case in A) above when we sought inspiration from the nearest 30 white space concepts (16 of 30). Meanwhile, we generated relatively more novel ideas.

For example, such concepts as “golf club” (*ZR*=-0.114) and “watch movement” (*ZR*=-0.812) are rather distant from flying cars, land vehicles, or aircraft, but inspired us to generate new ideas. One idea is the flyable golf cart that can transport golf clubs and/or even golfers across air on large golf fields. “Watch movement” (*ZR*=-0.812) semantically inspired us to generate the idea of incorporating the function of real-time monitoring and displaying the movement of a flying car itself and the moving objects in the surrounding. In another example, the relatively far “breakable” (*ZR*=-0.568) concept stimulated an abstract idea of a highly modular flying car architecture with breakable fly and drive modules. Such new ideas appear to be more novel but also less feasible or more abstract than those inspired by the nearest 30 white space concepts in the first stimuli set.

Among those inspirational concepts with positive *ZR* values, “marine environment” (*ZR*=0.364) inspired all three engineers to generate the same idea of a vehicle that can fly in the air, drive on the land, and sail on water (and even underwater). Another interesting idea is a self-roadable missile or a flying vehicle with bombs to be used as weapons, stimulated by the white-space concept “Load carrying missile” (*ZR*=2.045). “Removable juicer” (*ZR*=2.148) invoked the idea of designing a modular subsystem for the flying mode that can be removed or detached when the flying car is driven on the ground. “Scooter-like” (*ZR*=3.133) stimulated the idea of a flying scooter. “air-buoyant” (*ZR*=3.341) inspired all three engineers to generate new ideas, including one that combines a zeppelin, airplane, and car to increase the energy efficiency of the fly mode and assist take-off. These stimuli are neither related to aircrafts nor cars and contribute to greater novelty in the resultant ideas than those in Table 2.

Meanwhile, this set of 100 near field stimuli still includes some concepts from either land vehicle or aircraft design domains, such as “propfan engine”, “vtol augmentation”, “taxi system”, “hybrid diesel vehicle”, “agriculture vehicle”, “spanwise wing insert”, “supplemental weather radar”, and “altimeter”. Again, it is easy and straightforward to conceive their relevance to flying cars, but the synthesis only leads to ideas with limited novelty. For example, the “autonomous flying” (*ZR*=4.503) stimulus invoked the idea of flying cars with auto-pilot systems. In general, the second sample of stimuli from a wider but still confined near-field provides more diverse inspiration to designers, and the resulting ideas are also more diverse in terms of their novelty and feasibility.

C) Ideation with random stimuli in the total TechNet (more than 4 million concepts)

To generate even more novel design ideas, we explore an even wider space of concepts in the total TechNet as potential stimuli. In this case, we focus on the third set of 100 stimuli that were randomly sampled from anywhere in TechNet, without any preference regarding semantic distance. Again, we attempted to relate and synthesize each of the 100 concepts with flying cars to generate new design ideas. In this run, the three engineers generated 11, 4, and 18 ideas, respectively. Some of these ideas are rather similar or overlapping. The integration of them leads to a set of 27 unique ideas, with inspiration from 23 white space concepts, as reported in Table A2 in Appendix. While this case shows that even purely randomly retrieved concepts from TechNet can inspire us for idea generation, the stimulation efficacy (23 of 100) is lower than those of the nearest concepts (16 of 30) and the random stimuli from a confined near field (46 of 100).

As shown in Table A2 in Appendix, among this set of 100 random stimuli, the nearer stimuli inspired us to generate more ideas. We only made sense of a small portion of the 56 white space concepts with *ZR* < 0. Specifically, we were inspired by only two concepts with *ZR* < -0.244 and unable to obtain inspiration from any white space concept with *ZR* < -0.945. The ideas generated with far stimuli (which have *ZR* < 0) include using a flying car to spray paint on big structures or buildings, with the inspiration from the concept of "spray paint" (*ZR*=-0.945), applying "e-coating" (*ZR*=-0.711) technologies to coat flying car surfaces to prevent corrosives, using flying cars for "firefighting" (*ZR*=-0.244) and "large scale hydraulic mining" (*ZR*=-0.055) with installing specialty apparatuses, operating flying vehicles along a "single rail" (*ZR*=-0.185) in the air, and using a "quick release buckle" (*ZR*=-0.183) to allow easily detaching the wings or propellers of a flying car when transitioning to the land driving mode. These ideas exhibit moderate novelty and feasibility.

The concepts with positive *ZR* scores lead to more ideas and higher feasibility of the generated ideas. For instance, the concept of "sterilizing small object" (*ZR*=4.311) inspired one of the engineers to conceive the idea of using flying cars to sterilize neighborhoods or sites in a pandemic. This is a highly feasible and useful idea. In fact, after the COVID-19 outbreak in January 2020, helicopters and trucks had been used to spray disinfectants across several cities in China during the lockdown periods. The concept of "solid rocket booster" (*ZR*=2.127) is from the domain of rocket engineering, and all three engineers easily related it to flying cars and generated the same idea of incorporating an affordable rocket booster to assist flying car take-off. The "inflated" concept (*ZR*=1.761) invoked the idea of using an inflatable security system to cover the flying car cabin when crashing. "Paper currency collection" (*ZR*=1.473) invoked the idea of using armored flying cars to physically transfer money, which is carried out by trucks or helicopters in bank operations today. "Adaptive data communication" (*ZR*=0.809) can be adopted in a flying car to preserve effective data links between satcom, radio, and 4g/5g communication mediums. The concept "prediction objective" (*ZR*=0.798) suggests a proactive autopilot system that is based on predicting environmental factors on the pre-defined path of the flying car for updating the path accordingly. Observing the "minicam" (*ZR*=0.67) concept, we conceived the idea of using multiple minicams to capture and monitor the environment and surroundings of a flying car. "Conventional titanium alloy" (*ZR*=0.55) may be used to make the flying car body and parts.

4.4 Summary of the case study

The three ideation runs demonstrate three different strategies to retrieve white-space concepts as stimuli to inspire idea generation for a focal design domain. The first strategy favors the extremely nearest stimuli. The second strategy allows sampling a wider spectrum of stimuli in terms of their semantic distance to the focal domain, but still favours the near-field. The third strategy is a total random retrieval regardless of the semantic distance of stimuli to the focal design domain. The fact that these different strategies all retrieved inspirational stimuli shows the general effectiveness of the technology semantic network for idea generation.

At the same time, the idea generation efficacy, and the novelty and feasibility of the ideas generated vary with respect to the stimuli from different strategies. With the nearest stimuli, the first exercise had the highest stimulation efficacy, indicated by the portion of provided stimuli that invoked ideas. Both the first and second exercises favour near-field stimuli, despite the different extents, present higher stimulation efficacies than the third exercise when the stimuli were randomly drawn from the large technology semantic network of more than 4 million concepts.

While almost all the ideas generated in the first exercise are highly feasible given the nearest stimuli that appear mostly from the car and aircraft domains, these ideas are also not surprising or novel. In contrast, by retrieving and providing stimuli with a wider range of semantic distance to the focal domain, the second and third exercises allowed us to generate more novel ideas with varied feasibility. In general, the ideas generated using highly relevant (i.e., positive and high *ZR* values) stimuli also appear to be highly feasible. While the ideas generated with semantically distant stimuli (i.e., negative, and low *ZR* values) are naturally more novel, they also appear to be less feasible or more vague.

The stimuli set of the third exercise included farther stimuli and more stimuli with $ZR < 0$ than the stimuli set of the second exercise (Fig. 4). While the concepts from far fields may unleash the potential for novel idea generation, the engineers find it difficult to conceive their relevance to the original domain. As reported in Table A2 in Appendix, we attempted but failed to make sense of most of the far-field stimuli with $ZR < 0$. We were unable to obtain inspiration from any (and a large number) of far stimuli with $ZR < -0.945$ (Fig. 6B). By contrast, in the second exercise, we only retrieved a small number of far stimuli with $ZR < 0$ (with all of them having *ZR* > -0.815) but were able to find inspiration from most of them (Fig. 6A). These results suggest, despite the need to explore far stimuli for potential novel ideas, overly far concepts in the white space may be ineffective for idea stimulation. A balanced stimuli retrieval strategy with regards to the semantic distance from the stimuli to the original domain is needed.

FIGURE 6 ABOUT HERE

Fig. 6: Distribution of ZR_i of white space stimuli in the second (A) and third (B) exercises. Red histograms denote the distribution of all stimuli retrieved and provided to engineers. Textured histograms represent the distribution of the effective stimuli that invoked ideas.

These findings from our case study resonate with the prior studies on design stimulation that have suggested near-field stimuli are more effective to inspire designers and produce more feasible ideas (Fu et al., 2013b; Chan et al., 2015; Srinivasan et al., 2018; Goucher-Lambert & Cagan, 2019), whereas far-field stimuli are less effective but may contribute to novelty of the ideas once they are generated (Gentner & Markman, 1997; Ward, 1998; Chan et al., 2015; Luo et al., 2018; Srinivasan et al., 2018). Observing such tradeoffs, Fu et al (2013) hypothesized that the stimuli from the “middle ground” may be desirable. He and Luo (2017) suggested that the most valuable inventions are based on mainly conventional combinations of prior work and a minor insertion of highly novel combinations.

In practice, different designers may follow these theoretical understandings to explore, retrieve and mix design stimuli of varied semantic distance to a focal design domain according to their differed preferences in ideation effectiveness and idea feasibility versus idea novelty and radical innovation potential. In particular, the quantified semantic distance (*R* or *ZR* scores) between white space concepts and the focal design domain in the large technology semantic network provides a new basis for guiding the search, retrieval, and selection of near to far stimuli to support design idea generation and evaluation.

5. SUMMARY AND CONCLUDING REMARKS

In this paper, we have presented a methodology based on a large semantic network of technical terms (TechNet) for generating new design ideas. Specifically, the methodology infers new technical concepts away from the previously used ones in a focal design domain according to their semantic relevance in TechNet and synthesize the new concepts in the white space with the original ones to generate new design ideas. Our case study, including three flying car idea generation exercises based on three white space concept retrieval strategies with varied preferences toward near to far stimuli, shows the general effectiveness of our methodology for simultaneous idea generation and evaluation, as well as varied ideation performances from different stimuli retrieval strategies.

The methodology focuses on white space inspiration and the use of semantic distance to guide stimuli retrieval in the total technology semantic network. By focusing on retrieving and synthesizing design stimuli from the white space to the original domain, the novelty (and patentability) of new ideas is naturally ensured when they are generated. Meanwhile, our metrics on the semantic distance of white space concepts to the focal domain can provide indications of both the novelty of a new idea and the feasibility of realizing the idea. Thus, the stimulation distance in the semantic network is the key variable to guide the retrieval of stimuli for different ideation performance tradeoffs (e.g., quantity, feasibility, novelty) and to inform the instant evaluation and comparison of the ideas generated or to be generated. Moreover, we have developed a web-based interface (http://www.Tech-Net.org/) and public API (https://github.com/SerhadS/TechNet) to support the use of the proposed methodology for idea generation and evaluation with TechNet.

This study contributes to the growing literature on data-driven design (Altshuller & Altov, 1996; Mukherjea et al., 2005; Chakrabarti et al., 2006; Murphy et al., 2014) and NLP based design analytics (Mukherjea et al., 2005; Fu et al., 2013a; Murphy et al., 2014; Shi et al., 2017). Aside from design ideation support, the TechNet-based methodology can also be tweaked for an extensive range of applications, such as knowledge discovery, topic mapping, technology forecasting, innovation and business intelligence. That is, TechNet may serve as an infrastructure for artificial intelligence applications related to technology and engineering.

This research presents several limitations, which suggest future research opportunities and directions. First, there exist alternative semantic distance metrics and retrieval strategies than the ones covered in the present study and deserve further exploration. Second, TechNet consists of only one type of relation among terms and does not differentiate the type of terms, such as components, functions, structures, configurations, working principles, mechanisms, etc. Future development of TechNet may include different types of relations and also discern the relation and concept types during the retrieval process. Third, our proposed methodology starts with retrieving patents that can represent the focal domain (e.g., flying car). The completeness and the accuracy of the retrieved patent set bound the results. Hence, patent retrieval methods with high recall and precision rates need to be developed or adopted as complementary to this study (Benson & Magee, 2013; Song & Luo, 2017).

Furthermore, we only conducted one case study with three engineers to demonstrate the effectiveness of the proposed methodology. More case studies, in diverse technical contexts and with more engineers of different experience levels and backgrounds, may allow us to discover other contextual factors on outcomes of the proposed methodology. Also, comparative evaluation against alternative methods that retrieve ideation stimuli from such semantic networks as WordNet and ConceptNet by semantic distance (Han et al., 2020b) may further reveal the advantages and disadvantages of our methodology among the alternatives.

We hope the readers view this study as an invitation rather than the conclusion of the research efforts to construct, fine-tune, and apply the technology semantic network to data-driven design.

APPENDIX:

Ideas generated with stimuli randomly sampled from near-field and entire TechNet

TABLE A1 HERE

TABLE A2 HERE

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Binyang Song is a doctoral researcher in the School of Engineering Design, Technology, and Professional Programs at the Pennsylvania State University. She has interdisciplinary research interests in human-artificial intelligence (AI) hybrid teaming and data-driven design. She aims to leverage the complementary strengths of humans and AI to solve complex problems. Specifically, she focuses on how working with AI reshapes the design process of human designers and human AI interaction to augment human-AI collaboration. She also takes advantage of big data to advance engineering design through various data-driven design methodologies.

Jianxi Luo is an Associate Professor with SUTD, Director of Data-Driven Innovation Lab (https://ddi.sutd.edu.sg), and Director of SUTD Technology Entrepreneurship Programme. Prof. Luo holds a PhD in Engineering Systems and S.M. in Technology Policy from Massachusetts

Institute of Technology. He was a faculty member at New York University and chair of INFORMS Technology Innovation Management & Entrepreneurship Section. He is on the editorial boards of Design Science (Associate Editor), Research in Engineering Design, and IEEE Transactions on Engineering Management. His research focuses on developing data science and artificial intelligence for more creative engineering design and innovation.

Kristin L. Wood is Senior Associate Dean of Innovation and Engagement at University of Colorado Denver. Dr. Wood completed his M.S. and Ph.D. degrees in the Division of Engineering and Applied Science at the California Institute of Technology, where he was an AT&T Bell Laboratories Ph.D. Scholar. After UT Austin, Dr. Wood was the Associate Provost for Graduate Studies, a Professor of Engineering and Product Development, founding EPD Head of Pillar, and Co-Director of the SUTD-MIT International Design Center at the Singapore University of Technology and Design. Dr. Wood has published more than 500 refereed articles and books, has received more than 100 national and international awards in design, research, and education, consulted with more than 100 companies and government organizations on Design Innovation and Design Thinking, and is a Fellow of the American Society of Mechanical Engineers.

FIGURES

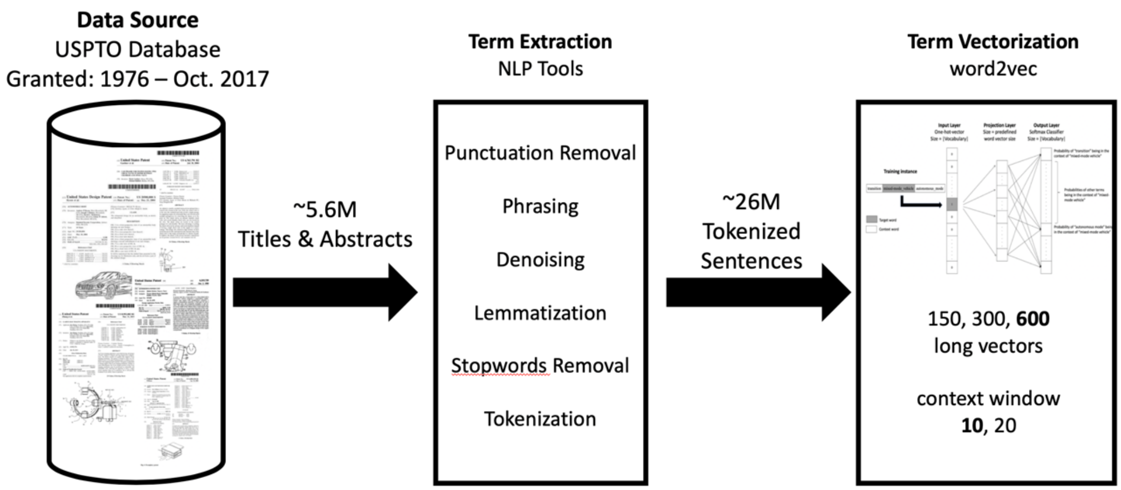

Fig. 1: A summary of TechNet construction process (Sarica et al., 2020)

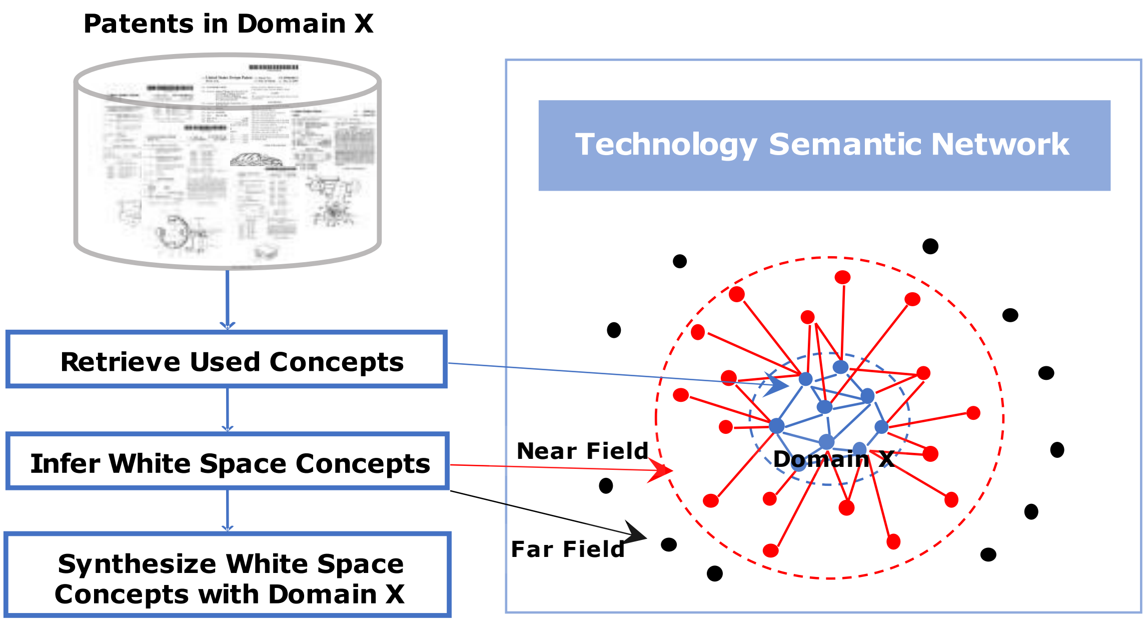

Fig. 2 The overall methodology.

(a) (b)

Fig. 3: Examples of flying cars: (a) VTOL designed by PAL-V[10], (b) STOL designed by Aeromobil[11]

[10] Image retrieved from https://www.pal-v.com/en/ (access date: 31/01/2020)

[11] Image retrieved from https://www.aeromobil.com/ (access date: 31/01/2020)

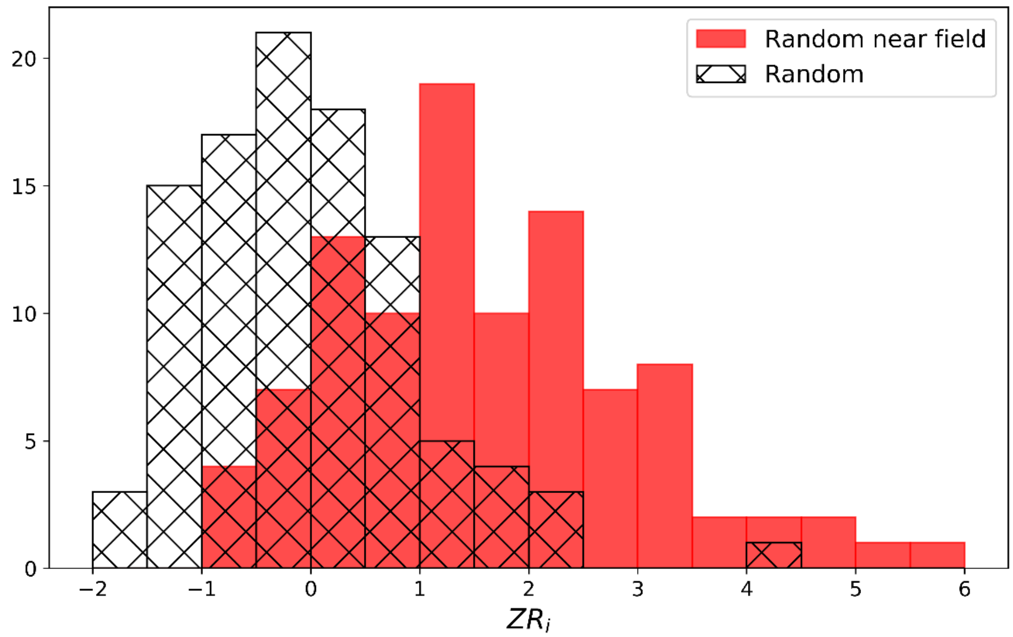

Fig. 4: Distributions of the stimuli by semantic distance to existing flying car designs, including 100 concepts randomly selected from the nearest 107,529 concepts (red) and the 100 concepts randomly selected from the entire TechNet (textured).

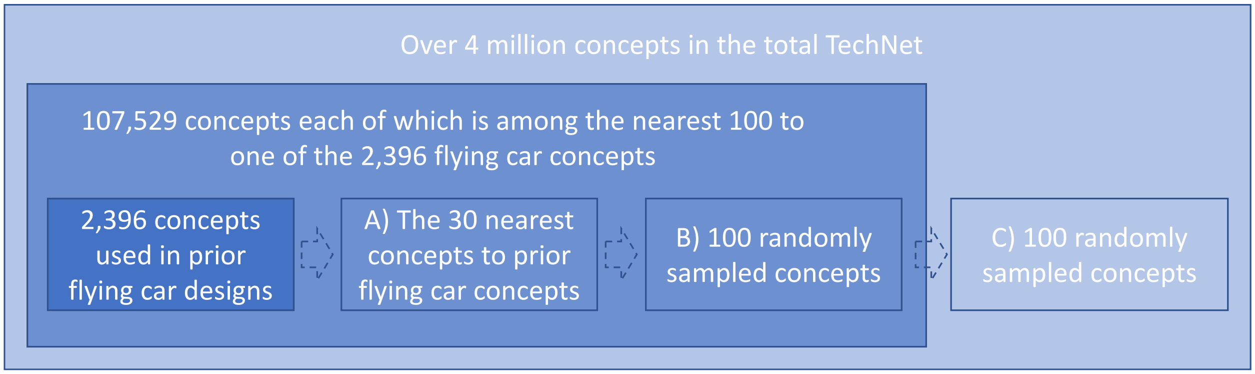

Fig. 5: The three stimuli sets

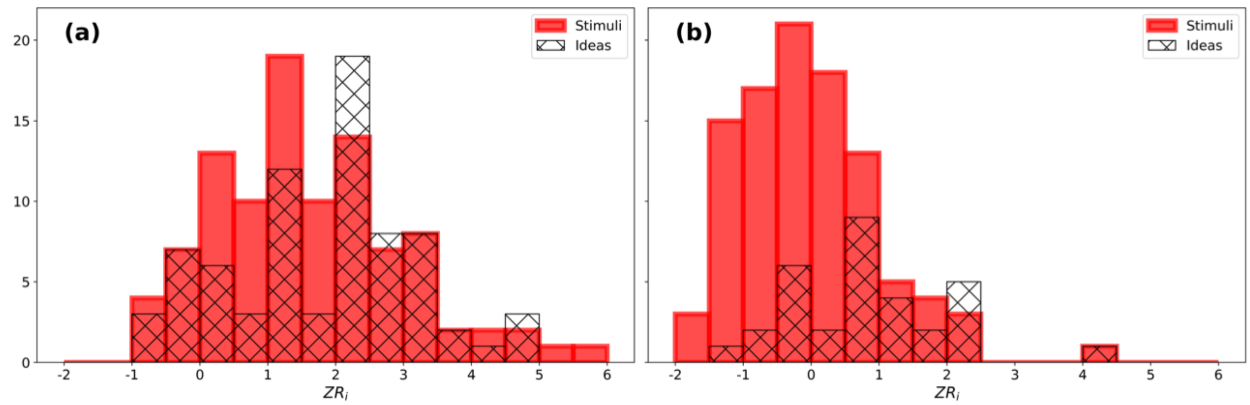

Fig. 6: Distribution of ZR_i of white space stimuli in the second (a) and third (b) exercises. Red histograms denote the distribution of all stimuli retrieved and provided to engineers. Textured histograms represent the distribution of the effective stimuli that invoked ideas.

TABLES

Table 1: Top 30 concepts already used in existing flying car designs

Rank	TechNet Concepts	Rank	TechNet Concepts
1	VTOL vehicle	16	Morphable air
2	Roadable aircraft	17	Directional flight propulsion
3	Upward lift force	18	Roadable vehicle
4	Center of gravity	19	Nose-height
5	Ground propulsion	20	Multiple ducted fan
6	ATV function	21	Ground module
7	Telescopic wing	22	Faster flight
8	Flying car	23	Roadable
9	Aerocar	24	Larger lift
10	Ducted fan vehicle	25	Medical transport
11	Advanced vertical agility	26	Lowered energy consumption
12	Payload clamp	27	Conventional rotorcraft
13	Ducted fan vtol vehicle	28	Powerful suction
14	Air module	29	Ducted fan
15	Variable-environment	30	Easily-convertible

Table 2: The ideas generated with the nearest 30 concept stimuli surrounding prior flying car designs. The table is sorted according to the *ZR* scores of the stimuli, whereas the sequence of the provision of the concepts to the engineers was randomized during the ideation process.

Terms	*ZR*	Generated Ideas
Payload mount adapter assembly	7.565	Add a “payload mount adapter” to a flying car for carrying useful payloads
Modular passenger seat	7.460	Adopt modular passenger seats to adopt for the needs of different passengers
Ordnance ejector system	7.318	Add an "ordnance ejector systems” to a flying car for carriage and easy delivery of small cargos
Fuel pipe joint	7.219	
Deicer control system	7.176	Add a deicer system to a flying car to enable continuous operations in cold environments
Inverted airfoil pylon	7.134	“Inverted airfoil” designs from prior aircraft designs can be adopted and tested for similar flight performance improvements in jet aircraft.
Toilet arrangement	7.110	
Wireless headset communication system	7.075	
Radio navigation antenna system	7.042	
Auxiliary hydrostatic drive system	7.011	
Wing tip docking system	6.995	“Wing tip docking systems” designed for conventional aircraft can offer inspiration for collective and combined operation of flying cars for highly demanding operations which may need higher thrust, or larger load capacity.
Bumper beam structure	6.976	
Solar battery mounting structure	6.972	Adopt solar power as a primary or secondary power source in flying cars.
Directional electroacoustical transducing	6.937	
Lane mark recognition	6.924	Add “lane mark recognition” to the flying / landing / driving assistance system of a flying car
Electric motor mounting structure	6.905	
Immobiliser/alarm	6.895	
Starting clutch control system	6.895	
Front underfloor structure	6.888	Design “front underfloor structure” to reduce air drag
Virtual-wheeled	6.874	Use transformable wheels to enable continuous motion even in rough terrain conditions
Vehicle battery diagnosis system	6.868	Design a batter diagnosis system that covers the battery performances in flying and driving modes

Retractable lifting blade	6.864	Retractable lifting blade designs can be used to achieve a more compact drive-mode operation
Brake pedal structure	6.812	
Jet engine nacelle	6.803	“Jet engine nacelle” for the design of the “ducted fan” of flying cars
Torque split gearbox	6.802	“Torque split gearbox”, which is often used in rotary-wing aircraft can be also applied to flying cars to enable dual counter-rotating rotor operation
Rolling motion stability control	6.802	“Rolling motion stability control” system for flying cars
Conduit harness retention	6.801	
Ice auger attachment	6.788	
Exterior mirror vision system	6.786	
Radio frequency connector assembly	6.460	

Table A1: The ideas generated with random concept stimuli from a confined near field. The table is sorted according to the *ZR* scores of the stimuli, whereas the sequence of the provision of the concepts to the engineers was randomized during the ideation process.

Terms	*ZR*	Generated Ideas
Glove box structure	5.964	
Automatic wedging	5.186	
Forced landing	4.909	
Autonomous flying	4.503	- Autonomous flying car or flying cars with auto-pilot systems
Plasma arc coating	4.282	
Propfan engine	4.182	- Flying cars driven by propfan engines
Vtol augmentation	3.980	- VTOL flying car
Taxi system	3.670	- The taxi system of airplanes can be adopted for landing and take-off operations of flying cars
Economical high speed	3.417	
Air-buoyant	3.341	- Inflatable air buoyant as an emergency and safety solution in a flying car - Flying cars with devices that can generate and remove air buoyancy - A design that combines a zeppelin, airplane, and car to increases the energy efficiency of flying cars and particularly decrease the power required for take-off
Low friction safety system	3.317	
Demountable disc	3.270	
Towing attitude	3.226	- Towable autonomous flying cargo compartment which is not physically but wirelessly attached to the flying car, holding only cargo. There may be multiple flying cargo compartment wirelessly attached to a flying car, towing the cargo autonomously, without powering the cargo compartment
Scooter-like	3.133	- Flying scooter - Transformable scooters for both flying in the air and running on the ground - A bicycle or scooter like vehicle which uses paths above pedestrian walkways (for example they can use the sheltered walkways) and they are highly automated to avoid crashing with other flying bicycles or scooters
Exhaust nozzle flap seal	3.071	
Lightweight rigid frame	3.027	- Flying cars made of lightweight rigid materials
Adjustable wheel set	2.905	- Adjustable wheels for the flying car - Flying cars with adjustable wheel sets for vehicle and aircraft scenarios (taking-off and landing)
Hybrid diesel vehicle	2.879	- Hybrid diesel + electric flying car
Multitrack vehicle	2.842	- Flyable multitrack vehicles that can operate in air and multi-terrain environment - A flying car which can land on anywhere independent of the landscape or ground structure
Infant seat support	2.732	- Adjust infant seat designs for seats in a flying car
Target roll angle	2.664	
Rotor-head-end	2.645	
Wet shaving cartridge	2.635	
Torque assist control	2.442	
Pickup hood	2.433	- A flying car like a cabriolet or convertible car that has a retractable roof for leisure.
High efficiency solar panel	2.424	- Solar powered flying car; providing most energy needs, at least for urban travels.
Agricultural vehicle	2.298	- Flyable agricultural vehicles - Low cost flying car may elevate the efficiency of agricultural spraying and animal herd control practices, especially maybe useful for large farms and large-scale farmers.
Wafer lift assembly	2.280	
Wearable swing	2.227	- Wearable swing for emergency uses in a flying car
Unutilized energy	2.212	- Flying cars that can recover unutilized energy, such as engines waste energy, brake energy

Spanwise wing insert	2.155	- Spanwise wing insert when the flying car is driving on the road - Flying cars with detachable wings
Assault bombing	2.155	- Multi-role short range flying cars that are capable of short-range surveillance and light attack to provide superiority on land-based operations. This can be achieved by integrated FLIR, light arms, and light infrared missiles
Removable juicer	2.148	- Flying cars with removable modules for flying functions - A removable battery compartment for electric flying cars
Piezo-resonance	2.085	
Supplemental weather radar	2.071	- Flying cars with a weather radar can plan paths according to the weather
Upward-arching	2.071	
Load carrying missile	2.045	- A self-roadable missile, or a flying vehicle with bombs to be used as weapons
Guitar cleaning kit	1.914	
Rear window module	1.877	
Radial imaginary line	1.836	
Mobile wireless platform	1.750	- Flying cars with mobile wireless platforms for communication
Dirt collection bag	1.738	
Divergent flap	1.691	
Turbo-fan	1.667	- Flying cars driven by turbofan engines
Cooling fan	1.632	
Forbidden network	1.600	- A flying car that can automatically avoid forbidden routes due to security issues
Disabler valve	1.544	
Distance estimation data	1.477	- Flying cars that can automatically accumulate surrounding data and adjust path accordingly
Standby emergency power	1.467	- Standby emergency fuel tank or battery pack in a flying car - Electric flying cars with spare batteries providing standby emergency power
Accelerator pedal	1.439	
Shearing ram	1.398	
High density artificial stone	1.280	
Fuel supply controller	1.277	
Portable telemetry device	1.277	- Flying cars can be used as a flock of telemetry devices travelling over the city to collect data
Cargo vehicle	1.256	- Flying cargo; Flying cars operating with pre-defined paths for delivering cargo - Autonomous delivery robots and flying car joint mission as cargo delivery service providers. All flying cars would have universal attachment apparatus for mid-size delivery robots that can handle a specific load of cargo. The individuals those have flying cars may collect those robots from their neighborhoods and drop them near their jobs or wherever they are going.
Altimeter	1.235	- Include an altimeter in the flying car
Physical dial	1.197	
Disposable apron	1.159	
Turbine section	1.127	- Designing the propeller blades of the flying car such that while not flying they can be used for generating electric using wind power
Actuating lever	1.126	
Control panel	1.073	
Rich fuel condition	1.064	- Flying cars that can plan paths according to the environment and fuel conditions
Back-twisted	1.052	
Cannula/needle	1.044	
Drive mode	1.044	
Multistage stroke	1.042	
Cross-ventilated	0.952	- Cross ventilation for flying car cabin air conditioning
Dual mode	0.941	
Personnel accountability	0.929	
Dissipate	0.852	
Bayonet-insertion	0.771	
Transient echo	0.711	
Inertia torque	0.592	
Yarn leaf	0.532	
Water-tight	0.527	- Water tight and buoyant passenger compartment in flying cars to allow water landing, cruise and take-off
Payload data segment	0.506	
Sealing	0.474	
Fluid medium	0.467	
Rotating speed	0.455	
Velocity compaction	0.427	
Detonate	0.386	
Marine environment	0.364	- A vehicle that can drive on road, fly in air, cruise on water, and swim under water
Position information	0.323	- Flying cars that can communicate real-time position information with other mobile systems and transportation control centers
Initial position	0.253	

Led light source	0.195	
Browsing	0.130	
Communications satellite	0.124	- A satellite-based communication module for autonomous operation and monitoring of flying cars and air traffic
Charge capacity limit	0.115	- Electric flying cars with large battery capacity
Performance requirement	0.102	
Traffic load	-0.074	- Flying cars that can communicate with other vehicles, airplanes and flying cars, detect and analyze the traffic around themselves, and plan their own paths accordingly
Pretensioner	-0.111	- Pretensioner for driver seats to adjust belt tightness during different flying or driving modes
Golf club	-0.114	- Flying golf carts for multi-mode transportation in large golf fields
Recursive radon	-0.126	
Folded portion	-0.144	- Flying cars with foldable components (e.g., wings) to reduce air drags during road driving
Amplitude	-0.458	
Increased turbulence	-0.483	- The structures required for driving and flying modes increase turbulence and novel designs to minimize such increased air turbulence are required - Flying cars that can detect turbulent environment and adjust paths accordingly - Design of two types of flying cars. One is for city transportation, with specifications for lower altitudes and not for extreme weather conditions. The other is for inter-city travels, which can withstand extreme weather conditions and provide safe travels in higher altitudes.
Breakable	-0.568	- Flying cars with a modular architecture, with standard detachable fly-mode subsystems that can be found in different distribution locations
Laser light	-0.680	- Flying cars that have laser-based obstacle detectors such as lidar to deal with high air traffic
Incomplete combustion	-0.792	
Watch movement	-0.812	- Flying cars with monitoring and displays of the movement of moving objects in the surrounding

Table A2: The ideas generated with random concept stimuli from TechNet. The table is sorted according to the *ZR* score of the stimuli, whereas the sequence of the provision of the concepts to the engineers was randomized during the ideation process.

Terms	*ZR*	Generated Ideas
Sterilizing small object	4.311	- Flying cars to sterilize neighborhoods or sites in a pandemic condition, using a spraying apparatus
Yawed vehicle	2.467	
Movable solar collector	2.439	- Mid-air charging stations for electric flying cars that restore electricity generated by solar cells - Retractable solar panels for flying car that can be extended when parked, and retracted on the go
Solid rocket booster	2.127	- An affordable rocket booster system for flying car take-off
Grille armor	1.903	
Interchangeable trailer	1.830	- Interchangeable car and flight modules for the flying cars
Inflated/deployed	1.761	- Inflatable security system that covers the cabin of the flying car in the case of crash
Color barcode pattern	1.682	
Paper currency collection	1.473	- Armored flying car to physically transfer money
Coad ministered antigen	1.371	
Detachable seat member	1.258	- Detachable air propeller for flying car; when only used as a land vehicle, detach the wings or propeller - A detachable seat to increase baggage capacity of the flying car
Grip dynamometer	1.153	
Flight test	1.120	- A decentralized autonomous pre-flight test system that runs on the flying car. Before authorized to fly, an autonomous networked system gets the result and controls if the flying car is fit for flying, and authorizes backward
Electric generator hydraulic pump	0.977	
Bioswellable suture	0.898	
Travel blade slot	0.870	
Adaptive data communication	0.809	- Adaptive data communication system that seamlessly channels between satcom, radio and 4g/5g communication mediums to preserve healthy data links
Prediction objective	0.798	- Proactive autopilot system that minimizes pilot's actions by predicting environmental issues on the defined path of the flying car and updating the path accordingly
Broken flywheel	0.726	- An intelligent computer system in the flying car for taking over controls in the case of malfunction
Weak magnet	0.705	- Use weak magnetized materials as sensors in flying cars to be used in parking spots
Minicam	0.670	- Use multiple minicams for capturing the environment of flying cars
Spacecraft attitude control system	0.658	- Use attitude control systems to guide the operations and control of flying cars

Generic source code	0.633	
Conventional titanium alloy	0.550	- Flying car body made of titanium alloy
Tokenized query	0.545	
Landing section	0.502	
Closed filtering system	0.462	
Reflectance inversion	0.461	
Spot sampling system	0.461	
Slidable leg part	0.333	- Flying cars with slidable wings or rotors that can adjust positions according to payloads and passengers on board
Coalescing dryer	0.295	
Bimetallic switching mechanism	0.294	
Rate matching parameter	0.279	
Read injector	0.250	
Malariae	0.200	
Data-duplicating	0.198	- Predictive inflight simulation of flying car to change the path
Myoclonic epilepsy	0.176	
Long range cable	0.161	
Savory flavor granule	0.135	
Floating drilling rig	0.129	
Oil vinegar	0.121	
Acoustical	0.118	
Semiconductor wafer fabrication equipment	0.062	
Stretched styrenic resin sheet	0.036	
Image/video content	-0.047	
Large scale hydraulic mining	-0.055	- Flying vehicle for hydraulic mining
Outgoer safety	-0.111	
Programmable nonvolatile memory eeprom	-0.171	
Quick release buckle	-0.183	- Quick release buckle for releasing the wings or propellers when transitioning to the land mode - Use a detachable interface like quick release buckle to detach the cabin from the rest of flying car in the case of distress
Single rail	-0.185	- Flying vehicle that can also attach to and move along single rail - Integration of flying cars to monorail systems to avoid traffic on the ground
Scatterometry regression	-0.238	
Firefighting helmet	-0.244	- Using flying car for fire fighting
Lofty fibrous	-0.259	
Electronic signal	-0.309	
Delay-buffer	-0.358	
Enlargement lens system	-0.377	
Electronic energy level	-0.380	
Interior cross section	-0.382	
Gene regulation system	-0.383	
Wet pigment	-0.392	
Bromoaromatic	-0.400	
Intermediary security	-0.414	
Moat nitride	-0.415	
Thermophilic denitrification	-0.464	
Tunnel medium	-0.473	
Roll-laminator	-0.550	
Strand guide member	-0.555	
Transparent flame retardant	-0.562	
Download request	-0.626	
Uncertain factor	-0.642	
Electroosmotic flow pump	-0.686	
E-coating	-0.711	- E-coating on the surface of the flying car to protect it from corrosives
Silicon-film	-0.738	
Multichromophore	-0.785	
Caulobacter	-0.795	
Oblivious	-0.803	
Storage capacity error	-0.809	
Dye bleach catalyst	-0.842	
Upkeep	-0.861	
Spray paint	-0.945	- Flying car with spray paint apparatus to paint big structures or building
Polyethylene polymerization	-0.959	

Flowback	-0.974
Adaptive speech	-1.024
Full resolution	-1.058
Electrosurgical probe	-1.074
Barrel distortion	-1.094
Network communication component	-1.130
Electrorheological material	-1.156
Bond gap	-1.177
Punishment	-1.226
Phosphosilicate glass layer	-1.233
Working time	-1.277
Clay nanocomposite	-1.291
Timing control section	-1.303
Organ tissue	-1.409
Total hip	-1.414
Fine nickel	-1.495
Acoustical stack	-1.542
Sinusoidal voltage waveform	-1.573
Spectrum-imaging	-1.673

TABLES AND FIGURES

Table 1	Top 30 concepts already used in existing flying car designs
Table 2	The ideas generated with the nearest 30 concept stimuli surrounding prior flying car designs. The table is sorted according to the *ZR* scores of the stimuli, whereas the sequence of the provision of the concepts to the engineers was randomized during the ideation process.
Table 3	The ideas generated with random concept stimuli from a confined near field. The table is sorted according to the *ZR* scores of the stimuli, whereas the sequence of the provision of the concepts to the engineers was randomized during the ideation process.
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