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Investigating a Mixed-Initiative Workflow for Digital Mind-mapping

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ABSTRACT

In this paper, we report on our investigation of human-AI collaboration for mind-mapping. We specifically focus on problem exploration in pre-conceptualization stages of early design. Our approach leverages the notion of query expansion — the process of refining a given search query for improving information retrieval. Assuming a mind-map as a network of nodes, we reformulate its construction process as a sequential interaction workflow wherein a human user and an intelligent agent take turns to add one node to the network at a time. Our contribution is the design, implementation, and evaluation of algorithm that powers the intelligent agent (IA). This paper is an extension of our prior work [1] wherein we developed this algorithm, dubbed Mini-Map, and implemented a web-based workflow enabled by ConceptNet (a large graph-based representation of "commonsense" knowledge). In this paper, we extend our prior work through a comprehensive comparison between human-AI collaboration and human-human collaboration for mind-mapping. We specifically extend our prior work by: (a) expanding on our previous quantitative analysis using established metrics and semantic studies, (b) presenting a new detailed video protocol analysis of the mind-mapping process, and (c) providing design implications for digital mind-mapping tools.

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1 Introduction

Mind-maps are now widely recognized as thinking tools for creative tasks such as conceptual design [2, 3]. Nonetheless, creating a mind-map can be challenging especially for beginners either due to a combination of lack of domain knowledge, personal inhibition, early convergence, and fixation [4–7]. This paper seeks to enable and understand how humans and computers can creatively *co-generate* ideas with equal participation to explore concepts around a design problem.

Our work draws from research by Yannakakis et al. [8] that proposes the use of human-computer collaboration tools not solely to demonstrate mixed-initiative *co-creativity* (MI-CC) but as a means to foster human creativity itself. Inspired by this view, we study a simple yet powerful workflow with mind-mapping as our tool of choice to investigate this notion of MI-CC. Furthermore, our focus is on the pre-conceptualization stage where a crisp problem statement is not yet available to the designer. While mind-mapping has mainly been studied for design conceptualization and solution space exploration [9–11], mind-maps are especially suitable for problem exploration. They allow for an unconstrained yet structured exploration of a variety of ideas along with the relationships between those ideas in a hierarchical fashion. Therefore, we specifically seek to investigate the usage of mind-maps during *problem-space exploration* since it is a crucial step in opening designers to ideas that seem out of scope but can potentially be useful.

The rules of creating a mind-map are rather simple: one starts with a central idea and creates two to three *branches* leading to related ideas repeating the process for each newly added idea. Furthermore, there are now several digital tools [12] that can be used to create and document mind-maps. However, instead of providing cognitive assistance for enhanced mind-mapping, these tools primarily serve as digital extensions of traditional pen-and-paper mind-mapping. Despite extensive knowledge databases on the web, there is currently limited computational support to augment users' ability to fully explore the vast information sources available at their disposal.

This paper is an extended version of our previous work Mini-Map [1], a digital workflow for **m**ixed-**ini**tiative mind-**map**ping wherein a human designer and a computer program take turns to create a mind-map for a given design problem. Mini-Map is based on a sequential interaction workflow where a human user and a computer algorithm take turns to add ideas to an evolving mind-map. Subsequently, we study how such a workflow leads to collaborative behavior between a designer and an Intelligent Agent (IA) while taking equal participation during mind-mapping. Mini-Map is powered by ConceptNet [13–15], which is presently one of the largest commonsense knowledge base that covers assertions between concepts through rich relational ontology. Note that throughout this paper, we use *IA* to denote the Mini-Map system we developed, and *AI* as reference to artificially intelligent systems.

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1.1 Contributions & Extensions of Previous work

We make two main contributions in this paper. First, we introduce a digital mind-mapping workflow that re-formulates mind-mapping as a collaborative activity between a human and a computer collaborator. This workflow is powered by a novel algorithm that utilizes the relational ontology offered by ConceptNet [13] in conjunction with statistical, topological, and temporal rules for adding ideas as nodes to the mind-map. Second, we present a comprehensive comparative analysis across two user groups: (a) human-human mind-mapping (**HH**), (b) human-IA mind-mapping using our algorithm (**HC**). Our evaluation is based on well-established creativity metrics proposed in design research [16] and a semantic analysis using word-embedding techniques. This comparison demonstrates the efficacy of our approach for digital mind-mapping and offers some critical insights into how digital mind-mapping can be advanced through mixed-initiative approaches.

Extension: In our prior work [1], our main focus was to propose the idea for mixed-initiative mind-mapping and explore several algorithmic variations to enable contextual query expansion for mind-mapping. We conducted a human subject study to compare how users responded to other human collaborators in contrast to the IA collaborator based on our algorithm. In this extended version, our main contributions beyond the prior work [1] are as follows:

1. We present a new detailed video protocol analysis (section 7) of the mind-mapping process to complement the analysis performed in our previous work. This analysis reveals deeper insights that explain the results obtained in our previous analysis and provides additional implications on the development of adaptive computer intervention during the process to enhance the users' engagement and performance. The new qualitative analysis reveals common patterns of user behavior during the mind-mapping processes in the two scenarios (human-human and human-IA) and also shows how such behavior relates to the ratings and semantic analysis.
2. We add to our prior quantitative analysis by offering a combined interpretation of the expert ratings of the mind-maps and semantic analysis (section 6.3). This offers a stronger evidence for the quantitative results observed in our previous paper.
3. We provide a more detailed and consolidated description of the algorithm behind Mini-map and we offer an elaborated rationale for the workflow (section 3). This rationale is informed by pilot experiments that were not included in the previous paper.
4. Finally, we offer guidelines for future work on computer support for AI-enabled mind-mapping based on what we learned from our investigation (section 9). While not a technical contribution, these guidelines may offer valuable information for future research directions in the area of mixed-initiative co-creativity as applied for early design. To complement these guidelines, we also offer a more comprehensive literature review encompassing a larger set of related fields that was not earlier provided in our previous paper.

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2 Background

The idea of mind-mapping originally comes from cognitive psychology and dates at least as back as Tolman's work on cognitive maps [17]. In their seminal paper on digital mind-mapping, Faste and Lin [18] note: "*Such cognitive maps are therefore a method of knowledge representation that are capable of capturing an individual's perception and understanding of a problem through interconnected sets of elements representing implicit views of one's beliefs*". They further identify distributed collaboration as one of the key differentiating factors between digital and pen-paper mind-mapping. In this work, we explore the confluence of three converging routes of study: (a) mixed-initiative co-creativity, (b) collaborative idea synthesis, and (c) cognitive maps. Below, we discuss these ideas as explored in previous works.

2.1 Mind-maps: Structure & Applications

Davies [19] studied three different variations of structured diagrams, namely, concept mapping, mind mapping, and argument mapping and noted that while each was different in terms of formalism, each augments one's ability to process and integrate information. Of these three kinds, mind-maps tend to be more informal, both in content and structure and are therefore suitable for situations where little is known about the problem at hand. The main advantage of mind-maps is that they enable learning about a certain topic by offering visual means to perform rapid idea expression and divergent exploration [20–22]. Their hierarchical structure makes them useful for a wide variety of applications ranging from document drafting [23], project planning [24], and decision making [25–27]. In fact, this structural quality has been shown to be particularly valuable in design data organization [28]. In the area of engineering education, mind-maps are found to be superior over conventional teaching methods in recalling technical concepts [29]. Zampetakis et al. [30] discuss the utility of mind-maps in the learning process of engineering students.

2.2 Mind-maps for Design Ideation

Mind-mapping, being a general mechanism for externalizing ideas, can be useful in different parts of early design and for serving different functions in the process. Mind-maps promote *active learning* and *meaningful engagement*, two factors that are important for problem exploration, design conceptualization, and prototyping [31]. The fundamental cognitive advantage of mind-maps in design, perhaps, is that they help connect logical and imaginative thinking [32]. Several works [33–35] have explored the utility of mind-maps for design reflection, note-taking, idea communication, and idea synthesis. Recently, Jensen et al. [11] applied mind-maps during design ideation and developed prototypes for mechanical climbing system before a "down-select" process and affirmed its effectiveness. Researchers have also recognized their capability in assisting students to structure the

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thinking process and tackle complex problems during collaborative design activities [36]. Apart from their structure, mind-maps can be further enriched by colors, images, arrows, and dimension to reflect personal interest and individuality [37]. Given our specific focus mixed-initiative interactions for mind-mapping, we have constrained the variations in the visual variables, restricting the idea representation to a simple node-link diagram with words (and potentially phrases) as the node content.

2.3 Digital Mind-mapping

Several works have investigated the effect of interactivity offered by digital tools on idea generation and collaboration in mind-mapping. For example, Lopes et al. proposed *planTEXT* [38] to offer integrated digital support for the planning, writing and revision activities during technical writing process. Karim et al. [39] investigated mobile-assisted mind-mapping technique (MAMMAT) using *MindMup* [40] and unfold its advantages in developing ESL undergraduate students' writing skills. Chief among them is work by Faste and Lin [18] who evaluated numerous existing mind-mapping software applications, performed ethnographic studies with a variety of users, and developed a framework of principles to guide future development of digital mind-mapping. They argue that contextual creative guidance is currently missing and necessary in digital tools to promote better design outcomes. However, Buisine et al. [41] note that merely offering a digital medium does not necessarily enable a significantly different outcome in terms of creativity. They further showed that there is no significant difference in idea production between digital tabletop-based and traditional paper-and-pencil mind-mapping workflows. Speaking of the advantages of digital mind-mapping tools, Orehovavcki et al. [42] address the quality in use of Web 2.0 applications. They found that participants feel highly satisfied with Web 2.0 applications that have the following attributes: ease of use, effectiveness, controllability, interactivity, navigability, customizability, efficiency, information content coverage, understandability, and reliability. Recent work by He et al. [43] introduced a novel core-periphery structure representation of the design concept space and a recombination methodology to augment designers' ability to synthesize new ideas. Their proposed computer-based recombination model mitigates design fixation and enables faster exploitation of the given design concepts. Works such as these motivate us to investigate how data-driven approaches can stimulate problem exploration before concept generation.

2.4 Automatic Mind-map Generation

Several works have investigated computational methods and interactive features needed for mind-map generation systems [44]. *M^2Gen* [45] is a tool that can automatically generate mind-maps from pure text through five steps of text processing. Elhoseiny et al. [46, 47] proposed a novel multi-level approach to generate mind-maps from English literature. Their approach uses Detailed Meaning Representation (DMR) to understand input text

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and retrieves corresponding images from Web to visualize the mind-maps. They also show first comprehensive evaluation of such mind-map generation system by human subjects. We wish to point out here that while these works position themselves within the context of mind-mapping, the involvement of the user in generating the maps is not explored in these works. Therefore, these works can be considered as ones that produce visual representations of documented data that look like mind-maps. In our work, we specifically explore user generation of maps.

2.5 Semantic Networks in Engineering Design

Another direction of work that closely relates to mind-mapping through knwoedlge databases is rooted in semantic network generation through engineering and technology knowledge-bases. Many such semantic networks have been explored in engineering design literature to structurally represent design-related information to assist designers in exploratory tasks. For example, Fu et al. [28] proposed a methodology to map the functional and surface content of the patents from design repository databases in node-link structures for analogy-based design inspiration. *B-Link* [48, 49] and *innoGPS* [50] provide relational representations of retrieval results from databases (design documents, U.S. patent database, etc.) to users for stimulating concept analogy and synthesis during design ideation. Recently, Sarica et al. [51] established *TechNet* — a technology semantic network based on utility patents and provide an application programming interface (API) to allow users to access information in TechNet for engineering knowledge discovery. TechNet also provides interfaces to create context-aware relational representations based on a user query in the form of a graph, a tree, a paragraph, or a list. While these works make a significant stride in bridging the gap between design conceptualization and knowledge-retrieval, they are fundamentally different from our work in two ways. First, our primary focus is to facilitate continuous interaction, evolution, and adaptation of the outcome in a conversational workflow. Second, our goal is to (a) provide and study the role of cognitive assistance to a user by drawing from a given semantic network and (b) emulate *collaborative behavior* in an exploratory task.

2.6 Mixed-initiative Co-creativity

The notion of *mixed-initiative interaction* was brought out first by Novick et al. [52]. Yannakakis et al. [8] further developed the concept of *co-creativity*, which implies that both the computer and the human proactively contribute toward the development of ideas to solve a problem. The vision in such a scenario is that the computer fosters the human's creativity through the iterative process of interactions, and vice versa. Drawing from this concept, many creativity support systems are designed and implemented based on robust corpus-trained machine learning techniques or evolutionary approaches [53]. For example, the *Drawing Apprentice* proposed by Davis et al. [54] uses deep-learned object recognition model to explore the potential of computers as co-creators in

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collaborative drawing tasks. Recently, Alvarez et al. [55] discusses how employing mixed-initiative workflow using evolutionary approach improves the quality diversity of generating dungeons in computer games. Huang et al. [56] proposed a mixed-initiative framework for multi-channel music composition using deep learning algorithms. Apart from creativity support, Nguyen1 et al. [57] also utilizes the efficiency and scalability of information retrieval and machine learning techniques to train classification models using specific databases to enhance decision-making process through human-AI partnership.

2.7 Identification of Gaps

There have been growing interests in enabling mixed-initiative systems in the domain of *game design* [58–60]. Most of these works are essentially targeted toward procedural content generation in computer games. While there are recent advances in aerospace design domains such as the *Daphne* system [61], there is currently little known about how human-computer co-creativity could be materialized for engineering and product design domains in early conceptualization. Furthermore, there is also a need for qualitative insights on how designers would perceive intelligent systems that could aid idea exploration in future design tools. Our work is a step toward filling this knowledge gap.

3 Methods & Tools

Two observations inform our technical approach. First, merely providing the user with the ability to query vast knowledge databases is not sufficient for supporting the cognitive processes underlying mind-mapping. The user should have a mechanism to expand upon those queries. Second, mind-maps lend themselves to a natural graph based structure with ideas (words/phrases) as nodes and their relations as the links or edges. Therefore, the knowledge database should preferably contain a rich set of relationships between the different data entities. Based on these, our approach is to use ConceptNet, a semantic network that contains a graph-based representation with nodes representing real-word concepts as natural language phrases (e.g. *block a door*, *be abandoned*, etc.), and edges representing semantic relationships. In comparison to engineering databases, our choice of ConceptNet was due to two main reasons. First, ConceptNet consists of explicit semantic relationships between nodes that are derived from WordNet and enriched through an Open Mind Common Sense project [14]. This feature plays a crucial role in our algorithm. Second, our goal is primarily to emulate collaborative behavior during problem exploration with the intention of making our workflow useful to wider audience. Here, ConceptNet offers a balanced level of specificity in terminology. In particular, while it does not provide highly specific technical terms in comparison to systems such as TechNet [51], it still offers better specificity when compared to data-sets such as WordNet. Therefore, the combination of a comprehensive canonical relationship types with the wide coverage

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of knowledge made ConceptNet a more suitable choice for our context of problem space exploration. Note that throughout the paper, we use *idea* to represent the content being added to the mind-map as a node, *concept* to represent the retrieval result from ConceptNet or a fundamental unit of knowledge.

3.1 Problem Formulation

We assume a mind-map to be a tree (an acyclic graph), say $M(V,E)$ with a set of nodes V_M and edges E_M and the construction of a mind-map can be viewed as an iterative sequence of breadth-first (i.e. exploring different aspects of a problem) and depth-first (i.e. adding detailed and concrete ideas to different aspects of a problem). The root node of this tree is the central problem around which we aim to emulate this behavior in a collaborative fashion wherein a human and an automated agent are collectively working to diversify ideas around the root node. We formulate the process of mixed-initiative mind-mapping as a collaborative interactive activity that is being participated equally by a human and an intelligent agent (IA). Given a central topic, the aim for the human and IA collaborators is to expand the map by exploring different aspects of the topic (breadth-first), and refine each of these aspects by adding detailed ideas (depth-first). In order to do this, the collaborators are given a seed topic as the root node of M and the human and IA players take turns to add nodes to M. Furthermore, each player is allowed exactly one node addition per turn.

Given any state of M (the simplest being a given root node representing the central idea), there are two primary algorithmic steps that are needed for creating a mini-map[1]. The first step is **target search** wherein the IA needs to determine a target node (a node where a new node will be added). Subsequently, the second step is **content generation** wherein the IA needs to define the content (words and phrases) that will be added to the target node to ultimately expand the space of ideas around the central problem.

The algorithm for Mini-Map was developed in an iterative manner wherein we experimented with several alternatives for target search and content generation and conducted small scale pilot studies (with $5-7$ participants with preliminary experience in mind-mapping). Our preliminary studies with these alternatives informed the development of our final algorithm that is included in this paper[2].

3.2 Algorithm: Target Search

The driving principle that informs our target search approach is to find a balance between exploring different aspects of a problem and in-depth exploration along each of those aspects. For this, our main goal is to model the behavior of theIA player in such a way that the mind-map M evolves in a breadth-first fashion in the initial stages of mind-mapping and transitions into a depth-first target selection during the later stages of the evolution of M. In

[1] For a complete list of symbols, see supplementary material.
[2] Please see our previous work [1] for details on our algorithmic iterations

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our previous work [1], we experimented with three alternatives for target search as enumerated below:

1. *Random Target Search:* The IA randomly selects a node from the map.
2. *Topo-temporal Search:* The IA searches for the target based on the topological and temporal properties of the existing nodes of M. Preference is given to nodes that have either not been explored for a long duration of time in conjunction with how far they are from the root node.
3. *Guaranteed Minimal Expansion:* Here, the idea was to give preference to nodes that have not crossed a certain threshold of expansion (measured by the number of children).

Contrary to our initial intuition that the topo-temporal approach will provide the most reasonable behavior, we found our expansion based approach to be most highly rated by participants in our preliminary studies.

Algorithm 1 Target Search
Note: Reprinted from the original source [1]

Input: Current mind-map $M = (V_M, E_M)$
Input: Bi-ordered Index Set $X \in Z^3$
Output: Target Node $v_T \in V_M$
Output: Updated Bi-ordered Index Set $X \in Z^3$

if $X = \emptyset$ **then**
  $X \leftarrow \emptyset \in Z^3$
  for $v_i \in V_M$ **do**
    $x_1 \leftarrow$ depth of v_i
    $x_2 \leftarrow$ number of children of v_i
    $x_3 \leftarrow i$
    $\mathbf{x} \leftarrow (x_1, x_2, x_3)$
    $X \leftarrow X \cup \{\mathbf{x}\}$
  end for
  $X \leftarrow Sort(X,\ descending\ order\ in\ x_1)$
  $D_{max} \leftarrow$ maximum depth of M
  for $d \in [1, D_{max}]$ **do**
    $X \supset X_d \leftarrow \{\mathbf{x} = (x_1, x_2, x_3) \in X | x_1 = d\}$
    $X_d \leftarrow Sort(X_d,\ descending\ order\ in\ x_2)$
  end for
end if
for $d \in [1, D_{max}]$ **do**
  $X \supset X_d \leftarrow \{\mathbf{x} = (x_1, x_2, x_3) \in X | x_1 = d\}$
  for $\mathbf{x}^j = (x_1^j = d, x_2^j, x_3^j) \in X_d$ **do**
    if $x_2^i < 3$ **then**
      $i \leftarrow x_3^j$
      $v_T \leftarrow v_i \in V_M$
      $x_1^i \leftarrow x_1^i + 1$
      return v_T, X
    end if
  end for
end for

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3.2.1 Expansion Threshold

One of the main challenges we seek to address is to avoid imbalanced addition of nodes to the map leading to heavily biased exploration of ideas (i.e. either high-breadth, low-depth or vice versa). In our studies with traditional mind-mapping (without computer intervention), we observed that users tended to explore ideas in specific and narrow directions that they felt more familiar with. To overcome this issue, we developed a target search strategy based on *expansion threshold*. This is to encourage users to brainstorm along non-obvious directions and perform divergent idea exploration. Therefore, we intended the IA player to specifically identify potential target nodes so as to enforce a breadth-first strategy (i.e. nodes closer to the root get preference) in a manner that ensures that every node has at least a prescribed minimum number of children (Figure 1(a), Algorithm 1). Specifically, the IA would traverse the mind-map starting from the root and will prefer the target closest to root with less than an *expansion threshold* (i.e. a pre-determined number of child nodes). We further designed the expansion threshold to be *three* based on our observation from the pilot study and a trial and error process.

Determination of Expansion Threshold: We determined our expansion threshold heuristically based on empirical feedback from the users in the pilot experiments. In these experiments, we compared the maps created with Mini-Map to the maps generated by human-human pairs with the goal of determining an appropriate threshold to maintain the breadth-depth balance. For an expansion threshold of two, we observed that there was a clear lack of diversity in the main branches (i.e. the nodes directly attached to the root node). For a threshold of four, we observed that the breadth of the maps was higher than those we had observed in the human-human pairs. While the users in the experiments did not raise concerns regarding this issue as well, the expansion threshold of *three* child nodes was determined to be reasonable. Note that this algorithm has a guaranteed termination criterion since there are always leaf nodes in M (i.e. nodes with no child nodes).

3.3 Algorithm: Content Generation

Our basic approach for determining what new content to add to a target node is to utilize the notion of query expansion and pseudo-relevance feedback via ConceptNet [62]. ConceptNet is a large graph of concepts where two concepts are directly connected with an edge if there is a semantic relation between them. Furthermore, each edge also has a *weight* that signifies the strength of the relationship. Our choice is based on the potential of ConceptNet for making more complex, multi-step inferences that are helpful in query formulation and the identification of poorly performing queries. Other existing methods for query expansion rely mostly on content-retrieval analysis (Wiki) or lexical-semantic database such as WordNet [63]. However, although WordNet is widely used to provide hypernym relations in a hierarchical fashion, ConceptNet allows for the organization of related concepts based on a

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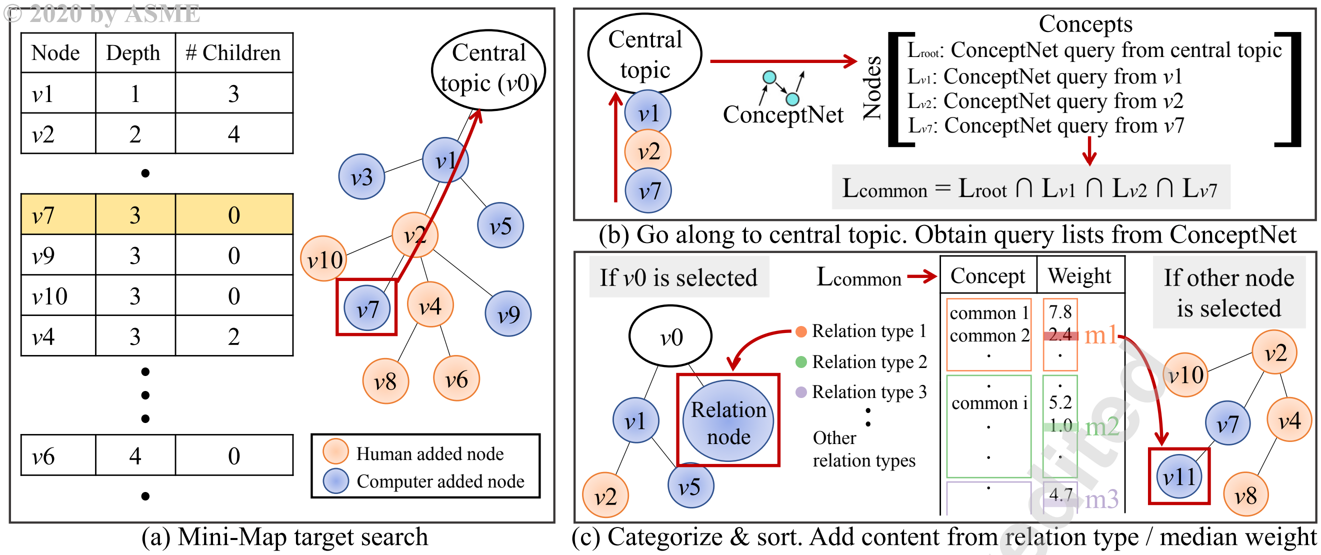

Fig. 1. Illustration of target search and content generation algorithm using retrieved weighted relations through ConceptNet Open Data API. (a) Consider a branch from current mind-map, find "where" to add based on sorted depth and number of children of all nodes. (b) Trace back to the central topic (root). Retrieve query results (L) from ConceptNet with respect to each node. Find common concepts across the retrieved results. (c) Categorize the common concepts and sort it by weights. Computer adds a new node from either relation type or median weight. **Note:** Adapted from the original source [1].

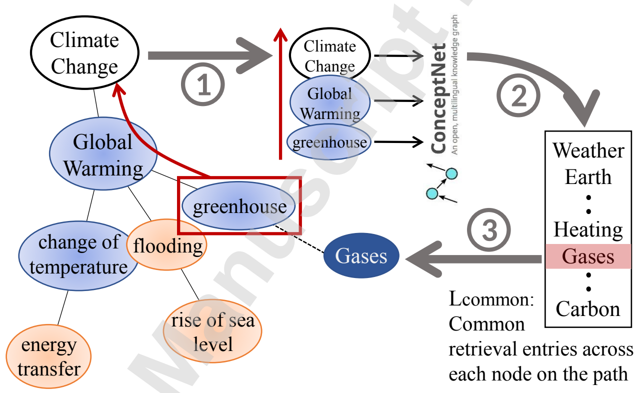

Fig. 2. Given a subset of nodes in an existing mind-map, the conceptual flow of generating a path-dependent content using common retrieval results from ConceptNet.

diverse set of relations (such as "*IsA*", "*HasA*", "*UsedFor*", "*CapableOf*") resulting in a broader scope of queries that WordNet synsets would not allow. Therefore, in this paper, we utilize *concepts*, *weighted assertions*, and *relation categories* provided by ConceptNet to determine the content to be added to a target node. In the following subsections, we introduce, in detail, two strategies for content generation: (1) path-dependent context wherein the target node has depth ≥ 1 (see sections 3.3.1 and 3.3.2), and (2) relation-dependent context wherein the target node is the root node (depth $= 0$, see section 3.3.3).

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Algorithm 2 Content Generation

Note: Reprinted from the original source [1]

Input: Target Node $v_T \in V_M$
Input: Relation Descriptor Set $R(v_T)$
Output: Concept $c \in V_C$ from ConceptNet graph $C = (V_C, E_C)$
Input: Relation Descriptor Set $R(v_T)$

$P_v \leftarrow$ list of nodes on the shortest path between v_T and Root Node
$L_{common} \leftarrow \emptyset$
for $p_i \in P_v$ **do**
  $L_i \leftarrow \{(c_j, r_j, w_j) | (p, c_j) \in E_C\}$ (r_j is the type of relation, w_j is edge weight)
end for
$L_{temp} \leftarrow \bigcap_{i=1}^{|P_v|} L_i$
$L_{temp} \leftarrow Sort(L_{temp}, alphabetical\ order\ of\ r_i)$
for all $r \in R$ **do**
  $L_{temp} \supset L_r \leftarrow \{l_i = (c_i, r_i, w_i) \in L_{temp} | r_i = r\}$
  $L_r \leftarrow Sort(L_r, descending\ order\ of\ w_i)$
  $W_r \leftarrow \sum w_i \forall l_i \in L_r$
end for
$RL \leftarrow \{L_{r1}, L_{r2}, \dots\}$
$RW \leftarrow \{W_{r1}, W_{r1}\}$
$L_{common} \leftarrow Sort(RL, descending\ order\ of\ RW)$
$R(v_T) \leftarrow Sort(R(v_T), descending\ order\ of\ RW)$
if Depth of $v_T = 0$ **then**
  $c \leftarrow r_1 \in R(v_T)$
else
  $c \leftarrow c_j \in L_{r1} | w_j = median(w_j \forall l_j \in Lr1)$
  $R(v_T) \leftarrow R(v_T) - \{r_1\}$
end if
return c, $R(v_T)$

3.3.1 Path Dependent Context

Given a target node, the simplest method to query for new content would be to search for concepts that are closely related to the target in the database (ConceptNet in our case). However, we argue that adding a new node to some chosen target is conceptually akin to expanding the "*line-of-thought*" starting from the central problem (root node of M) itself. Therefore, the first part of our content generation algorithm was to encapsulate this line-of-thought by computing the path from the target node to the root node and search for a concept that was common across all nodes on this path (Figure 2).

Our approach is further reinforced by our observations of our previous iterations [1] wherein we either used the entire mind-map (all nodes) to determine a shared concept (i.e. a global context) or we used only the target node to determine the content (i.e. a local context). In the first case, the resulting content is abstract as expected. This was further noted by our pilot study participants who stated: *"out of context"*, *"became too abstract as the map grows"*. This is natural because the concepts in the entire mind-map, since reasonably dissimilar, are bound to be connected only by the most generic concepts. The issue with using only the target node was that the newly added content did

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not usually relate to the rest of the mind-map. For example, *"emergency"* leads to *"fight-or-flight"*, and *"machine oil"* leads to *"make artificial snow"* for the central topic *"Aircraft"*.

Our path-dependent algorithm adds ideas that represent different aspects of the target node and avoid repetition of very similar or very dissimilar ideas being added. To do this, three steps were taken. First, given a target node $v_T \in V_M$, we compute the path from the target node to the root node, search for weighted concepts that are common on this path, and create L_{common} (Figure 1(b)). Second, all entries in L_{common} are listed categorically based on the 25 relationships provided by ConceptNet. We sort these categories based on the sum of weights of the concepts each category contains. Third, the entries in each category are further ordered with decreasing weight. The last two steps give us a doubly-sorted list (Figure 1(c), steps $1-16$ in Algorithm 2). This algorithm takes the relation categories provided by ConceptNet as different aspects of a target node, where the weights represent their strength of connection. The usage of these two properties (relation category and weight) is further described in the following subsections.

3.3.2 Selecting Content for a New Node

Given a list of common ConceptNet queries along a path, we subdivide the list into relation-categories for allowing IA player to be able to add a diverse set of nodes to an existing concept. In each relation-category, the seemingly obvious choice would be to generate content based on the highest weighted result. However, this approach clearly leads to more generic concepts being added to the map as it grows — a scenario that is in contrast with how mind-mapping is typically performed. For instance, for a central topic such as *"Aircraft"*, adding a node *"fly"* leads the IA player to add the concept *"sky"* followed by *"blue"* and *"a colour of the rainbow"*. These concepts have weights that are high up in the order in ConceptNet potentially because they are more general and therefore have significantly higher number of links in comparison to other more specific nodes. We also observed that the edge weight distribution of the linked concepts in ConceptNet is skewed towards a standard value of 1, when the highest edge weight can be larger than 10. Therefore, our approach takes median-weighted concepts from ConceptNet and adds them as ideas in the mind-map. This choice avoids repetition of very similar ideas and allows for diversification. Furthermore, this choice is more robust than using statistical aggregates such as mean in terms of preserving the relatedness (higher weights) and novelty (lower weights) of the added concepts. For example, for the concept "*heat*", the highest and lowest weighted relations in ConceptNet are *energy* and *what makes something hot*. On the other hand, the concept that is close to median weight is *geothermal energy*. This median-weighted concept provides two aspects of thinking — energy and context related to earth's interior — on the central topic *Solar Energy*.

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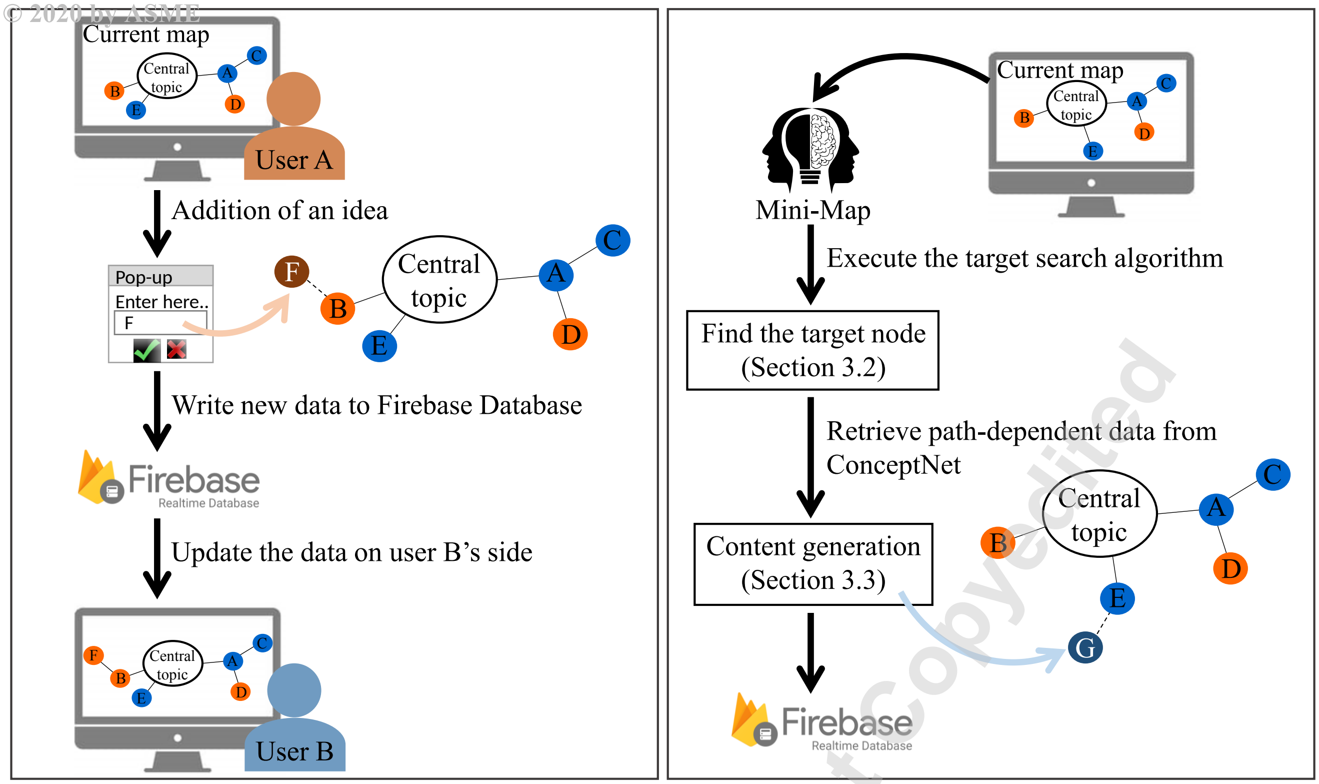

(a) Workflow of user A adding one node in **HH** group. (b) Workflow of Mini-Map adding one node in **HC** group.

Fig. 3. Flow showing an example of the front-end (user interaction) and back-end (data processing) pipeline in (a) **HH** and (b) **HC**. In **HC**, the user does exactly the same thing as user A does in **HH**.

3.3.3 Using ConceptNet Relations as Nodes

In a typical mind-map, the nodes connected to the central idea usually determine the type of details that will be consequently added. For instance, for a topic such as *Pollution*, one may first add nodes such as *causes*, *effects*, *mitigation* etc. instead of mentioned what the causes are or what the effects will be or how to mitigate pollution. This is difficult to achieve by simply adding median-weighted queries from ConceptNet. We observed that the relationship types in ConceptNet are themselves helpful to users in organizing their ideas, particularly during early phases of mind-map evolution. We capture this by enforcing the IA player to add ConceptNet *relations* as content nodes as the first several main branches from central topic contained in the root node (Figure 1(c), steps 17 – 22 in Algorithm 2). For example, in the beginning phase of mind-mapping with a central topic "*Car*", the IA player adds relation-dependent contents — "*parts (from ConceptNet PartOf)*", "*properties (from ConceptNet HasProperty)*", "*uses (from ConceptNet UsedFor)*", etc. — as nodes directly linked to the root node (which is *Car*). Here, the relation-dependent contents are selected from the categorized retrieval results of the term "*Car*". This step aims to encourage mind-map creators to span and organize their ideas in early stages.

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4 Implementation Details

4.1 Front-end Design

Visual Encoding: Similar to traditional pen-and-paper mind-maps where the size of the central topics are always larger than the ideas generated, the font size of the central topics are 1.5 times the font size of its direct children in our study. This size choice is by-and-large heuristic and is based on informal user feedback from our studies with mind-mapping interface development. From main branches to details, we further encode varying font size and color gradient to visually represent the emphasis of the information. Ideas added from different users will be given a different color scheme, which helps users easily recognize the flow of thoughts. Ideas are spatially organized in the mind-maps using forced-link structure in D3JS. Such force-directed layout can help produce elegant spreading of nodes and reasonable visibility of links even with large data-set.

User Interactions: We designed a sequential interaction workflow for users to collaboratively create a mind-map; users take turns to add nodes. In each turn, user can only add one node by double-clicking on any of the existing nodes. An input dialogue box pops up after double-clicking. Once a valid answer is submitted, our system creates a new child node with the double-clicked one being its parent node. A link is created automatically between them. This offers users minimal manipulation in the construction of a tree type structure. On the other hand, while it is not your turn, an layer appears on top of the interface to prevent any interactions.

4.2 Back-end

Firebase Pipeline: Mini-Map was implemented using Firebase Database REST API written in JavaScript (Figure 3). All data pertaining to a mind-map (node content, node position, links between nodes, etc.) is stored in the Firebase real-time database with a corresponding user identification code. In a collaborative setting where two human users are working with the same mind-map, Mini-Map employs a listener function to scan Firebase database at intervals of 3 seconds. Specifically, our interface checks for changes in the mind-map data, and updates the current mind-map based on the latest data found from Firebase.

MiniMap.js Library: For the interaction management, we implemented our own library (MiniMap.js) that reads and writes a JSON data structure specifically designed for mind-mapping. The data structure includes two components: a node object and a link object. The *Node* object has several attributes including screen position, properties (unique label, parent, children, depth, etc.) and time-stamped events (when a node was added and modified). The *Link* object has several attributes including source node, target node, and a unique label. Whenever a mind-map is imported or loaded into the workspace, the JSON file is read by Mini-Map and the corresponding mind-map is regenerated.

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ConceptNet API: In order to implement the content generation algorithm (section 3.3), we used the ConceptNet Open Data API in conjunction with the JSON-LD API (Link-ed Data structure). These APIs allow for querying a word or a phrase through HTTP request and provides a URL to a page containing all related words and phrases to the query in a linked data format. For each concept in the linked data, */en/* stands for its language code, *rel* contains corresponding relation such as "*UsedFor*", "*CapableOf*", etc., and the strength with which this relation expresses this concept is stored in *weight*. The linked data also provides human-readable label in *start* and *end*.

5 Experiment

We conducted a comparative study to understand how humans interact with their collaborator and explored human behavior in a controlled experimental setup. Our study tasks were designed with two major goals in mind. First, we wanted to measure how our approach compares with a typical human-human collaboration scenario in terms of quality, variety, and novelty of ideas generated through mind-mapping. Second, we wanted to understand the ways in which our approach could facilitate a human-like collaboration experience for design applications.

5.1 Participants

With these goals in view, we performed a user study with two distinct groups of participants. The first group (**HH**) comprised of 28 human participants who were asked to create mind-maps in pairs (i.e. 14 human-human pairs). The second group (**HC**) of participants comprised of 14 individuals who co-created their mind-maps with Mini-Map as the collaborator. Our participants were primarily undergraduate and graduate students from engineering, sciences, and architecture majors to help us sample from a wide variety of disciplines and age groups.

Choice of Dyad: To explore human-computer partnership in a controlled set-up for mind-mapping, we chose pairs (or dyads) as a natural and simple unit system to study. While our goal is not to study whether dyads can create better mind-maps than individuals, we did find previous works on collaborative brainstorming that support our choice. Osborn's early view [64] on collaborative brainstorming was that a group of individuals can produce better results in terms of both quantity and quality by minimizing the effects of criticism from self and others. However, the size of the group comes at a cost — the loss of productivity in brainstorming. A meta-analysis conducted by Mullen et al [65] further reinforced that this loss is relatively small for dyads and increases rapidly with group size.

Study Conditions: In the **HH** group, the participants were seated in two different rooms. Therefore, both the **HC** and **HH** participants did **not** know the type of agent (human or IA) they are collaborating with. In order to simulate human-like behavior for the **HC** group, we delayed the response from the computer by 5 to 10 seconds.

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This was based on our observations in our pilot experiments without computer intervention.

5.2 Procedure & Participant Tasks

The total duration of the experiment varied between 30 to 35 minutes. Our pre-task procedure involved:

1. A demographic survey
2. A verbal description of the purpose of the study
3. Introduction of the features of the software system
4. Practice with the system for 5 minutes to allow participants some time to get acquainted with the software

Participants were encouraged to ask questions for any further clarifications regarding the study. Following the pre-task procedure, the main task for the participants was to create a total of 2 mind-maps for two pre-defined central topics (therefore, one mind-map per topic). The participants were given 10 minutes to work on each mind-map. We recorded the participants' screen activity for each mind-mapping task. The participants were asked to follow basic principles of mind-mapping along with the sequential node addition rule we set. The participants were also requested to externalize ideas/concepts rapidly in keeping with the general spirit of brainstorming.

Choice of Topics: Based on a preliminary study with various topics, we chose *Solar Energy* and *Space Travel* as the topics for the user study. *Solar Energy* is a specific topic and we want to test whether our algorithm is able to add constructive nodes in any given context. *Space Travel*, on the other hand, is a general topic which stimulates the user to imagine and explore various directions. Specifically, we gave the following guidelines to the users in both groups at the beginning of each mind-mapping task [66]:

Solar Energy — Create a mind-map to explore the characteristics and ideas around the central topic of solar energy. Explore its needs and limitations in the context of engineered technologies and potential solutions for enabling such technologies.

Space Travel — Create a mind-map to explore the needs, challenges, general ideas to enable space travel and the associated current technological progress or potential solutions. Also, explore real-life scenarios wherein space travel becomes pervasive in daily life.

We further aimed to observe how differently our algorithm aided the user in organizing their thoughts in specific and open-ended problem domains.

5.3 Data Collected

We collected a total of 56 mind-maps from the study (14 each for *Solar energy*-**HC**, *Solar energy*-**HH**, *Space travel*-**HC**, and *Space travel*-**HH**). Upon completion, each participant was asked to complete a feedback

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questionnaire based on their experience during the mind-map creation tasks. Here, we wanted to understand the differences in perception of the mind-mapping process from our participants in the **HH** and **HC** groups. For this, we conducted a "*peer evaluation*" from each participant at the end of the mind-mapping session. Our peer evaluation is based on the recent work by Gilon et al [67].

In addition to questions regarding the interface and collaborator, the users were also asked to predict whether their collaborator is a human or computer. The reasons behind every participant's choice was also elicited and collected. The aim of this question was to gain insights on how the users perceived their collaborator's typical behavior and what would constitute human-like behaviour in mind-mapping.

5.4 Metrics

5.4.1 Metrics based on Semantics

We used *ConceptNet Numberbatch* to perform automatic semantic analysis on ideas generated across the 56 mind-maps. It is a word embedding model that is known to counteract several known biases and stereotypes (ethnic bias, gender bias, etc.) that are commonplace in current methods. The Numberbatch model learns from what people say by applying a retrofitting and merging process [68] with two popular sources of English word embedding and one knowledge graph — word2vec Google News embeddings (100B words) [69], GloVe embedding (840B words) [70], and ConceptNet 5.5 [13] which contains over 21 million edges and 8 million nodes. With this level of improvement, ConceptNet Numberbatch is, to our knowledge, the state-of-the-art embedding to compute word vectors and perform fair semantic comparison between words or phrases. With each word having its unique vector representation, we subsequently use cosine distance (1–cosine similarity) to measure semantic distance between the respective central topic and each idea in the resulting mind-maps.

5.4.2 Metrics for Rating Mind-Maps

The mind-maps created at the end of the user study were evaluated by three expert raters. The raters selected were unaware of the study design and any information regarding study assumptions and hypotheses other than final mind-maps created. Further, the mind-maps generated by **HC** and **HH** study were randomized and de-identified before being assigned to the raters. All the raters were senior graduate research students (a prospective faculty member in one case) in engineering and product design disciplines and were asked to rate each mind-map based on well-established metrics. From the mind-map assessment rubric [71], we adapted the *Structure*, *Exploratory*, *Communication*, and *Extent of Coverage* metrics for a comprehensive assessment of the quality of the mind-maps. The raters were asked to evaluate every mind-map based on each of these metrics on a scale of 1 to 4. In addition to the mind-map assessment rubric, we adapted the novelty and variety metrics from Linsey et al. [16] for evaluating

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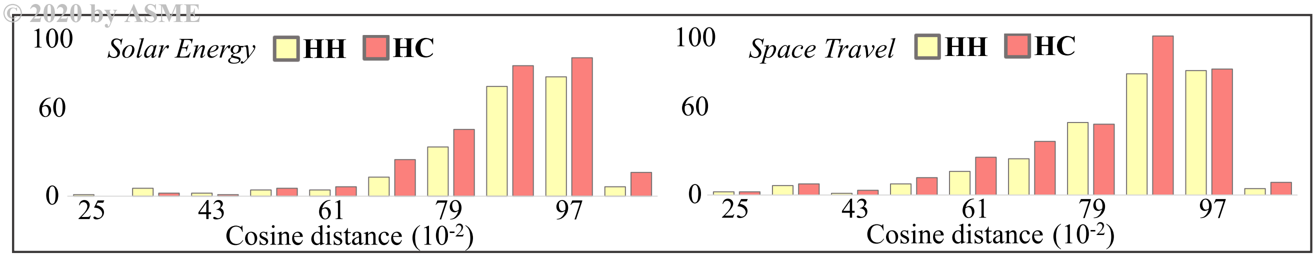

Fig. 4. Distribution of cosine distances for word vectors between ideas and corresponding central topic in **HH** and **HC**.

the ideas generated from our studies. Each rater first constructed a list of clusters (say: $C_1, \ldots, C_n$) and subsequently calculated the variety score of each mind-map as the percentage of clusters present in the respective mind-map. The novelty score for the ideas were calculated by considering the number of other ideas present in the same cluster. That is, lower the number of ideas in cluster, higher the novelty. The following formulae was used for evaluation of the novelty, where N_j is the Novelty score of the j^{th} idea, T is the total number of ideas, C_i is the number of similar ideas in the i^{th} cluster and n is the number of clusters occupied by the j^{th} mind-map.

$$N_j = \frac{T - C_i}{T}$$

Rating Procedure: The raters were given all the mind-maps and the specific grading rubric. Initially, we asked two raters to independently evaluate all the mind-maps for each of these metrics. We also encouraged them to discuss and come to a consensus on their grading rubric. After checking for reliability of agreement between the two raters, we found that they did not possess a good agreement specifically for the metrics *Structure*, *Exploratory*, *Communication*, and *Extent of Coverage*. Therefore, we recruited an additional rater to improve the reliability. This additional rater followed the same rating process — worked independently, discussed, and fine-tuned scores based on their consensus. The modified values of the metrics were then again checked for reliability using the Fleiss' kappa coefficient [72].

6 Results: Analysis of Outcome

Here, we discuss two methods, semantic analysis and expert ratings, for measuring the differences between the mind-maps generated by the **HH** and **HC** groups.

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Condition	Structure (1-4)	Exploratory (1-4)	Communication (1-4)	Extent of Coverage (1-4)	Quantity (raw)	Variety (0-1)	Novelty (0-1)
HH Solar Energy	2.41	2.5	2.38	2.21	21.50	0.67	0.16
HH Space Travel	2.59	2.36	2.48	2.52	28.29	0.68	0.20
HC Solar Energy	3.12	3.2	2.83	3.05	34.71	0.78	0.21
HC Space Travel	3.55	3.33	3.19	3.48	44.43	0.82	0.19
Average **HH**	2.5	2.43	2.43	2.37	24.9	0.68	0.18
Average **HC**	3.34	3.26	3.01	3.27	39.57	0.8	0.20

Fig. 5. The values of various metrics were averaged across topics and type of the collaborator. This table summarizes the mean values of various metrics calculated by the raters.

6.1 Semantic Analysis

For each topic, we used t-SNE to visualize word embedding[3] collected from mind-maps created in both groups of users (**HH** and **HC**) using the pre-trained model from Numberbatch (English only, 300 dimensions) [68]. For a given topic, we observe that most of the generated ideas seem to cluster in the proximity of identifiable regions and close to central topics regardless of **HH** or **HC** group. This indicates that the maps generated by the **HC** group have content similar to those created by the **HH** group. However, the structure of the mind-maps is observably different in **HC** as compared to **HH**; users in **HH** tended to link more ideas directly to the central topics while users in **HC** were confined to the standard radial layout. Such non-hierarchical structure of the **HC** participants can be used as an effective design thinking tools [34].

Using the Numberbatch vector space embedding, we performed semantic similarity comparison by measuring cosine distance between word vectors of ideas with their corresponding central topics. There are two main observations to be made regarding the corresponding semantic distance distribution with *Solar Energy* and *Space Travel* (Figures 4). First, the maximum distance in *Solar Energy* recorded for **HH** (1.1173), is very close to that recorded for **HC**. In *Space Travel*, however, the maximum distance is 1.0867 for **HH**, whereas **HC** gets a higher score of 1.125. Thus, Mini-Map is able to both generate problem-specific content for typical problems and is also helpful in exploring atypical open-ended topics. Second, apart from the measured maximum distance (which can be interpreted as a measure of breadth of ideas covered in a mind-map), we observe interesting trends in the distribution of distances between word vectors across **HH** and **HC** groups (Figures 4). Ideas from both groups display high frequency in the distance range between 0.52 to 1.06. However, for mind-maps from the **HC** group, the frequency stays higher than those from **HH** up to the maximum distance ranges observed for both *Solar Energy* and *Space Travel*. This suggests that Mini-Map is capable of introducing diversified but still related content to users in the creation of mind-maps.

[3]Please see supplementary material for the full visualization

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6.2 Mind-map Ratings

Initially, The Cohen's kappa value for the *Structure*, *Exploratory*, *Communication*, and *Extent of Coverage* were found to be in the range of 0.3 - 0.4, showing only fair level of agreement and reliability between the two raters [73]. With the addition of one more rater, we further calculated Fleiss' kappa coefficient to assess the agreement since the mathematical foundations of Cohen's kappa make it to be mainly suitable for two raters [74]. The Fleiss' kappa coefficients for these metrics were improved to be in the range of 0.76 - 0.82 presenting substantial agreement among the ratings [75]. Also, the Pearson's correlation between raters for variety and novelty scores was found to be above 0.8 (0.83 and 0.92). This value of correlation coefficient is identified strong [73].

Two-way ANOVA was conducted with two independent variables — (1) type of collaborator and (2) choice of topic. While we did not assume the data to be normally distributed, we note that ANOVA is generally less sensitive to normality [76], particularly for low sample sizes. We found that the p-values across the **HH** and **HC** groups were near zero for nearly all metrics (except for novelty whose p-value across **HH** and **HC** was 0.12). However, the p-values across topics were not less than 0.05 showing that the differences were not significant across the topic. Results show that the mean of the scores given by the raters for all metrics except novelty was greater in **HC** study compared to **HH** for both the topics (Figure 5). This suggests that Mini-Map helped the users to develop a better mind-maps overall. Specifically, the high values of *Structure* indicate that the mind-maps created using Mini-Map helped the user create a well-organized map. We believe this to be the case because of our expansion threshold strategy in the target search algorithm. Other important metrics that showed significant improvement from **HH** to **HC** groups are *Exploratory* and *Extent of Coverage*. This indicated the effectiveness of the content generation algorithm. The considerable increase in the value of *Quantity* (raw) shows that the Mini-Map algorithm could potentially help the users to generate more ideas within a stipulated time compared to a human collaborator. Also, higher values of *Variety* scores in **HC** suggest that the median-weight algorithm has assisted the user to explore diverse directions. Such differences were not observed significantly for *Novelty* scores. This could mean that although the Mini-Map algorithm allowed one to cover more number of ideas, the number of unique ideas was similar to the **HH** group.

6.3 Agreement between Semantic Analysis & Ratings

Semantic analysis and expert ratings provide two different methods of assessing the resulting mind-maps. Through expert ratings, we can see that the quality of **HC** maps are comparable to **HH** maps in general (Structure: **HC** 3.34, **HH** 2.5; Exploratory: **HC** 3.26, **HH** 2.43; Communication: **HC** 3.01, **HH** 2.43; Extent of Coverage: **HC** 3.27, **HH** 2.37). We found significant differences in terms of the structure and exploratory metrics (both p-values < 0.001). This observation is corroborated by the visualization of t-SNE maps of embedding of ideas. It

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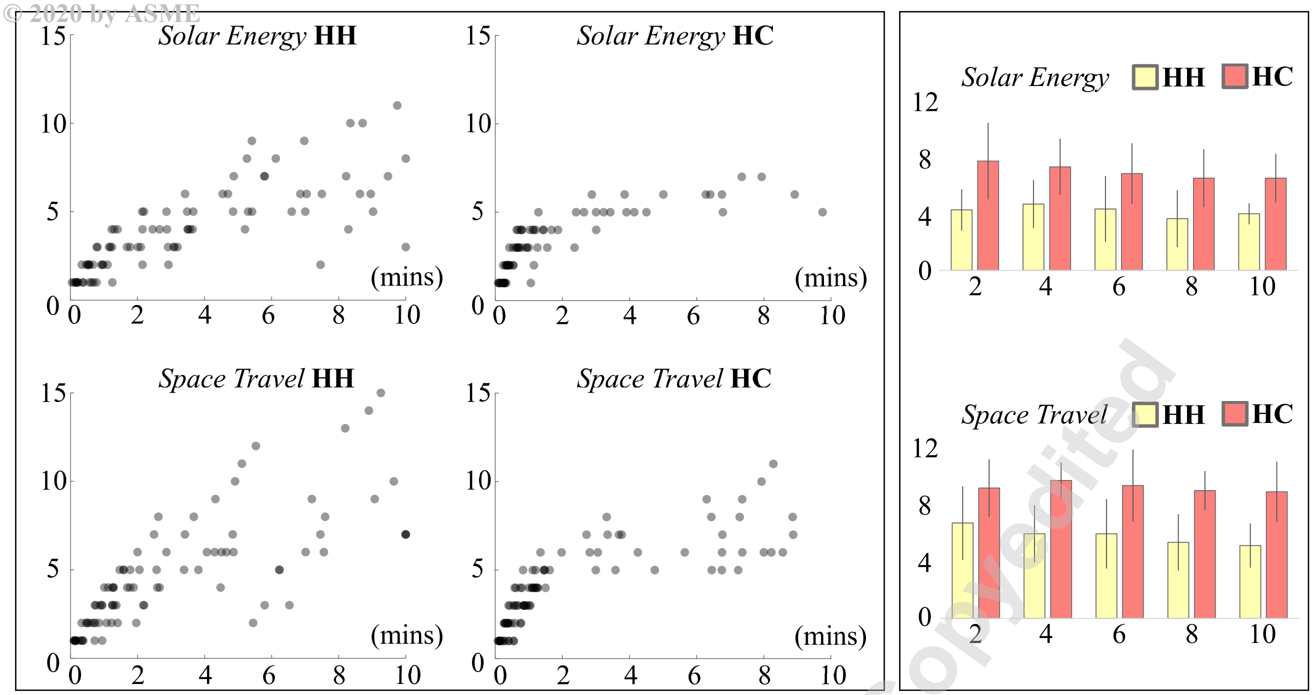

(a) Time distribution for generating i^th depth=1 node. X-axis: time. Y-axis: i. (b) Node addition per 2 minutes

Fig. 6. (a) Time distribution for generating i^{th} main branch (depth=1 node) and (b) number of nodes added every two minutes for the corresponding central topic (*Solar Energy* and *Space Travel*) and participant group (**HH** and **HC**). Note that in (a), the markers were plotted using $\alpha = 0.4$.

can be seen that ideas generated in **HH** groups are closer to the central topic, while ideas from **HC** groups are still densely located in regions that are not close to the central topic. This phenomenon is also evident in *Space Travel* maps.

Raters gave higher ratings on the variety metric for **HC** maps on average (0.8 for **HC** and 0.68 for **HH**), indicating users were capable of exploring diverse directions with respect to both topics using Mini-Map. The results from semantic similarity measure corroborate this by pointing out that more ideas with higher dissimilarity were generated in **HC** groups regardless of the topic of the map. For example, in the distance range between 0.79 to 1.06, **HH** groups have 175 ideas for *Solar Energy* and 202 ideas for *Space Travel*, whereas **HC** groups have 211 ideas for *Solar Energy* and 226 ideas for *Space Travel* (Figure 4). Both semantic analysis and expert ratings indicate that the **HC** participants were able to generate diverse yet related content during the 10 minutes creation of mind-maps. Finally, the high scores for novelty of ideas in **HC** maps (0.2 for **HC** and 0.18 for **HH** on average) can be explained by the relatively higher number of ideas generated [77]. Specifically, on average, **HC** groups generated 13 more ideas for *Solar Energy*, and 16 more ideas for *Space Travel* (Figure 5 Quantity(raw)).

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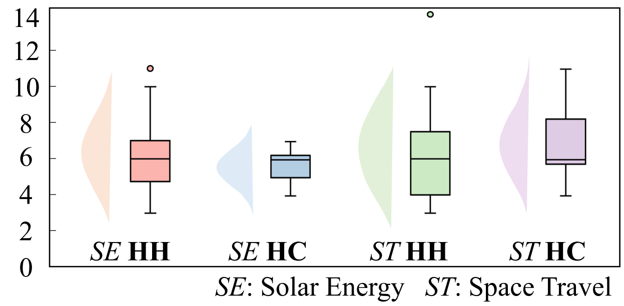

Fig. 7. The number of main branches generated in the final **HH** and **HC** mind-maps with respect to *Solar Energy* and *Space Travel*.

7 Results: Analysis of Process

We conducted a video protocol analysis of the created mind-maps by manually going through the video recordings and developing codes for making systematic observations. The mind-map creation process can be formulated as an iterative two-step sequence — breadth-oriented and depth-oriented exploration, in the sense that the creator can either generate as many ideas as possible to the central topic, or choose a smaller subset to develop details. We also noticed behaviors that are related to impasse or interpersonal conflict during our mind-mapping study [78]. To address these, our analysis therefore focuses on identifying the actions that accompany one of the aforementioned intents. We developed codes to record the time and potential reasons for the following user activities and events: (1) diversification of the central topic (breadth-oriented exploration), (2) development of long chain of ideas from the central topic (depth-oriented exploration), (3) taking rest during their turn ($>$ 15 seconds), and (4) hesitation in adding ideas. The videos were coded by two graduate researchers (one is the author of this paper; another one is formally trained in design theory and methodology), with an overlap of 12 mind-mapping videos ($\sim$21%) between them. Using two-minute windows to compare codes, they reached a substantial inter-coder agreement Cohen's kappa of 0.73.

7.1 Map Evolution Over Time

To understand the strategies participants applied in both breadth and depth aspects during creation of mind-maps, we also recorded the number of nodes, the number of branches directly added to the central topic (main branches), and corresponding depths (distance to the central topic from each leaf node) of each mind-map at intervals of 2 minutes. Our intention of recording the number of main branches was to see how the different aspects of the central topic had been explored during the given time. There are two reasons for us to record at a 2 minutes interval. First, participants can only add one node each turn because of Mini-Map's design. Second, we noticed that human participants tended to spend a lot of time thinking before adding nodes to the map. Thus, significant observations can be made within longer time intervals for most cases. We analyzed the records across the assigned central topics and the types of groups.

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For *Solar Energy*, most of the final mind-maps (24 out of 28 combining both **HH** and **HC**) have more than 5 main branches, which indicates that the participants were able to diverge and discover multiple aspects around the central topic. These main branches were mostly generated during initial 5 minutes of mind-mapping for **HH** participants, where **HC** participants took around 4 minutes (Figure 6(a)). we also noticed that several participants in **HH** group kept adding new main branches to the central topic until later stages of mind-mapping. However, even though they created new main branches continuously, we observed that many such maps created have more than 3 leaf nodes (node without a subsequent child node) of depth 1 (directly added to the central topic). In such cases, the participants tended to put instances directly to the central topic instead of creating broader categories. On the other hand, one pair of **HH** participants created only one main branch until 7.30 minutes mark. The general imbalance in the structure of *Solar Energy* maps created by **HH** participants is further in agreement with the lower ratings of Structure and Communication aspects by expert raters.

For *Space Travel*, both **HH** and **HC** participants were able to broadly explore concepts/possibilities around a relatively open-ended central topic. All 28 maps for *Space Travel* have the number of main branches varying from 5 to 10 (Figure 6(a), Figure 7), which is greater than *Solar Energy* maps (5 to 8). However, contrary to *Solar Energy*, most of the participants in **HH** group (10 out of 14) created less than 1 new main branch on average after they had created 5 to 7 during the first 5 minutes. This is similar to the **HC** participants, where 9 participants developed most of their main branches (4^{th} to 6^{th}) during initial phases of mind-mapping. Unlike the case for *Solar Energy*, these participants developed the newly added main branches to some extent in later stages. This is likely because of the open-ended and imaginary nature of *Space Travel*. Many **HH** participants (6 pairs) were also observed to perform a fast depth-first exploration (create long chains of nodes) during mind-mapping for *Space Travel*.

As expected, the evolution of mind-maps was relatively uniform in terms of breadth and depth for **HC** groups for both topics. In the **HH** group many main branches have leaf nodes of depth 1. On the other hand, in the **HC** group we found that each individual branch beginning from the central topic had at least 2 or more nodes not counting the central topic. This could be attributed to the Mini-Map algorithm where the computer is enforced to perform a breadth-first exploration in a manner that ensures a bare minimum expansion of a given node. This was especially true for *Space Travel* wherein the number of nodes directly linked to the central idea was higher. For instance, most main branches have depth from 2 to 4. That our expansion threshold strategy was successful in enforcing a balance between breadth and depth is further indicated by the higher expert ratings for structure and communication.

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7.2 Idea Generation Frequency

We found that for both **HH** and **HC** groups, the rate of idea generation differed across the two topics — p-values were near zero measured between *Solar Energy* and *Space Travel* maps regardless of the type of groups (p-value was 0.0014 for **HH** and 0.0005 for **HC**, Figure 6(b)). However, it is notable that participants tended to generate a larger number of ideas at a higher rate for *Space Travel* in both conditions (**HH** and **HC**). We believe this happened due to the difference in the breadth of the central topics as perceived by the participants. In case of *Solar Energy*, most mind-maps focus primarily on the notion of sustainability, energy alternatives, and photo-voltaic cells. This narrowed down the nature of concepts that were explored by both, the human and the IA partner. While this resulted in a better depth-exploration (provided at least one of the team-mates was knowledgeable), not enough breadth was explored. *Space Travel*, on the other hand, had a better variety of contexts including entertainment (such as science-fiction movies), engineering innovation needed, geo-politics, etc. This provided participants with a larger set of concepts to imagine.

We also observed that, overall, **HC** participants were able to record ideas at a faster rate for both topics. This is indicated by the quantity score (Figure 5). Specifically, 6-13 (mean=9.42, SD=2.91) ideas were generated by **HC** participants every 2 minutes for *Space Travel* and 4-13 (mean=7.23, SD=2.29) for *Solar Energy*, whereas in **HH** groups, 2-12 (mean=5.94, SD=2.2) for *Space Travel* and 1-10 (mean=4.34, SD=1.78) for *Solar Energy*. This can be attributed to two primary reasons. First, the Mini-Map target search algorithm stimulated participants to consider directions that they originally were either not certain about or did not consider important. Second, the amount of knowledge possessed by participants has great impact on collaborative behavior in this sequential interaction workflow, especially for a problem that is reasonably scoped (or less open-ended such as *Solar Energy*).

7.3 Idea Exploration Directions

Apart from the topological characteristics of the generated mind-maps, we also investigated the type of ideas added by the participant during the mind-mapping process. We discuss the popular category of ideas generated for the two topics and how it influenced the final quality of the mind-map across the two groups (**HH** and **HC**).

For *Solar Energy* (Figure 9), most of the **HH** participants started adding ideas that can be directly associated such as *sun*, *solar panel*, *heat*. etc. They were also able to categorize their flow of thoughts by adding main branches discuss cost constraints, environmental impacts, efficiency and properties (e.g. *renewable*) of solar energy. The ideas generated by **HH** participants are generally similar, which might be owing to their familiarity with the central topic. **HC** participants, on the other hand, mostly started with nodes such as *types*, *pros*, *cons*, *property/characteristics*, etc. They are observed to be able to explore more concrete and diversified ideas on solar energy compared with **HH** participants. For example, one **HC** participant expanded the category *property* into

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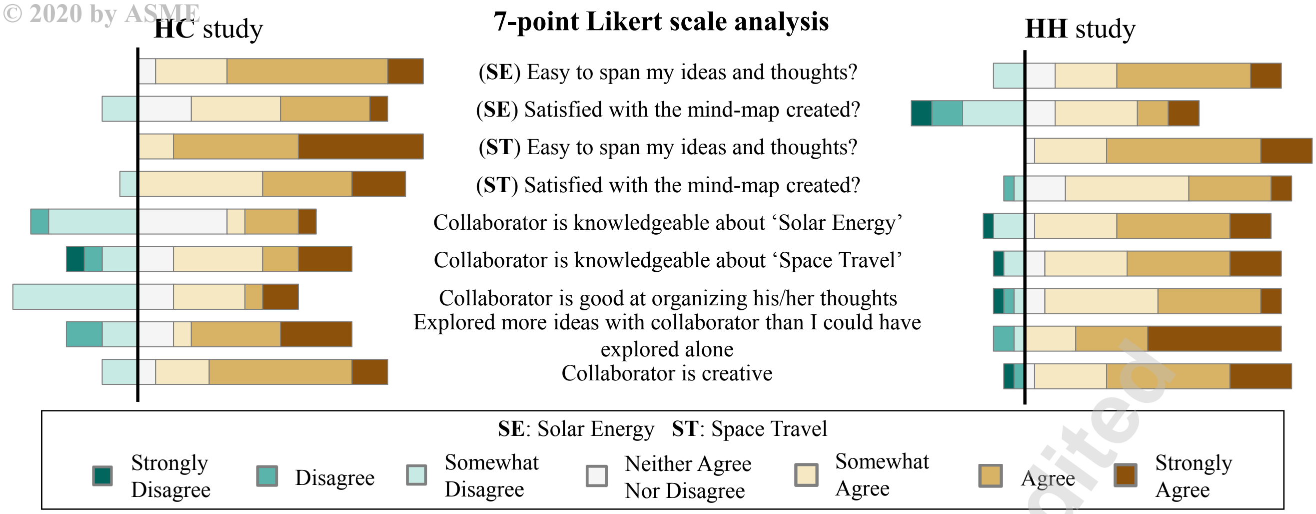

Fig. 8. 7-point Likert scale feedback from the user study conducted. The brown bars towards the right of the central line indicate positive responses and blue bars to the left indicate negative responses. **Note:** Reprinted from the original source [1].

four sub-categories: transportational, residential, industrial and commercial. Another **HC** group examined solar energy not only from its capability but also from the aspects of *government funding* and *tax breaks* to *public policy* and *employment*. The organized and broader aspects of solar energy ideas generated in **HC** mind-maps indicating that Mini-Map algorithm assisted the participants to develop a systematic understanding of the central topic and stimulated their associative capability.

Common main branches generated for *Space Travel* (Figure 10) by **HH** and **HC** participants including transportation (*rocket* and *spacecraft*), exploration (*Mars*, *aliens*, etc.), difficulties (*gravity*, *no oxygen*, *costly*, etc.) and agencies (*NASA*, *ISRO*, etc.). There are several **HH** groups specifically interested in exploring categories such as *fiction* and *people* of space travel. For example, one **HH** group generated over 25 ideas under the category of *movies*. Their flow of thoughts spanned a broad spectrum ranging from the movie *Interstellar* to *galaxies*, *dwarfs*, *worm holes*, etc. **HC** participants also explored extensively on the *requirement* of space travel. They developed several ideas that could allude to solution-oriented methods for space travel such as *liquid fuel*, *optimum health conditions*, *high-grade materials*, *communication with satellites*, etc. *Science* and *research* were also popular main branches associated with *Space Travel* in **HC** maps, wherein ideas such as *propulsion*, *rocket dynamics*, and *control for anti-gravity robot* were explored.

8 Results: User Feedback

8.1 Qualitative Feedback

We elicited the participant's experience in collaborative mind-mapping using a 7-point likert scale survey questions (Figure 8). In terms of ease of expansion of ideas and thoughts, the results show that Mini-Map was

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equally conducive compared to a human collaborator. Interestingly, in the **HH** study for the topic *Solar Energy*, around 40% of the participants were not satisfied with the mind-maps they created compared to **HC** study (about 10%). This might potentially be because of the mismatch of ideas that the two users wanted to externalize causing a dissatisfaction in the quality of the mind-map created, from the perspective of the user. Moreover, the response time was totally dependent on the human collaborator in **HH** studies. Given a limited time, delayed responses from the users might have curbed the user to develop a mind-map to their fullest potential — which likely causes a dissatisfaction between the users in the **HH** study.

Majority of the users felt that the collaborator was creative in both **HH** and **HC** study. This shows that the median-based algorithm used for idea generation gave interesting responses commensurate with human-level creativity. Though a bit lower in the **HC** study, majority of the users from both the studies felt that the collaborative mind-mapping would be a better environment for exploring more ideas than individual mind-mapping. These results suggests that Mini-Map is at par with a human collaborator not only in terms of assisting the users to developing greater number of ideas, but also by giving intriguing responses. As per one participant from **HH** study, *"Integration of ideas from the collaborator increased the overall quality of the mind-map"*. Another user from **HC** study stated: "*My collaborator was Smart and creative, helped explore ideas - and gave perspectives I hadn't thought of*". Thus, a controlled collaborative setup, like our system, can be particularly helpful in early design stages.

Up to 50% of the users *Somewhat disagreed* that the collaborator was not good at organizing their thoughts in the **HC** study. Potential reason for this observation include the difference in approach of making mind-maps of the user compared to the Mini-Map algorithm. This is contrasting to the outcome from the inter-raters claiming that mind-maps created by the **HC** fared significantly well in terms of metrics like Structure and Extent of coverage. Although our algorithm does not go well with the user approach wise, it guides the user to create a better mind-map overall. This is also corroborated by the fact that majority of the participants were satisfied with the mind-maps they created at the end of the **HC** study.

In **HC** study, one general observations was that the context of the node generated slowly started to depend on the nodes added by the human as time progresses. A participant of **HC** study stated: *"At first it was making too good of thoughts. Then it made some dull contributions"*. So, if the nodes added by the human is well related to the central topic, then the nodes added by the computer maintained the context and gave valuable responses. However, in some cases the connection between the nodes added by human were not explicit. This might not always be identified with the limited semantic data base available, resulting in content generated using median weight method. In **HH** study, there all more than 80% of the users felt that their partner was knowledgeable. However, there were mixed responses from the user about the collaborator's knowledge in the **HC** study. In the topic *Space Travel*, about

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75% of the responses were neutral or above. One user stated: *"It was helpful for the topic Space Travel as I had minimal knowledge on that"*. The responses regarding the collaborator's knowledge were slightly more negative for the topic *Solar Energy*. Since this is a more specific topic, there could have been a greater room for diversifying, thereby increasing the possibility of losing context to the idea generated by the median weight method.

8.2 User's Perception of the Collaborator

From the study survey, 5 out of 14 users predicted their collaborator to be a human in the **HC** study conducted. This result is rather surprising since 35% of participants choose to believe that the computer was a human even though it is not our goal. Interestingly, 12 out of 28 users from the **HH** study predicted their collaborator to be computer. Interesting reasons for predicting Mini-Map to be human includes feedback such as *"Smart and creative"* and even *"sly humour"*.

In both **HH** and **HC** study, 35.7% (5 out of 14) and 42.8% (12 out of 28) of the participants predicted their collaborator wrongly. Therefore, there may exist uncertainty in claiming human-like behavior in Mini-Map algorithm just from this answer. However, open-ended feedback from the users helped us elicit the reason behind their prediction of the type of collaborator, develop understanding of how Mini-Map can simulate the useful aspects of human-like behaviors, and ways in which Mini-Map can prove to be more helpful than a human collaborator.

8.3 Median-weighted Node vs Relation Node

Adding relationship node was mainly found to be helpful for categorizing the central ideas into branches. For example, user responses suggests that nodes like *'Space Travel has...'*, *'Requirement'*, in the topic *Space Travel* and nodes like *'Capable of...'* in *Solar Energy* specifically gave fundamental directions to think about the given central idea. Additionally, these nodes could have assisted the users to get started with mind-mapping analogous to initiating a discussion to increase a person's engagement. Moreover, one of the user's statement: *"I felt some part like a conversation"* might allude to the relationship type nodes.

9 Limitations and Design Implications

The combination of the topological rule (expansion threshold), the use of a knowledge base, and also the method of interaction imposed (two collaborators adding nodes sequentially) helps us successfully demonstrate a mixed-initiative workflow for an open-ended and unstructured task. Specifically, among the metrics used for assessment, higher scores for the structure metric for **HC** maps indicates that the *guaranteed minimal expansion* rule does seem to improve the user's ability to balance the breath and depth of the map. However, there are also maps that have good scores on structure receive low scores on the exploratory metric. This is because the flow of

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the linked ideas from central topic is not clear. ConceptNet, therefore, comes into play with its large *relational* ontology and more importantly a generic set of relationship types that we used for the nodes at depth 1 (what we called main branches in section 7.1). In addition, the use of path-dependency (section 3.3.1) further ensures that the nodes added by the computer do not stray away from the context of the central topic. Having said that, we still noticed several key limitations of Mini-Map based on the analysis of process and user feedback (section 7 and 8). We state these limitations and offer suggestions on how future systems for human-AI mind-mapping may be designed to address these limitations.

Workflow Design: The first limitation is the sequential node addition mechanism. While this decision helped us develop this simple yet novel mixed-initiative mind-mapping tool, more work is required to enable non-sequential process to enhance group satisfaction. Our recent exploration of collaborative mind-mapping [66] with human-human peer-pairs showed that a free-form, non-sequential addition of nodes offers a richer mode of collaboration. Second, the workflow — allowance for only node addition — also affects the mind-mapping process. We intended to enable fast idea externalization with minimum emphasis on the modification of the existing ones. However, this strategy inevitably affects users' comfort in two situations: (a) when they make several typographical errors and (b) when they want to reorganize ideas. Therefore, more modalities need to be considered such as non-sequential input from the AI, allowing users to re-link existing nodes, enabling the AI collaborator to provide real-time suggestions for map reorganization.

Algorithm: Two limitations are noted here. First, the breadth-oriented target search algorithm. This was designed under the premise that users subconsciously tend to explore depth during brainstorming. Our strategy, while effective under this assumption, was limited in responding to users when they were expecting the collaborator to expand on a specific line of inquiry in the map. Therefore, mechanisms are needed to facilitate necessary albeit subtle communication between the human and AI collaborators. These mechanisms could either be automatic or even interactive. For example, a simple solution would be to include interactions for a user to *flag* a newly added node to indicate that they need prioritized help. This may, in fact, even be an interesting feature to study in collaboration dynamics in human-human teams. In the back-end, a potential direction would be to assign dynamic attention weights to existing nodes or utilize graph-based salience detection model [79]. Second, the IA-generated context is a direct retrieval from the *label* in ConceptNet and they are mostly represented in a single word or phrase. As research in psychology reveals that a knowledge component is much like a sentence that expresses a particular idea [80], recent works in engineering design have also started to explore analysis on sentence-level design concepts [50, 81]. Therefore, we believe that adding phrases and sentences to the map will allow more clarity for the user about the ideas being explored and enhance comprehension and learning of the scope of the central

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topic. This could be achieved by either using the data stored in *surfaceText* in ConceptNet or the incorporation of sentence generation techniques [82, 83].

Choice of Data-set: In principle, the cognitive assistance framework in Mini-Map is independent of which data-set is chosen. We chose ConceptNet because it provides semantic relationships and commonsense knowledge in a descriptive way to help make better contextual inferences. However, for solution-space exploration, ConceptNet is not particularly suitable as it does not necessarily offer technical specificity as noted in a comparative study conducted by Sarica et al. [51]. Therefore, in order to show a full-fledged demonstration in a design scenario, other data-sets such as WikiData, Google Knowledge Graph, and U.S. patent databases should be considered. An advantage of these data-sets is that they contain both textual and visual elements that will provide a richer experience to the user. There is additionally a significant amount of work in the engineering design community [28, 84–89] that offers a variety of engineering databases that can be utilized to improve mixed-initiative workflows. We believe that the ability of such databases should be merged with the interactive-algorithmic workflow proposed in Mini-map toward a truly powerful human-AI collaboration system.

Evaluation: From a methodological perspective, our evaluation was currently focused on developing a qualitative understanding collaboration in a human-IA pair. While we generated a total of 56 maps in total, our sample size per group was currently low (14 groups of participants in each **HH** and **HC**). This allowed us to study the collaborative behavior specifically in this mixed-initiative scenario in depth. However, more data is needed to train machine-learned models to develop robust intelligent systems for digital mind-mapping. More importantly, to gain insights on how the brainstorming outcomes truly affect the later stages of design, we plan to include conceptualization tasks after each brainstorming session to examine several aspects such as (a) whether the user understands the problem space better, and (b) whether the user is able to associate ideas to create novel ones after doing so. We also believe that the metrics currently used for evaluating mind-maps should be re-visited. This is due to the fact that the specific temporal and topological structure of mind-maps is currently under-emphasized.

10 Conclusions and Future Directions

We presented a new digital mind-mapping workflow for co-generating ideas with an intelligent agent as a collaborating partner. We make two main algorithmic contributions in this work. First, we designed an algorithm to identify potential target nodes for idea addition. Second, we demonstrated a relation-dependent and path-dependent method to extract relevant content from ConceptNet to enable mind-map evolution.

There are several promising research directions that we envisage continuing with research. Our goal in the future is to improve target search algorithm through new interactions and automatic assessment of user attention,

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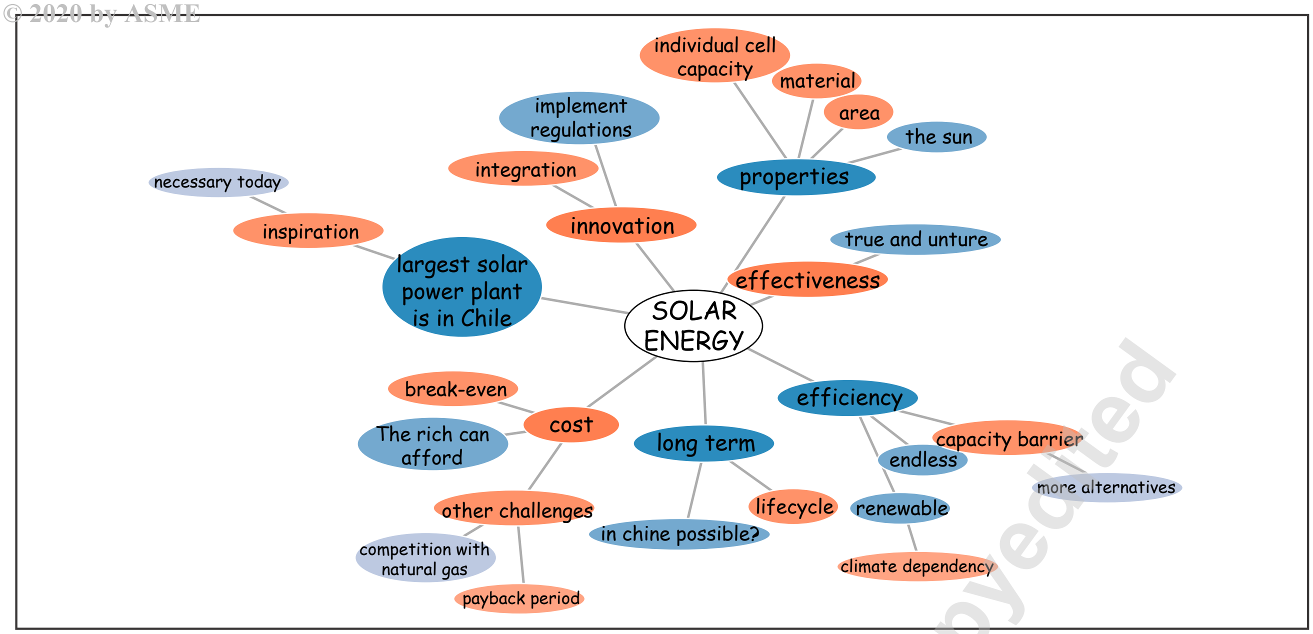
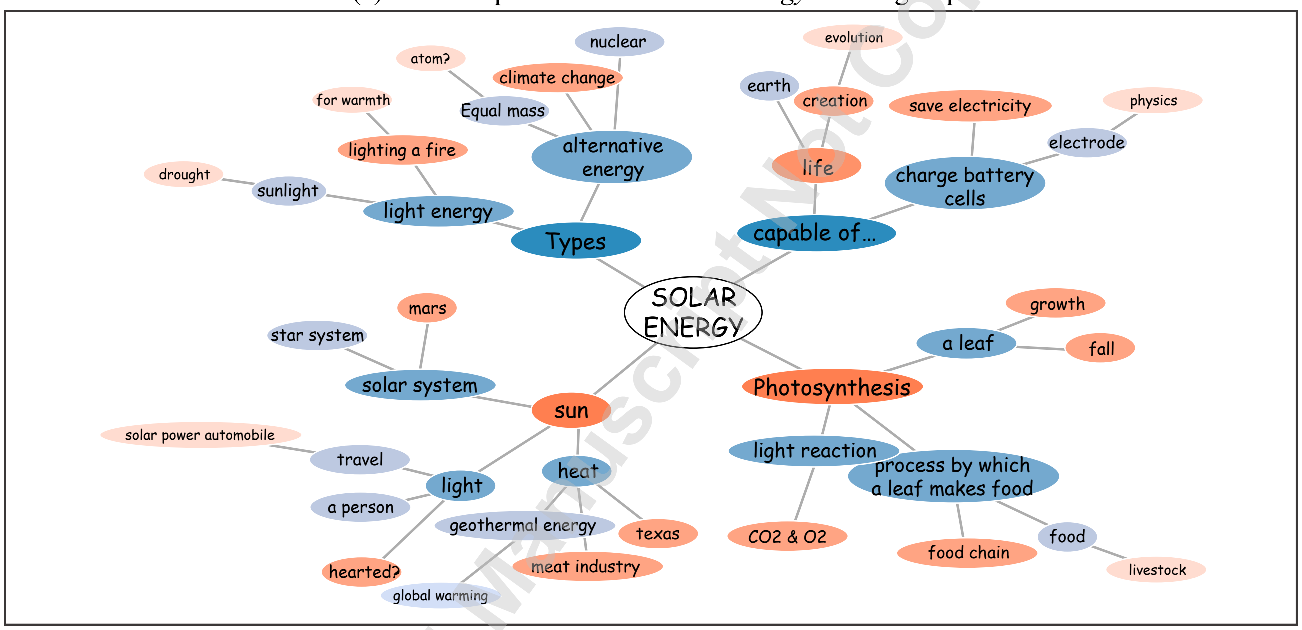


(a) Mind-map created with *Solar Energy* in **HH** group



(b) Mind-map created with *Solar Energy* in **HC** group

Fig. 9. Sample user created mind-maps with central topic *Solar Energy* in (a) HH and (b) HC. In (b), orange nodes represent user added nodes, and blue nodes represent Mini-Map added nodes. **Note:** Reprinted from the original source [1].

preference, and expertise in a given area of exploration. We also intend to conduct a large scale crowd-sourced repository of mind-maps across different demographic groups, expertise levels, central topics, and engineering domains. Not only would this help in collecting significant amount of data for a comprehensive analysis, it will lead to a database for several other research groups.

Recent years have seen a prolific change in the way we interact with computers. For example, current state-of-the-art systems such as Siri, Cortana, and Alexa have reached a high level of sophistication in terms of

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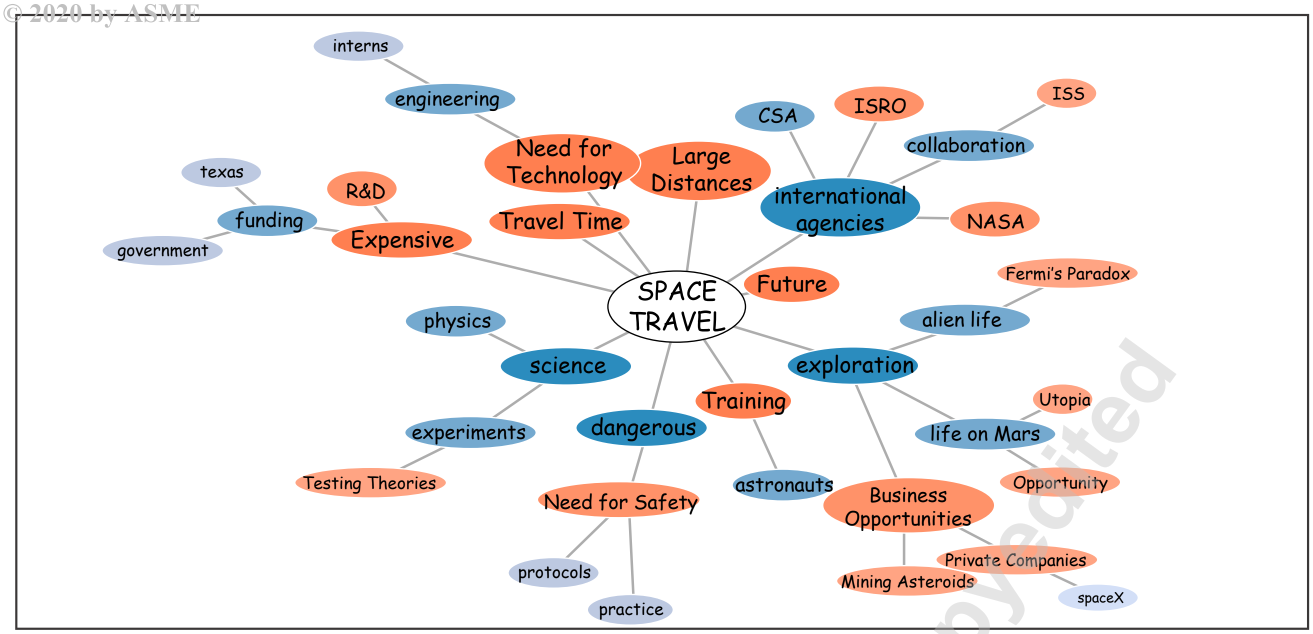
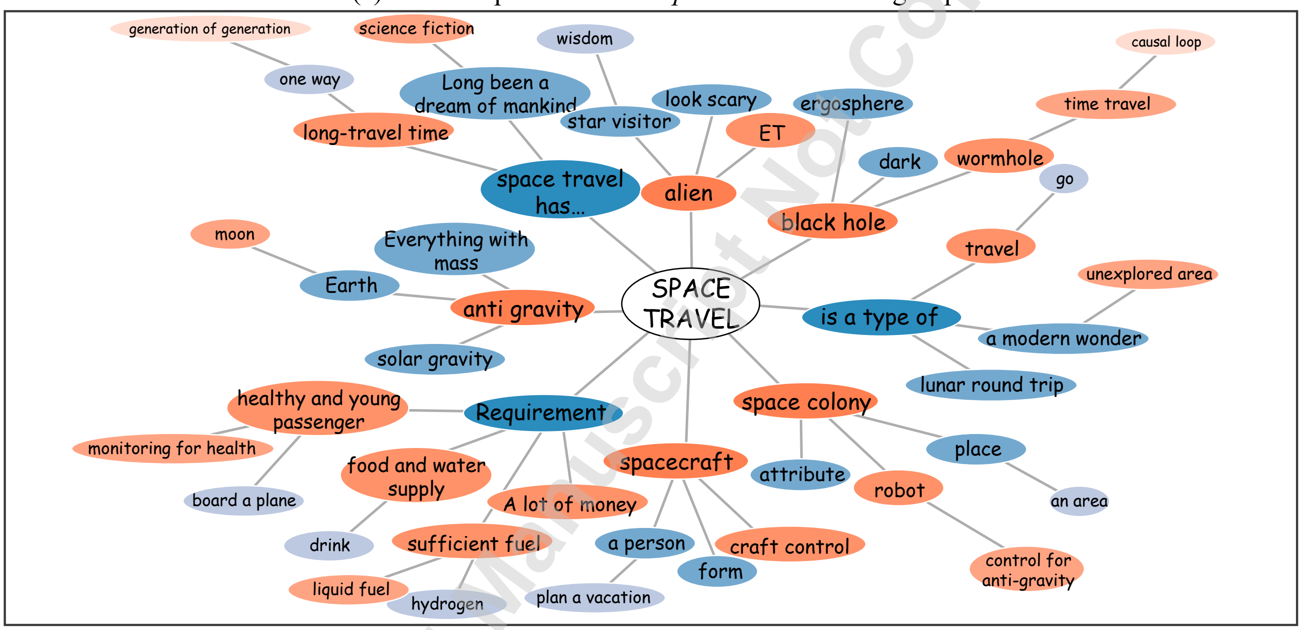


(a) Mind-map created with *Space Travel* in **HH** group



(b) Mind-map created with *Space Travel* in **HC** group

Fig. 10. Sample user created mind-maps with central topic *Space Travel* in (a) HH and (b) HC. In (b), orange nodes represent user added nodes, and blue nodes represent Mini-Map added nodes. **Note:** Reprinted from the original source [1].

conversational interactions with the user. However, the context within which these systems function is primarily information retrieval rather than exploratory ideation. To this effect, there have been a few works on mixed-initiative design for domains such as AI-assisted development of video game environments [90]. While Mini-Map nowhere close to the level of sophistication when compared to these systems, we believe that it is a starting point toward human-computer collaboration for exploratory tasks such as problem finding and problem understanding in design.

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References

[1] Chen, T.-J., Subramanian, S. G., and Krishnamurthy, V. R., 2019. "Mini-map: Mixed-initiative mind-mapping via contextual query expansion". In AIAA Scitech 2019 Forum, p. 2347.

[2] O'Connell, R. M., 2014. "Mind mapping for critical thinking". In *Cases on teaching critical thinking through visual representation strategies*. IGI Global, pp. 354–386.

[3] Kokotovich, V., 2008. "Problem analysis and thinking tools: an empirical study of non-hierarchical mind mapping". *Design studies,* **29**(1), pp. 49–69.

[4] Dinar, M., Shah, J. J., Cagan, J., Leifer, L., Linsey, J., Smith, S. M., and Hernandez, N. V., 2015. "Empirical Studies of Designer Thinking: Past, Present, and Future". *Journal of Mechanical Design,* **137**(2), 2, p. 021101.

[5] Crilly, N., 2015. "Fixation and creativity in concept development: The attitudes and practices of expert designers". *Design Studies,* **38**, 5, pp. 54–91.

[6] Crilly, N., and Cardoso, C., 2017. "Where next for research on fixation, inspiration and creativity in design?". *Design Studies,* **50**, 5, pp. 1–38.

[7] Vasconcelos, L. A., and Crilly, N., 2016. "Inspiration and fixation: Questions, methods, findings, and challenges". *Design Studies,* **42**, 1, pp. 1–32.

[8] Yannakakis, G. N., Liapis, A., and Alexopoulos, C., 2014. "Mixed-initiative co-creativity.". In FDG.

[9] Linsey, J. S., Markman, A. B., and Wood, K. L., 2012. "Design by Analogy: A Study of the WordTree Method for Problem Re-Representation". *Journal of Mechanical Design,* **134**(4), 04.

[10] Marshall, K. S., Crawford, R., and Jensen, D., 2016. "Analogy seeded mind-maps: A comparison of verbal and pictorial representation of analogies in the concept generation process". In ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, American Society of Mechanical Engineers Digital Collection.

[11] Jensen, D., Wood, K., Bauer, A., Doria, M., Perez, K., Anderson, M., and Jensen, L., 2018. "A bio-inspired mind map to assist in concept generation for wall climbing systems: Development, assessment, and resulting prototypes". In Proc. 125th ASEE Conference.

[12] Wikipedia contributors, 2019. List of concept- and mind-mapping software — Wikipedia, the free encyclopedia. `https://en.wikipedia.org/w/index.php?title=List_of_concept-_and_mind-mapping_software&oldid=913172732`. [Online; accessed 14-October-2019].

Journal of Mechanical Design. Received October 21, 2019;
Accepted manuscript posted March 11, 2020. doi:10.1115/1.4046808

[13] Speer, R., Chin, J., and Havasi, C., 2017. "Conceptnet 5.5: An open multilingual graph of general knowledge.". In AAAI, pp. 4444–4451.

[14] Liu, H., and Singh, P., 2004. "Conceptnet—a practical commonsense reasoning tool-kit". *BT technology journal,* **22**(4), pp. 211–226.

[15] Havasi, C., Speer, R., and Alonso, J., 2007. "Conceptnet 3: a flexible, multilingual semantic network for common sense knowledge". In Recent advances in natural language processing, Citeseer, pp. 27–29.

[16] Linsey, J. S., Clauss, E., Kurtoglu, T., Murphy, J., Wood, K., and Markman, A., 2011. "An experimental study of group idea generation techniques: understanding the roles of idea representation and viewing methods". *Journal of Mechanical Design,* **133**(3), p. 031008.

[17] Tolman, E. C., 1948. "Cognitive maps in rats and men.". *Psychological review,* **55**(4), p. 189.

[18] Faste, H., and Lin, H., 2012. "The untapped promise of digital mind maps". In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI '12, ACM, pp. 1017–1026.

[19] Davies, M., 2011. "Concept mapping, mind mapping and argument mapping: what are the differences and do they matter?". *Higher Education,* **62**(3), Sep, pp. 279–301.

[20] Kommers, P., and Lanzing, J., 1997. "Students' concept mapping for hypermedia design: Navigation through world wide web (www) space and self-assessment". *J. Interact. Learn. Res.,* **8**(3-4), Dec., pp. 421–455.

[21] Willis, C. L., and Miertschin, S. L., 2005. "Mind tools for enhancing thinking and learning skills". In Proceedings of the 6th Conference on Information Technology Education, SIGITE '05, ACM, pp. 249–254.

[22] Willis, C. L., and Miertschin, S. L., 2006. "Mind maps as active learning tools". *J. Comput. Sci. Coll.,* **21**(4), Apr., pp. 266–272.

[23] Faste, R. mindmapping. `http://www.fastefoundation.org/publications/mind_mapping.pdf`.

[24] Holland, B., Holland, L., and Davies, J., 2004. "An investigation into the concept of mind mapping and the use of mind mapping software to support and improve student academic performance.". University of Wolverhampton.

[25] Burke, L. A., and Miller, M. K., 1999. "Taking the mystery out of intuitive decision making". *The Academy of Management Executive,* **13**(4), pp. 91–99.

[26] Ma, F., Fan, R., Huang, C., Guo, B., Li, Z., Liu, Q., Liu, P., and He, W., 2018. "The solution of excess ingredients in hotels deduced by extensible mind mapping". In ITM Web of Conferences, Vol. 17, EDP Sciences, p. 03004.

[27] Zarzour, H., Abid, T., and Sellami, M., 2014. "Conflict-free collaborative decision-making over mind-mapping". In 2014 Fourth International Conference on Advanced Computing & Communication Technologies, IEEE, pp. 509–515.

Journal of Mechanical Design. Received October 21, 2019;
Accepted manuscript posted March 11, 2020. doi:10.1115/1.4046808

[28] Fu, K., Cagan, J., Kotovsky, K., and Wood, K., 2013. "Discovering structure in design databases through functional and surface based mapping". *Journal of mechanical Design,* **135**(3), p. 031006.

[29] Selvi, R. T., and Chandramohan, G., 2018. "Case study on effective use of mind map in engineering education". In 2018 IEEE Tenth International Conference on Technology for Education (T4E), IEEE, pp. 205–207.

[30] Zampetakis, L. A., Tsironis, L., and Moustakis, V., 2007. "Creativity development in engineering education: The case of mind mapping". *Journal of Management Development,* **26**(4), pp. 370–380.

[31] Telenko, C., Wood, K., Otto, K., Rajesh Elara, M., Foong, S., Leong Pey, K., Tan, U.-X., Camburn, B., Moreno, D., and Frey, D., 2015. "Designettes: An Approach to Multidisciplinary Engineering Design Education". *Journal of Mechanical Design,* **138**(2), 11.

[32] Chen, J., 2008. "The using of mind map in concept design". In 2008 9th International Conference on Computer-Aided Industrial Design and Conceptual Design, IEEE, pp. 1034–1037.

[33] Isaksen, S. G., Dorval, K. B., and Treffinger, D. J., 2000. *Creative approaches to problem solving: A framework for change*. Kendall Hunt Publishing Company.

[34] Kokotovich, V., 2008. "Problem analysis and thinking tools: an empirical study of non-hierarchical mind mapping". *Design studies,* **29**(1), pp. 49–69.

[35] Linsey, J., Markman, A., and Wood, K., 2012. "Design by analogy: a study of the wordtree method for problem re-representation". *Journal of Mechanical Design,* **134**(4), p. 041009.

[36] Zahedi, M., Heaton, L., et al., 2016. "Mind mapping as a tool, as a process, as a problem/solution space". In DS 83: Proceedings of the 18th International Conference on Engineering and Product Design Education (E&PDE16), Design Education: Collaboration and Cross-Disciplinarity, Aalborg, Denmark, 8th-9th September 2016, pp. 166–171.

[37] Buzan, T., 2006. *The ultimate book of mind maps: unlock your creativity, boost your memory, change your life*. HarperCollins UK.

[38] Lopes, S. F., Castro, R., and Arajo, S., 2018. "A mind-mapping front-end for text writing". In 2018 IEEE 16th International Conference on Industrial Informatics (INDIN), IEEE, pp. 1–6.

[39] Karim, R. A., and Abu, A. G., 2018. "Using mobile-assisted mind mapping technique (mammat) to improve writing skills of esl students". *Journal of Social Science and Humanities,* **1**(2), pp. 01–06.

[40] , 2013. MindMup. `https://www.mindmup.com/`.

[41] Buisine, S., Besacier, G., Najm, M., Aoussat, A., and Vernier, F., 2007. "Computer-supported creativity: Evaluation of a tabletop mind-map application". In International Conference on Engineering Psychology and Cognitive Ergonomics, Springer, pp. 22–31.

[42] Orehovački, T., Granić, A., and Kermek, D., 2011. "Exploring the quality in use of web 2.0 applications: the

Journal of Mechanical Design. Received October 21, 2019;
Accepted manuscript posted March 11, 2020. doi:10.1115/1.4046808

case of mind mapping services". In International Conference on Web Engineering, Springer, pp. 266–277.

[43] He, Y., Camburn, B., Liu, H., Luo, J., Yang, M., and Wood, K., 2019. "Mining and Representing the Concept Space of Existing Ideas for Directed Ideation". *Journal of Mechanical Design,* **141**(12), 09. 121101.

[44] Kudelić, R., Konecki, M., and Maleković, M., 2011. "Mind map generator software model with text mining algorithm". In Proceedings of the ITI 2011, 33rd International Conference on Information Technology Interfaces, IEEE, pp. 487–494.

[45] Abdeen, M., El-Sahan, R., Ismaeil, A., El-Harouny, S., Shalaby, M., and Yagoub, M. C. E., 2009. "Direct automatic generation of mind maps from text with m2gen". In 2009 IEEE Toronto International Conference Science and Technology for Humanity (TIC-STH), pp. 95–99.

[46] Elhoseiny, M., and Elgammal, A., 2012. "English2mindmap: An automated system for mindmap generation from english text". In 2012 IEEE International Symposium on Multimedia, pp. 326–331.

[47] Elhoseiny, M., and Elgammal, A., 2016. "Text to multi-level mindmaps". *Multimedia Tools and Applications,* **75**(8), Apr, pp. 4217–4244.

[48] Shi, Feng and Chen, Liuqing, 2016. B-link. `http://www.imperial.ac.uk/design-engineering/research/engineering-design/creativity/b-link/`. [Online; accessed 21-January-2020].

[49] Shi, F., Chen, L., Han, J., and Childs, P., 2017. "A Data-Driven Text Mining and Semantic Network Analysis for Design Information Retrieval". *Journal of Mechanical Design,* **139**(11), 10. 111402.

[50] Luo, J., Sarica, S., and Wood, K. L. "Computer-aided design ideation using innogps". In ASME 2019 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, American Society of Mechanical Engineers Digital Collection.

[51] Sarica, S., Luo, J., and Wood, K. L., 2020. "Technet: Technology semantic network based on patent data". *Expert Systems with Applications,* **142**, p. 112995.

[52] Novick, D. G., and Sutton, S., 1997. "What is mixed-initiative interaction". In Proceedings of the AAAI spring symposium on computational models for mixed initiative interaction, Vol. 2, p. 12.

[53] Karimi, P., Grace, K., Maher, M. L., and Davis, N., 2018. "Evaluating creativity in computational co-creative systems". *arXiv preprint arXiv:1807.09886.*

[54] Davis, N. M., Hsiao, C.-P., Singh, K. Y., and Magerko, B., 2016. "Co-creative drawing agent with object recognition". In Twelfth artificial intelligence and interactive digital entertainment conference.

[55] Alvarez, A., Dahlskog, S., Font, J., and Togelius, J., 2019. "Empowering quality diversity in dungeon design with interactive constrained map-elites". *arXiv preprint arXiv:1906.05175.*

[56] Huang, A., Chen, S., Nelson, M., and Eck, D., 2018. "Towards mixed-initiative generation of multi-channel sequential structure".

Journal of Mechanical Design. Received October 21, 2019;
Accepted manuscript posted March 11, 2020. doi:10.1115/1.4046808

[57] Nguyen, A. T., Kharosekar, A., Krishnan, S., Krishnan, S., Tate, E., Wallace, B. C., and Lease, M., 2018. "Believe it or not: Designing a human-ai partnership for mixed-initiative fact-checking". In The 31st Annual ACM Symposium on User Interface Software and Technology, ACM, pp. 189–199.

[58] Deterding, S., Hook, J., Fiebrink, R., Gillies, M., Gow, J., Akten, M., Smith, G., Liapis, A., and Compton, K., 2017. "Mixed-initiative creative interfaces". In Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems, CHI EA '17, ACM, pp. 628–635.

[59] Liapis, A., Smith, G., and Shaker, N., 2016. "Mixed-initiative content creation". In *Procedural content generation in games*. Springer, pp. 195–214.

[60] Liapis, A., Yannakakis, G. N., and Togelius, J., 2013. "Sentient sketchbook: Computer-aided game level authoring.". In FDG, pp. 213–220.

[61] Bang, H., Virós Martin, A., Prat, A., and Selva, D., 2018. "Daphne: An intelligent assistant for architecting earth observing satellite systems". In *2018 AIAA Information Systems-AIAA Infotech@ Aerospace*. p. 1366.

[62] Kotov, A., and Zhai, C., 2012. "Tapping into knowledge base for concept feedback: Leveraging conceptnet to improve search results for difficult queries". In Proceedings of the Fifth ACM International Conference on Web Search and Data Mining, WSDM '12, ACM, pp. 403–412.

[63] Miller, G. A., 1995. "Wordnet: a lexical database for english". *Communications of the ACM,* **38**(11), pp. 39–41.

[64] Osborn, A. F., 1957. "Applied imagination (rev. ed.)". *New York: Scribner*, p. 379.

[65] Mullen, B., Johnson, C., and Salas, E., 1991. "Productivity loss in brainstorming groups: A meta-analytic integration". *Basic and applied social psychology,* **12**(1), pp. 3–23.

[66] Chen, T.-J., Mohanty, R. R., Hoffmann Rodriguez, M. A., and Krishnamurthy, V. R., 2019. "Collaborative mind-mapping: A study of patterns, strategies, and evolution of maps created by peer-pairs". Vol. 7: 31st International Conference on Design Theory and Methodology of *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*.

[67] Gilon, K., Chan, J., Ng, F. Y., Liifshitz-Assaf, H., Kittur, A., and Shahaf, D., 2018. "Analogy mining for specific design needs". In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems, CHI '18, ACM, pp. 121:1–121:11.

[68] Speer, R., and Lowry-Duda, J., 2017. "Conceptnet at semeval-2017 task 2: Extending word embeddings with multilingual relational knowledge". *arXiv preprint arXiv:1704.03560.*

[69] , 2013. word2vec google news embeddings. `https://code.google.com/archive/p/word2vec/`.

[70] Pennington, J., Socher, R., and Manning, C. D., 2014. "Glove: Global vectors for word representation". In Empirical Methods in Natural Language Processing (EMNLP), pp. 1532–1543.

Journal of Mechanical Design. Received October 21, 2019;
Accepted manuscript posted March 11, 2020. doi:10.1115/1.4046808

[71] , 2008. Scoring rubric for mind maps. https://www.claytonschools.net/cms/lib/MO01000419/Centricity/Domain/206/Mind%20Map%20Rubric.pdf.

[72] Scott, W. A., 1955. "Reliability of content analysis: The case of nominal scale coding". *Public opinion quarterly*, pp. 321–325.

[73] Clark-Carter, D., 1997. *Doing Quantitative Psychological Research: From Design to Report*. Taylor & Francis, Inc., UK.

[74] Cohen, J., 1960. "A coefficient of agreement for nominal scales". *Educational and psychological measurement,* **20**(1), pp. 37–46.

[75] Landis, J. R., and Koch, G. G., 1977. "The measurement of observer agreement for categorical data". *biometrics*, pp. 159–174.

[76] Khan, A., and Rayner, G. D., 2003. "Robustness to non-normality of common tests for the many-sample location problem". *Advances in Decision Sciences,* **7**(4), pp. 187–206.

[77] Paulus, P. B., Kohn, N. W., and Arditti, L. E., 2011. "Effects of quantity and quality instructions on brainstorming". *The Journal of Creative Behavior,* **45**(1), pp. 38–46.

[78] VanGundy, A. B., 1984. "Brain writing for new product ideas: an alternative to brainstorming". *Journal of Consumer Marketing,* **1**(2), pp. 67–74.

[79] Choi, E., Bahadori, M. T., Song, L., Stewart, W. F., and Sun, J., 2017. "Gram: Graph-based attention model for healthcare representation learning". In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '17, ACM, pp. 787–795.

[80] Sternberg, R. J., and Ben-Zeev, T., 2001. *Complex cognition: The psychology of human thought.* Oxford University Press.

[81] Camburn, B., He, Y., Raviselvam, S., Luo, J., and Wood, K., 2019. "Machine learning based design concept evaluation". *Journal of Mechanical Design*, pp. 1–48.

[82] Lee, J.-H., Lee, S. H., Chung, W.-H., Lee, E. S., Park, T. H., Deaton, R., and Zhang, B.-T., 2011. "A dna assembly model of sentence generation". *BioSystems,* **106**(1), pp. 51–56.

[83] Yogatama, D., Blunsom, P., Dyer, C., Grefenstette, E., and Ling, W., 2016. "Learning to compose words into sentences with reinforcement learning". *arXiv preprint arXiv:1611.09100.*

[84] Song, H., and Fu, K., 2018. "Approaches for supporting exploration for analogical inspiration with behavior, material and component based structural representations of patent databases". In ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, American Society of Mechanical Engineers Digital Collection.

[85] Luo, J., Song, B., Blessing, L., and Wood, K., 2018. "Design opportunity conception using the total technology

Journal of Mechanical Design. Received October 21, 2019;
Accepted manuscript posted March 11, 2020. doi:10.1115/1.4046808

space map". *AI EDAM,* **32**(4), pp. 449–461.

[86] Sarica, S., Song, B., Low, E., and Luo, J., 2019. "Engineering knowledge graph for keyword discovery in patent search". In Proceedings of the Design Society: International Conference on Engineering Design, Vol. 1, Cambridge University Press, pp. 2249–2258.

[87] Song, H., and Fu, K., 2019. "Design-by-analogy: Exploring for analogical inspiration with behavior, material, and component-based structural representation of patent databases". *Journal of Computing and Information Science in Engineering,* **19**(2), p. 021014.

[88] Song, B., Luo, J., and Wood, K., 2019. "Data-driven platform design: Patent data and function network analysis". *Journal of Mechanical Design,* **141**(2), p. 021101.

[89] He, Y., Camburn, B., Luo, J., Yang, M. C., and Wood, K. L., 2019. "Visual sensemaking of massive crowdsourced data for design ideation". In Proceedings of the Design Society: International Conference on Engineering Design, Vol. 1, Cambridge University Press, pp. 409–418.

[90] Baldwin, A., Dahlskog, S., Font, J. M., and Holmberg, J., 2017. "Mixed-initiative procedural generation of dungeons using game design patterns". In 2017 IEEE Conference on Computational Intelligence and Games (CIG), pp. 25–32.

Journal of Mechanical Design. Received October 21, 2019;
Accepted manuscript posted March 11, 2020. doi:10.1115/1.4046808

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