Proceedings of the 2022 ASME International Design Engineering Technical Conferences &
Computers and Information in Engineering Conference
IDETC/CIE 2022
August 17-19, 2022, St. Louis, MO, USA

DETC2022-90697

CAPTURING DESIGNERS' EXPERIENTIAL KNOWLEDGE IN SCALABLE REPRESENTATION SYSTEMS: A CASE STUDY OF KNOWLEDGE GRAPHS FOR PRODUCT TEARDOWNS

Nicole Goridkov
Dept. of Mechanical Engineering
University of California, Berkeley
Berkeley, CA, USA
goridkov@berkeley.edu

Vivek Rao
Dept. of Mechanical Engineering
University of California, Berkeley
Berkeley, CA, USA
vivek.rao@berkeley.edu

Dixun Cui
Dept. of Mechanical Engineering
University of California, Berkeley
Berkeley, CA, USA
dixuncui@berkeley.edu

Daniele Grandi
Autodesk Research
San Francisco, CA, USA
daniele.grandi@autodesk.com

Ye Wang
Autodesk Research
San Francisco, CA, USA
ye.wang@autodesk.com

Kosa Goucher-Lambert*
Dept. of Mechanical Engineering
University of California, Berkeley
Berkeley, CA, USA
kosa@berkeley.edu

ABSTRACT

Knowledge collection, extraction, and organization are critical activities in all aspects of the engineering design process. However, it remains challenging to surface and organize design knowledge in a scalable and accessible manner given it often contains implicit or tacit dimensions that are difficult to capture. Knowledge graphs have been explored to address this issue but have been primarily semantic in nature in engineering design contexts, typically focusing on sharing explicit knowledge. In this work, we explore how knowledge graphs could offer a mechanism to organize experiential design knowledge and afford its use in complex queries. We develop a searchable knowledge graph based on data from a previous virtual product teardown activity with 23 professional designers. Examples of the underlying data within this corpus include descriptions of product components and their purpose as well as participant-determined relationships between these components. To structure the knowledge graph, we develop a schema that uses its constituent nodes and edges to represent design knowledge, relational information, and properties such as the node author's discipline and the node's function-behavior-structure classification. We propose and demonstrate two user-driven graph search types - intentional and exploratory - and four data-driven graph search methods, and illustrate through two extended examples their potential to reveal insights and patterns from teardown knowledge. These findings suggest that knowledge graphs can be a valuable approach to organizing and availing experiential design knowledge emerging from complex design activities.

1 INTRODUCTION

Design can be considered a learning process, in which knowledge is collected, synthesized, and organized to achieve an outcome [1–3]. Representations of knowledge, its organization, and transformation underpin foundational models of the engineering design process, such as the function-behavior-structure (FBS) model and C-K design theory [4,5], but the importance of knowledge in design is not simply theoretical. By Robinson's accounting, engineers spend more than 55% of their work hours acquiring or sharing knowledge [6], making knowledge organi-

*Address all correspondence to this author.

zation and structuring a critical element of engineering design practice. This is perhaps most evidenced from the importance of knowledge structuring, organization, and sharing in organizations, where it is considered a critical strategic focus and a basis of competitive advantage [7, 8].

Efforts to codify and structure engineering knowledge through knowledge graphs (KGs), like TechNet, have been very successful. However, semantic approaches like TechNet's require well-structured semantic data [9–11], what may be considered *explicit* knowledge, or knowledge that is readily expressible and transferable [12]. However, much of design knowledge results from design activities, such as prototyping or teardowns; knowledge resulting from these activities is not easily structured in an explicit manner. Such knowledge may be considered implicit, meaning that it exists internally to a designer, or tacit, meaning that it is not readily expressed externally [12]. Much of design knowledge, then, can be considered a result of what the Kolb Learning Model describes as 'experiential learning' [13], where tacit knowledge can be conveyed practically. Combining the experiential nature of design activity data with the organizational advantages of a KG could address key challenges in knowledge structuring and sourcing at both the designer and organization levels.

In this work, we explore how we might adapt KGs to capture and avail complex knowledge sourced from real engineering design activities. We seek to explore three research questions:

R1. How can we incorporate experiential design knowledge into accessible and scalable knowledge representation systems?
R2. What modes of interaction do knowledge systems describing experiential design enable for designers?
R3. How can knowledge systems describing experiential design knowledge support learning and data exploration?

To address these questions, we develop a KG based on experiential data drawn from real design activity: virtual product teardowns conducted by 23 professional designers. Product teardowns are a widely-used technique in reverse engineering to surface nuanced knowledge about a product's components, architecture and affordances [14–17], and here serve as an example of a heavily experiential design activity that could be modeled by a KG. With the KG organizing teardown data, we illustrate two user-driven search modes in extended examples and discuss the latent insights and patterns they can reveal. We also highlight four data-driven search modes that can afford insight development. The main contributions of this work are (1) presenting a novel KG grounded in experiential design data and (2) demonstrating scalable search interactions across this graph.

In this paper, we first review related work that contextualizes our study (Sec. 2). We then describe our research methodology (Sec. 3), and present and discuss results from our study, including limitations and future work (Sec. 4).

2 RELATED WORK

In this section we review related work on knowledge organization and structuring in design, KGs in engineering design, and product teardowns.

2.1 Knowledge Organization in Complex Design Activities

Engineering design and innovation has been described as a learning process [1, 16], with a designer's ability to incorporate and structure knowledge essential to shaping design outcomes [18], frame meaningful design problems [19], and connect design activities to design intent [2]. Knowledge in the design process can take many forms: from design briefs to customer interactions to institutional technical knowledge [3]. How knowledge is organized during the design process shapes not just the process itself and its immediate outcomes, but its transition to a finished product, e.g. through product architecture [20].

In order to describe how designers engage with and organize knowledge, an ontology describing design knowledge is necessary. A foundational framework in understanding knowledge during the design process is the Function, Behavior, Structure (FBS) model, which combines an ontology for understanding design knowledge [21, 22] with consideration of a designer's cognition and experience. The FBS framework has been applied to manage knowledge in a diverse range of activities across the engineering design process, from information extraction from patent databases [23] to defining product requirements [24].

Many studies have sought to describe knowledge structuring and organization during a variety of engineering design phases, from research to prototyping and manufacturing [18, 25–28]. Damen and Toh observed three modes of organization by professional designers during ideation: clusters, relations, and nests [25], and connected the mode of organization to aspects of design ideation results. How designers develop relationships between knowledge appears to shape the outcome of design activity. Previous work has explored knowledge and learning generated from reverse engineering [29]. While our earlier work described how designers organize and structure knowledge during teardowns [30], we did not explore how such knowledge could subsequently be organized, accessed, and queried to identify critical patterns and insights in a given engineering design knowledge base.

More recent work from Damen and Toh presented the Information Archetype Framework, which described the types of knowledge surfaced across the design process, and how they manifest in practice with software engineers and designers [25, 31]. Three concepts from Damen and Toh's work are important to our discussion of knowledge organization, which the authors render as balance between two levels that exist in tension. First, information source describes whether information is internal to the designer or sourced externally. Second, generality of information describes whether information is sourced from across disciplines or from a designer's own discipline. Lastly, effectuation of information describes the utilization of existing knowledge and knowledge networks (inclusive people) versus a causal engagement with the end goal of a proposed design activity, and utilization of any knowledge necessary to achieve it. Damen and Toh's research suggests that designers' ability to navigate tensions between these knowledge archetypes, what the authors call designers' trajectories, is critical to their ability to practice design.

Design of increasingly complex systems is performed in teams, and beyond how *individual* designers structure and organize knowledge, an understanding of how *organizations* structure and transfer knowledge is essential. We focus our discussion here on organizational knowledge related specifically to engineering design, as the broader topic has been reviewed in detail elsewhere [32]. McMahon et al. described a key aspect of knowledge organization behavior of firms as *codification*, where information is stored and shared digitally across the organization, as opposed to *personalization*, in which knowledge is mediated by personal relationships. One key way of distinguishing types of design knowledge is by its accessibility: explicit knowledge can be articulated externally and easily transferred; implicit knowledge exists internally to a designer and is typically involved in application; and tacit knowledge cannot be readily expressed externally, typically gained experientially [12]. Polyani and Sen stated that tacit knowledge cannot be explicitly shared [33], but Rust argued that design activities, like prototyping, can actually facilitate transfer of tacit knowledge to the explicit [34]. Knowledge may be further distinguished by content: Wallace et al. identified product design and design process knowledge as separate categories [35]. Organizations require effective ways to surface relevant information from large knowledge bases [36, 37], a challenge approached through low-intent vs high-intent data discovery methods [38]. These methods support engineers who both have specific information in mind as well as those who are unsure what they are searching for and need some guidance. Navigating, sharing, and managing knowledge is a critical source of competitive advantage for firms today [7, 8].

This study extends from previous research on design knowledge organization in two ways. First, we study how product and process knowledge generated by professional designers can be organized into a relational KG structure, affording various modes of inquiry representative of knowledge searches. Second, we probe these modes of inquiry by using the FBS ontology, designer role data, and frequencies of links as starting points. We illustrate that these modes, in turn, offer novel ways of capturing and surfacing knowledge from an engineering design activity-specific knowledge database. Finally, we consider the role of designer intention in the synthesis and navigation of such a design knowledge database. These contributions build on Damen and Toh's description of levels of knowledge, and illustrate how designers across an organization could potentially navigate large amounts of knowledge effectively.

2.2 Knowledge Graphs in Engineering Design

KGs are networks of data containing *nodes*, which store information, and *edges*, which are the relationships connecting various nodes. KGs and semantic networks have long served as important references for large sets of general information (e.g., Google, etc.), but more recently have begun playing a large role in engineering, helping accelerate innovation and design. Databases like TechNet [1] and ConceptNet [2] are designed to hold vast arrays of technical data and meet growing knowledge retrieval and sharing needs [9, 10]. Such semantic networks use natural language processing (NLP) techniques to collect data from large databases like the US Patent network (Technet) and consolidate them into a single tool. Modeling this information in a multi-domain KG that is easily navigated by algorithms enables users to access large amounts of interconnected technical data and drives novel, innovative solutions [39].

Among this range of existing KGs, semantic vs experiential graph types are particularly interesting for design. The databases mentioned above are built by extracting a large data corpus and mapping it onto a proposed ontology. While mining large databases like the patent database produces thorough semantic networks, they have limited application and can be difficult to navigate [40] at a purely semantic level. Bhatia et al. explores the importance of adding descriptive support to KGs in order to add context and support user interaction [41]. By building our KG from a detailed, interactive experience, the data is supplemented by descriptions and low-level detail that helps situate knowledge, which has been shown to aid users' understanding during information retrieval [42].

KGs have been used to support data-driven engineering design [40, 43] as well as collaboration amongst large groups like companies [44]. This particular type of KG's relevance in design has been shown to offer strong insights in product-level design [39], whereas our study explores the utilization of KGs in systems design, where various electromechanical elements are working in conjunction with one another. KGs have also begun appearing as efforts to effectively transfer design knowledge [45], a task that has been shown to be highly dependent on existing structures or practices [37]. Furthermore, studies have shown the importance of visual interactions for seeking inspiration and supporting exploration, validating the use of KGs for user-driven exploratory search [46].

In this work, we extend upon prior research studying knowledge organization in virtual product teardowns through representation and exploration of our dataset within a KG. Unlike previous KGs built for engineering design applications, our graph captures *experiential* details collected during the teardown activity,

[1] http://www.tech-net.org/
[2] https://conceptnet.io/

offering in-depth insights into what relationships people create on the same set of knowledge. Additionally, we capture the roles of the participants who contributed to the data in the KG, imparting a level of participant diversity and nuance to the graph [47]. We use the unstructured teardown data to inform the structure of our graph, which can then query domain-specific ontologies constructed through a real design activity. We are able to run user-driven queries on this graph that are systems and large-scale design-behavior specific, and present the high-level ability to execute four types of data-driven graph searches: intensity-driven, insight-driven, perspective-driven, and ontology-driven.

2.3 Product Teardowns

Designers and engineers deconstruct products, services, and systems in a process known as reverse engineering, which is practiced in a wide range of engineering domains to help designers understand how products and systems work [48–50]. Many studies focus on how reverse engineering enables designers to describe a product's physical characteristics [50], which may be considered factual knowledge about a product, its components and its architecture. However, reverse engineering has also been shown to help designers better understand and more effectively capture a product's affordances, that is the range of actions possible with a given object [17,51], which may be considered more experiential knowledge about a product [52]. Within reverse engineering, a critical practice is the product teardown, a method that systematizes the deconstruction of a product and the analysis of its constituent components [29].

Studies of product teardowns in engineering design practice have examined how teardowns integrate within a broader product engineering process. Lauff et. al, examined several sectors and observed that while some sectors - consumer electronics and medical device products - employed teardowns during product design, while another - footwear - did not [53]. Morgan and Liker describe the role of teardowns in the Toyota Production System's approach to product development [54]. Similarly, Gerhardt foregrounded the product teardown as part of the first stage of broader value engineering activities in industry practice, citing Ingersoll-Rand, Pratt & Whitney, and other firms that engage with teardowns to transfer knowledge in value engineering [55]. Gerhardt argues that teardowns are a key part of identifying opportunities in engineering design and new product development, suggesting their knowledge-generating value is unique and impactful. Junior et. al observed the centrality of product teardowns in a Brazilian auto manufacturer's workflow, and described a corporate teardown database that captured key knowledge emerging from teardowns for transfer across the organization [56]. Thus, while the teardown's centrality in engineering practice is well-understood, and many studies highlight the method's effectiveness as a source for organizational engineering design knowledge, few studies have explored how professional engineers and designers construct knowledge from product teardown activities, and how this knowledge could be organized, made actionable, and transferred.

Product teardowns have received significant attention in engineering design education research, where they are more frequently referred to as "product dissection." The method has been shown to provide experiential learning [57–59], even when conducted virtually [60]. Students are known to differ from professionals, however, in their engagement with design process [61], as they appear to leverage cross-disciplinary collaborations [62] and significant experience in manufacturing and product development [63] in their work.

In this work, we extend upon prior research on reverse engineering and product teardowns, including our previous work on organization of teardown knowledge [30] in two ways. First, while Gerhardt and Junior described that companies capture and share knowledge generated from teardowns, we examine how a novel organizational framework, KGs, could potentially offer such knowledge access in a scalable fashion. Second, we seek to explore how the uniquely experiential knowledge gained through product teardowns can inform a scalable knowledge representation approach via KGs, and illustrate its use through several extended examples.

3 RESEARCH METHODOLOGY

This section describes the methodology used to create and explore knowledge organization from product teardowns in KGs.

3.1 Teardown Study and Data Collection

The data used to build our KG was created during our previous study outlined in Wang et al. [30]. In this study, the product teardown data comes from deconstructing Bose Tenor Frames, smart sunglasses with built-in speakers and user interactivity, due to the complexity and varying components [30]. Two professional engineers and one product manager from the Teardown Library[3] performed the teardown, documenting product features, observations, and highlights. The research team curated the data to improve clarity, resulting in 24 media and 52 knowledge artifacts.

In a follow-up user study, twenty-three professionals from various backgrounds and levels of experience were recruited to organize the teardown knowledge artifacts using Mural[4]. A summary of the roles and levels of experience of the participants are summarized in Table 1. The resulting organization of the knowledge artifacts provided views on different design priorities while allowing for interesting queries and filters to see how data was arranged depending on user backgrounds.

First, the professionals were asked to group similar knowledge and media artifacts and assign names, to either groups or subgroups. The participants were instructed to create these

[3] https://teardownlibrary.com/

[4] https://www.mural.co/

TABLE 1: Overview of the domain and experience of study participants.

Role	Number of participants	Average years of experience
Electrical Engineer	1	>5 years
Mechanical Engineer	10	3 years
System Engineer	2	>5 years
CEO/Manager	2	4 years
Industrial Designer	2	>5 years
Manufacturing Engineer	6	3 years

groups based on function, behavior, or structure. Next, they were asked to link knowledge and media to each other by drawing an arrow between them and assigning a strength from one to five (slightly related to very related) and a description. Finally, the participants were asked to draw links between groups they made, also providing a description and strength. Further detail about the study protocol can be found in Wang et. al [30].

3.2 Knowledge Graph Construction

Raw data were coded using the FBS ontology, with three researchers independently categorizing each artifact. After all three researchers finished coding, differences were resolved to reach a 100-percent inter-rater reliability. After the knowledge and media were coded, the concepts with similar descriptions were consolidated. Keywords were extracted using natural language processing (NLP) from the TechNet API[5], used to generate higher-level names from the participant names. Then, three researchers categorized 159 individual concepts into 28 new consolidated concepts. Further details about consolidation of concepts can be found in Wang et. al [30].

For the input into the knowledge graph, the descriptions of links were consolidated. The categories of links and frequencies assigned are summarized in Table 2. Two categories of note are *Collaboration* and *Tradeoff*, which describe relationships where two nodes have elements which either rely on one another or must be sacrificed for one another, respectively. Knowledge nodes were classified using an additional category for labels that described the knowledge itself, a set of descriptions that was not present for group links. To categorize the links, two researchers independently classified all links according to the categories, before resolving discrepancies.

To create the KG, spreadsheets containing study data were

[5]https://github.com/SerhadS/TechNet

TABLE 2: Number of occurrences for each link type.

	Frequency of link between *concept* nodes	Frequency of link between *knowledge* nodes
Collaboration	42	26
Tradeoff	26	26
Requirement	32	27
Manufacturing-related	17	14
User needs-related	15	13
Description	-	21
Total links	125	127

formatted and imported as a csv file into Neo4j[6], an open-source graph database management system. Next, mappings were made to properties within the spreadsheets, so that they could be effectively attached to nodes and edges in the graph. Using Neo4j's native Cypher query language, the data was converted from csv files into nodes and edges within the Neo4j KG. Additional details from the spreadsheets were attached as properties of nodes and edges (Section 4.1.1). Finally, the graph in Neo4j was exported as a dump file, to be used in the Neo4j Bloom interface for easy queries.

3.3 Query Execution

Queries for the KG are executed using the Cypher query language. Templates for queries based on certain attributes were generated to allow for easy execution of similar queries (Section 4.2). Queries begin with matching certain properties to find a node or group of nodes. From there, additional operations can be performed, including searching through connected nodes and relationships.

An example of a Cypher query used to find the most-linked concept in the graph (Section 4.2.1) is listed below, to illustrate its modular nature.

```
MATCH (a) -[:LINKED_TO]->(b:Concept)
RETURN b, COLLECT(a) as Outers
ORDER BY SIZE(Outers) DESC LIMIT 1
```

This study also leveraged Neo4j's Bloom data platform[7] for visualizing various interaction modes. This tool provides near-natural language search on the KG and intuitive navigation not explicitly requiring Cypher code, easing graph navigation and representation.

[6]https://neo4j.com/
[7]https://neo4j.com/product/bloom/

4 RESULTS AND DISCUSSION

This section presents and interprets insights on the teardown KG, highlighting its capabilities. We first present and describe the schema that was used to build the experientially-based KG. Then, we explore the use of this teardown KG in enabling both intentional and exploratory modes of user-driven search, featuring these modalities with two extended examples. Finally, we present four search lenses that leverage the experiential nature of the KG.

4.1 Knowledge Graph Schema

In order to situate the teardown data in a KG, we propose the schema in Figure 1. This identifies the four node types found in the KG: *knowledge, media, consolidated concepts*, and *concepts*. *Knowledge* and *media* both exist as raw data generated during the product teardown activity. The *consolidated concepts*, *concepts*, and edge types were established by a separate set of participants in the knowledge organization portion of the previous study (Section 3.2). *Concepts* are groups of *knowledge*, *media*, and/or other *concepts*. *Consolidated concepts* are high-level groupings of *concepts*. Examples of each node type appear in Figure 1, with further examples listed here: *consolidated concept* - ”Housing”, *concept* - ”Enclosure Design”, and *knowledge* - ”One piece effective bi-stable hinge design”. Additionally, the two edge types are identified: *relates* and *belongs*. *Relates* refers to the direct linking between two nodes, while *belongs* refers to the nesting of one node under another, following ontology proposed by Damen and Toh [25]. Edges categorized as *belongs* are directed, while edges categorized as *relates* are undirected. Figure 1 identifies the relationships that exist within the KG and visualizes the hierarchical relationship between the node types.

4.1.1 Graph Properties

The KG combines the experiential nature of the teardown study with ontology-based data coding and consolidation. These features manifest themselves as properties of the graph. Table 3 shows the properties of each node type. The Product property associates the node to the specific product it refers to, while Name and Description are used as individual node identifiers. FBS is used to encode specific nodes according to this ontology. Role refers to the job and years of experience that the participant who encoded a specific node held. Table 4 shows the properties of each edge type. Description appears as a label explaining the reason why two nodes were connected by participants using the *relates* link. The edges also identify the Role and years of experience of the participant who created them. The Strength property refers to a participant-rated strength value of the connection between its two nodes. Finally, the Type property refers to the consolidated code assigned to the edge, summarized in Table 2. Here, we have transformed our data into an accessible and scalable representation, with properties that enable insightful graph traversal, as seen in the next

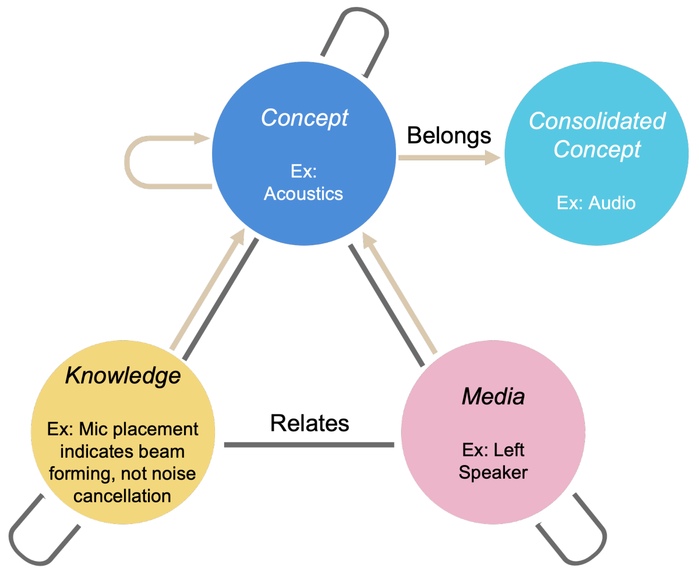

FIGURE 1: Guiding schema of the teardown KG. Nodes and edges are color coded to their type (*Consolidated Concept* - light blue, *Concept* - dark blue, *Knowledge* - yellow, *Media* - pink, *Relates* - gray, and *Belongs* - beige). Examples for each node type appear below their labels for clarity.

section.

TABLE 3: Node properties in the KG. Note that *media* nodes contain images and illustrations from the teardown activity.

	Product	Name	Description	FBS	Role
Consolidated Concept	✓	✓			
Concept	✓	✓		✓	✓
Knowledge	✓		✓	✓	
Media	✓		✓	✓	

TABLE 4: Edge properties in the KG. The additional properties from those in Table 3 are Strength (participant-assigned value of how related two nodes are) and Type (see Table 2).

	Product	Description	Role	Strength	Type
Relates	✓	✓	✓	✓	✓
Belongs	✓				

4.2 Graph Search Methods

Given the various node properties of the graph, we envision this graph will serve as a tool to execute queries in order to filter through the data and find specific insights. We present these queries as modular Cypher searches, which can be combined to answer complex questions on the teardown data, as seen in the extended examples. Queries for both intentional and exploratory search are presented, allowing graph users to find both answers to specific questions as well as use the graph as a tool to explore the teardown data meaningfully.

4.2.1 User-Driven Intentional Search

Navigating the graph with a specific query in mind is enabled by the intentional search features of the dataset. These provide results to directed questions that may arise from product teardowns or experiential activities as a whole, which many designers use as tools to discover and understand existing products' designs. In this section, we propose several envisioned search queries and user interactions that are driven by the graph properties and which leverage the experiential nature of the graph, and then situate them in an extended example (Section 4.2.2).

FBS Ontology. The graph can be filtered to see nodes tagged under a specific FBS heading, in order to find the important functions, structures, or behaviors of the product. This supports the idea that teardowns are commonly used to discover a product's architecture and leverages one of the driving ontologies of the previous study (Section 2.3) [30].

Most-Linked Nodes. The graph can find the most-linked nodes (i.e. most linked *concept*, most linked *knowledge node*, etc.) in order to see which features are most heavily connected within the graph. This query allows users to view which components are most connected and thus seen as important across a diversity of participants and roles. In dissecting a complex electromechanical product like the smart glasses, recognizing which features stand out across domains is an important step in understanding product anatomy.

Tradeoff or Collaboration Links. The graph can also be navigated through the connections between nodes to find links classified as tradeoffs or collaborations in order to highlight where important design decisions and sacrifices must be made. The ability to search the graph by link type helps users learn more about design intent and why certain features are designed that way relative to neighboring features. These links can be considered important decision-making areas.

Participant Role or Experience. The graph can be filtered for nodes appearing by participant role (manager, engineer, etc.) or by participant experience (in years) in order to learn how diversity in participants brings new paths and connections to the graph. This allows different organizational techniques to come together and inform the graph, accentuating the various perspectives that different levels of experience and unique careers bring to knowledge formation.

Strength of Connections. Finally, the strength of connections within the graph can be used in order to find and rank the most important paths in the knowledge base. This metric can be used by considering the participant-ranked relationship strengths, which provides insights into connections the participants found particularly significant. Additionally, the strength metric can be calculated through either the number of unique paths between a start and end node or by the number of unique contributors to a particular path or subsection of the graph. Both of these metrics are indicators that those particular connections were consistently produced among the variety of participants.

4.2.2 Extended Example: User-Driven Intentional Search

By combining many of the envisioned search queries above, we look to enable users to learn through intentional search, navigating the graph to answer specific queries. We envision that the KG can serve many purposes to designers, from enabling analogical inspiration to gauging existing products. Here, we explore an example centered around intentional search, showcasing the many insights and abilities our KG holds for benchmarking an existing product. Because of the "smart" nature of the product dissected in the teardown, we can infer that an important feature will be the *battery* that runs the specialized features of the glasses.

We begin by looking at the question "Which elements are dependent on the battery?", a query a designer might be interested in learning more about. By querying for *battery* and finding its related *concepts*, we identify groups that are directly relevant to the high-level idea of the *battery*. Next, we explore a level of *concepts* further away, filtering for relations which are classified as *collaborations* or *tradeoffs*. Now, we've identified the specific *concepts* that are considered interconnected with or tradeoffs with the battery, and want to abstract one level further, in order to get a clearer understanding of which high-level *consolidated concepts* answer our initial query. Navigating the graph shows us the final elements that are dependent on the battery functioning and the result to our query: *Audio, Logic board, Cost, Housing, Weight, Right assembly* (Figure 2). These elements are represented as nodes in Figure 2, appearing as the outermost light-blue nodes.

We rate the strength of our results using the metric of number of unique paths. Here, we count how many unique paths exist between a start and end node, with a higher number of paths indicating more participants created relationships between these nodes. In this case, our start node is always *battery* and our end nodes are each of the 6 results mentioned above. As seen in Figure 2, the audio node is ranked as the strongest result with 4 unique paths between it and the *battery*. These 4 pathways are highlighted in green to show their prominence in the overall results. Users can explore the pathways between the two nodes to learn more low-level details of the importance of this connection.

Finally, there are 8 unique contributors to this overall resulting graph across 5 unique roles, exemplifying the diversity of participants involved in this knowledge organization process. This suggests the importance of curating knowledge from different backgrounds to account for varying design priorities, captur-

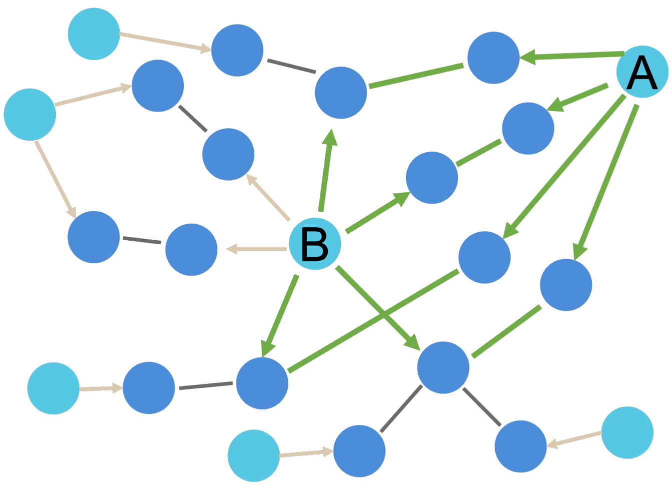

FIGURE 2: Intentional search query results, showing the small portion of the graph relevant to our search. The battery node is labeled B, and the results to our query appear as the outermost light blue nodes. The strongest result is the audio node, given 4 unique paths starting from battery (labeled B) and ending at audio (labeled A). These paths are highlighted in green in the graph. Note, each node contains text that is legible to user but does not appear in the figure for visualization purposes.

ing both very common threads as well as unique perspectives.

Implications. These findings suggest that the intentional search capabilities of this KG can support knowledge retrieval from a design organization activity, and have several implications for organization and management of engineering design knowledge. First, at the level of an individual designer, specific to Wallace et al.'s concept of product knowledge [35] and to product teardowns especially, intentional search of our KG can help designers uncover design intent and understand a product's affordances. This can facilitate the key objectives of product teardowns [17, 51].

Second, also at the level of an individual designer, intentional search as illustrated here can help navigate the inherent tensions in levels of information that Damen and Toh identified in the engineering design process [31]. In particular, queries related to *roles* could allow designers to navigate tensions in generality of information, by easily accessing information disciplinarily distinct from their own roles; in our example, a single query accessed knowledge generated by 5 different roles. Intentional queries could also allow designers to more easily navigate tensions related to levels of effectuation of information (effectuation and causation), by allowing them to rapidly iterate on various modes of understanding an existing knowledge base, rather than awaiting acquisition of new knowledge to support their goal.

Lastly, at the level of organizations, the intentional search presented here offers a way for organizations to connect open-ended, nonspecific queries with detailed engineering design knowledge related to both product design and design process. Particularly intriguing is the possibility for KGs like ours to avail implicit or tacit knowledge across organizations beyond specific engineering design contexts. This builds upon the capabilities of current semantic networks built for engineering design, which are well-supplied with explicit, easily-transferable information, but lack this critical element of detailed, implicit knowledge. Additionally, our KG's descriptive and accessible properties add a dimension not commonly seen in the current KG space. Following Rust, design activities can transfer tacit knowledge to the explicit [34]; however, there is a limited number of collaborators who could participate in a product teardown. Generating a KG grounded in design activities could connect tacit knowledge across an organization in valuable ways.

4.2.3 User-Driven Exploratory Search

Apart from very directed queries, the graph also supports more undirected exploration. This lends itself to users spontaneously finding insights and supports the open-ended, fact-finding nature of product dissections. In this section, we propose several pattern structures that hold interesting design implications, situating them in an extended example.

Collaborations and Tradeoff Triangles. The graph can identify collaboration and tradeoff triangles to find elements that are heavily interconnected. These triangles ($A \to B \to C \to A$) indicate critical decision-making areas where some elements must be sacrificed for others, a useful tool in identifying design intent. Because these chains of connections are rated in strength by the study participants, we can calculate the total strength, or cost, of each triangle in order to find which areas are considered more strongly connected or important to engineers and designers.

Collaboration/Tradeoff Patterns with FBS Grouping. We can discover tradeoff or collaboration patterns that are tied to FBS grouping, allowing for additional patterns that expose critical decision-making areas and pathways. For example, given that pathway A is a tradeoff of B and B is reliant on C, we infer that A is reliant on C and establish a new important link. An example is shown in Figure 3, where the behavior-classified *concept* of Works-Like (left) is a tradeoff of the structure-classified *concept* of Assembly/Manufacturing of a Prototype (middle). The middle node is reliant on Engineering Validation Tests (right) and therefore creates a new inferred collaboration link between the outer two nodes, generating new knowledge from the graph by emphasizing the need to have operational "works-like" models in order to complete the validation tests run on these prototypes. The detailed KG also contains descriptions for links, providing a level of rationale behind these connections. Exploring these various relationship types among specific FBS types can expanded to longer pattern pathways and drives insights into understanding design intent. An example of this is explored in Section 4.2.4.

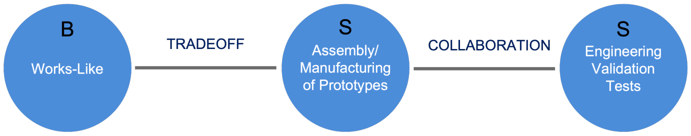

FIGURE 3: Subsection of the graph showing an example of a linear pattern highlighting a tradeoff-collaboration relationship. The Works-Like *concept* (left) is a tradeoff of the Assembly/Manufacturing of a Prototype *concept* (middle). Finally, the middle node is labeled as reliant on Engineering Validation Tests *concept* (right), creating a new inferred link between the outer two nodes.

4.2.4 Extended Example: User-Driven Exploratory Search

This KG enables users to learn through open, exploratory search, browsing the graph in an undirected fashion in order to learn about the product. Here, we present an example centered around exploratory search, using the various tools and filters this graph provides. Given that the smart glasses are wearables, we can infer that an important feature will be the *lightweight* nature of the product.

We begin by looking at the question "What can I learn about the lightweight aspect of these smart glasses?". The natural language capabilities of Neo4j Bloom allow us to query the term *lightweight* and explore connected nodes. While a user may freely explore by observing relationships around the lightweight node, we will focus on exploring patterns that appear in the data.

Structure-behavior tradeoffs. In this pattern, we wish to utilize the FBS ontology and link classifications to learn more about these relationships. To begin, we have a desired behavior we wish to achieve (*lightweight*) and want to learn which structures are important towards achieving this behavior. We search for a structure-behavior tradeoff pattern linked to our desired behavior node and learn that the right temple structure is important (Figure 4), with the graph providing an image of the temple area directly from the teardown activity. In Figure 4, we see the detailed pathway and nodes connecting our desired behavior and its supporting structure, and have the ability to abstract a level to the *concept* level to learn about the higher-level structure that is playing a role in this behavior, in this case, the glasses' frame. This pattern opens up the graph to explore these relevant areas and provides link descriptions to justify why this pattern appears.

Shortest Path. In order to learn more about how our data is connected, we can choose two nodes of interest and view the shortest path between them. This pattern unearths the elements connecting pieces of interest and can provide clarity in the context of a product teardown. In this example, we explore how the idea of being *lightweight* connects to the important *battery* component (Figure 5). Through this path, we learn about the relevance of the battery size to the lightweight aspect of the glasses and gain awareness of the design choices made for the user.

Implications. Many salient implications of intentional

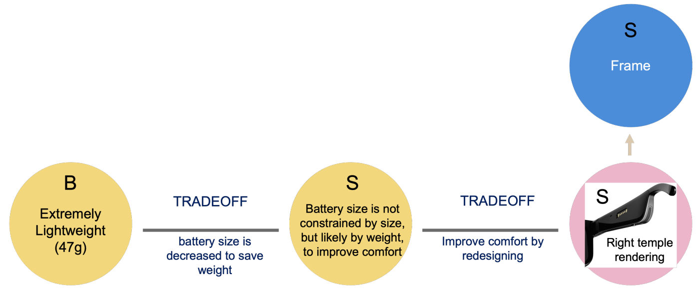

FIGURE 4: Example of a structure-behavior tradeoff connected to our *lightweight* node of interest. Starting at the *lightweight* node on the bottom left, the pathway is shown with edge descriptions to show the detailed justification of connections to a related structure, the glasses' right temple.

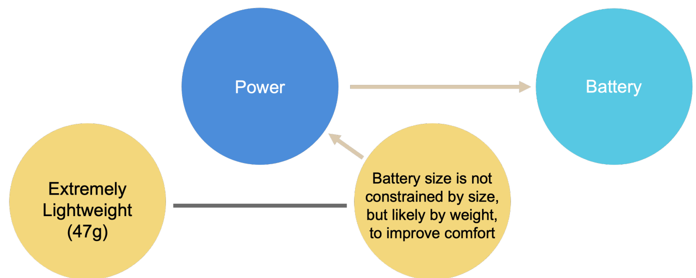

FIGURE 5: The shortest path between two nodes of interest (*lightweight* on the bottom left and *battery* on the top right) highlights the connections participants create between major elements of the teardown.

search described earlier apply to exploratory search as well: enabling more effective discovery of product architecture and affordance during teardowns; helping designers navigate tensions between levels of information; and more readily availing design-specific and implicit or tacit knowledge across an organization. There are several implications specific to exploratory search capabilities of this KG, however. First, extending on previous findings by Li et al. that suggest KGs can be used to drive novelty in product design [39]. In particular, navigating the graph using the proposed patterns can aid in clarifying design intent and identifying critical decision-making areas. This connection highlights the support that KGs provide in using teardown information to identify areas of value and opportunity in engineering design. Second, exploratory search via the proposed "shortest path" pattern can particularly afford a balance between effectuation of knowledge and causation [31] by having a designer articulate an open-ended question (causation), then assembling existing knowledge in the most efficient manner (effectuation) to address it. Finally, while many other engineering KGs allow for exploratory search of their data, the nature of our teardown KG builds upon these KGs by facilitating clarity of connections between multiple nodes, and incorporating visualizations and media that support the descriptive nature of the graph.

4.3 Experiential Data-driven Search

While the previous sections have focused on searches begun by a user's inquiry - either an intentional, specific question, or an exploratory, open-ended one - here we consider how experiential data embedded in the KG alone can offer compelling insights. We present four high-level search lenses to illustrate this capacity: intensity-driven, insight-driven, perspective-driven, and ontology-driven search. These lenses on our KG demonstrate the value of building and detailing an experiential KG for both directed and undirected graph exploration: the constituent data of the graph itself, independent of an intentional or exploratory query, can offer insight.

Intensity-Driven Search By identifying which pathways are most frequently used or which nodes are most highly connected, this graph highlights commonalities among a large range of participants. For example, identifying that *audio* and *battery* are two of the most connected *consolidated concepts* in the smart glasses KG could draw designers' attention to these and naturally highlight their prominence in the product. By featuring recurring connections, the graph uncovers the major components of a product and emphasizes elements that are considered of relevance across many disciplines, potentially aiding future tools looking to automate knowledge retrieval of highly important product attributes.

Insight-Driven Search Navigating the graph by edge types (i.e. tradeoffs, collaborations etc.) can lead to valuable insights on knowledge that is inductively linked and can highlight where important decision making areas appear. Adding the depth of link descriptions to the graph layers on an important level of design rationale and provides details rooted in the experiential nature of the data. These queries help provide understanding of the design rationale that went into the product being dissected and support the transfer of an unstructured experiential dataset to a searchable graph.

Perspective-Driven Search The variety of participants in the knowledge organization activity means that diverse opinions are proxied by different roles from the searcher's own. For instance, comparing the pathways that an electric engineer creates as opposed to an industrial designer can provide role-based perspective to portions of the KG, and identifying queries that weave together many roles and participants provides range in results. The ability to bring together a wide set of viewpoints and levels of experience, while still maintaining the small, detailed nature of this graph, allows for unique results to be discovered while differentiating the graph from larger-scale semantic networks.

Ontology-Driven Search Using the FBS ontology to organize and categorize the data allows for graph users to consider specific design decisions that need to be made and consequently search on those. For example, a designer who is focused on design intent may wish to search based on *function* nodes, while a designer focused on a product's makeup will wish to search based on *structure* nodes. In this way, the graph is able to provide levels of design understanding and rationale in an algorithmic fashion.

4.4 Future Work and Limitations

This paper provides a foundation for future work hoping to leverage KGs to support knowledge organization and exploration. First, we can conduct user studies of the knowledge graph to further explore the modes designers and organizations interact with knowledge organization, both with and without a KG. Second, the current data collection process can be time consuming, which restricts the number of insights and products included the graph. Future work might leverage the current findings as a guide for collecting specific design knowledge data from other sources, such as online repositories of design challenges, or at the time of creation in CAD and other design tools. Last, NLP could be leveraged to automatically classify links and entities in the graph. Automated collection of design data, on the order of 1000 products, might enable the use of graph neural networks for deriving latent feature representations of entities and relations. This would enable retrieval of implicit knowledge beyond current methods of querying for explicit knowledge, and support tasks such as style transfer, similarity search, and unsupervised learning of unstructured design knowledge.

Future work might compare direct knowledge extraction from design activities against other automated large-scale knowledge extractions methods, from sources such as patent databases or Wikipedia. Leveraging the underlying explicit relationships contained in existing semantic KGs might help automate the construction of the graph schema, as well as support unsupervised classification of entities and relationships.

5 CONCLUSION

In this work, we developed a knowledge graph based on experiential data from a previous product teardown activity. Leveraging the knowledge graph, we demonstrated user-driven and data-driven search patterns to extract insights from the experiential nature of the data and support knowledge transfer of implicit or tacit information. By transforming unstructured design data into a structured, easily traversable tool, we support knowledge retrieval and sharing. These findings enable valuable insights into design intent and innovation, and how to structure and share knowledge in complex design activities and organizations.

ACKNOWLEDGMENT

This work has been partially supported by the Regents of the University of California. We would like to thank Autodesk Tech Centers, Autodesk Research, and the Teardown Library for facilitating the data collection.

REFERENCES

[1] Beckman, S. L., and Barry, M., 2007. "Innovation as a learning process: Embedding design thinking". *California management review,* ***50***(1), pp. 25–56.

[2] Mistree, F., Smith, W., Bras, B., Allen, J., Muster, D., et al., 1990. "Decision-based design: a contemporary paradigm for ship design". *Transactions, Society of Naval Architects and Marine Engineers,* ***98***(1990), pp. 565–597.

[3] Heisig, P., Caldwell, N. H., Grebici, K., and Clarkson, P. J., 2010. "Exploring knowledge and information needs in engineering from the past and for the future–results from a survey". *Design studies,* ***31***(5), pp. 499–532.

[4] Qian, L., Gero, J. S., et al., 1996. "Function-behavior-structure paths and their role in analogy-based design". *AI EDAM,* ***10***(4), pp. 289–312.

[5] Hatchuel, A., and Weil, B., 2009. "Ck design theory: an advanced formulation". *Research in engineering design,* ***19***(4), pp. 181–192.

[6] Robinson, M. A., 2010. "An empirical analysis of engineers' information behaviors". *Journal of the American Society for information Science and technology,* ***61***(4), pp. 640–658.

[7] Barão, A., de Vasconcelos, J. B., Rocha, Á., and Pereira, R., 2017. "A knowledge management approach to capture organizational learning networks". *International Journal of Information Management,* ***37***(6), pp. 735–740.

[8] Adams, M., and Oleksak, M., 2010. *Intangible Capital: Putting Knowledge to Work in the 21st-Century Organization: Putting Knowledge to Work in the 21st-Century Organization*. ABC-CLIO.

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

[10] Speer, R., Chin, J., and Havasi, C., 2017. "Conceptnet 5.5: An open multilingual graph of general knowledge". In Thirty-first AAAI conference on artificial intelligence.

[11] Murphy, J., Fu, K., Otto, K., Yang, M., Jensen, D., and Wood, K., 2014. "Function based design-by-analogy: a functional vector approach to analogical search". *Journal of Mechanical Design,* ***136***(10).

[12] Wölfel, C., 2008. "How industrial design knowledge differs from engineering design knowledge". In DS 46: Proceedings of E&PDE 2008, the 10th International Conference on Engineering and Product Design Education, Barcelona, Spain, 04.-05.09. 2008.

[13] Kolb, D. A., 2014. *Experiential learning: Experience as the source of learning and development*. FT press.

[14] Otto, K., and Wood, K., 1996. "A reverse engineering and redesign methodology for product evolution". In Proceedings of the 1996 ASME Design Theory and Methodology Conference, Vol. 96.

[15] Otto, K. N., and Wood, K. L., 1998. "Product evolution: a reverse engineering and redesign methodology". *Research in engineering design,* ***10***(4), pp. 226–243.

[16] Otto, K. N., et al., 2003. *Product design: techniques in reverse engineering and new product development*.

[17] Maier, J. R., and Fadel, G. M., 2009. "Affordance-based design methods for innovative design, redesign and reverse engineering". *Research in Engineering Design,* ***20***(4), pp. 225–239.

[18] Brun, J., Le Masson, P., Weil, B., et al., 2018. "Getting inspiration or creating inspiration? the role of knowledge structures in idea generation". In DS 92: Proceedings of the DESIGN 2018 15th International Design Conference, pp. 1793–1804.

[19] Harfield, S., 2007. "On design 'problematization': Theorising differences in designed outcomes". *Design Studies,* ***28***(2), pp. 159–173.

[20] Ulrich, K., 1995. "The role of product architecture in the manufacturing firm". *Research policy,* ***24***(3), pp. 419–440.

[21] Gero, J. S., 1990. "Design prototypes: a knowledge representation schema for design". *AI magazine,* ***11***(4), pp. 26–26.

[22] Gero, J. S., and Kannengiesser, U., 2004. "The situated function–behaviour–structure framework". *Design studies,* ***25***(4), pp. 373–391.

[23] Valverde, U. Y., Nadeau, J.-P., and Scaravetti, D., 2017. "A new method for extracting knowledge from patents to inspire designers during the problem-solving phase". *Journal of Engineering Design,* ***28***(6), pp. 369–407.

[24] Zha, X. F., and Sriram, R. D., 2006. "Platform-based product design and development: A knowledge-intensive support approach". *Knowledge-Based Systems,* ***19***(7), pp. 524–543.

[25] Damen, N. B., and Toh, C. A., 2020. "From information to ideas: How designers structure information to support idea generation". In ASME 2020 IDETC/CIE, ASME Digital Collection.

[26] Damen, N. B., and Toh, C. A., 2019. "Investigating information: A qualitative analysis of expert designers' information representation and structuring behaviors". In ASME 2019 IDETC/CIE, ASME Digital Collection.

[27] Kleinsmann, M., Maier, A., Roschuni, C., Goodman, E., and Agogino, A. M., 2013. "Communicating actionable user research for human-centered design". *Artificial Intelligence for Engineering Design, Analysis and Manufacturing: AI EDAM,* ***27***(2), p. 143.

[28] Tomko, M., Schwartz, A., Newstetter, W., Alemán, M., Nagel, R., and Linsey, J., 2018. ""'a makerspace is more than just a room full of tools": What learning looks like for female students in makerspaces". In IDETC/CIE, Vol. 51845, ASME, p. V007T06A036.

[29] Dalrymple, O. O., Sears, D. A., and Evangelou, D., 2011. "The motivational and transfer potential of disas-

semble/analyze/assemble activities". *Journal of Engineering Education,* ***100***(4), pp. 741–759.

[30] Wang, Y., Grandi, D., Cui, D., Rao, V., and Goucher-Lambert, K., 2021. "Understanding professional designers' knowledge organization behavior: A case study in product teardowns". In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Vol. 85420, American Society of Mechanical Engineers, p. V006T06A046.

[31] Damen, N. B., and Toh, C. A., 2021. "Reflections on designing in the wild: How theories of design information manifest in practice". In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Vol. 85420, American Society of Mechanical Engineers, p. V006T06A041.

[32] Attar, M. M., 2020. "Organizational culture, knowledge sharing, and intellectual capital: directions for future research". *International Journal of Business and Economics Research,* ***9***(1), pp. 11–20.

[33] Polanyi, M., and Sen, A., 2009. *The tacit dimension*. University of Chicago press.

[34] Rust, C., 2004. "Design enquiry: Tacit knowledge and invention in science". *Design issues,* ***20***(4), pp. 76–85.

[35] Wallace, K., Ahmed, S., and Bracewell, R., 2005. "Engineering knowledge management". In *Design process improvement*. Springer, pp. 326–343.

[36] Yassine, A., and Braha, D., 2003. "Complex concurrent engineering and the design structure matrix method". *Concurrent Engineering,* ***11***(3), pp. 165–176.

[37] Boston, O., Culley, S., McMahon, C., et al., 1998. "Design information issues in new product development". In *The design productivity debate*. Springer, pp. 231–254.

[38] Maher, A., 2020. How we improved data discovery for data scientists at spotify, February. [Online; posted 27-February-2020].

[39] Li, X., Chen, C.-H., Zheng, P., Wang, Z., Jiang, Z., and Jiang, Z., 2020. "A knowledge graph-aided concept–knowledge approach for evolutionary smart product–service system development". *Journal of Mechanical Design,* ***142***(10), p. 101403.

[40] Hao, J., Zhao, L., Milisavljevic-Syed, J., and Ming, Z., 2021. "Integrating and navigating engineering design decision-related knowledge using decision knowledge graph". *Advanced Engineering Informatics,* ***50***, p. 101366.

[41] Bhatia, S. K., Dwivedi, P., and Kaur, A., 2018. "That's interesting, tell me more! finding descriptive support passages for knowledge graph relationships". In SEMWEB.

[42] Tombros, A., and Sanderson, M., 1998. "Advantages of query biased summaries in information retrieval". In Proceedings of the 21st annual international ACM SIGIR conference on Research and development in information retrieval, pp. 2–10.

[43] Feng, Y., Zhao, Y., Zheng, H., Li, Z., and Tan, J., 2020. "Data-driven product design toward intelligent manufacturing: A review". *International Journal of Advanced Robotic Systems,* ***17***(2), p. 1729881420911257.

[44] Carbone, F., Contreras, J., Hernández, J. Z., and Gomez-Perez, J. M., 2012. "Open innovation in an enterprise 3.0 framework: Three case studies". *Expert Systems with Applications,* ***39***(10), pp. 8929–8939.

[45] Huet, A., Pinquié, R., Véron, P., Mallet, A., and Segonds, F., 2021. "Cacda: A knowledge graph for a context-aware cognitive design assistant". *Computers in Industry,* ***125***, p. 103377.

[46] Song, H., and Fu, K., 2022. "Design-by-analogy: Effects of exploration-based approach on analogical retrievals and design outcomes". *Journal of Mechanical Design*, pp. 1–44.

[47] Li, X., Chen, C.-H., Zheng, P., Jiang, Z., and Wang, L., 2021. "A context-aware diversity-oriented knowledge recommendation approach for smart engineering solution design". *Knowledge-Based Systems,* ***215***, p. 106739.

[48] Samuelson, P., and Scotchmer, S., 2001. "The law and economics of reverse engineering". *Yale LJ,* ***111***, p. 1575.

[49] Raja, V., and Fernandes, K. J., 2007. *Reverse engineering: an industrial perspective*. Springer Science & Business Media.

[50] Lefever, D., and Wood, K., 1996. "Design for assembly techniques in reverse engineering and redesign". In ASME Design Theory and Methodology Conference, pp. 1–28.

[51] Keller, R. K., Schauer, R., Robitaille, S., and Pagé, P., 1999. "Pattern-based reverse-engineering of design components". In Proceedings of the 21st international conference on Software engineering, pp. 226–235.

[52] Pucillo, F., and Cascini, G., 2014. "A framework for user experience, needs and affordances". *Design Studies,* ***35***(2), pp. 160–179.

[53] Lauff, C. A., Kotys-Schwartz, D., and Rentschler, M. E., 2018. "Design methods used during early stages of product development: Three company cases". In IDETC/CIE, Vol. 51845, ASME, p. V007T06A002.

[54] Morgan, J., and Liker, J. K., 2020. *The Toyota product development system: integrating people, process, and technology*. CRC Press.

[55] Gerhardt, D. J., and Rand, P., 2006. "Managing value engineering in new product development". *Value world,* ***29***(2), p. 26.

[56] Junior, I. R. M., Ogliari, A., and Back, N., 2007. "Guidelines for reverse engineering process modeling of technical systems". In *Complex Systems Concurrent Engineering*. Springer, pp. 23–30.

[57] Sheppard, S., Jenison, R., Agogino, A., Brereton, M., Bocciarelli, L., Dally, J., Demel, J., Dym, C., Evans, D., and Faste, R., 1997. "Examples of freshman design education".

International Journal of Engineering Education, ***13***(4), pp. 248–261.

[58] Bhatnagar, A., 2015. "Product dissection: A method for hands on engineering education". *Journal Of Engineering Education Transformations*, pp. 99–104.

[59] Simpson, T. W., and Thevenot, H. J., 2005. "Using product dissection to integrate product family design research into the classroom and improve students' understanding of platform commonality". In ASME 2005 IDETC/CIE, ASME Digital Collection, pp. 375–382.

[60] Starkey, E. M., Spencer, C., Lesniak, K., Tucker, C., and Miller, S. R., 2017. "Do technological advancements lead to learning enhancements?: An exploration in virtual product dissection". In IDETC/CIE, Vol. 58158, ASME, p. V003T04A005.

[61] Becker, K., Gero, J., Pourmohamadi, M., Abdellahi, S., Almeida, L., and Luo, Y., 2018. "Quantifying differences between professional expert engineers and engineering students designing: Empirical foundations for improved engineering education". In ASEE Annual Conference & Exposition, Salt Lake City, Utah: ASEE2018 Paper ID, Vol. 21338.

[62] Chandrasegaran, S. K., Ramani, K., Sriram, R. D., Horváth, I., Bernard, A., Harik, R. F., and Gao, W., 2013. "The evolution, challenges, and future of knowledge representation in product design systems". *Computer-aided design*, ***45***(2), pp. 204–228.

[63] Friedman, K., 2003. "Theory construction in design research: criteria: approaches, and methods". *Design studies*, ***24***(6), pp. 507–522.