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UNDERSTANDING PROFESSIONAL DESIGNERS' KNOWLEDGE ORGANIZATION BEHAVIOR: A CASE STUDY IN PRODUCT TEARDOWNS

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ABSTRACT

Knowledge organization is an essential component of engineering design, and a deeper understanding of how designers organize knowledge could enable more effective insights in support of the design process. To explore this, we examine 23 professional designers' knowledge organization practices as they virtually engage with data collected during a teardown of a consumer product. Designers organized this data by forming groups of related data, nesting subgroups of data within groups, and creating directional links between groups of data and individual data. Our results indicate three insights about how designers organize and acquire knowledge from product teardowns. First, we observe that while designers find grouping data to be more effective for learning, linking proved more helpful for knowledge transfer. Second, we find that designers employ links between data much more frequently than they do nests, and that links primarily serve to identify trade-offs, requirements, and opportunities for team collaboration. Finally, a graph analysis indicates that design features, product housing, cost, and manufacturing coexist as separate but central groups in designers' knowledge organization, reflecting the diversity of perspectives on knowledge organization emergent in a constrained teardown activity. These findings provide insight into professional designers' knowledge organization practices, and represent a preliminary step toward design knowledge bases that more accurately reflect designer behavior, ultimately enabling more effective data-driven support tools for design.

1 Introduction

Acquiring and applying knowledge is a foundational activity of the design process [1], and effective organization of that knowledge promises more effective design outcomes [2, 3]. In particular, knowledge structuring is highly impactful both when optimizing existing designs [4] and when envisioning entirely new ones [5, 6]. Here we define knowledge organization as how knowledge is structured and connected around core concepts to enable a designer to interpret new information and capture new knowledge [7, 8]. Numerous studies have examined how knowledge structuring affects the outcomes of design activities such as idea generation [9] and user feedback [10]. However, to effectively structure their knowledge, engineers and designers must navigate a large space of complex information [11, 12], recon-

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cile it with collaborators [13], and manage it towards a singular design outcome [14]. Despite many advances in virtual collaboration, remote work exacerbates these challenges [15].

While gathering and organizing knowledge during design activities, designers engage in a learning process analogous to the Kolb learning model [16]. Kolb's model describes experiential learning as the product of concrete experience, reflective observation, abstract conceptualization and active experimentation [17]. Within Kolb's model, the intersection of active experimentation and concrete experience describes a wide range of design activities [16], including reverse engineering, a rich source of knowledge for designers [18]. Reverse engineering allows designers to ascertain a product's structure, function, and behavior afforded [18–20]. This empowers design teams to develop models and analysis based on the form and function of products, ultimately enabling them to design or redesign products [21].

Central to reverse engineering is the *product teardown*, also known as product dissection, in which designers disassemble and analyze an existing product and its constituent parts [18]. Numerous studies have described how teardowns help designers and design teams acquire knowledge, but little is captured in academic literature about how professional designers organize information emerging during and after teardowns. Understanding designers' knowledge organization and structuring behavior is essential as products become increasingly complex, making their function, structure, and behavior increasingly accessible only to designers or groups of designers with specialized domain expertise [22, 23]. Reconciling knowledge organization from a design cognition perspective with knowledge management practices that accommodate distributed expertise [24] is critical to the advancement of theory. Furthermore, careful elucidation of the knowledge extraction and organization behavior of professional designers engaging in teardowns are requisite for the development of impactful design support tools. Because teardowns can uniquely afford designers' learning through active experimentation and concrete experience, insights gleaned from studying the approach can be extrapolated to describe other knowledge generating and organizing activities. Similarly, a nuanced understanding of knowledge organization practices could better inform not just better support tools, but more realistic knowledge bases in support of more effective data-driven design.

In this work, we explore how experienced designers, engineers, and managers structure and organize knowledge developed during a virtual teardown of a consumer product. We seek to address four research questions:

R1. Do designers organize knowledge describing the function, structure, and behavior of a product differently?

R2. How do the methods designers use to organize knowledge influence their learning and knowledge transfer to others?

R3. How do designers connect groups of similar elements in a knowledge space?

R4. What patterns emerge in the graph networks formed by designers' organization of teardown knowledge?

To address these questions, we review related work that contextualizes our study (Sec. 2). We then describe our research methodology and experiment (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, including design cognition, and product teardowns and product dissections.

2.1 Knowledge Organization in Design Activities

Engineering design and innovation can be framed as a learning process [16, 18], with knowledge organization and structuring a core activity therein. A designer's ability to incorporate and structure new knowledge has been demonstrated to uniquely shape innovative design outcomes [25]. Organizing design knowledge is essential not just for design results, but fundamentally shapes what Harfield calls "the problematization" of design: how a designer reconciles existing and new knowledge with a given problem frame, ultimately creating an addressable design problem [26]. 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 [27].

At a macro-level, in the engineering design field, knowledge has been represented in large semantic networks, or knowledge bases, which represent knowledge via entities and relations interconnected in a graph structure [28, 29]. Knowledge bases have served as key enablers for data-driven design methods [30]. Efforts have been made to create more engineering design-specific knowledge bases, for example by mining technical publications, patent databases, or through manual labeling of design knowledge [31–33]. With their continued development and expansion, these design knowledge bases promise to support further data-driven product design methods, such as assessing similarity between design components, providing embeddings of design concepts, or supporting functional modeling [30, 34].

At a micro-level, designers have been shown to structure information in a variety of ways, from narratives [35, 36] to sketches [37]. Of paramount importance across all of these approaches is the linking and grouping of knowledge in design [25], behavior which is foundational to both rules-based design [38] and less structured, e.g. 'innovative' design [39], approaches. In Damen and Toh's recent study of experienced design professionals' knowledge structuring activity during idea generation, three modes of organization were observed: clusters, relations, and nests, each describing a unique way of linking different types of information [8]. The researchers found that while participant experience and discipline did not determine their mode of organization, the mode of organization was related to elements of design ideation results. Thus, how designers develop relationships between knowledge appears to shape the outcome of design activity. Earlier work by Le Masson et. al suggested that engineering design appeared to prioritize a much more systematic and rigorous structuring of linked knowledge than architectural design, highlighting the importance of linking and grouping in engineering design [40]. Beyond knowledge immediately relevant to the design task, analogies and similar knowledge have been shown to shape how designers reach a design outcome, even when such similarity is distant [41, 42]. C-K design theory distinguishes knowledge (K) from concepts (C) as core elements to explain design reasoning, and introduces the importance of knowledge spaces in enabling designers to develop new design concept, what the theory refers to as a K-C transformation or disjunction [43]. In contrast, linking between elements in a design knowledge space is also a fundamental operation in design reasoning, known as a K-K operator or expansion: forming links to expand the knowledge space through optimization, deduction, or other activities [5].

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 [44, 45] 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 [46] to defining product requirements [47]. *Function* describes what a designed object is for, or its purpose; for example, Qian and Gero describe an umbrella's function to be to block raindrops [48]. *Behavior* describes what a designed object does or its attributes; for example, Qian and Gero describe the behavior of fluid flow through a faucet to be characterized by a variable, flow rate [48]. *Structure* describes the components of an object and their relationship; for example, Qian and Gero describe the structure of a chair as consisting of a seat, four legs, and a back [45, 48].

With the established importance of knowledge structuring and organization on design, numerous studies have explored how knowledge structuring and reconciliation shapes core design activities including idea generation [8, 25], developing insights [49], communicating outcomes [10] and production activities in makerspaces [50]. Despite this breadth of research, few studies of knowledge structuring and organization *during* product teardowns have been reported. Many studies have explored knowledge and learning *outcomes* of reverse engineering tasks [51], but little is known about the process of organizing and structuring knowledge that enables such outcomes.

This study extends from previous research on design knowledge organization in two ways. First, we study knowledge organization *during* a virtual teardown activity, allowing us to understand how professional designers structure knowledge and information as they engage with teardowns. Second, we examine knowledge organization through two complementary lenses. We use the FBS framework as an ontology to describe **types** of knowledge *content* represented by information from a virtual teardown, and also as a **prompt** for designers to guide their grouping activity. We next use linking and grouping behaviors to identify knowledge *relations*. By examining knowledge organization during teardowns through these lenses, we can uniquely understand knowledge organization activities and abstract broad patterns from them.

2.2 Product Teardowns and Dissections

Reverse engineering is a cornerstone activity of professional design work, practiced by engineers in sectors ranging from software to machine design [52–54] as a way to ascertain an existing product's structure, function, and value created, ultimately affording the design of new products [18, 20]. The product teardown, or product dissection, is a core component of the reverse engineering of physical products, and involves, as Dalrymple et. al describe it, "a systematic deconstruction of an artefact, and the subsequent analysis ... of its components for the purpose of understanding [its] physical, technological, and developmental principles" [51].

Studies of teardowns in companies have focused on descriptive accounts of how teardowns integrate with a broader product development process. Lauff et. al, in their study of of methods employed in firms engaging in early-stage product development, observed that companies developing consumer electronics and medical device products leveraged product teardowns during concept generation, while a company developing footwear products did not [55]. Morgan and Liker describe the role of teardowns in the Toyota Production System's approach to product development [56]. However, despite the teardown's centrality in engineering practice, few systematic studies have explored how companies and professional engineers and designers engage with teardowns, and specifically, how they generate and organize knowledge from teardowns.

The product teardown is widely used in engineering education, where it is prized for its experiential learning and preparation of students for industry [57, 58]. Accordingly, its usage in classroom studies has been extensively studied. Teardowns in classroom contexts have been shown to help students understand the relationships between components of a product, and relate products to each other within product families [59]. Recent work has shown that virtual teardowns yield similar knowledge as in-person teardowns [60] and that augmenting virtual teardowns with rich interactions holds promise for improved outcomes [61]. Explorations of teardowns in engineering education provide a robust foundation for studies of professional designers, who are known to differ from students in their engagement with design process [62] while leveraging cross-disciplinary collaborations [13] 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 in two ways. First, we specifically examine knowledge *organization* behavior during teardowns, building on previous studies of knowledge *acquired* from teardowns. This allows us to examine relationships between knowledge that emerge from the active experimentation inherent in a virtual teardown activity, helping us understand teardowns from a knowledge perspective. Second, we study professional designers with an average experience of more than three years, collecting unique insights on their relationship to product teardowns, and how professional designers in industry environments engage with knowledge generated during teardowns.

3 Research Methodology

This section describes the methodology used to determine how professionals organize knowledge from product teardowns.

3.1 Teardown Knowledge Collection

Our teardown examined the Bose Tenor Frames, smart sunglasses with integrated speakers and a user interaction component. This product was chosen for its complexity and mix of mechanical and electrical components. Three volunteers from the Teardown Library[1] performed and documented the teardown[2].

One mechanical engineer with a background in smart glasses design initiated the teardown, documenting product highlights, disassembly process, and observations. This individual then organized the observations based on the bill of materials hierarchy. Then, two other volunteers with electrical and mechanical engineering and product management backgrounds added more observations relevant to their domains. Following this knowledge extraction stage, the research team took notes and images generated by the teardown volunteers and curated them to improve clarity, replace short-hand technical terminology, and reduce the number to an appropriate amount given the time restrictions of the study. This process of knowledge extraction and curation resulted in 24 images and 52 text notes to be used for the study. The images and text described above were then placed in Mural[3], a digital collaboration tool used for the study.

3.2 Participatory Study

The study participants were asked to organize the teardown knowledge in a guided think-aloud session. Participants were provided with the same teardown knowledge (as described in Section 3.1) and asked to perform four tasks: grouping the notes, linking the notes, linking the groups, and rating the links. Afterwards, the participants also answered a survey to collect qualitative data about the tasks they performed.

[1]https://teardownlibrary.com/

[2]https://medium.com/teardown-library/a-prototype-process-for-remote-collaborative-teardowns-3250788a7628

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

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

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

Twenty-three professional designers were recruited for this study. By recruiting professionals with various backgrounds, the study captures design priorities driven by multi-disciplinary factors, such as manufacturing constraints and marketing demands, which professionals are exposed to over their careers. A summary of the role and average years of experience of the participants is shown in Table 1. The variability in domain expertise and role will allow us to learn how different groups organize knowledge differently.

The experiment was conducted on Mural, chosen to enable the researchers to perform the study remotely but synchronously, and to streamline data collection. Before the study, participants familiarized themselves with the online tool and practiced the required functionality.

3.2.1 Study Protocol

After a brief introduction of the tasks, and the Mural learning session, the participants had five minutes to read through the raw teardown notes. The participants were given 60 minutes for the grouping, note and image linking, group linking, and rating tasks, while thinking out-loud to explain their decisions. An example of these actions is shown in Figure 1.

First, participants were asked to **group similar notes and images** and to assign a name to each group. Subgroups were allowed. The participants were instructed to group the notes and images based on three prompt variations: grouping by function, behavior, and structure. Of the participants, 7 were instructed to group the notes and images by function, 8 by behavior, and 8 by structure. Second, participants were prompted to **link related notes and images** to each other by drawing an arrow between the notes that had been previously grouped. They were also asked to label the links and to think out-loud about the rea-

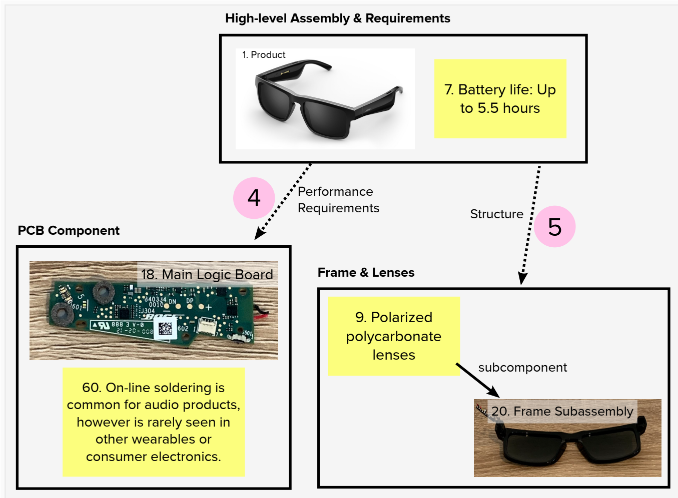


FIGURE 1: Example participant activity, showing organized notes and images, groups (boxes), note links (solid arrows), group links (dashed arrows) and ratings (pink circles).

soning behind this connection. Third, participants were asked to **find and draw links between groups** they had created, and to label these connections with a descriptive name. Fourth, participants were asked to **rate the links they had drawn** from one to five (slightly related to very related). Following the completion of these tasks, participants were asked to complete a survey to report demographic information and reflect on the usefulness of the tasks for learning and knowledge transfer.

3.3 Data Coding and Consolidation

Mural diagrams and survey results were registered into a spreadsheet for further analysis to prepare for coding. Notes and images were coded using the FBS ontology. Three researchers independently categorized each note, using rules to guide coding (Table 2). These rules are developed around the definitions and examples cited in Section 2.1. Notably, we distinguish structure attributes from behavior variables by arguing that dimensions, weight, etc. of the *product, subassembly, or other components* are what Qian and Gero consider behavior variables derived directly or indirectly from structural factors these elements [48]. After triple-coding, disagreements were discussed and resolved to reach a 100-percent inter-rater reliability, which are the final codes presented here and used for further analysis.

After the data were encoded, groups with similar descriptions were consolidated before analyzing the data. To do so, keywords were extracted from the group names using natural language processing (NLP) with the TechNet API[4]. TechNet is a semantic network of technical terms that was used to identify higher-level semantic names from the participant-created group names [32]. Three researchers independently associated participant-created groups with consolidated groups using the TechNet-generated group names, and added additional names. In total, 159 individual groups were consolidated into 28 new groups.

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

Category	Note	Generalized Rule
Function	*"Mic placement indicates beam forming, not noise cancellation"*	Action verbs associated with use and assembly
Behavior	*"Diameter of speaker"*	Product traits such as weight, dimensions, etc.
Structure	*"Qualcomm-QCC5127, Bluetooth Audio"*	Components of the product

TABLE 2: A small sample of rules used to classify notes and images

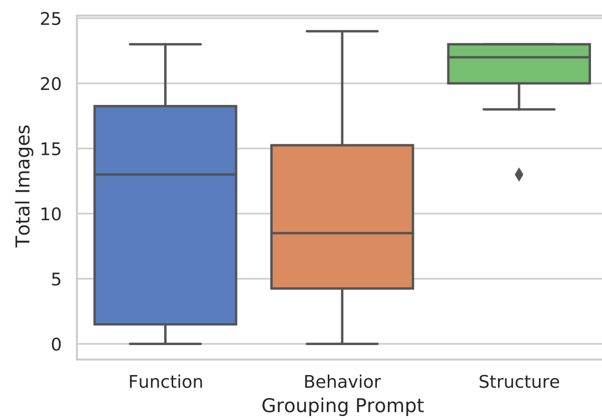


FIGURE 2: Total number of images per participant used in studies with different FBS grouping prompts.

4 Results and Discussion

This section presents and interprets results addressing the four research questions of this work.

4.1 Do designers organize knowledge describing the function, structure, and behavior of products differently?

In the experiment, designers were prompted to group either by function, structure, or behavior (see Section 3.2.1 for more details). On average, designers used 60% of the total notes (SD=11.5). Based on single factor ANOVA, there was no significant difference in the number of notes used by participants with different prompts, showing little effect of the prompt on the number of notes used.

Notes' FBS type, as described in Section 3.3, had little effect on their use frequency. On average, designers used 63% of behavior notes, 60% of structure notes, 55% of function notes. Designers given the Behavior prompt used 10% more Behavior notes than those given other prompts, but this difference was not statistically significant.

Designers created 6 groups on average (SD=2.0). Designers from 9 of 23 studies create nested groups, 3 with each FBS grouping prompt. Among the studies with nested groups, designers given the Behavior prompt on average have 3 nested groups (SD=2.5), those given the Structure prompt have 4 (SD=2.5), and those given the Function prompt have 5 (SD=2.0). Again, these differences are not statistically significant.

Designers created 6 note links (SD=6.3) and 6 group links (SD=2.8) on average. Different FBS grouping prompts do not affect the number of links participants use. Three participants used more than 15 note links; this was attributed to their linking of images and notes to illustrate their relationships, which was not done by other participants.

4.1.1 Designers given the Structure prompt used images earlier and more often

Every designer used at least one image; those with the Behavior prompt used 10 images (SD=8.0) on average, while those with the Function prompt used 11 images (SD=9.2). Designers given the Structure prompt used, on average, 21 images (SD=3.8) of the 24 provided (see Figure 2). This difference is significant under a single factor ANOVA ($p<0.05$, N=23, F=4.54). Qualitatively, designers given the Structure prompt also generally chose to drag images around their workspace before they did notes. Some participants reported visual cues help them map out components and systems easier than notes, thus they use images to guide grouping.

These findings highlight the reliance on visual elements by designers when organizing design knowledge related to structure. Designer's use of images to convey information related to structure warrants further investigation around the use of other visual means of visualizing structure, such as CAD models.

4.1.2 Behavior notes were over-represented among the most-used notes

The 52 notes provided to participants consisted of 11 function, 14 behavior and 27 structure notes. Of the top six notes used most by participants, half are behavior, despite relatively fewer behavior notes overall (see Table 3). These popular Behavior notes were used by nearly all designers. Two were about the overall product design, two were about the hinge, and two were about the battery, indicating the high priority of such behavior knowledge to designers.

These findings point towards the importance given to product behavior by designers when describing the product. Definition and extraction of product behavior should be an important focus of future work hoping to automate extraction from teardowns.

Note	FBS Type	Studies
"Extremely Lightweight (47g)"	behavior	20
"Hinge body and cover appear to be MIM steel"	structure	19
"Battery size is not constrained by size, but likely by weight, to improve comfort"	behavior	19
"Polarized poly-carbonate lenses"	structure	18
"This hinge is an effective design, simple, low cost, low part mechanism"	behavior	18
"Battery life: Up to 5"	behavior	18

TABLE 3: The six most-used notes, their FBS type, and the number of participants that used them.

FIGURE 3: Total number of note links between different FBS types of notes

4.1.3 Function notes were the least linked

Among the 67 note links designers created across all studies, only 13 involved Function notes (see Figure 3), none of which linked one Function note to another. As can be seen in the links, both other note types are equally represented.

The lack of note links to and from Function could suggest 1) an implicit prior understanding of Function-Behavior relationships describing the purpose of the product, allowing them to remain undocumented; 2) design trade-offs, a key observed purpose of links (Section 4.3), do not involve Function and happen instead between Behavior and Structure; and 3) designers might prefer using group links to illustrate functional requirements, as discussed in Section 4.3.2.

4.2 How do the methods designers use to organize knowledge influence their learning and knowledge transfer to others?

In our survey, participants commented that the activity of note organization help them learn about the product, as well as transfer this knowledge to others. On a 1-5 scale, designers rated the overall organizing activity 4.2 (SD=0.5) for learning, and 4.5 (SD=0.7) for knowledge transfer. Table 4 lists selected quotes for different ratings. All designers found that organizing knowledge helped enhance their understanding of the product. Several designers commented that different team environments may have varying dynamics and yield different outcomes for the organization task. In regards to knowledge transfer, several designers expressed that access to physical components or components in virtual reality environments would improve knowledge transfer. However, for learning, all designers found photos sufficient for transferring knowledge to others.

Overall Organization

	Score	Quotes
Learning	5	*"5 star on the learning about the product. The organization would change based on the team size and skills."*
	3	*"Needed a lot more time on the grouping stage which may have helped the subsequent stages."*
Transfer	5	*"This would help individuals better understand the impact and downstream affects of different design choices."*
	3	*"Better schematics of the glasses and its components. Photos of components weren't helpful to get an idea of where they are in reference to other components. Physical artifact to hold or within VR environment."*

TABLE 4: Selected quotes from designers about the usefulness of the overall organization.

4.2.1 For learning, designers find grouping more helpful than linking or rating.

Grouping is rated the highest for learning. We conducted a one-way analysis of variance (ANOVA) and found significant difference between each task and learning effectiveness ($p < 0.05$, N=23, F=8.04). Post-hoc comparisons using Tukey's HSD test revealed significant differences between grouping and linking ($p<.05$) and rating ($p<.01$), revealing that grouping is more impactful for learning than other actions. In the survey, designers rated grouping equally important for learning (4.5, SD=0.6) and knowledge transfer (4.4, SD=0.7), on average. Table 5 shows selected quotes related to grouping from different designers.

These findings suggest that designers view different teardown activities to be useful for different purposes. The selected quotes in Table 5 show that designers find grouping helpful in identifying commonalities in design and discover design intents of individual components. Grouping also leads designers to consider how different aspects of the design inform and affect each other. These quotes, and the survey rating, indicate that grouping is the most helpful activity if the goal is to learn from a teardown. Moreover, designers reported that in a professional environment with multiple teams involved, grouping could help identify relevant design goals for each team, while group nesting could help propagate design tasks across teams. This suggests that the activity of grouping of teardown knowledge could play an important role in knowledge transfer between teams.

These findings indicate that, during teardowns, activities around grouping of design knowledge, rather than linking or rating, are most effective for personal learning, as well as transferring knowledge to others. These results indicate that groups and group names would be a rich source of design knowledge for future work investigations of teardowns.

Grouping

	Score	Quotes
Learning	5	*"Grouping gives the opportunity to think deeply about the intent of each item of the design."*
	4	*"Grouping helps to view commonalities in the design like the PCB placement in conjunction with the user controls."*
Transfer	5	*"This method can be equally effective if individual members partake in the activity on their own then regroup and exchange their findings."*
	5	*"Looking at sub-assemblies and how they are related to their parent parts could be helpful when approaching complex design tasks spread across multiple individuals or teams."*

TABLE 5: Selected quotes from designers about the usefulness of grouping.

4.2.2 Designers find linking more helpful for knowledge transfer than for learning.

Participants rated linking as more valuable for knowledge transfer (4.2, SD=0.8) than for learning (3.8, SD=0.9). However, single-factor ANOVA ($p=0.16$, N=44, F=2) did not reveal a significant difference. Table 6 shows some comments from participants around the usefulness of the linking activity. Together with the selected quotes, this suggests that the activity of searching for relationships between groups is conducive to thinking at a higher-level about disparate aspects of the design. The selected quotes suggest that finding links between related notes, images, and groups can help uncover trade-offs between different design goals, which in turn

	Linking	
	Score	**Quotes**
Learning	5	*"Linking helps designers or a team find better product wide trade offs."*
	4	*"Linking between groups helps to find commonalities and overlaps that should be addressed in the design and future iterations."*
Transfer	5	*"Linking can guide design iterations because it shows how changes will propagate."*
	5	*"Grouping and linking is extremely helpful when sharing knowledge with others. It can explain the nature of the design and what key design features should be expanded upon, or avoided."*

TABLE 6: Selected quotes from designers about the usefulness of linking.

supports knowledge transfer between teams in professional environments. However, as no statistical significance was found in the ratings, these findings warrant further investigations.

4.2.3 On the usefulness of rating.

The survey results show that rating scored the lowest compared to the grouping and linking activities both for learning (3.5, SD=1.0) and knowledge transfer (3.8, SD=1.2). According to quotes from participants, while rating might help them emphasize importance during knowledge transfer, most designers did not find rating to help them learn more about the product. Several designers commented that rating was too subjective and likely dependent on the designers' backgrounds. While our results suggest that rating itself may not be valuable to designers, rating link strength might be valuable data in support of further research.

4.3 How do designers connect groups of similar elements in a knowledge space?

In this section, we first look at patterns that emerge in group linking (Section 4.3.1), and then dive into what designers represent using links (Section 4.3.2).

4.3.1 Designers more frequently use linking between groups than nesting of groups to organize knowledge.

There are two ways designers connect groups: **nesting** a child group under another (e.g. hinge is a child group under the mechanical group), and **linking** two groups with a directional arrow and giving it a descriptive name. Linking and nesting are both directional; linking has a start and an end, and nesting has a parent and a child.

Linking was used to create five times as many connections between groups than group nesting, and less than 20% of all connections are repeated (see Figure 5 in Appendix A for more information). Designers from the 23 studies created 128 group links in total. Among these links, 22 links are repeated across different studies. For example, four designers create links from battery to audio. In comparison, 27 group nesting relationships are created, and four are repeated, for example, audio in features, battery in electrical. No overlapping connections were created between linking and nesting.

The greater use of linking suggests that designers more readily organize knowledge spaces by connecting groups of knowledge rather than nesting them. In many ways, this exemplifies C-K design theory's perspective on the expansion (K-K) operator: that connecting different types of knowledge (in our case, groups), *expands* the knowledge space. Thus, we see designers preferentially gravitating towards knowledge structuring activities that yield greater expansion of their understanding. For future efforts at developing knowledge bases that resemble designers' own creations, this finding suggests that an emphasis on links of groups of knowledge rather than nests would have greater similarity to designers' knowledge structures. However, further research is necessary to explore how designers distinguish linking from nesting during knowledge structuring.

	Start	End	Link Name
Trade-offs	durability	cost	*"Plastic is cheaper than metal"*
	weight	battery	*"Mass target > battery life"*
Req.	housing	hinge	*"Sends information/controls"*
	logic board	frame	*"Dictates required space"*
Team	features	aesthetics	*"The art of give and take between design and engineering"*
	aesthetics	manufacturing	*"The first processes towards design sacrifice"*

TABLE 7: Selected group links by different designers, grouped by topics of team, requirements, and trade-offs.

4.3.2 Designers primarily use links to describe design trade-offs, requirements and team collaboration.

We observed three distinct reasons why designers developed links between groups of information (Table 7). First, designers made links to represent **design trade-offs**. Participants used specific language to express trade-offs, such as comparative adjectives (e.g. cheaper, more) and signs (e.g. $>$, $=$). Second, designers used links to identify **design requirements**, particularly regarding functional or structural aspects. Specific language that signified design requirements links included verbs for the name of the link. Finally, participants also used links to represent opportunities for **team collaboration**. During these studies, we observed these participants discussing how their knowledge groups map to different teams within their organization, and how frequent communication between these teams may help the design project. Perhaps of note is that the three designers in question held management roles within their professional organization (e.g., company founders and project managers).

These findings highlight the diverse roles that relational knowledge, captured in links, can play in establishing a designer's knowledge space. Designers' use of language is particularly important in distinguishing types of knowledge in links. Designers differentially use adjectives, verbs, and explicit references to organizational teams to indicate trade-offs, requirements, and collaboration, respectively. This suggests that language can be a useful mechanism to uncover insights about participants' knowledge organizing behavior. Furthermore, specific types of language could be a crucial facet in developing realistic design knowledge networks, and warrants further investigation.

4.4 What patterns emerge in the graph networks formed by designers' organization of teardown knowledge?

Representing the knowledge in a graph allows leveraging of graph algorithms for analyzing knowledge from different designers. The groups are encoded as nodes, and the linking and nesting relationships between groups are encoded as edges. For simpler visualization and analysis, edge directions are omitted. The weight of the edges represents the number of designers that create the relationship between two groups. Figure 4 shows examples of graph representations of group neighborhoods.

4.4.1 Measuring centrality of nodes in the graph.

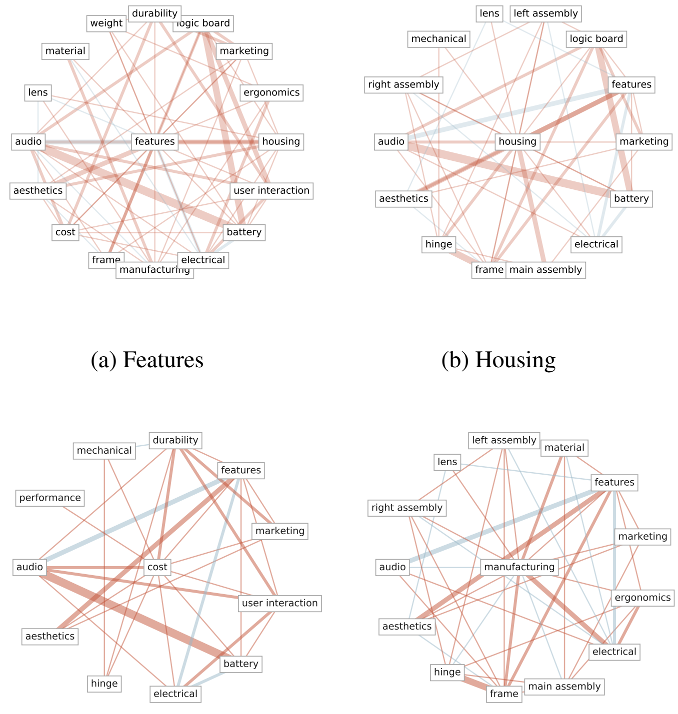
Betweeness centrality of a node v measures the proportion of shortest paths between all nodes that pass by v, and is defined as follows:

$$c_B(v) = \sum_{s,t \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)} \tag{1}$$

where V is the set of nodes, $\sigma(s,t)$ is the number of shortest (s,t)-paths, and $\sigma(s,t|v)$ is the number of those paths passing through some node v other than s,t.

For example, 16% of shortest paths between all groups pass through cost. Features, housing, cost and manufacturing have the highest betweeness centrality among all nodes. These highly connected neighborhoods are shown in Figure 4, highlighting important aspects for successful smart glasses products.

The number of central nodes in the graph suggests that the participants might have various opinions regarding the most important aspects of the product. This could be an indicator of the diversity in backgrounds of the participants, ranging from



(a) Features (b) Housing

(c) Cost (d) Manufacturing

FIGURE 4: Neighborhoods of the highest betweeness centrality nodes. Features 0.13, housing 0.09, cost 0.09, manufacturing 0.07. Links are coded in red, and nesting are coded in blue.

technical domains like manufacturing and electronics, to managerial roles. This finding also points to the wide range of design knowledge that is possible to collect from teardowns, an important aspect to consider as future work explores how to leverage design knowledge from teardowns to inform data-driven design approaches, e.g. machine learning models.

4.4.2 Identifying interdependencies in the graph with triads.

The graph has many triads, or chains of dependencies ($A \rightarrow B \rightarrow C \rightarrow A$). Transitivity, the fraction of all possible triangles, is defined as $3 \times (\#triangles/\#triads)$, where triangles are identified by the number of triads. The transitivity of the graph is 0.38. Examples of triads are $cost \rightarrow audio \rightarrow battery$ and $cost \rightarrow aesthetics \rightarrow marketing$. The presence of the links that form these triads may suggest that designers often link interdependent triplets of groups together. Furthermore, the inclusion of cost in several triads suggests that design trade-offs are present in the product, as designers may be considering the effects of different groups on cost of the product. The multitude of triads also show the diversity of knowledge gathered from a teardown, as several interdependent smaller networks of groups such as triads can be created. Together, this extends on existing knowledge by showing both the presence and relevance of triads in knowledge network graphs and suggests that triads may be relevant in training machine learning models in the future.

4.4.3 A diversity of links evidence a variety ways designers organize knowledge in design tasks.

Each neighborhood of nodes represents links from multiple studies. For example, the groups connected to cost are from five different studies, and two connections are made multiple times by different designers. The groups connected to manufacturing are from seven studies, and four connections are made multiple times by different designers. The groups connected to aesthetics are from three studies, and two connections are made multiple times by different designers.

The varying connections and relatively low overlap suggest that designers form relationships between groups of product knowledge differently, and that there may be value in sourcing knowledge organization from larger numbers of designers to reveal unexpected ways of relating knowledge. The observed diversity in knowledge organization might be an indicator of the diverse backgrounds of the participants, as different expertise may cause varying information to be linked together. If true, this indicates that varied backgrounds in generating product knowledge can lead to valuable, diverse information. This extends on current knowledge suggesting that crowd-sourcing could be a valuable way to gather unique insights on designers' approaches to knowledge organization, not just knowledge itself.

4.5 Future Work and Limitations

Our findings provide a foundation for several directions for future inquiry at the nexus of knowledge organization, design theory, and data-driven design. First, to effectively support the expansion of design knowledge bases, further study into *why* designers distinguish nesting, linking, and group knowledge structuring is essential. Second, exploration of other knowledge-intensive design activities besides teardowns - e.g., product lifecycle management (PLM) or user research synthesis - would help expand upon and validate our insights about knowledge organization. Lastly, a deeper investigation of the nature of interdependencies surfaced in the knowledge graphs we developed, with a particular eye to procedural and disciplinary knowledge, would help reveal more meaningful insights about how to best extend and connect disparate design knowledge bases.

There are several improvements that would make the approach presented in our work more scalable and generalizable and address its limitations. First, the notes from the teardown could be made more generic and applicable to several products, to remove any bias from emotional connections to details such as the company name. Second, more than one product could be shown, providing a wider range of information for participants and generating more diverse knowledge organization data across multiple products. In the study, there were more structure notes and images than function or behavior, leading to data imbalance. Finally, group consolidation could be done with the use of NLP for consistency, leading to more accurately consolidated groups for data analysis.

Addressing the above limitations would help expand the work presented in this paper towards an automated knowledge organization tool. By taking in data from current and future design knowledge bases, our work points towards a tool which learns to organize sparse and biased design knowledge. We look to expand the graph representation and leverage graph neural networks to learn how to present design knowledge to maximize learning by the designer, while supporting knowledge transfer to stakeholders in other domains. We see our work as an initial step towards this vision.

5 Conclusion

In this work, we examined how designers and engineers organize design knowledge from product teardowns by conducting a participatory study with 23 professionals. By giving participants unstructured design knowledge from a teardown, and guiding them through a series of tasks to add structure, we identify organizational patterns useful for learning and knowledge transfer, and share a method for extracting the most important knowledge in a teardown via a graph representation.

There are several research directions to expand on this work. Increasing the number of products from which we source the teardown knowledge would eliminate some bias and make the results more generalizable between domains and industries. Moreover, given a larger dataset of structured design knowledge, the graph representation used in this paper would support learning with machine learning models, specifically graph neural networks. We see our work as an initial step towards automated learning of unstructured design knowledge to support designers in learning and transferring knowledge to others.

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APPENDIX A Relationships Between Groups

A visual count of all the links (red) and group nests (blue) created by participants are shown in Figure 5. When no connections in linking or group nesting were made, the block is colored in grey. The darker the block is, the more designers who make the connection. No overlapping connections signal designers use linking to represent different relationships.

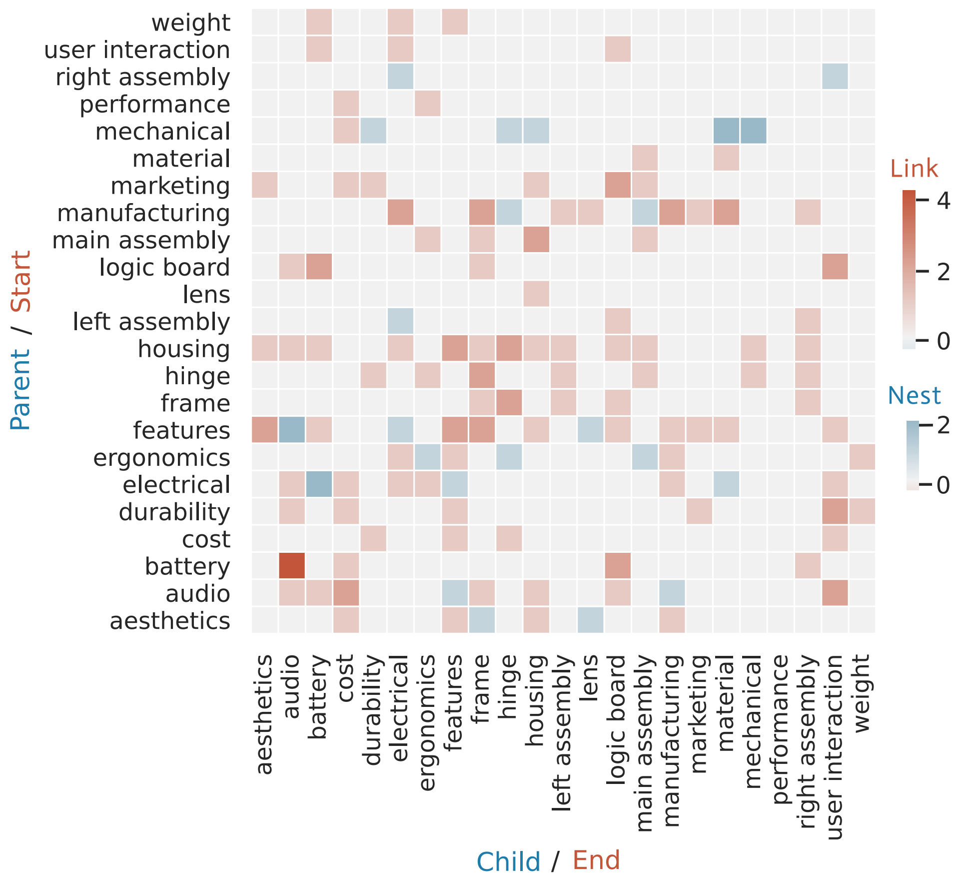

FIGURE 5: Adjacency matrix for group linking and nesting. Links are in red and nesting are in blue. The darkness shows the number of designers who connect the groups. For example, there are four links from aesthetics (marked in red). One designer links aesthetics to cost. Aesthetics is also the parent group of lens and frame (marked in blue). There is no overlap between linking and nesting, i.e. if there is a link between A and B, A is not a parent of B, and vise versa.