A STUDY OF GRAPHICAL REPRESENTATIONS OF UNCERTAINTY IN LCA GUIDE

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ABSTRACT

This study user-tested different data visualizations for highly uncertain life cycle assessments (LCAs) to determine what best supported decision-making. Precise LCAs can only be performed once designs are finalized, due to the information necessary to complete them, but design changes in such late stages are costly. If designers could have environmental impact data earlier in the process, sustainable design choices could instead be built into the initial designs. We compiled LCAs for various product categories, finding the best means of visualizing the data for online and printable dissemination. Because this LCA data varied widely within each product category, it was necessary to display uncertainty and require users to acknowledge the uncertainty. Here, four different data visualizations were tested with engineering, design, and STEM students and professionals; both quantitative and qualitative analysis determined what visualizations were most favored and forced users to consider uncertainty. We hope that this research helps LCA data be more accessible to designers and engineers in the early phases of design, allowing those without the resources or ability to perform LCA to benefit from it and design more sustainably.

Keywords: Sustainability, Visualisation, Design engineering

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1 INTRODUCTION

For designers and engineers, understanding a product's impacts throughout its entire life-cycle is critical for setting priorities in sustainable design. Different products have their highest environmental impacts in different life-cycle stages. For instance, the major impacts of a refrigerator is the energy consumption during usage (Baxter et al., 2009), while the major impact of furniture is raw materials and manufacturing (Gamage et al., 2008). While many assume that transportation is a large impact because transportation of people is one of the top global impacts, in fact, those who quantify product life-cycle impacts have known for over 20 years that it is almost never a significant percentage of a product's full life-cycle impacts (Hanssen, 1998). To make intelligent design decisions, make the best use of their time and budget, and avoid greenwashing, product developers should quantify the impacts of their products' different life-cycle stages.

In order to do so, many use life-cycle assessment (LCA), as it boasts a rigorous and credible system for quantifying environmental impacts (Hallstedt, 2017). LCAs are useful for setting design priorities, benchmarking current impacts, setting improvement targets, measuring progress, and deciding among alternative designs. However, there are significant problems with LCAs that hinder their adoption in product development. Even though LCA data would be most useful in early stages of design, when it is cheaper and easier to make large changes, the detailed data for LCA is often not available until late in the design process, after design decisions have been made. Designers who seek sustainability certifications like ISO 14040 (ISO 14040:2006, 2016) for an LCA report or ISO 14025 for product eco-labels (14:00-17:00, no date) also have a similar issue, requiring specific data that is only available at the end of the design process. Precision and certainty are valued in LCAs, so results can be trusted. In addition, LCAs also often involve expensive software and specialized training (Hollerud et al., 2017). Because of this effort and expense of performing LCAs, results are typically published in proprietary systems for paid subscribers, such as The Sustainability Consortium (www.sustainabilityconsortium.org) or academic journals. Oftentimes the results are not shared outside the company. And finally, even when LCAs are published, they are often not consistent about which environmental impact categories they measure, making them hard to compare.

By contrast, many designers use checklist-based design guides such as the Lunar Field Guide to Sustainability (LUNAR, 2008), Factor Ten Engineering (Lovins et al., 2010), or the CFDA Guide to Sustainable Strategies (Leibowitz and Croke, 2019). They do not analyze a specific product; instead, they list widely-applicable design strategies. These green design guides are easy to apply with none of LCA's research / analysis time, and are valued by designers and engineers (Lewis et al., 2017). However, because they are not targeted to specific products, they are required to be generic, which means they do not prioritize the sustainability strategies that will provide the most improvement for specific products. Since sustainability is usually perceived to add time (and therefore cost) to the product development process (Faludi, 2017; Lewis et al., 2017), it is important to prioritize sustainable design strategies that will provide the most benefit for the least development effort for each potential product.

To try to bridge the gap between LCAs and green design guides, this research team created a design guide based on LCA by pre-calculating impacts for various product categories, graphing them, and connecting the highest impacts with relevant sustainable design suggestions. The calculations were based on LCAs published by academia and industry, with 4 - 6 sources per product category to include variance in product design and LCA methodology. This LCA-based design guide is published online as http://ProductDesign.green. It makes LCA data more accessible to designers, engineers, and business managers in the earliest stages of design, and to those without the time, software, and/or expertise to perform their own LCAs. It also provides sustainable design guidance customized to each product category.

However, this method also presented several flaws. Creating personalized data for every possible product in advance is unrealistic. Precision is impossible in early stage design because many important engineering and design decisions have not yet been made. In addition, the inclusion of variance in product design and LCA methodology caused variance in LCA scores. Finally, single-score LCAs, which are useful for decision-making because they combine all types of environmental impacts into one unified unit for easy comparison, also introduce uncertainty due to their value judgments. Using different single-score methodologies for the same data can change results by 20% or more (Speck et al., 2016).

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These high uncertainties can lead to poor decisions if not considered. Therefore, it is crucial that this new LCA design guide forces design teams to acknowledge uncertainty, not ignoring it for the sake of convenience. It is also necessary for the design guide's data visualization to communicate the high uncertainty in a form that designers, engineers, and business managers easily understand without LCA expertise. In addition, it is important to make sure we understand why participants prefer certain methods of visualization, as, "decisions may be improved by visualisations the user does not favour, or may be impaired by the visualisations the user regards as helpful" (Levontin and Walton, 2020). This is often hard, because people are inherently uncomfortable with uncertainty in expensive long-term endeavors such as product development (Krishnan and Bhattacharya, 2002), and engineering culture especially values certainty. But for product development teams just starting their sustainability journey, even highly uncertain data can be more helpful than no data at all. A complete lack of data leaves engineers and designers to operate on guesswork and superstition. Even with high uncertainties, many product categories have clear priorities for what the most effective sustainability strategies will be.

This study prototyped and user-tested four types of LCA data visualization with design and engineering students to determine what would most effectively support fast and intuitive decision-making without ignoring large uncertainties. The overall goal was to create and analyze data visualization techniques to make the LCA-based design guide, ProductDesign.green, easy for novice designers and engineers to understand without sacrificing rigor. More specifically, the goal of this particular study was to ensure high levels of uncertainty in impacts were understood and acknowledged, rather than being ignored or misunderstood, even by non-experts.

2 METHODS

To visualize LCA data and its uncertainty, first LCA data was gathered from literature for each product category and synthesized into an overall LCA score with average values and standard deviations for the different life cycle stages. These standard deviations were used for uncertainty ranges. Next, four methods to visualize the data and uncertainty were prototyped, including standard and novel methods. Finally, the data visualizations were tested with 32 engineering, design, and STEM-focused students and young professionals to determine which was both easily read and forced readers to acknowledge the high uncertainties, rather than ignoring them or misunderstanding them. These procedures are described in more depth below.

2.1 LCA Data Collection & Synthesis

LCA data was collected from publications on these product categories: laptops, smartphones, monitors, refrigerators, office chairs, t-shirts, and jeans. Acceptable LCA publications included academic journal articles, manufacturer Environmental Product Declarations, or other environmental reports. Peer-reviewed academic studies were preferred for thoroughness and credibility, but manufacturer publications were deemed valuable because manufacturers generally have more access to life cycle inventory data than academics. Publications were sought on Web of Science, Scopus, Google Scholar, and Google. For each product category, 4 - 6 published LCAs were collected. Office chair data was also supplemented with direct empirical measurement (a product teardown and LCA). Smartphone data was also supplemented with an unpublished analysis by a Thinkstep LCA professional. Finally, one of the refrigerator LCAs was an empirical study by one of the authors for teaching LCA.

Studies covering multiple environmental impact categories were strongly preferred, but publications of only CO2 equivalent emissions were also accepted. Impacts were divided into the following life cycle stages: materials and manufacturing, packaging, transportation, usage, and end of life. For products with large material and manufacturing impacts, that stage was subdivided to provide more specific guidance. Some studies neglected some life cycle stages, such as packaging, and many did not subdivide materials and manufacturing stages, which limited the precision of such recommendations. The PDFs available at ProductDesign.green shows the literature used and what impact categories they measured.

Each LCA's results were normalized such that the life cycle stage impacts were listed as percentages of whole life cycle impacts. Then the 4 - 6 LCAs were combined into a single set of scores per product category by computing an average and standard deviation for each life cycle stage. The uncertainty of the combined results was chosen to be the standard deviation of the results from the specific LCAs, which was often large. Reasons for the wide range of different results included missing inventory data (e.g. packaging) that had to be estimated, differences in time, location, product design variations,

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usage scenarios, inventory modeling methods, and usual database quality. When combining multiple impact categories, all were given equal weight. (For example, if five studies measured three impact categories each, the final result was calculated as the average and standard deviation of all fifteen data points.) This is not ideal, because some impact categories will have more emissions than others and some will be more harmful than others; a rigorous system of normalization and weighing such as ReCiPe (Huijbregts et al., 2016; Bare, 2002) would have been preferred, but most literature sources here did not list enough data to perform such normalization and weighing. To accommodate this methodological weakness, uncertainties were increased 10% over their already high values, and regardless of data agreement, no uncertainties were allowed to be below 20%.

2.2 Data Visualization

Four visualizations were prototyped to show LCA data using the laptop data. This data set was specifically chosen because two variables had large, overlapping uncertainties, enabling us to test user responses to data without a clear determination of which variable had higher environmental impacts. The goal was to be understandable to non-technical, novice designers or businesspeople, enable quick intuitive decision-making, make users acknowledge uncertainty in their decision-making, and be aesthetically engaging. Rather than testing the design guide as a whole, the uncertainty was focused on to ensure the data visualization techniques were effective before adding them to a guide where their direct results could be affected by other variables. Two prototypes were based on existing graph formats ("error bars" and "violin"), and two were new graph formats ("slant" and "gradient"). See Figure 1.

The "error bars" format is standard in engineering, but does not display probability distribution, only a binary threshold at one standard deviation above and below the mean. "Violin" is not commonly used in engineering design, but has been used for over a decade and was specifically invented to display probability distribution (Potter et al., 2010). The version here was modified to connect to the x-axis in hopes of improving readability by non-experts. "Slant" was created for this study because it is visually more similar to a standard bar graph, and would be easy for software to draw; an earlier version was also prototyped that displayed probability distribution, but this earlier "dolphin-nose" slant graph was strongly disliked in preliminary user feedback, so it did not reach full user testing. "Gradient" was a bar graph with a gradient fill, extending from 100% opaque at one standard deviation below the mean to 100% transparent at one standard deviation above the mean. Others have used gradients (Jackson, 2008) and user testing has found them to improve accuracy of reading statistical uncertainty in other data types (Gschwandtnei et al., 2016).

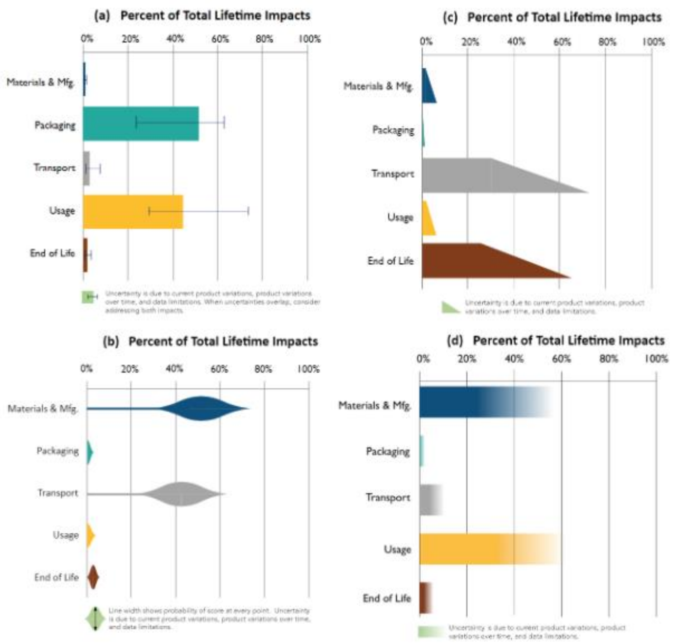

Figure 1. Four different types of graph designs: (a) error bars; (b) violin; (c) slant; (d) gradient.

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User testing of the data visualizations was conducted with 32 students and young professionals in various engineering or sustainable design backgrounds. Users were chosen to be representative of the target audience: engineers and designers who are educated and numerate but who may not be familiar with LCA and may be new to eco-design.

Table 1. Demographics of participants

User Demographics	
Gender	56% Female 34% Male 9% Other
Major	82% Engineers 19% Other
Year in School	0% 1st year 9% 2nd year 19% 3rd year 31% 4th year 28% Graduate student 13% Recent graduate

User testing was performed through semi-structured interviews over video calls with screen-sharing. Sessions averaged 20 minutes, with the following procedure: Participants were shown an image of one of the four data visualization prototypes and asked,

- What do you like about it?
- What do you dislike about it?
- Which life cycle stage has the biggest environmental impact?
- How sure of your response are you? Please name a percentage of certainty.

Then the next prototype was shown and the questions repeated. Note that the prototypes were not explained; users were left to interpret the graphs themselves. This was to simulate the default expected scenario of industry professionals seeing data visualizations in publications or meetings without tutorials and with no background training. Once this feedback was obtained for all four prototypes individually, all four prototypes were shown at once, and the participant was asked which one they liked best and why. All feedback was collected and saved as text for analysis.

For fair user-testing comparisons across data visualization formats, all prototypes used the same numeric data. These numeric values were randomly assigned to different life cycle stages for each data visualization technique to ensure participants would not try to learn from previous techniques. There was the potential for participants to learn and be influenced by seeing certain techniques before others, so to avoid bias three different sequences of prototypes were used, so different participants viewed them in different orders.

In addition to totalling the number of participants who preferred each technique and their reported certainty levels for each, the text of their responses was analyzed qualitatively and quantitatively. First, responses were qualitatively coded to group them into categories, e.g. “liked aesthetics”, “disliked aesthetics”, “easy to read”, “easy to rank”, “hard to rank”, and more. Next, the number of participants mentioning each category were counted for each graph. These results were analyzed to determine if one technique performed better than others at conveying uncertainty while still being easily understandable.

3 RESULTS AND DISCUSSION

When analyzing the data from the interviews, it was broken down into the quantitative data -- how confident they felt, how many chose each graph as their preferred; and qualitative -- coding the comments made when asked about what they liked and disliked about each graph.

3.1 Quantitative Results

Figure 2 shows the number of participants choosing each graph as their preferred.

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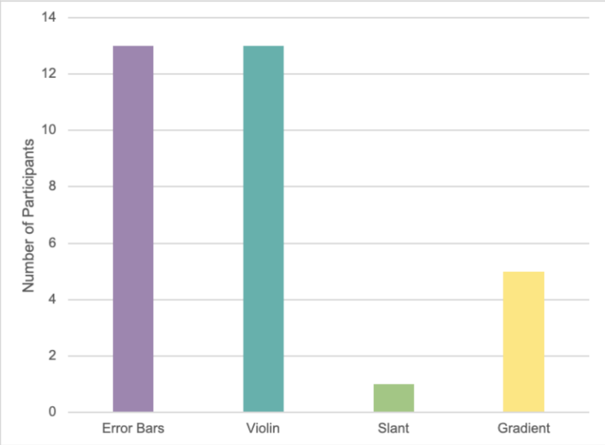

Figure 2. Selected preferred graph.

Figure 2 shows a significant preference for the "error bars" and "violin" graphs with 40% selecting each respectively; the "gradient" graph had 15% participants prefer it and the "slant" graph had 5%. However, the popularity of the graphs did not necessarily show their effectiveness in forcing users to acknowledge uncertainty.

Figure 3 shows the quantitative analysis of differences in users listing their percentage confidence in which life cycle stage was the highest impact in each graph. While there does not appear to be much difference, ANOVA and one-sided t-tests were calculated for comparisons of all graphs, and a slight significance was found. "Error bars" and "gradient" gave users lower confidence in their answer (the correct interpretation) than "violin" or "slant". Assuming a null hypothesis that all of the mean values of the groups were the same, a single factor ANOVA test found statistically significant differences between the self-reported confidence from the users on the different graphs. For this data, the $F_{crit}=2.7$ at $\alpha=0.05$, $F=3.5$, and the p-value is 0.018. In order to understand how the means differ, more testing needed to be performed.

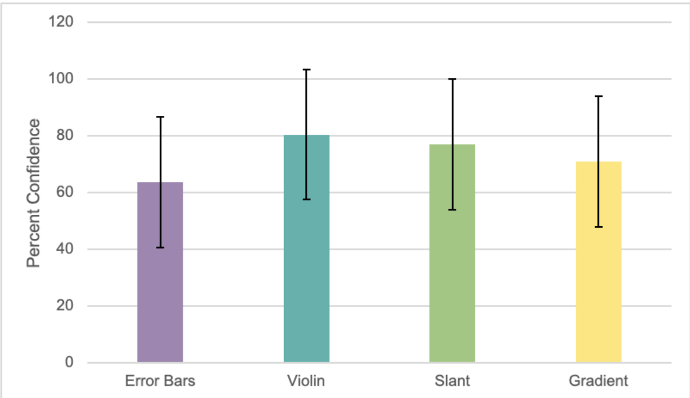

Figure 3. Percent confidence in top impact, with standard deviation (error bars)

One-sided paired t-tests were performed comparing each combination of graph type to test for differences in the means (Lakens, 2017). The statistical evidence in Table 2 shows that all but 2 of the graphs, "violin" and "slant," are statistically different. This means that there is a difference in how confident participants felt when looking at each of the graphs, except for "violin" and "slant", which were nearly the same. Based on this information, the "error bars" graph might be preferred, as it led to the lowest self-proclaimed confidence from participants, but the difference between it and "gradient" was small. There was statistical significance, but because the effects were small, they may not be conclusive. Thus, qualitative data was examined.

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Table 2. Statistical results from t-tests

Comparison	P-value
Error Bars and Violin	.00001
Error Bars and Slant	.00017
Error Bars and Gradient	.025
Violin and Slant	.21
Violin and Gradient	.0069
Slant and Gradient	.043

Showing graphs in different orders did not cause uncertainties to be more accurately read in some graphs than others. Figure 4 shows there was no correlation between percent confidence and the order that the graphs were shown in.

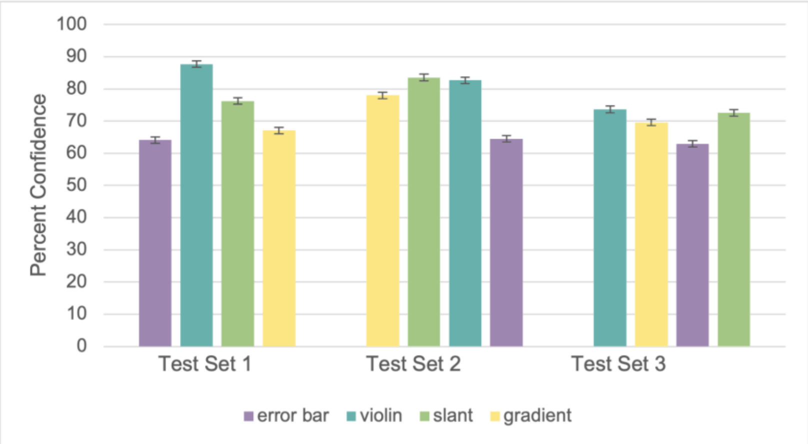

Figure 4. Percent confidence in top impact, shown by order of viewing

3.2 Qualitative Results

Even though there was statistical significance in the quantitative data, the differences in forcing users to acknowledge high uncertainties were small. Thus, qualitative data was also used to better understand the user thought process while examining each graph. Participants were asked to discuss what they liked and disliked about each of the graphs, which was then used to count the number of times certain ideas or phrases were mentioned.

Table 3. Table of comments

Comments	Error Bars	Violin	Slant	Gradient
Liked aesthetics	8	9	1	9
Disliked aesthetics	4	1	10	1
Easy to read	9	3	3	5
Confusing / hard to understand	4	15	10	6
Hard to choose highest impact / see where error starts and stops	6	1	2	18
Clear / defined / easy to rank	7	6	8	4

Table 3 shows clustered categories of comments made by users about the graphs; some were mentioned as reasons why a graph was their preferred; some were mentioned as reasons why they disliked it.
As Table 3 shows, “error bars” received the most positive comments ("aesthetic" and "easy to read"), reinforcing the quantitative findings of Figure 1. The “error bars” graph was often selected as the preferred because it was familiar and therefore easy to interpret. For example, “[this graph is] familiar and [I] automatically know assumptions, [so it is] easy to read.” However, seven users said that it was more certain, e.g. “[I like] where the clear cut off is for each category,” meaning users can ignore the uncertainty.

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Participants who selected the "violin" graph as their preferred often selected it because it was clear / defined / easy to rank -- this could mean that they were able to ignore the uncertainty. It was extremely popular with 40% of the participants selecting it as their preferred, but almost 50% of the participants said it was hard to read or confusing, which means they may have liked how it looked, but it was not valuable for conveying uncertainty information. As one said, they were "not too distracted by the uncertainty factor." This was surprising, because it was the opposite of why the graph was invented, and the opposite of what was desired here.

The "slant" graph was a combination of everything unwanted. It was hard to read, hard to understand, and not aesthetic. It was liked by the fewest number of people. Thus, it was easily removed from consideration.

The "gradient" graph was most often mentioned as forcing users to acknowledge uncertainty. Sometimes this was mentioned positively, but often it was mentioned as a frustration, e.g. "[it is] hard to see where the limit is, so doesn't like the fade." It was not liked by as many people, and it could be because of this. However, it was found to be easy to read, aesthetic, and difficult to see where the error starts and stops, which is desirable when you want users to immediately and intuitively acknowledge uncertainty.

The "error bars" graph was clearly the most familiar, and the error bars elicited an immediate connection with uncertainty. However, some participants took this familiarity and comfort to ignore the uncertainty instead of acknowledging it. The "violin" graph was aesthetic, but many participants were confused by it. Worse, many ironically said they liked it because they were able to ignore the uncertainty "bubble" and that the shape made it easier, rather than harder, to be certain of which variable had the highest impact. The "error bars," "violin," and "slant" graphs were more often mentioned as providing certainty (clear / defined / easy to rank), the opposite of what was desired. The contrast between these results and Figure 3 may indicate a weakness in the initial testing methodology -- users asked how certain they are of a result can think rationally and give a "correct" answer, regardless of how easily and intuitively they read the graphs. Perhaps if users were only able to view the graphs for five seconds each, or only had a few seconds to decide on their answers, or other constraints, Figure 3's results might have been different. Further study is required

Note, however, the difference between the graph that best conveyed uncertainty versus the graph that was most liked. Many of the comments about the "gradient" graph forcing uncertainty recognition were dislikes, not likes. This is likely because of people's discomfort with uncertainty, as noted in the introduction. It may be a cultural barrier that must be overcome for such tools to be used in industry.

The results above were used to decide on using "gradient" graphs in the sustainable design website Productdesign.green. Figure 5 shows two samples in context: the pages with LCAs and design recommendations for a monitor and a mobile phone.

As Figure 5 shows, the monitor's combined LCA results show that lifetime energy impacts overlap somewhat with material and manufacturing stage impacts in their uncertainties, so both variables should be targets for sustainable redesign. Each has corresponding design strategies suggested on the right side, with links to online tutorials. By contrast, the mobile phone's combined LCA results show that material and manufacturing stage impacts dominate regardless of the uncertainties, so the only sustainable redesign strategies listed are for that life cycle stage. This was the ultimate goal, to display each product's LCA results in a way that is easy to read but conveys the high uncertainties in a way that cannot be ignored.

3.3 Limitations

There are several ways in which future studies could improve on this study's methods. A larger sample size could be used to provide better precision in quantitative results. A larger variety of data could be tested in the graphs, to test different levels of uncertainty in each graph. A control graph with no uncertainty could be compared to these. By randomizing the order of the graphs in four different versions, we believe we minimized order effects, but future studies could randomize presentation order for every participant.

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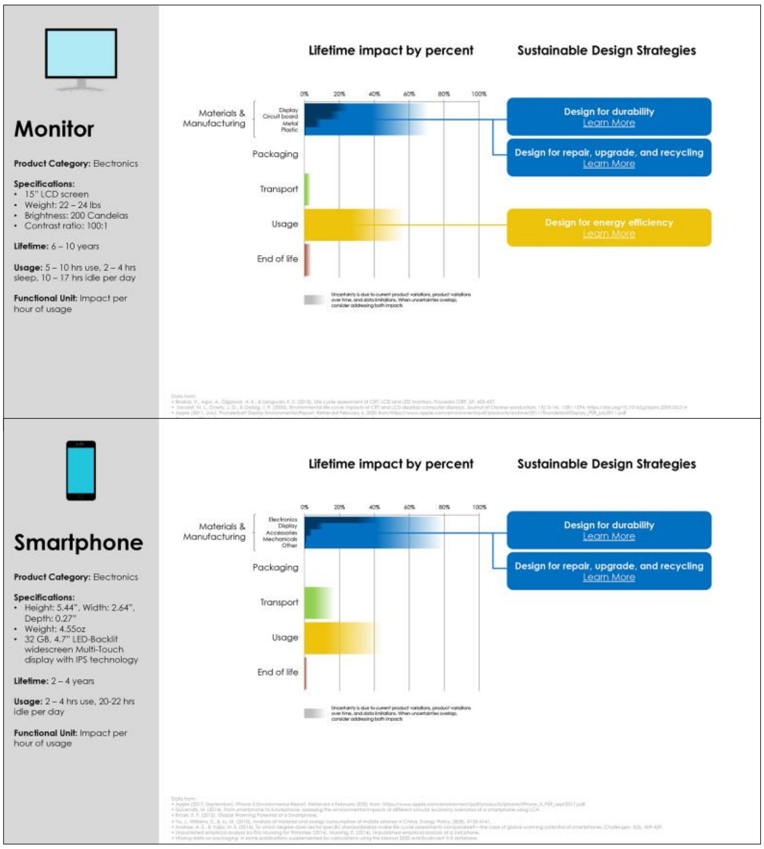

Figure 5. Visualizations in context on Productdesign.green

While we believe the users tested here would represent the industry users of the LCA-based design guide, students do differ from industry professionals, so future studies could test only industry practitioners. More intuitive reactions could be sought by only showing graphs for five seconds, or other such limitations. Finally, the user testing could put the data visualization into a more real-world context by asking users to make decisions to redesign a product based on the graphs, e.g. allocate a fixed budget to different life cycle stages, or do actual product redesigns and observe how they differ. We encourage future studies such as these.

4 CONCLUSION

The goal of this research was to determine the most effective and desired data visualization for an LCA-based design guide, where "effective" meant users acknowledging large uncertainties in their decision-making rather than intuitively ignoring them. Analysis of semi-structured interviews showed the most desired graphs to be "error bars" and "violin." The results of the quantitative analysis about effective uncertainty visualization produced very small but statistically significant results that the participants were more uncertain about the "error bars" graph. However, analyzing the qualitative data provided different insights, including that the "gradient" graph appeared to convey uncertainty that users could not ignore. Even though participants were sometimes uncomfortable with the difficulty seeing where the bars end, it did force them to acknowledge the uncertainty, rather than merely noting it intellectually but ignoring it in practice.

Therefore, even though the "gradient" graph was not the most liked, it most effectively forced users to deal with the uncertainty, unlike "error bars" and "violin," where the uncertainties could possibly be ignored. The "errors bars" graph quantitively had the most uncertainty, which was the goal of the visualization. However, 11 people found it familiar and traditional, which could be concerning as people who are familiar with it often ignore the error bars and therefore the uncertainty. Because of this, we cannot say with certainty whether the "gradient" or "error bars" graph would be more effective, as it can depend on the user's background.

The goal for future work is to test if this data visualization, used in the LCA-based design guide, actually helps designers make more sustainable products. Future work should also test the

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effectiveness of the design guide overall, and add data for more products, such as more consumer electronics, kitchen goods, soft goods, perhaps even medical devices or other niches. Allowing designers to request consumer products will ensure the guide provides the greatest impact.

This research helps LCA data become more accessible to designers and engineers in the early phases of design, allowing those without the resources or ability to perform LCA to still benefit from it and design more sustainably. The future health of the world and society requires product development to include sustainability.

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