Evaluating Visualizations Used in Communication of Life Cycle Assessment Results

Undergraduate Research Thesis

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By

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Abstract

Life Cycle Assessment (LCA) provides insight into the environmental and human health impacts of processes and products like electric vehicles. However, the complexity of LCA results often leads to ineffective communication of key environmental impacts and hinders their interpretation, preventing non-expert audiences from making informed sustainability decisions. My study addresses these communication challenges by evaluating visualizations commonly employed in LCA results.

Using A/B testing through a Qualtrics survey, my study evaluates four common visualizations seen in LCA results: (1) stacked bar charts, (2) unstacked bar charts, (3) pie charts, and (4) Sankey diagrams. My survey collected responses from a total of 172 participants from Ohio State University and local Columbus communities, which I analyzed. My findings offer insights into the effectiveness of the visualizations and identify those that best bridge gaps in understanding between technical experts and general audiences. Based on these insights, I developed a set of recommendations to make complex LCA results more accessible and support informed decision-making. These recommendations crafted are from the survey results, but they also follow common best practices in visualization design.

Acknowledgements

First, I would like to thank my committee, Dr. Daniel Gingerich and Dr. Mike Rayo, who have provided me with the resources, guidance, and support necessary to complete a thesis. I first met with Dr. Gingerich in January 2024, where I learned about his Knowledge for Water and Energy Systems Transitions (KWEST) Lab and the research he engaged in, the Facilitating Local Electrified Energy and Transportation Services for All (FLEETS for All) project. Additionally, I found Dr. Rayo's course, ISE 5760: Visual Analytics for Sensemaking to be informative and enjoyable. His work with the Cognitive Systems Engineering Laboratory is highly interesting and relevant to my study. While I wish I had gotten involved in undergraduate research earlier, I am grateful for both Dr. Gingerich's and Dr. Rayo's mentorship that has allowed me to pursue a thesis in a rather brief time.

I would also like to thank Samuel Copeland, a current second-year Civil Engineering PhD student under Dr. Gingerich and GEM Fellow whom I have had the pleasure of working with throughout my time as a young researcher. Sam has offered me professional and personal mentorship, and his expertise in life cycle assessment is a big reason this thesis was even possible. He has been an invaluable resource in my research journey, and I will miss his guidance after my graduation.

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Finally, I thank my friends, my parents, and mentors who have inspired me to pursue undergraduate research and help me realize the power of curiosity. This power of curiosity is certainly something I will hold dear as I move to the country of Peru following my graduation.

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Introduction and Background

The digital revolution has created the incomprehensibly large amount of data present in the world today; however, people's ability to accurately interpret this data has not kept pace.[1] To assist in interpretation, data can be visualized as a picture, chart, or graph designed to make the information more digestible for its audience. Visualization techniques have evolved into complex, multivariate forms that synthesize large amounts of data to highlight comparisons or trends, especially in the sustainability realm. Although visualization means to simplify data, poor design can overwhelm the reader with too much information, obscure relevant data, or misrepresent the problem, hindering comprehension and the ability to make informed decisions.

Data visualizations are commonly used when reporting life cycle assessment (LCA) results. Life cycle assessments analyze the environmental impact of a process or product throughout its entire life – from raw material acquisition to manufacturing, transportation, use, and decommissioning.[2] The linear path of an LCA is shown in Figure 1, along with end-of-life alternatives ranging from simply disposing of the product via waste management to pathways such as recycling and remanufacture. The goals of LCAs are to create data that supports sustainability policy, visualizes environmental emissions, and informs stakeholders in decision-making. LCAs are typically broken into four phases: (1) Goal and Scope Definition, (2) Inventory Analysis, (3) Life Cycle Impact Assessment, and (4) Interpretation.[3] Combined, these four phases define the LCA's objectives, collect and quantify inputs and outputs, assess environmental impacts, and interpret results to drive informed decision-making, respectively. In the Interpretation phase, results of an LCI, LCIA, or both are summarized as a basis for conclusions and recommendations in accordance with the goal and scope definition.[4]

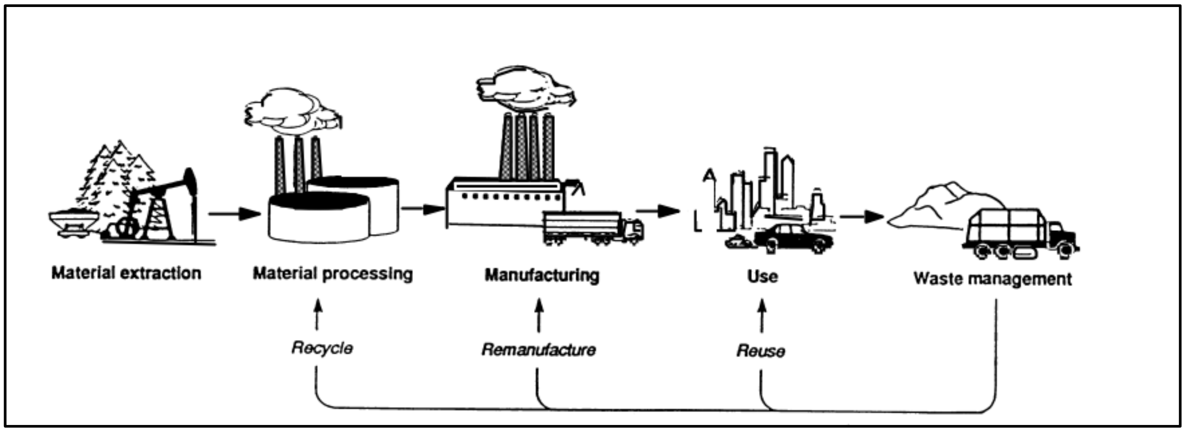


Figure 1: Overview of a Physical Product Life Cycle (OTA, 1992)[5]

Two commonly used categories of LCA visualizations are comparative and part-to-whole visualizations. **Comparative visualizations** typically highlight differences between alternatives, allowing for easy comparison across categories. In the LCA context, an example comparative visualization is a bar chart that shows the tons of carbon dioxide (CO_2) emitted in each life cycle phase of an electric vehicle. The side-by-side bars may allow for easy comparison of each phase of the vehicle's life cycle but do not clearly convey how each phase contributes to total CO_2 emissions, making it more difficult to determine the part-to-whole relationship. Prado et al. highlight four key challenges often faced when communicating comparative LCA results: irrelevance, inaction, indecision, and misconception. These issues stem from how uncertainty and relative differences are represented in visualizations and create difficulties in applying insights for informed action.[6]

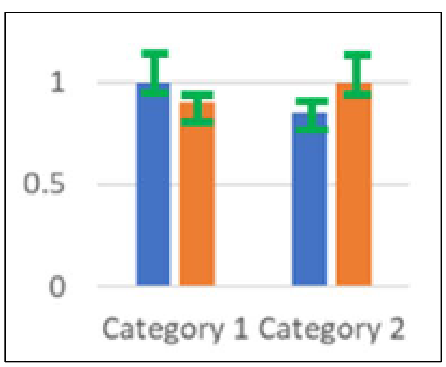


Figure 2: Example of LCA Comparative Visualization (Prado et al., 2022)[6]

Conversely, **part-to-whole visualizations** highlight how individual components contribute to the overall impact, thereby showing the relative significance of each part within the process. For example, a pie chart in Figure 3 shows the overall global warming potential (GWP) of a theoretical process – each slice of the chart reflects the contribution of one life-cycle phase to the overall GWP. However, this may not effectively convey precise numerical comparisons between phases, as the relative size of each slice is given by a percentage instead of a numerical quantity. Furthermore, part-to-whole visualizations often lack the detailed side-by-side comparisons needed when exact magnitudes or benchmarks must be evaluated.

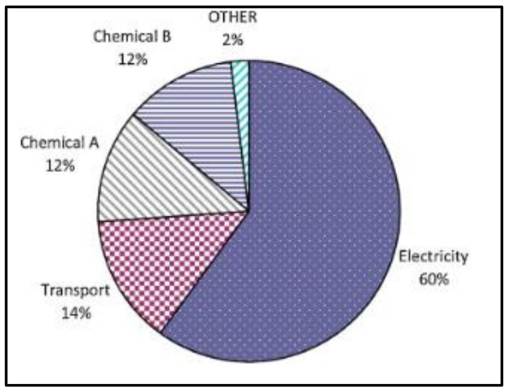


Figure 3: Example of LCA Part-to-Whole Visualization (Harding, 2013)[7]

Visualization Guidelines

While LCA encompasses vast information on environmental impacts, practitioners face challenges in effectively communicating the results to non-expert audiences, limiting their interest or comprehension.[8,9] This challenge stems from LCA's highly technical nature, which, without adequate guidance and standardization, proves difficult to interpret for non-expert stakeholders including policymakers, industry professionals, and the general public.[10] The International Organization for Standardization (ISO) sets standards for each of the four phases of LCA and has been instrumental in maintaining consistency in the LCA framework. Although

ISO 14040: LCA Principles and Framework outlines general goals for the interpretation phase, such as providing a consistent set of conclusions and assessing data quality, it does not offer specific recommendations for visualizations or strategies to effectively communicate LCA results. Furthermore, ISO 14044: LCA Requirements and Guidelines, like ISO 14040, reinforces requirements and outlines detailed protocols for each phase, including reporting the LCA scope, system boundary, study methodology, and “significant issues” contributing to emissions. ISO 14044 also requires reporting checks of completeness, sensitivity, and consistency. Despite this thorough detail, ISO 14044 lacks explicit guidance on implementing visual tools such as charts or diagrams for presenting LCA results. It also fails to include emphasis on the need for strategies for audience engagement, non-expert decision-making, or user-centric design principles. In fact, despite an Interpretation section, terms like “visualization,” “non-expert,” and “accessible” do not appear throughout the guidelines. This shows that despite robust procedural detail throughout, ISO 14040 and 14044 do not fully equip practitioners to ensure LCA results are accessible, actionable, and informative for all audiences.

In addition to limited guidance from formal ISO LCA standards, current research also falls short in providing tools and strategies to aid decision-making among non-expert audiences, further underscoring the communication gap in LCA. Most LCA literature focuses on applying or developing methods, while far fewer studies investigate how decision-makers interpret LCA results.[10] Prado et al. explain the “tension” between LCA’s descriptive role in analyzing environmental impacts and its prescriptive role to guide decision-making for individuals, communities, and governments.[6] Ultimately, without clear comprehension of LCA results, stakeholders cannot use LCA to address sustainability in their lives. Therefore, investigating how LCA-related data is currently perceived will improve LCA’s effectiveness.

Research Overview and Significance

By relying on industrial engineering disciplines of decision analysis, data visualization, and human factors, this interdisciplinary study addresses the growing need to effectively communicate data to facilitate public understanding, analysis, and action. It addresses critical challenges in environmental decision-making and offers feedback to LCA practitioners on how to better communicate results. My study fills a critical gap in understanding how people interpret LCA results through community-engaged visualization testing.

The primary goal of my study is to evaluate the effectiveness of four LCA data visualizations through a survey. My project contributes to existing LCA literature by providing practical guidelines to bridge the gap between LCA data and its application in policy and daily life. The community engagement throughout my work is an example of fostering dialogue between the University and communities to address related challenges.

My study is part of the broader, federally-funded Facilitating Local Electrified Energy and Transportation for All (FLEETS For All) project led by Ohio State University researchers. The project engages underserved communities to understand engineering challenges faced, create communication strategies that support environmental decision-making, and develop solutions to improve health, environmental, and social conditions.[11] While FLEETS involves communities throughout Franklin County, my study pulls from a population more central to Columbus and the University. One established output of the FLEETS project is an LCA comparing electric vehicles and internal combustion engine vehicles.[12] This LCA study reveals the tradeoffs between air quality and greenhouse gas emissions of electric vehicles when transitioning from all-overnight charging towards a mix of charging scenarios. All visualizations created and used in my study originate from this electric vehicle LCA.

Methodology

Survey design, preparation, and implementation

When considering various methods of community engagement, it was clear that a survey was the most effective instrument for achieving my research goals, which centered around understanding participants' interpretations of LCA visualizations. A survey allowed me to test visualizations through A/B testing, and to easily compare their scores. Surveys are typically less of a time commitment than in-person focus groups, formal interviews, and open-ended discussions. While these methods were appealing, the project timeline necessitated a more time-efficient approach to obtain sufficient responses. This time limit made deep analysis of qualitative feedback impractical, therefore, I chose a survey to achieve community insights.

Research Hypotheses

Before designing and implementing the Qualtrics survey, I developed the following hypotheses, which were critical in shaping the direction and framework of the entire project.

H1: People are equally comfortable viewing stacked bar charts compared to unstacked bar charts as comparative visualizations.	$\mu_{C,USB,Comp} = \mu_{C,SB,Comp}$
H2: People are equally accurate in comprehending stacked bar charts compared to unstacked bar charts as comparative visualizations.	$\mu_{A,USB,Comp} = \mu_{A,SB.Comp}$
H3.1: People are equally comfortable viewing pie charts compared to stacked bar charts as part-to-whole visualizations.	$\mu_{C,P,PtW} = \mu_{C,SB,PtW}$
H3.2: People are equally comfortable viewing stacked bar charts compared to Sankey diagrams as part-to-whole visualizations.	$\mu_{C,SB,PtW} = \mu_{C,SD,PtW}$
H3.3: People are equally comfortable viewing Sankey diagrams compared to pie charts as part-to-whole visualizations.	$\mu_{C,SD,PtW} = \mu_{C,P,PtW}$
H4.1: People are equally accurate comprehending pie charts compared to stacked bar charts as part-whole visualizations.	$\mu_{A,P,PtW} = \mu_{A,SB,PtW}$
H4.2: People are equally accurate comprehending stacked bar charts compared to Sankey diagrams as part-whole visualizations.	$\mu_{A,SB,PtW} = \mu_{A,SD,PtW}$
H4.3: People are equally accurate comprehending Sankey diagrams compared to pie charts as part-whole visualizations.	$\mu_{A,SD,PtW} = \mu_{A,P,PtW}$

Table 1: Hypotheses being assessed; where

$$\mu_{i,j,k} = Mean\ of\ i\ perspective\ using\ j\ visualization\ type\ with\ k\ comparison$$

$$i = Comfort\ (C)\ or\ Accuracy\ (A)$$

$$j = Unstacked\ bar\ (USB),\ Stacked\ bar\ (SB),\ Sankey\ Diagram\ (SD),\ Pie\ (P)$$

$$k = Comparative\ (Comp)\ or\ Part - to - Whole\ (PtW)$$

Survey Design and Content

I took multiple steps before implementing the survey to ensure it accurately tested the hypotheses. With guidance from my graduate mentor, I developed five visualizations from the electric vehicle LCA data previously mentioned, and shown in Appendix A. These consisted of four visualization types commonly used in communication of LCA results: (1) stacked bar chart, (2) unstacked bar chart, (3) pie chart, and (4) Sankey diagram.[13,14] Sankey diagrams, commonly used in LCA, differ from traditional charts by representing resource flows between stages and highlighting interconnected pathways rather than cumulative totals. With the exception of the Sankey diagram, we designed the visualizations in Excel, which enabled me to follow common practices such as ensuring clear labels and titles, consistent color schemes, and proper scaling of data. My graduate mentor and I developed the Sankey diagram in SimaPro, an LCA-building software following ISO guidelines.

Question Design and Rationale

Both versions of the survey contained eight total visualization-related questions, two per figure. Each of the four visualizations was accompanied by two questions: a Likert-scale question measuring participants' comfort with the visualization and a question assessing their comprehension. I designed the comfort question to gauge participants' familiarity and emotions about seeing the given visualization. I designed comprehension questions to assess participants' ability to identify key aspects of the LCA data, and they are meant to be relevant to real-world, current sustainability issues. As seen in Table 2, the questions required participants to compare cancer risk across different vehicle types, extract quantitative information about one LCA phase, and identify specific sources of global warming in the EV life cycle. Before releasing the official survey, I conducted pre-testing with a select group of students to ensure the layout, wording, and message of the questions was effective. I meticulously developed these questions so that they asked participants about key themes related to human health risks and environmental emissions that LCA visualizations seek to communicate. To ensure the questions were Questions required the participants to understand the key themes of each visualization, therefore ensuring that their comprehension reflects an accurate understanding of the data's main messages. The survey layout, versions, and questions asked are in Table 2.

<table>
<tr><th>Question</th><th>Version A</th><th>Version B</th><th>Comfort Question</th><th>Comprehension Question</th></tr>
<tr><td>Comparative 1</td><td>Unstacked Bar</td><td>Stacked Bar</td><td rowspan="4">I am comfortable with viewing and interpreting this visualization.

Options:
"Strongly Agree,"
"Agree"
"Neither"
"Disagree"
"Strongly Disagree."</td><td>In the Operation and Maintenance phase, does the Internal Combustion Engine Vehicle (ICEV) or Electric Vehicle (EV) appear to cause a higher risk of cancer?</td></tr>
<tr><td>Part-to-Whole 1</td><td>Pie</td><td>Stacked Bar</td><td>Based on this visualization, the Production-Body component contributes approximately ____ percent to overall global warming levels.</td></tr>
<tr><td>Part-to-Whole 2</td><td>Stacked Bar</td><td>Sankey</td><td>Based on this visualization, the largest source of global warming in the EV life cycle is the ____ stage.</td></tr>
<tr><td>Part-to-Whole 3</td><td>Sankey</td><td>Pie</td><td>Based on this visualization, which component of the EV Production phase contributes most to overall emissions?</td></tr>
</table>

Table 2: Questions and Versions of Qualtrics Survey

Survey Mechanics and A/B Testing

After creating visualizations and survey questions, I designed the survey in Qualtrics, which allowed me to implement survey logic that presented participants with one of two possible versions, Version A or B. Essentially, for my study, I set up an A/B test – a user experience test designed to show different groups of participants different versions of data.[15] The first comparison focused on comparative visualizations, while the last three evaluated part-whole visualizations. There was only one comparative comparison because of the four visualization types chosen, pie charts and Sankey diagrams are not designed as a comparative visualization. Likewise, there were three part-to-whole comparisons because I identified that three of the four visualization types enable part-to-whole visualizations (pie, stacked bar, Sankey), while unstacked bar charts do not illustrate part-to-whole relationships as well. In Version B, the comparative stacked bar chart is distinct from the part-to-whole stacked bar chart. The presence of two stacked bar charts is why there are four visualization types, but that I created a total of five distinct visualizations.

Survey Recruitment

Before recruiting any participants, I sought and obtained Category 2B Exemption from the Ohio State University Institutional Review Board (IRB). After securing this exemption, I recruited participants using two methods: flyers around communities and ESSREP. First, I posted flyers around Columbus communities and the Ohio State University surrounding campus, offering a financial incentive in the form of a $25 Amazon gift card for completing the survey. To reach a large audience, I posted flyers in places such as the North Market and surrounding coffee shops with messaging boards inside. I specifically sought out community members because they are an integral stakeholder in this project; a generally non-expert audience with diverse backgrounds, education levels, and experiences that may struggle to interpret LCA visualizations in their current form. Second, I worked with Ohio State University's Environmental and Social Sustainability Research Experience Program (ESSREP) within the College of Food, Agricultural, and Environmental Sciences to survey students. I sought out students because of their technical background, availability, willingness to participate, and their potential as future leaders of the scientific community. While it does not offer financial incentives, ESSREP offers students class credit or bonus points to complete and participate in research studies. Targeting both community members and ESSREP students ensured a diverse base of participants, including a range of experiences and backgrounds.

Regarding the participant pool, the goal was to survey a minimum of 60 participants, with at least 30 participants assigned to each survey version (Version A and B) and at least 30 participants from each group (community members and ESSREP). A sample size of 60 was adequate because, according to the Central Limit Theorem, it ensures the sampling distribution is approximately normal with 30 participants for each version. Additionally, 60 was an attainable number given the time limits. Fortunately, I exceeded this goal, as I surveyed a total of 172 participants.

Data Analysis

Hypothesis Testing

After collecting the 172 responses, I began the process of hypothesis testing, which evaluated the differences between the means of two groups. In all four hypotheses, the null hypothesis (H0) predicts that there is no statistically significant difference between the two versions, and the alternate hypothesis (H1) aims to reject the null, predicting that there is a statistically significant difference between the versions. For all hypotheses, I assumed a 90 percent confidence level (alpha value of 0.1) instead of the conventional 95 percent interval (alpha value of 0.05) due to statistical power concerns. The lower threshold for significance in a 90 percent interval allows for a greater likelihood of rejecting the null hypothesis, therefore offering more insight and flexibility. Through analysis, I gained an understanding of how participants responded to my survey. Specific data analysis methodologies for both data types are shown in Table 3.

Type of Data	Hypothesis Test Used	Analysis process
Likert Scale responses	Mann-Whitney U test	Code responses as numbers, calculate mean and standard deviation, calculate and combine ranks, calculate test statistic, run the test.
Comprehension-based questions	Two-Proportion Z-test	Determine proportion correct responses for each question, calculate test statistic and Z-critical value range, check whether test statistic is within range.

Table 3: Statistical analysis of results

Analysis for Comfort Questions

Hypotheses 1 and 3 examined participant self-reported comfort levels between different visualizations. I measured comfort levels through a Likert-scale question, where participants indicated their level of agreement with the statement: “I am comfortable with viewing and interpreting this visualization” on a five-point scale from “Strongly Agree” down to “Strongly

Disagree." During data analysis, I assigned numerical values to each choice based on level of increasing comfort: 1 for "Strongly Disagree," 2 for "Disagree," 3 for "Neither agree nor disagree," 4 for "Agree," and 5 for Strongly Agree. Quantifying each response enabled easier calculation of mean and standard deviations, which were essential for hypothesis testing, and added additional context to the data. Given that responses generally clustered around "Agree" to "Strongly Agree," this data did not follow the normal distribution, which requires a symmetrical bell curve around a center value. Regarding the data type, while I was able to assign numerical values to each response, Likert-scale responses are inherently categorical data, with ordinal levels between each response. Consequently, I deemed a t-test to be inappropriate for this data. Instead, I used the Mann-Whitney U test – a non-parametric statistical test – to determine whether one visualization yielded a higher or lower mean comfort level compared to another. This test involved coding responses as numerical values, calculating the 'ranks,' and finally comparing the test statistic to the critical values.

Analysis for Comprehension Questions

Hypotheses 2 and 4 examined the proportion of correct responses to comprehension questions. During the survey construction process, I designated correct answers to each question, enabling Qualtrics to automatically score each question with a zero or one and each entire survey response with a score from zero to four. In Excel, I aggregated all responses together and calculated the percentage of correct answers for each question. Given that there were proportions of correct answers for both populations and a sufficiently large sample size ($n > 30$), I determined that a two-proportion Z-test was most appropriate. For this test, the 90 percent confidence level corresponded to the critical value range of (-1.645, 1.645); if the test statistic was outside of this range, then I was able to reject the null hypothesis.

Results

	Unstacked Bar	Pie	Stacked Bar	Sankey	Calculated p-values
H1: $\mu_{C,USB,Comp} = \mu_{C,SB,Comp}$	4.47		4.2		0.189**
H2: $\mu_{A,USB,Comp} = \mu_{A,SB,Comp}$	92%		59%		0.00*
H3.1: $\mu_{C,P,PtW} = \mu_{C,SB,PtW}$		4.58	4.27		0.04*
H4.1: $\mu_{A,P,PtW} = \mu_{A,SB,PtW}$		83%	88%		-0.280**
H3.2: $\mu_{C,SB,PtW} = \mu_{C,SD,PtW}$			4.45	3.37	0.00*
H4.2: $\mu_{A,SB,PtW} = \mu_{A,SD,PtW}$			97%	88%	0.0434*
H3.3: $\mu_{C,SD,PtW} = \mu_{C,P,PtW}$		4.44		3.17	0.00*
H4.3: $\mu_{A,SD,PtW} = \mu_{A,P,PtW}$		23%		70%	0.00*
* **Reject the null:** Statistically significant difference between the two groups ($p < 0.1$)					
** **Do not Reject**: Not a statistically significant difference between the two groups ($p > 0.1$)					

Table 4: Summary of Results for all four comparisons

Comparative Visualizations

There was one comparison of comparative visualizations, which was Questions 1-2 in both survey versions. The comparison was between an unstacked bar chart and a stacked bar chart. H1 assessed whether or not there was a significant difference in participants' comfort level when viewing both of these visualizations. Looking at the results, there is not enough evidence to suggest a significant difference between comfort levels with unstacked and stacked bar charts. H2 assessed whether or not there was a significant difference in participants' ability to correctly answer questions based on the visualizations. There is enough evidence to suggest a significant difference between the participants' scores of the unstacked bar chart and the stacked bar chart.

Part-to-Whole Visualizations

There were three comparisons of part-to-whole visualizations, which were Questions 3-8 in both survey versions. The comparisons were between a 1) pie chart and stacked bar chart, 2) stacked bar chart and Sankey diagram, and 3) Sankey diagram and pie chart. For all hypotheses, the null hypothesis predicted that there was no difference in comfort level or accuracy between visualizations, while the alternate hypothesis predicted a statistically significant difference.

Hypotheses 3.1, 3.2, and 3.3 assessed whether or not there was a significant difference in participants' comfort level when viewing these visualizations. As seen in the table, each test statistic is less than the alpha value of 0.1, so I can reject the null hypothesis for each comparison, concluding that there is a significant difference in comfort levels. Hypotheses 4.1, 4.2, and 4.3 assessed whether or not there was a significant difference in participants' ability to correctly answer questions based on the visualizations. H4.1 found there to be no significant difference in accuracy between the pie and stacked bar, so I cannot reject H4.1. However, I can reject H4.2 and H4.3 as their accuracy differences were found to be significant.

Discussion

Comparative Visualizations

The results of the comparative comparison indicate that the unstacked bar chart had both a higher comfort level and a higher rate of correct answers, although the difference in comfort score was not statistically significant. In the comprehension question, participants were asked to examine the Operation and Maintenance phase and determine whether ICEVs or EVs posed a higher risk of cancer. To answer correctly, the participant would need to locate the Operation and Maintenance bar, which is grey in both charts, and determine whether the bar is larger for ICEVs or EVs.

The higher score with the unstacked bar chart makes sense, as all bars extend from a common baseline in the origin, making side-by-side comparisons straightforward. Participants likely focused on these consistent baselines and the simplicity of identifying that the higher bar contributed to a higher risk of cancer. In contrast, viewing the stacked bar chart presented more challenges to participants. While still yielding correct answers, participants had to focus on comparing segments that did not share a consistent baseline in the origin. The lower bounds for the Operation and Maintenance phase are set at around 0.2 and 0.3, respectively, and this inconsistency forces participants to estimate and extrapolate values, making comparisons across graphs more difficult.

Because the unstacked bar chart scored higher in both comfort and accuracy, one recommendation for LCA practitioners moving forward is to prioritize the use of unstacked bar charts when presenting data related to risk comparison. Unstacked bar charts facilitate a clear side-by-side comparison with all bars extending from the baseline and minimize the need for comparisons across different levels, which increases visual clarity and decreases cognitive load.

The results provide the conclusion that when creating visualizations for comparative comparisons, practitioners should focus on maintaining consistent reference points and avoid floating segments, which makes unstacked bar charts the ideal choice.

Part-to-Whole Visualizations

Part-to-Whole Comparison 1’s results between the pie chart and stacked bar chart are interesting but difficult to draw strong conclusions from. Both visualizations had high accuracy scores, with participants correctly identifying the Production – Body component’s 15 percent contribution to overall EV global warming. To answer correctly, participants needed to use the legend to correctly identify the red section in each graph, labelled “Production – Body,” and estimate that section’s contribution to the whole. Each graph performed well because it clearly communicated the data; namely, the pie chart’s straightforward, color-coded design facilitated easy identification of the correct slice. On the other hand, this pie chart consists of different slices, and seven of the ten add up to only 25 percent of the entire proportion of the global warming breakdown. The high number of slices in the chart raises a concerning issue, as small slices become hard to distinguish, making it difficult to quickly identify key information – especially if the slice that needs to be examined is small. Because this is a part-to-whole comparison, there is no need to compare multiple stacked bar charts with different baselines; thus, it is easier to identify 15 percent with only one stacked bar chart. High scores across the board illustrate a limitation of my study: when both visualizations score well in both comfort and accuracy, it is difficult to draw definitive conclusions. However, this is a positive development, indicating that the visualization effectively communicated the data. If both visualizations accurately convey the information, practitioners should then design for comfort.

However, Part-to-Whole Comparison 2's results between the stacked bar chart and Sankey diagram are more conclusive. The stacked bar chart scored significantly higher than the Sankey diagram in comfort level and slightly higher in accuracy. The question required participants to identify the EV stage that contributed the most to global warming. While there are ten categories given in each graph, participants are given three choices to choose from, representing each phase: production, use, and disposal. This makes interpreting each graph intuitive, especially in the stacked bar chart, where it is obvious that the Use-Electricity phase alone contributes over 50 percent of total levels, making production correct. While the stacked bar chart shows bars, the Sankey diagram shows the actual numerical proportions in each box, and the thickness of its lines along with the meter level in the right side of each box show the proportion of each stage's contribution. Despite this, one reason for the low comfort scores of the Sankey diagram is the different, complex structure compared to the other three "traditional" charts. While participants had low comfort levels viewing Sankey diagrams, this low comfort did not necessarily translate to poor accuracy, as 88 percent answered the Sankey diagram question accurately. To increase participant comfort with confusing visualizations like the Sankey diagram, practitioners should provide readers with additional context in the form of a step-by-step guide or background information on the visualization. Providing this additional context to potentially confusing visualizations will improve readers' comfort, thus bridging the gap between initial confusion and effective comprehension. Given that both visualizations received extremely high accuracy scores, there is hope that if practitioners design visualizations with focus on the non-expert's ability to interpret, people can correctly interpret them.

Part-to-Whole Comparison 3's results between the Sankey diagram and pie chart are also somewhat inconclusive. While participants reported feeling more comfortable with the pie chart, they scored more accurately with the Sankey diagram. Considering the Sankey diagram's low scores in Comparison 2 and its low comfort score in both comparisons, it is rather surprising that participants answered the comprehension question at such a higher rate than the pie chart. One explanation for the low accuracy rate of the pie chart is a potential miscommunication – the question asked which component **of the EV production phase** specifically contributes most to emissions, which would eliminate the most selected response of Use-Electricity because this is from the Use phase. This miscommunication illustrates the potential for nuances in all visualization types that can severely impact comprehension – the designer is responsible for creating a user-friendly visualization, and the participant is responsible for intently trying to comprehend the visualization. If either stakeholder does not fulfill their end of the bargain, a situation like Comparison 3 may arise, where almost 80 percent of participants answer incorrectly despite the question having one correct answer.

Conclusions, Limitations, and Future Work

Conclusions

The findings from my study hold important implications for visualizing the environmental and health impacts of electric vehicles through LCA. The main conclusion of my study is that more attention needs to be directed toward how LCA data is visualized. The results show varying degrees of comfort levels and accuracy with different visualizations. This work is meant to be a starting point for future research to continue. From the results of the survey, I developed a set of recommendations to follow in Table 5:

1	When showing comparisons between two alternatives, maintain consistent baselines. Ensure bars start from same baseline and add gridlines. Example: Use an unstacked bar chart over a stacked bar chart with comparisons.
2	When communicating LCA data to broader, non-expert audiences and aiming to ensure participants feel more comfort with the visualizations, prioritize the use of simple visualizations like pie charts and bar charts.
3	Try to minimize the number of data categories in visualizations, especially pie and bar charts, where an excessive number of categories can make it difficult to distinguish information.
4	Ensure clarity in visual labels. Distinguish LCA phases such as “production” with specific components within that phase (chassis, body, motor) to avoid mixing up LCA terminology.
5	Include a title, axis labels, and a color-coded legend whenever possible. Follow general best practices within visualization.
6	For complex visualizations like Sankey diagrams: Provide readers with additional context through a step-by-step guide, tutorial video, or background information on the visualization.

Table 5: Set of Recommendations for LCA Practitioners

Limitations

One limitation with my study is the scope of community outreach for survey responses. Because of the limited funds and strict timeline, I was unable to reach as broad a group of survey participants as initially desired. Although feedback from students was valuable, students are but one of many populations that should be surveyed, and my study does not fully capture perspectives of all demographics. Collecting responses from a more diverse demographic across various locations in the greater Columbus region would have strengthened my study's generalizability and provided a richer understanding of how different community segments interpreted the visualizations.

The second limitation involves the data response formats. While the survey effectively captured participant feedback on LCA visualizations, its close-ended nature limited participants' ability to elaborate on their answers. This restriction impacted the depth of information I was able to collect from participants, particularly for complex visualizations where qualitative feedback would provide richer insights. Interactive methods such as in-person focus groups or interviews would have helped me understand why participants felt uncomfortable or misunderstood a certain visualization, thus offering more nuanced feedback. Overall, while the survey offered a high number of responses, the quality and depth of each individual response were somewhat constrained.

The third limitation is with the questions chosen. Since the comfort-based questions measured participants' perceptions of their knowledge rather than their actual knowledge, it is challenging to draw definitive conclusions such as, "Participants felt more comfortable with stacked bar charts over pie charts; therefore, stacked bar charts should be used over pie charts all the time." Additionally, while the comprehension questions certainly tell me whether participants comprehended the visualization, they were limited to a single multiple-choice question per visualization. This is a limitation because a single multiple-choice question cannot capture all aspects of chart interpretation, and participants can randomly guess an answer, impacting the true reliability of results.

Future work

While limitations exist with my study, it has nevertheless unveiled an exciting path for future LCA visualization research. Future work should adopt a mixed-methods approach that incorporates long-form conversations with community members to gather open-ended feedback, which helps researchers further understand the interpretation challenges. One interesting approach is to incorporate cognitive load analysis by measuring and comparing the mental effort required to interpret visualizations. Cognitive load can be measured through several methods: self-reporting using tools like the NASA Task Load Index, physiological measures such as pupil dilation or eye movement tracking, and time-on-task methods that measure the amount of time a participant focuses on a specific question or task.[16] Such work would provide insight into what aspects of graphs confuse people, why they are confusing, and how to correct this confusion.

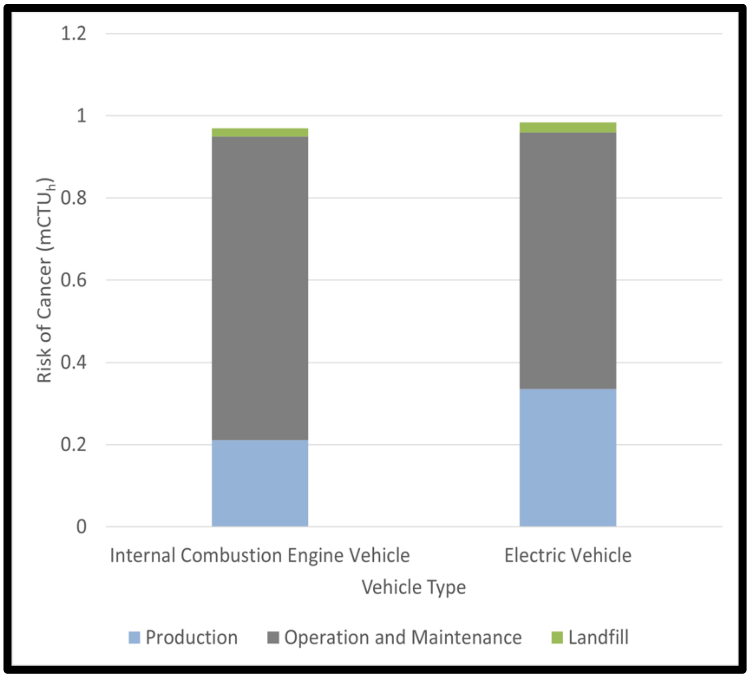
In addition to deeper analysis of participant results, future work should be committed to surveying a diverse range of participants from different backgrounds and socioeconomic levels to ensure findings reflect broader society, not just LCA experts. Future studies should compare scores between different participant groups (college students, non-college graduates, LCA experts) to address the question of how educational level is related to one's ability to understand LCA visualizations. Overall, this broader approach will contribute to increasing the overall effectiveness of scientific communication by tailoring visualizations to meet the growing needs of diverse audiences.

Finally, future work should broaden the scope of study by including more visualization types studied and exploring different processes or products being analyzed in the LCA than just electric vehicles. Assessing additional visualization types, such as radar charts enabling multi-category comparisons, heat maps highlighting density, and geospatial maps contextualizing data within locations, can reveal deeper insights and nuances within LCA visualization that practitioners should be aware of. Furthermore, a widened scope will increase the generalizability of my study to broader audiences and more LCA applications. For example, assessing visualizations used in LCAs of water usage, waste management, or cell phones may yield different insights than my study, which studied electric vehicles. To ensure the most common visualizations are being tested, researchers should conduct literature reviews to identify the visualizations most used, then focus on those. Overall, future work should prioritize the establishment of standardized best practices for visualizing LCA results. With this development, we can hope that the ever-increasing impacts of LCA studies are accessible to the widest audience possible, driving meaningful change for a more sustainable tomorrow.

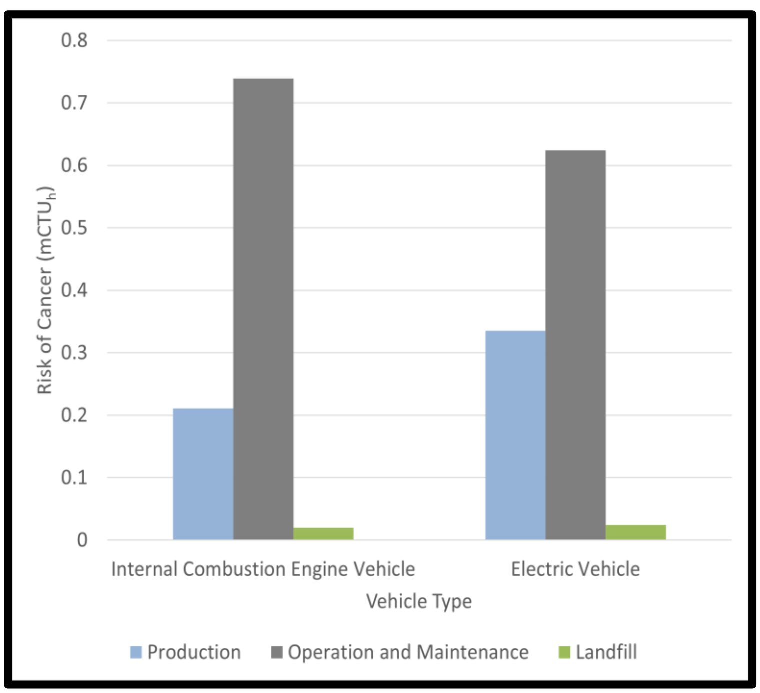
Appendices

Appendix A: 5 visualizations created for Qualtrics survey

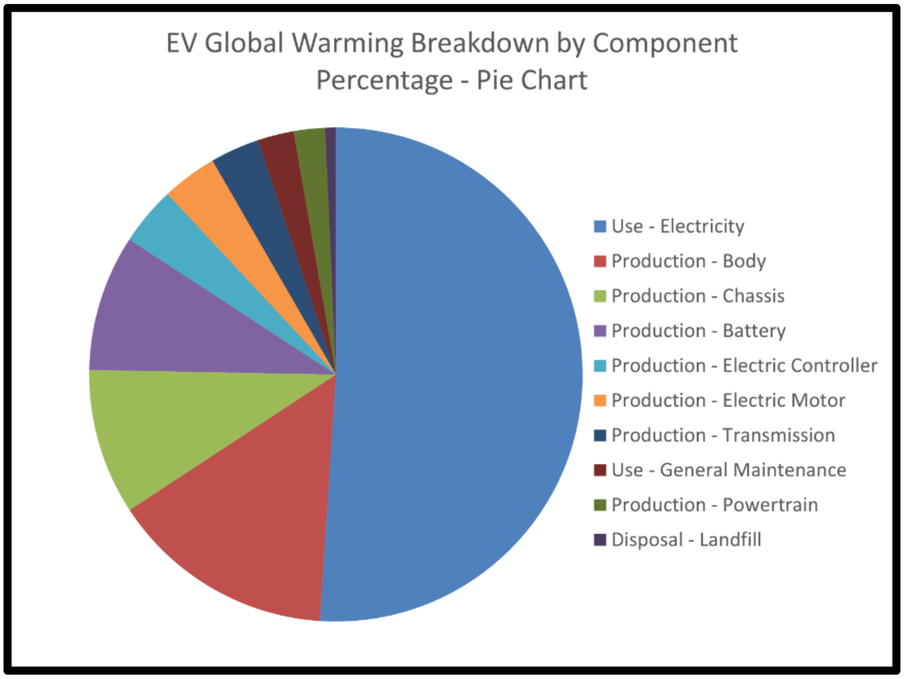
Visualization 1: Comparative Stacked Bar Chart. Shows the risk of cancer (in mCTUh) in each phase of both EVs and ICEVs.



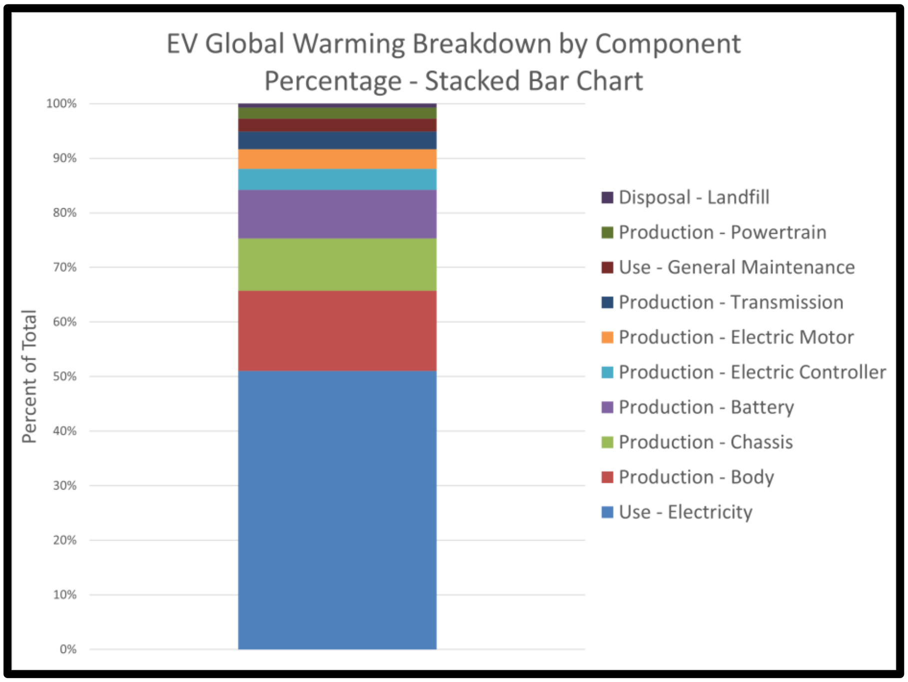
Visualization 2: Comparative Unstacked Bar Chart. Shows the risk of cancer (in mCTUh) in each phase of both EVs and ICEVs.



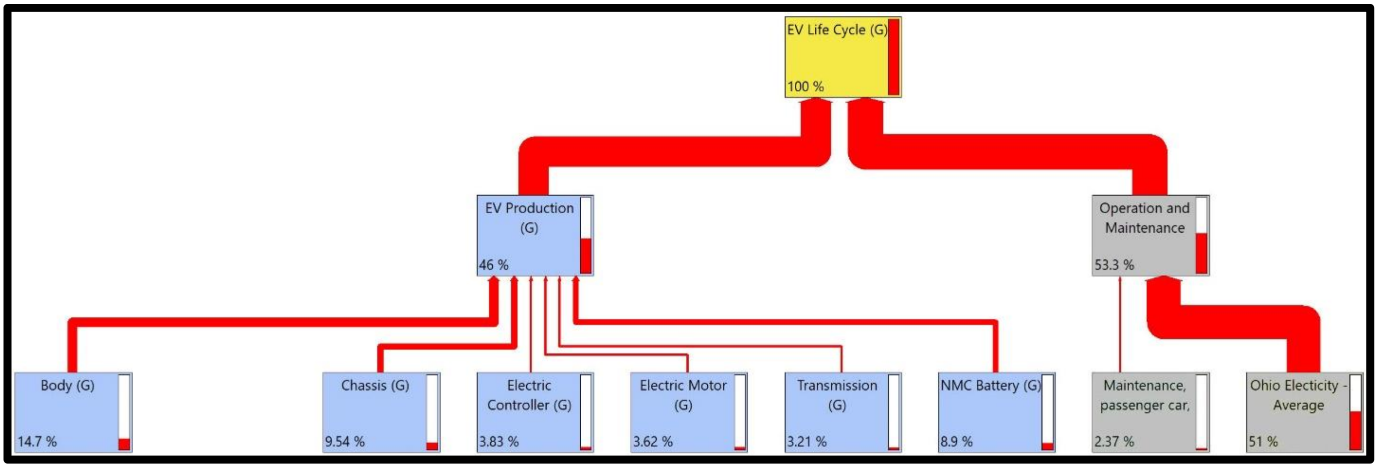
Visualization 3: Part-to-Whole Pie Chart. Shows the percentage of global warming that each component phase contributes to the entire EV life cycle.



Visualization 4: Part-to-Whole Stacked Bar Chart. Shows the percentage of global warming that each component phase contributes to the entire EV life cycle.



Visualization 5: Part-to-Whole Sankey Diagram. Shows the percentage of global warming that each component phase contributes to the entire EV life cycle.



Appendix 2: Answers to visualizations

Question	Comparison	Comprehension Question	Answer for both charts
Comparative 1	Unstacked Bar vs Stacked Bar	In the Operation and Maintenance phase, does the Internal Combustion Engine Vehicle (ICEV) or Electric Vehicle (EV) appear to cause a higher risk of cancer?	EV phase
Part-to-Whole 1	Pie vs Stacked Bar	Based on this visualization, the Production-Body component contributes approximately ____ percent to overall global warming levels.	15 percent
Part-to-Whole 2	Stacked Bar vs Sankey	Based on this visualization, the largest source of global warming in the EV life cycle is the ____ stage.	Use phase
Part-to-Whole 3	Sankey vs Pie	Based on this visualization, which component of the EV Production phase contributes most to overall emissions?	Body component

Appendix 3: Participant Demographics

- Did not collect data on participant name, race, education level, etc.
- Community members: 31/172 (18%)
- Students: 141/172 (82%)

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