INCENTIVIZING A LOW-IMPACT DIET:
An Analysis of Food Product Databases and Behavior Change Techniques

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Client: Ajay Varadharajan, CEO of GreenSwapp

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Abstract:

To effectively address the climate crisis, emissions of greenhouse gasses must be curbed in all sectors. Given that one-third of all global anthropogenic greenhouse gas emissions (GHGE) are attributable to the food and agriculture sectors, diets heavily reliant on carbon-intensive foods must change in response to climate change. (Tubiello, 2021). Our client, GreenSwapp, sits at the intersection of climate action, consumer behavior, technology, and the food industry. As such, if it can effectively promote the adoption of climate-friendlier food choices, GreenSwapp's business can limit food-related GHGEs. Our project aims to compare two food product life cycle assessment (LCA) databases via statistical analysis to identify significant differences at the category, subcategory, and product type resolution so that GreenSwapp can incorporate lessons learned from this comparative analysis in order to better estimate carbon footprint. In addition, our team also derived a list of behavior change techniques for our client's implementation into its consumer-facing business and an experimental design to test the effectiveness of the implemented techniques.

Acknowledgements:

Our team would like to thank **Martin Heller, PhD**, our project advisor, and **Ajay Varadharajan, CEO, GreenSwapp**, who have each supported our efforts throughout completion of this project. We have enjoyed and greatly benefitted from working with and learning from them. Thank you both for devoting your expertise and time to aid us in our academic and professional development.

About the Team:

Hang Chen is an international student who is pursuing a Master of Geospatial Data Science track at University of Michigan's School for Environment and Sustainability in Ann Arbor, Michigan. He participated in a range of laboratory works regarding environmental protection, GIS, and data analyzing, and he finished his undergraduate study with an environmental science major in the University of Alberta, Canada. Right now, he aims to connect environmental data and GIS with other fields of study like data science or user experience design.

Valerie Fritts is pursuing a Master of Science in Environmental Policy and Environmental Justice at University of Michigan's School for Environment and Sustainability in Ann Arbor, Michigan. Going forward, as a Sustainability Consultant, she will work to aid the private sector in limiting its environmental impact. Prior to returning to graduate school, she practiced law in the areas of healthcare regulation, criminal prosecution, and estate planning. Born and raised in the Sunshine State, she obtained a Juris Doctorate and a Bachelor of Science in Journalism from the University of Florida in Gainesville. She has a natural curiosity about the world, and her varied academic and professional interests include, but are not limited to, climate change, food and agricultural systems, clean energy, energy justice, sustainable development, environmental economics, successful communication, and effecting change both on an individual level and through the private and public sectors.

Brett Pickett is pursuing a Master of Science in Behavior, Education, and Communication at the University of Michigan's School for Environment and Sustainability. He obtained a Bachelor of Science in Psychology at the University of New Orleans in 2019 and decided to pursue graduate school after briefly working in the healthcare industry. Born and raised just outside of New Orleans, his exposure to the beautiful swamps and culture of Louisiana has shaped his academic interest in studying the interactions between people and their environments. For the future, he hopes to work in the areas of community engagement, nature-based therapies, community resilience, and behavior change strategies. Some non-academic interests include cooking, hiking, traveling, music, and socializing with friends.

Tianyi Zhang is pursuing a dual degree Master of Science in Sustainable Systems of School of Environment and Sustainability and Mechanical Engineering of College of Engineering at the University of Michigan Ann Arbor. He had lab research experience on renewable energy system modeling and optimization. Before coming to University of Michigan, he obtained a Bachelor of Science in Aerospace Engineering from University of California San Diego in 2020, where he had research experience in solar energy optimization. After graduation, he plans to continue to pursue a Ph.D. degree further doing research on the application of renewable energy.

About the Client:

Our client, GreenSwapp, is a food sustainability consulting company that provides life cycle assessment services and carbon footprint estimation of food products for distributors, restaurants, and consumers, with the ultimate goal of tracking and reducing the environmental impact of the food and agriculture sector (GreenSwapp website, 2022).

GreenSwapp works with businesses to calculate the carbon footprints of their food products. It then adds these products to its carbon footprint database. In its database, GreenSwapp has categorized each individual product in a way that allows it to compare relative carbon footprints of products within the same broader category, and as such, it can recommend foods with lower associated GHGEs as "swapps" for foods with higher carbon footprints. GreenSwapp has also developed scannable and color-coded "climate labels" to be used on grocery store shelves to indicate the GHGE footprint of food products to consumers.

Table of Contents

SCHOOL FOR ENVIRONMENT AND SUSTAINABILITY
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Introduction

The food and agriculture sector is currently responsible for one third of global anthropogenic Greenhouse Gas Emissions (GHGE). (Tubiello, 2021). Our diets and global food system are not compatible with limiting global temperature increase to under 1.5 degrees Celsius. (Macdiarmid & Whybrow, 2019, #). One estimate found that "the GHGE from the agricultural sector alone would exceed the carbon budget for keeping the global temperature rise below the 1.5 degree Celsius limit" as established by the Paris Agreement. (Ritchie et al., 2018, #). Therefore, it is of great significance to inform people of the carbon footprint of their food. With better knowledge on carbon footprint, people can make more sustainable choices so as to reduce carbon emissions. Through this project, we aim to research the scientific landscape of food product life cycle assessment (LCA) in an effort to gain a better understanding of what makes a food product exhibit higher or lower GHGE and to aid our client, GreenSwapp in improving its LCA estimation model.

Project Background and Evolution

Headquartered in Amsterdam, Netherlands, GreenSwapp is an online subscription based impact tracking platform where companies are able to track, reduce & offset the climate impact of their food and communicate it with customers effectively. Throughout the course of working on this project, our client's focus and end product has shifted from, first, an online shopping platform that allowed GreenSwapp application users located in Amsterdam to purchase local food products, to, second, an application with which consumers could use to scan either their post-shopping receipts or food products while shopping to obtain carbon footprint information, to, finally, a QR-scanning function linked to the GreenSwapp database, which allows users shopping in grocery store to scan QR codes on GreenSwapp's associated climate labels to discover more information about a product's carbon footprint at the time of purchase. Our project methods and objectives necessarily pivoted to best meet our client's transitioning needs.

Overview of Objectives/Deliverables

1. Comparing and Assessing GreenSwapp's Carbon Footprint Estimation Based on the Tesco Report.

In the first section of our analysis, we will present the results from comparing GreenSwapp's carbon footprint estimation and Tesco LCA data, which is treated as our reference. Furthermore, we will identify in which product types, subcategories, or categories major differences in carbon footprint estimation occur. Lastly, we will provide several recommended next steps regarding data quality and uncertainties for GreenSwapp to implement or address in order to build on our research.

2. Developing Behavior Change Nudges.

In this second section of our project, our team focused on reviewing scientific literature regarding behavior change through the lens of consumer purchasing of food products. We developed a list of over 30 techniques based on choice architecture, social norm marketing, and feedback for our client to implement. Our team also devised an experiment for GreenSwapp to test the efficacy and effectiveness of the nudges or other behavior change techniques it chooses to use.

Impact

The overall goal of this project is to aid consumers in choosing food products with lower carbon footprints through analysis of available LCA data and through promotion of effective behavior nudge and choice architecture techniques. Through visual and statistical comparisons between GreenSwapp carbon footprint estimations and additional carbon footprint sources, we are able to provide our client with specific food categories where its estimation significantly differs from other LCA sources. For such categories, GreenSwapp will then be able to revise its estimations based on the information our team has provided. This project will also provide GreenSwapp and others at the nexus of tech and environmentalism with behavioral science techniques they can incorporate in tech-based applications to incite positive behavioral change and reduce consumers' GHGE footprints.

Objective 1. Comparing and Assessing GreenSwapp's Carbon Footprint Estimation Based on the Tesco Report.

Introduction:

What is life cycle assessment?

Life cycle assessment (LCA) is a methodology to assess the environmental impact of products, processes, or services, including their associated material impacts, water use, and GHGEs. It is becoming an increasingly important tool in implementing environmental policies, forecasting energy fluxes between industrial sectors, and simply choosing which one between two products is "greener" (Ayres, 1995). Therefore, although frequently being used to analyze greenhouse gas emissions, LCA is a useful tool that provides a comprehensive environmental profile to products and services, and it is important to avoid "slimlining" LCA to cover GHG emissions only (Weidema et al., 2008).

Issues regarding use of data in the Context of Food/Agriculture LCA

In this project, we will mainly focus on the application of LCA on food products. However, there are issues within the current state of the science of LCA as applied to the food and agriculture sector. These issues include over-reliance on secondary data and lack of consistent methodologies. We explain each issue in the section below and then throughout our report connect each issue with our project to explore how those issues can be applied to or have arisen in our analysis.

1. Over-Reliance on Secondary Data

Conducting a full-scale LCA requires collecting a considerable amount of primary data, which makes the LCA process time-consuming and expensive. (Ciroth et al., 2019). Therefore, the majority of studies have utilized secondary data, which provides a higher level of uncertainty (Collotta et al., 2016). As more and more parties rely on the same pool of secondary data, it becomes more likely that faulty data is recycled. In creating a LCA database, practitioners should be cognizant of what data points or datasets to include so that the scopes and methodologies across product data are as consistent as possible (Ciroth et al., 2019). Thus, if GreenSwapp's database utilizes data from various sources and GreenSwapp does not thoroughly vet the data it includes, it may lead to discrepancies or under or overestimated LCA estimations.

2. Lack of Standardized Process

LCA has been criticized for its low accuracy and lack of standardization in the accounting procedure (Raugei et al., 2014) as the completion of a LCA is not entirely objective. Also since one limitation of current LCA methods is that they lack standardization (Anand and Amor, 2017), certain assumptions are made in different work, which leads to discrepancies. As a solution, submitting a LCA project for peer review can lead to greater scientific credibility because the peer review process allows for scrutiny of the assumptions inherent in and the process followed for the project. Those engaging in peer review should have both LCA and sector-relevant expertise.

Data Sources and Assumption

Our work with the GreenSwapp database has aided us in our understanding of how the company collects data and estimates carbon footprints for complex food products. GreenSwapp adopts an "ingredient based" approach to calculate the carbon footprint of food products. The GreenSwapp database aggregates the carbon footprints of single ingredients, such as tomatoes, water, salt, collected from third party sources, like Concito and Agribalyse, or scientific research studies. Using this data, GreenSwapp is able to approximate the carbon footprint of a complex food product based on the carbon footprints of the individual ingredients in that complex product. When a client requests GreenSwapp to calculate the carbon footprint of a product, it must provide GreenSwapp with information about that product's supply chain, including the recipe specifying the ingredients and how much of each component ingredient is used to form the finished product. Through its client relationships, GreenSwapp can continue to expand its product database.

Thus, considering the main issues regarding LCA analysis mentioned earlier, our team aims to understand how well GreenSwapp is able to estimate food carbon footprint through the compilation of secondary data. To test this, our team has (1) input a set of "experimental products", whose carbon footprints have already been calculated under a customized LCA context, into the GreenSwapp's database, (2) obtained the corresponding carbon footprints of those products, and (3) compared those two sets of values, in order to reveal potential inconsistencies and better understand the issue of secondary data and standards within the LCA realm. Similar comparative studies were also conducted by Cherubini et al, where the environmental impact of swine production was evaluated across five different LCA models through statistical simulation, in order to study methodological uncertainties (2018). Also, Ayres compared carbon footprints of the same building materials from three LCA frameworks, which alluded to the concerns about the inconsistent methodologies of different LCA models (1995).

To identify suitable "experimental products", we turned to the Tesco carbon footprint report completed in 2012 (Tesco product report, 2012). Tesco is a UK-based supermarket chain with over 4,500 stores (TESCO, PLC, n.d.). With approximately 500 European food products covering a wide range of food categories, such as meat, dairy, and vegetables, Tesco's database makes a rather comprehensive and publicly available data source. Prior to finding the Tesco report, our team had issues identifying a suitable database for our comparison. According to the report (Tesco product report, 2012), Tesco utilized a cradle-to-grave (below) approach to calculate the carbon footprint of the food products sold in its Tesco stores. The discussion around the system boundaries will be covered in the conclusion and limitation section.

Tesco's system boundary.

Since secondary data is commonly used in the LCA realm, one assumption we have to make is that the carbon footprints from the Tesco report are "customized" to the Tesco company itself, and therefore should act as a reference point for our comparative analysis. Although secondary data is occasionally used to translate primary data to carbon footprint calculation, Tesco's estimation is based on the primary data provided by Tesco's suppliers, and the estimations provided are restricted to Tesco branded products only. (Tesco report, 2012). Tesco's approach induces less uncertainty, as it has estimated carbon footprints under a more consistent method, using internal data on food supply, production, delivery, and storage. Indeed, both GreenSwapp and Tesco utilize secondary data to different extents. However, simply from the scope and resolution of the analysis, Tecso report is more specific and customized. Since the LCA results are usually sensitive to input used for the calculation, customizable LCAs and project-specific data are ideal to produce a better estimate than that based on the standard available information (Inti & Tandon, 2021). Thus, we assume that it is more appropriate to treat Tesco's estimation as a reference or target for comparison, rather than referring to GreenSwapp's estimations, which are applied at the broader product type resolution, and thus sacrifice some accuracy for broader applicability.

One difference in the organization of the GreenSwapp and Tesco data is that while GreenSwapp categorizes each individual product by product type, subcategory, and category, Tesco does not group its specific products into broader categories. (See Table 1. below)

Table 1. Table of categorization scheme between two frameworks.

Categorization of Products - GreenSwapp vs. Tesco				
	Specific Product	**Product Type**	**Subcategory**	**Category**
Tesco	X			
GreenSwapp	X	X	X	X

As we explain later in this report, our team assigned the Tesco products to existing GreenSwapp product types, subcategories, and categories, in order to be able to compare the two frameworks.

Tesco also assigns a unique carbon footprint value to each product listed in the report, whereas the GreenSwapp database assigns the same carbon footprint to each product that falls within the broader product type class. (See Table 2. below)

Table 2. Table of resolution in estimating food carbon footprint between two frameworks.

Resolution of Carbon Footprint - GreenSwapp vs. Tesco		
	Specific Product	**Product Type**
Tesco	X	
GreenSwapp		X

Tesco's more customized product-specific LCA data is the main reason that we choose the Tesco database as our reference point for comparison.

Research Questions:

Thus, using carbon footprint values from the Tesco report as reference, our team formed the following two research questions:

> **Question 1:** Are the average carbon footprints calculated from the GreenSwapp and Tesco values significantly different from one another at the product type, subcategory, and category level after aggregation?
>
> **Question 2:** Taking into account the number of products in and distribution of each class (i.e. product type, subcategory, and category) in the Tesco report, where do GreenSwapp's estimations show a difference or gap?

Methods and Results:

Product Categorization and Data Compilation:

Given that GreenSwapp and Tesco categorization frameworks differ, we first assigned each Tesco product a GreenSwapp product type, subcategory, and category. Our team categorized the specific products into GreenSwapp categories because while Tesco assigns specific carbon footprint values to each individual product (e.g. 2-liter plastic bottle of Coca-Cola), the finest resolution at which GreenSwapp assigns carbon footprint values is at the product type level (e.g. soft drinks), which by comparison is a more generic categorization. For those Tesco products that do not fit into any GreenSwapp categories, we assigned them as missing values. See the "Range Comparison" tab of the "Comparing Methodologies - SEAS Masters project" Google Sheet attached as Appendix A to this report.

Next, our team excluded the products with missing associated values and aggregated the data at the category, subcategory, and product type levels. In doing so, we considered, (1) the number of Tesco products that fall within the GreenSwapp product type (e.g., "soft drinks"), subcategory (e.g. "Soda & carbonated drinks"), and category (e.g. "Coffee, teas, juices & alcohol"), (2) the average carbon footprints and standard deviations at the three product resolutions, and (3) the carbon footprints as estimated by GreenSwapp at each of those resolutions. This preliminary data processing was done primarily through data analysis packages in Python.

Method for Addressing Question 1:

In addressing the first research question, we aggregate the Tesco products and obtain the average carbon footprints for different product types, subcategories, and categories correspondingly. For instance, although the product type "fruit juice" itself contains 44 Tesco observations, we averaged the 44 individual carbon footprints and treated the result as one observation at the product type level. For this comparison, we compared the average carbon footprints of Tesco values to the GreenSwapp value at the product type, subcategory, or category level. We will compare the average carbon footprints of specific products from the Tesco report with their corresponding estimations from the GreenSwapp database.

At the product type and subcategory level, we will first visualize the comparison side by side. Then we will treat the average carbon footprint of each of the different product types or subcategories as a single observation and check whether the difference between two estimations are roughly normally distributed. Later, we will perform a paired two sample t test to further explore the significance of such difference, if present. The null hypothesis is that the difference between average carbon footprint between two estimations is not significantly different from 0, and the alternative hypothesis is that the difference is significantly different from 0.

At the category level, one challenge is that there are not enough categories to perform a parametric analysis. To address this, we decided to apply a two-sample Wilcoxon Mann Whitney test, which can be substituted for a t test when dealing with small sample sizes and when samples that are not normally distributed. However, the statistical power for this analysis is still not strong, which is why we will first plot the result, visually observe the difference between two frameworks, and use this test as a reinforcement to our observation. For the Wilcoxon Mann Whitney test, the same conditions to determine whether the estimations differ remain applicable.

Results and Deliverables for Question 1:

Product type level.

Figure 1, below, is a visual representation that compares the average carbon footprints at product type level between the values in the Tesco report and GreenSwapp estimated values. Notice that, except for several product types like meatball, lamb, and beef related ready meals, the GreenSwapp values seem to be close to Tesco's estimations across different product types.

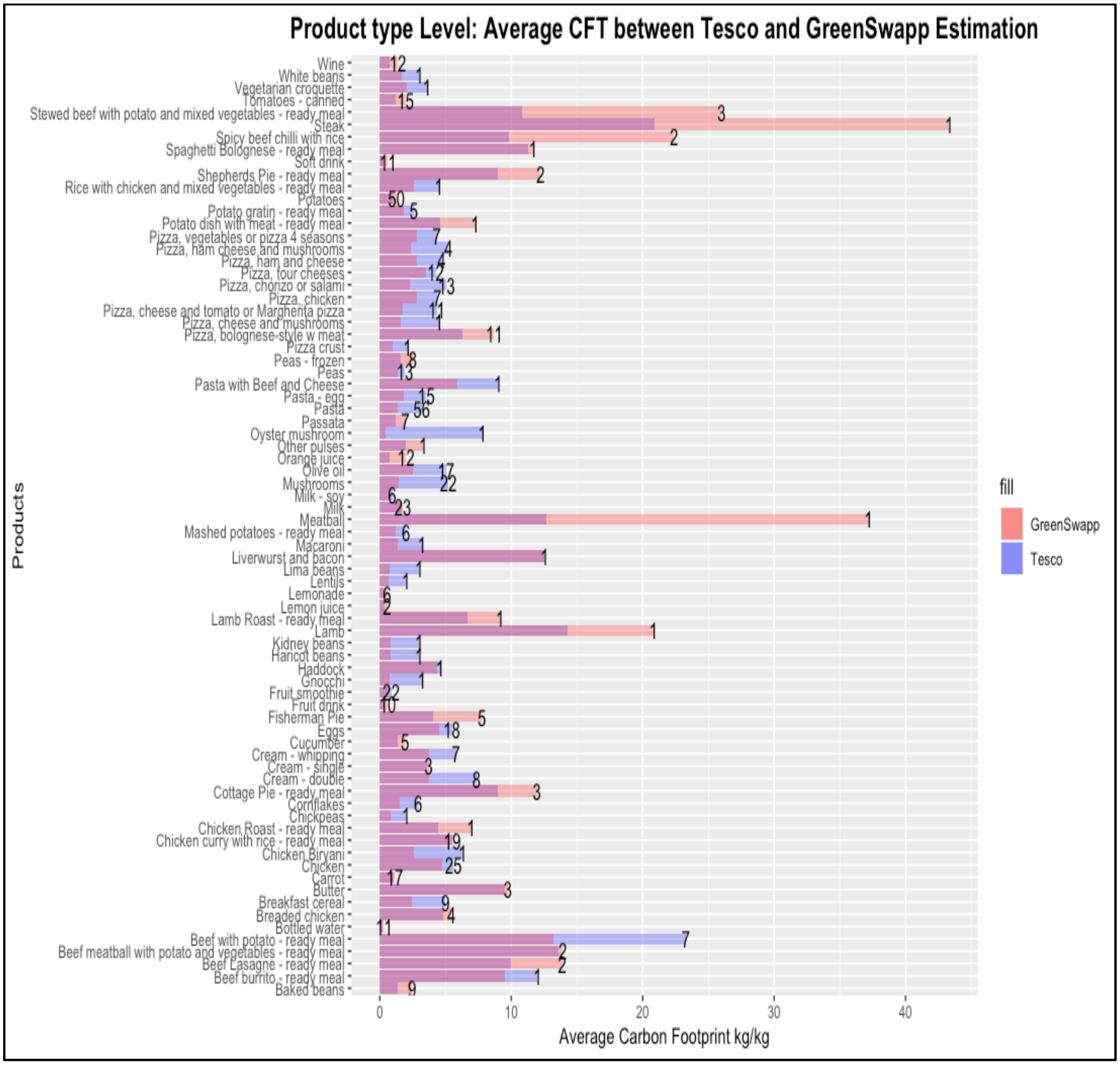


Figure 1. Bar plot of average carbon footprint for different product types, with red being GreenSwapp estimation and blue being Tesco estimation. Numbers on the columns refer to how many Tesco products are categorized into that product type.

The below histogram of the average carbon footprint difference, obtained by subtracting Tesco estimation by GreenSwapp's stated value for each product type, further verifies the differences between two frameworks (Figure 2). This difference roughly satisfies a normal distribution, which is one crucial assumption for hypothesis inference. From the test result of paired two-sample t test, the p value (at a 5% alpha level), is 0.5153, which is greater than 0.05. This means that we failed to reject the null hypothesis, and the difference of average carbon footprint between two frameworks is not significantly different from 0, which further indicates that, on average, estimations generated from two frameworks are not significantly different from each other.

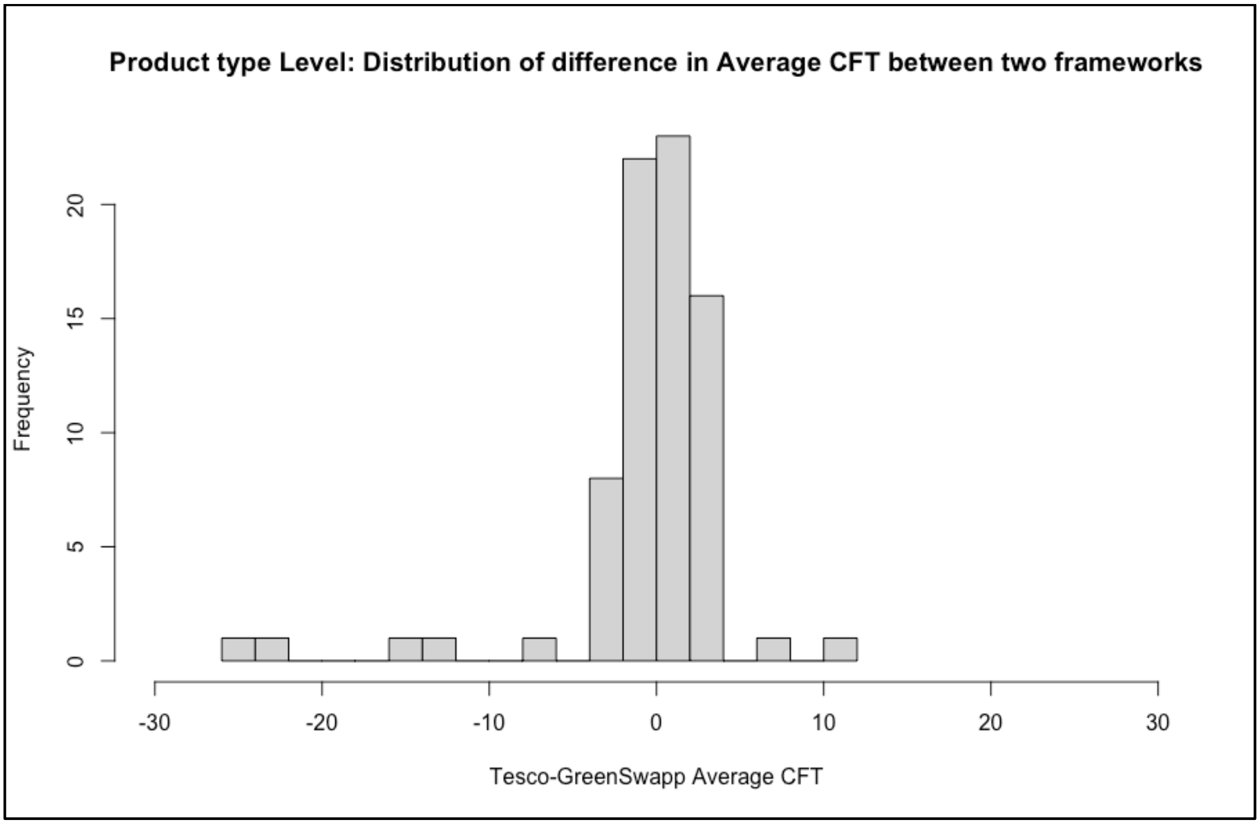


Figure 2. Histogram of carbon footprint difference between two frameworks at product type level, obtained by average Tesco's value - average GreenSwapp's estimation.

Subcategory level.

Similarly, if we look at the data aggregated at subcategory level (Figure 3), the meat & vegetables, meatball, and steak subcategories show quite different results, and minor differences can also be seen in subcategories like mushrooms. For the rest of the subcategories, average carbon footprints from two frameworks are fairly similar.

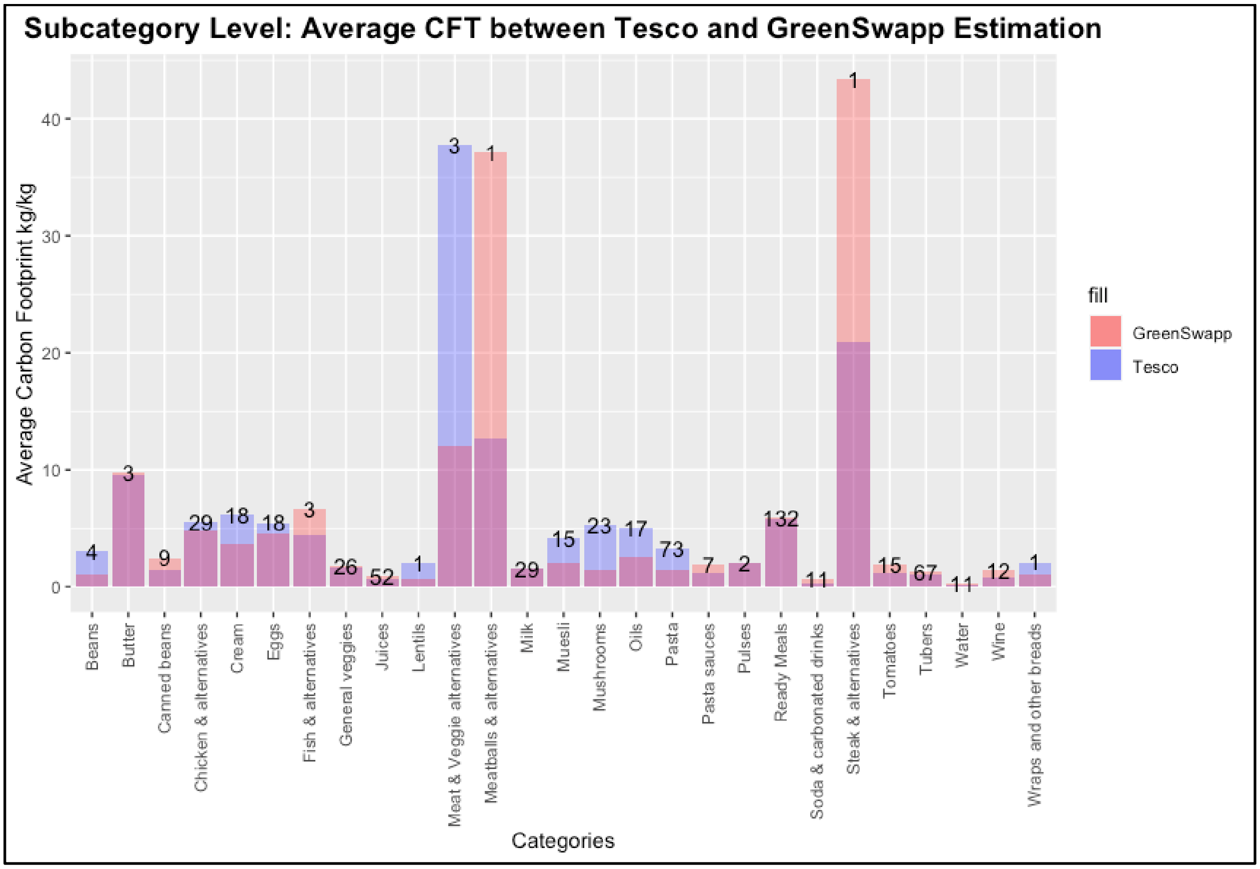


Figure 3. Bar plot of average carbon footprint for different subcategories, with red being GreenSwapp estimation and blue being Tesco estimation. Numbers on the columns refer to how many Tesco products are categorized into that subcategory.

Again, to further explore the differences and be able to make a statistical inference, we created the below (Figure 4) histogram of average carbon footprint difference at each subcategory. Note that the difference at subcategory level also roughly satisfies a normal distribution, with mean centered around 0. Indeed, the p value obtained from the paired two sample t test is 0.8321, which is still greater than 0.05. This means that we fail to reject the null hypothesis again in that the carbon footprint difference is not significantly different from 0, and the estimation obtained from two frameworks are also not significantly different from one another on average.

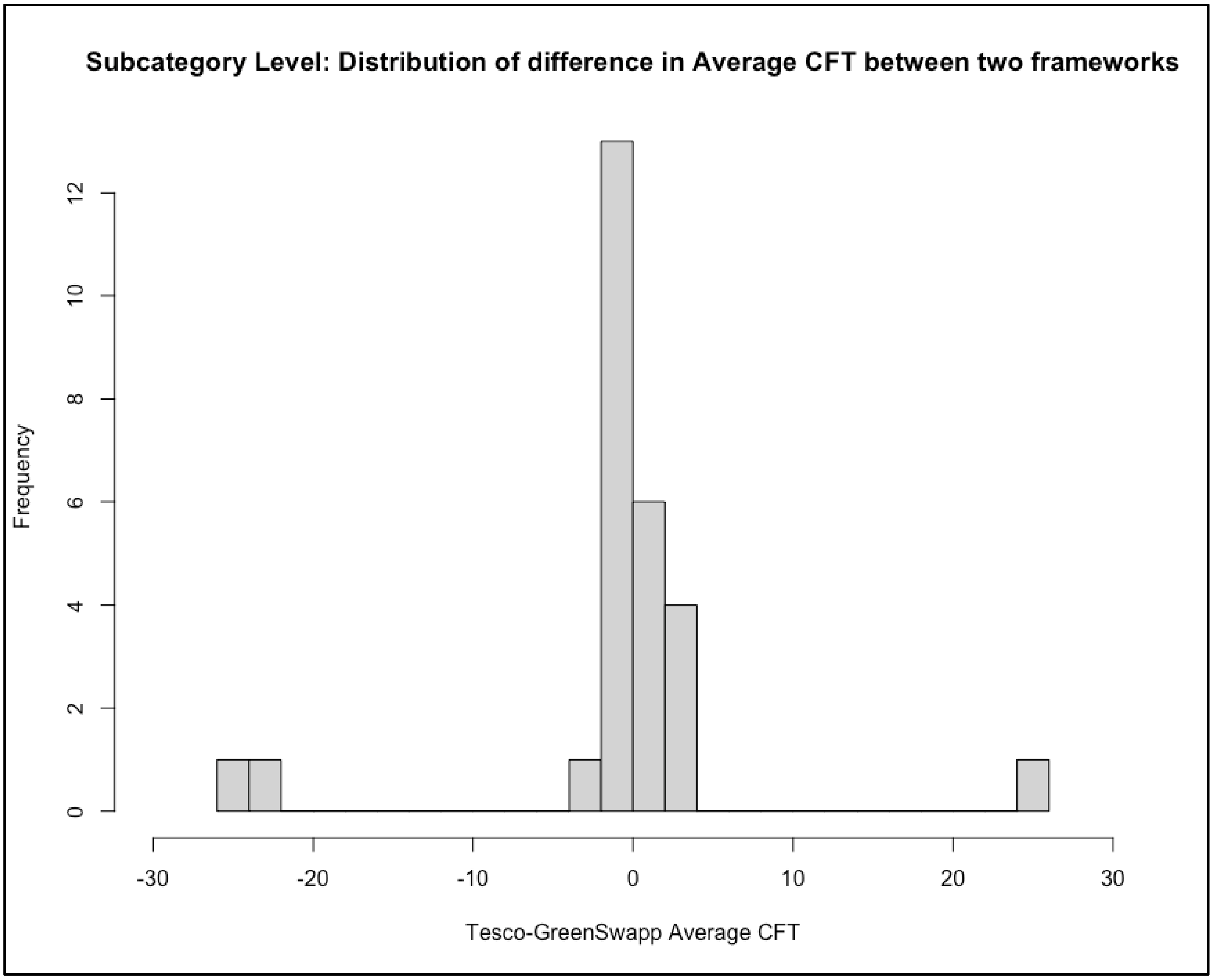


Figure 4. Histogram of carbon footprint difference between two frameworks at subcategory level, obtained by average Tesco's value - average GreenSwapp's estimation.

Category level.

Finally, Figure 5 shows that the average carbon footprint and patterns from two frameworks are very similar at category level. With this in mind, we performed the Wilcoxon Mann Whitney test to obtain a p value of 0.5737, which is larger than 0.05. Therefore, we do not reject the null hypothesis and conclude that the average carbon footprint estimations at category level are not significantly different between two frameworks.

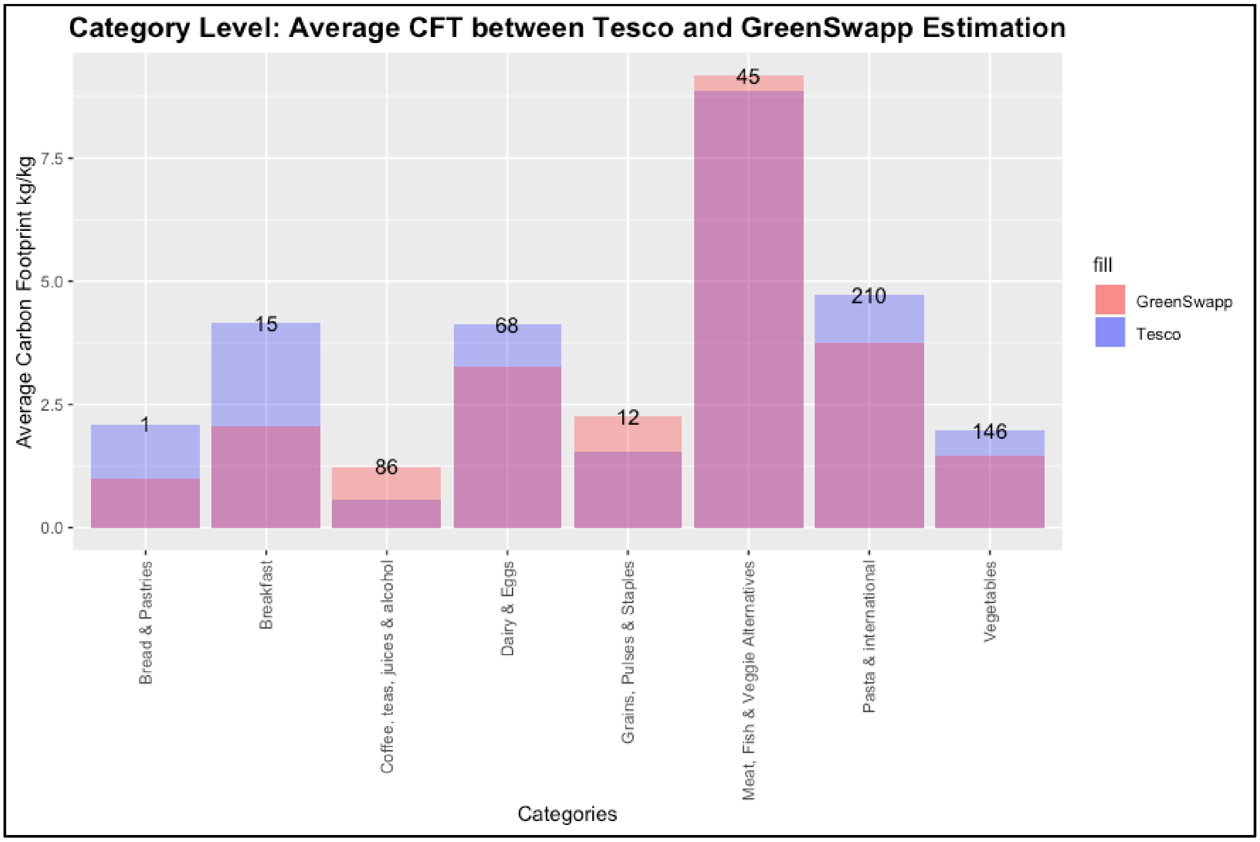


Figure 5. Bar plot of average carbon footprint for different categories, with red being GreenSwapp estimation and blue being Tesco estimation. Numbers on the columns refer to how many Tesco products are categorized into that category.

In synthesizing the results from those three resolutions, one can notice that some product types or subcategories have quite limited sample size (count) but drastically different average carbon footprints. For instance, there is only one Tesco product, Aberdeen Angus Meatballs, that is categorized into the GreenSwapp's "meatball" product type and subcategory. This is caused by 1) the Tesco products are not evenly distributed into the GreenSwapp classification system, and 2) the method for question 1 is a rather general analysis and simply uses the lumped averages for comparison, without considering the sample size and distribution of each product type, subcategory, and category. Understanding this limitation, we will further analyze carbon footprint gaps and differences between two frameworks by considering the distribution and sample size in the next section.

<u>Method for Addressing Question 2:</u>

In addressing our second research question, after we assigned each Tesco product to a GreenSwapp product type, subcategory, and category, we were able to consider how each product was distributed at those three resolution levels. Compared with Tesco data, to identify where we can find the differences in carbon footprint estimation for GreenSwapp methodology, we constructed 95% confidence intervals for carbon footprints of different product types, subcategories, and categories from the Tesco products, while excluding confidence intervals with small sample sizes. The reason that we do not generate intervals for the GreenSwapp estimation and compare the other way around is because 1) our assumption is that Tesco estimation is the reference and more accurate. 2) GreenSwapp does not have a "distribution" at the product type level (see table 1, 2, 3), since GreenSwapp only has one value for a specific product type, whereas there can be more than one Tesco products being categorized into this product type. Thus, for simplicity, we will just use the average carbon footprint from GreenSwapp's database as comparison.

Next, we compared the corresponding average carbon footprint estimated by GreenSwapp to determine if the GreenSwapp values fell inside the intervals or not. For instance, the product type "fruit juice" contains 44 Tesco observations, which by itself forms a distribution. We then constructed a 95% confidence interval from this distribution and compared GreenSwapp's juice estimation (1.711 kg CO2 eq/kg) with this interval. If 1.711 kg/kg falls inside the interval, we will say that for juices, GreenSwapp's estimation does not show a gap or significant difference, compared with Tesco's value.

<u>Results and Deliverables for Question 2:</u>

Product type level.

In this section, we researched the main gaps in carbon footprint estimations between two frameworks by showing 95% confidence intervals constructed from the Tesco products. We have excluded those intervals created from product types with sample sizes that are too small, those with fewer than 20 values, as a small number of products would fail to generate a distribution with a reasonable interval for comparison. Figure 6 shows that although the variation for chicken products is quite large, GreenSwapp's estimation is within the interval and decently close to the mean estimation of Tesco, which is the same for milk products. For mushroom and pasta, GreenSwapp's values are underestimated, and for potatoes, GreenSwapp's values are slightly overestimated.

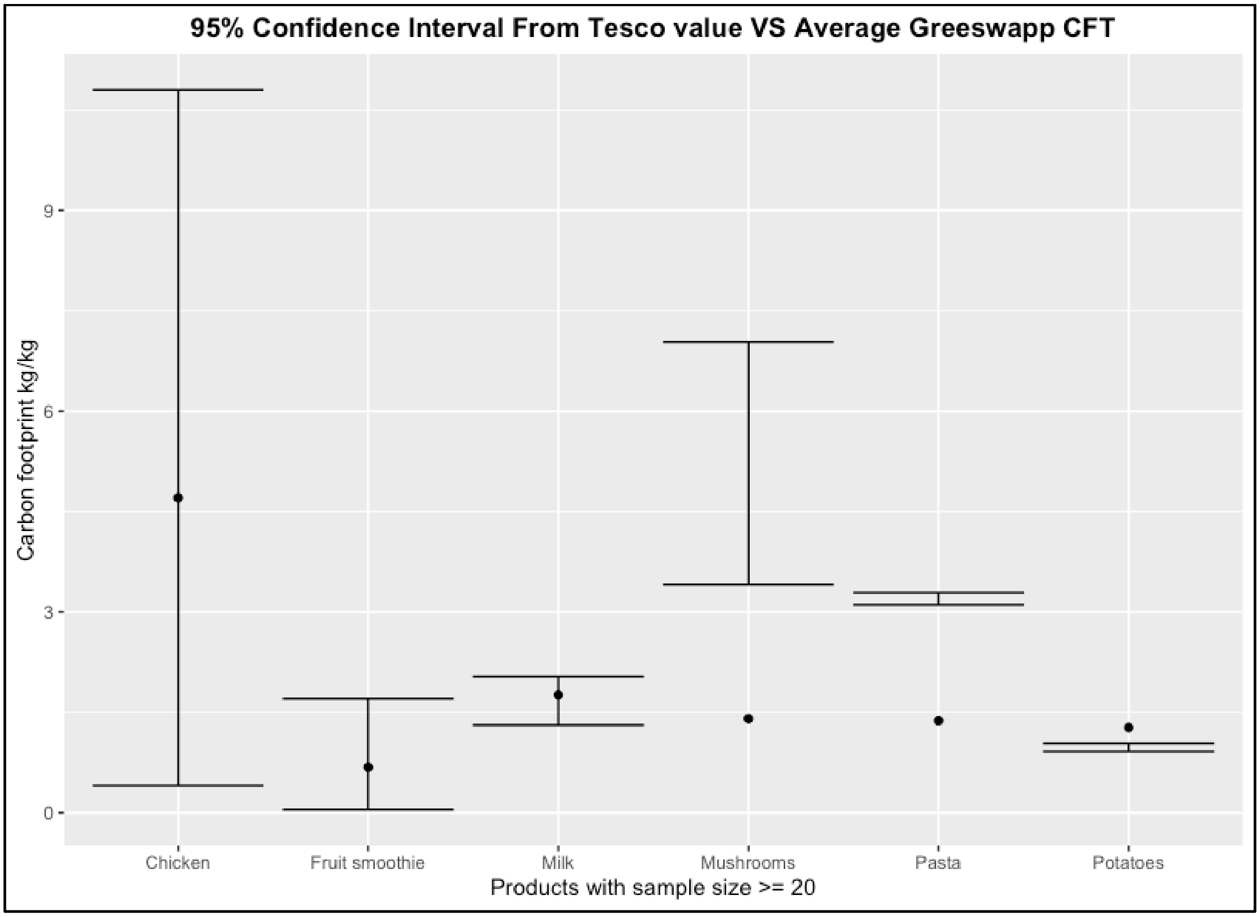


Figure 6. Filtered 95% confidence intervals created from Tesco products are shown in ranges, and GeenSwapp's average carbon footprint estimations at product type level are shown in dots.

Subcategory level.

As we move from the product type to subcategory level, each subcategory includes more products and their associated values as provided by the Tesco report. As depicted below in Figure 7, the two frameworks produce similar carbon footprint estimations at the Chicken and alternatives, General vegetables, Milk, and ready meals subcategories. Again, for mushroom and pasta, GreenSwapp's values are underestimated, and for juices and tubers GreenSwapp's values are again slightly overestimated.

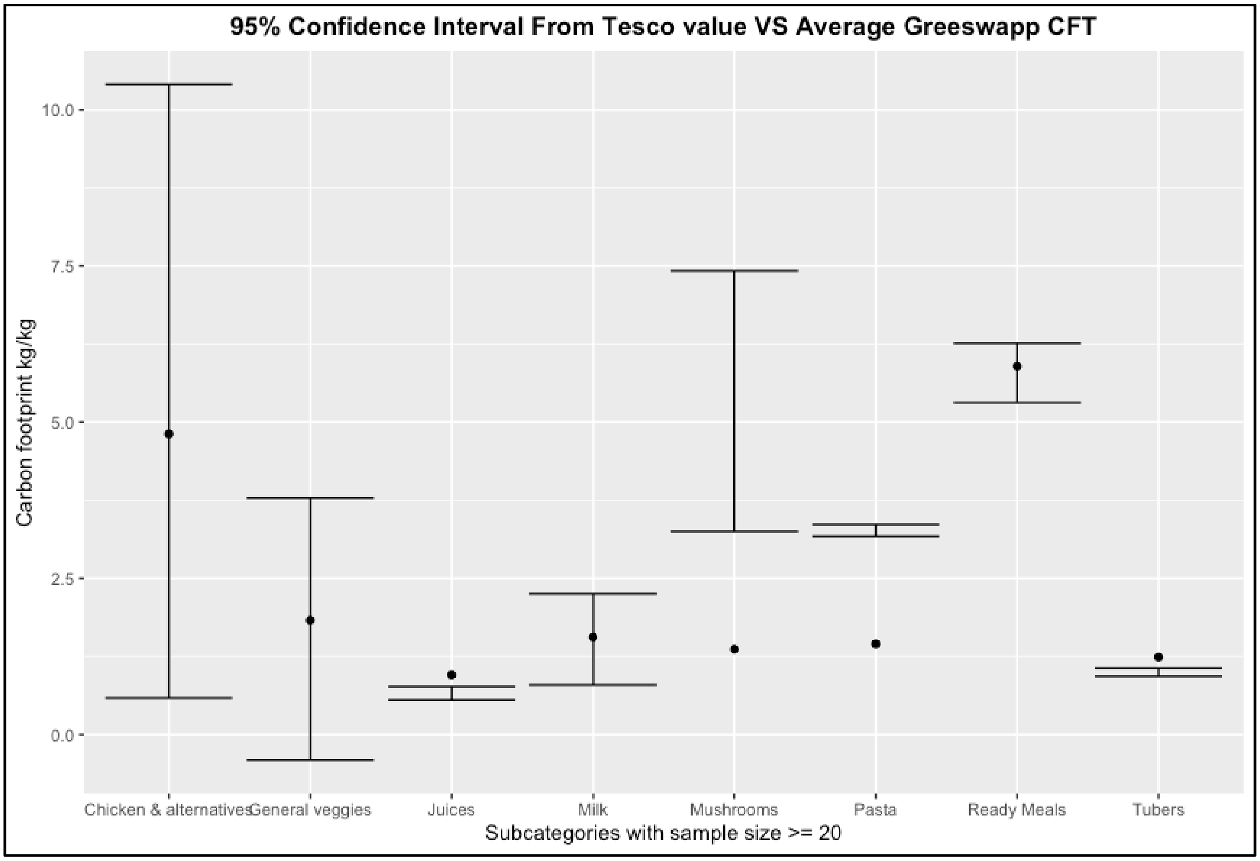


Figure 7. Filtered 95% confidence intervals created from Tesco products are shown in ranges, and GeenSwapp's average carbon footprint estimations at subcategory level are shown in dots.

Category level.

In moving from the subcategory to the broader category level, each category now grows in the number of specific products it contains. Figure 8 below, aside from meat, fish & vegetable alternatives, demonstrates the extent of differences between each model's carbon footprint estimation for the remaining classes categories (i.e. Coffee, teas, juices & alcohol; Dairy & Eggs; Pasta & international; and Vegetables).

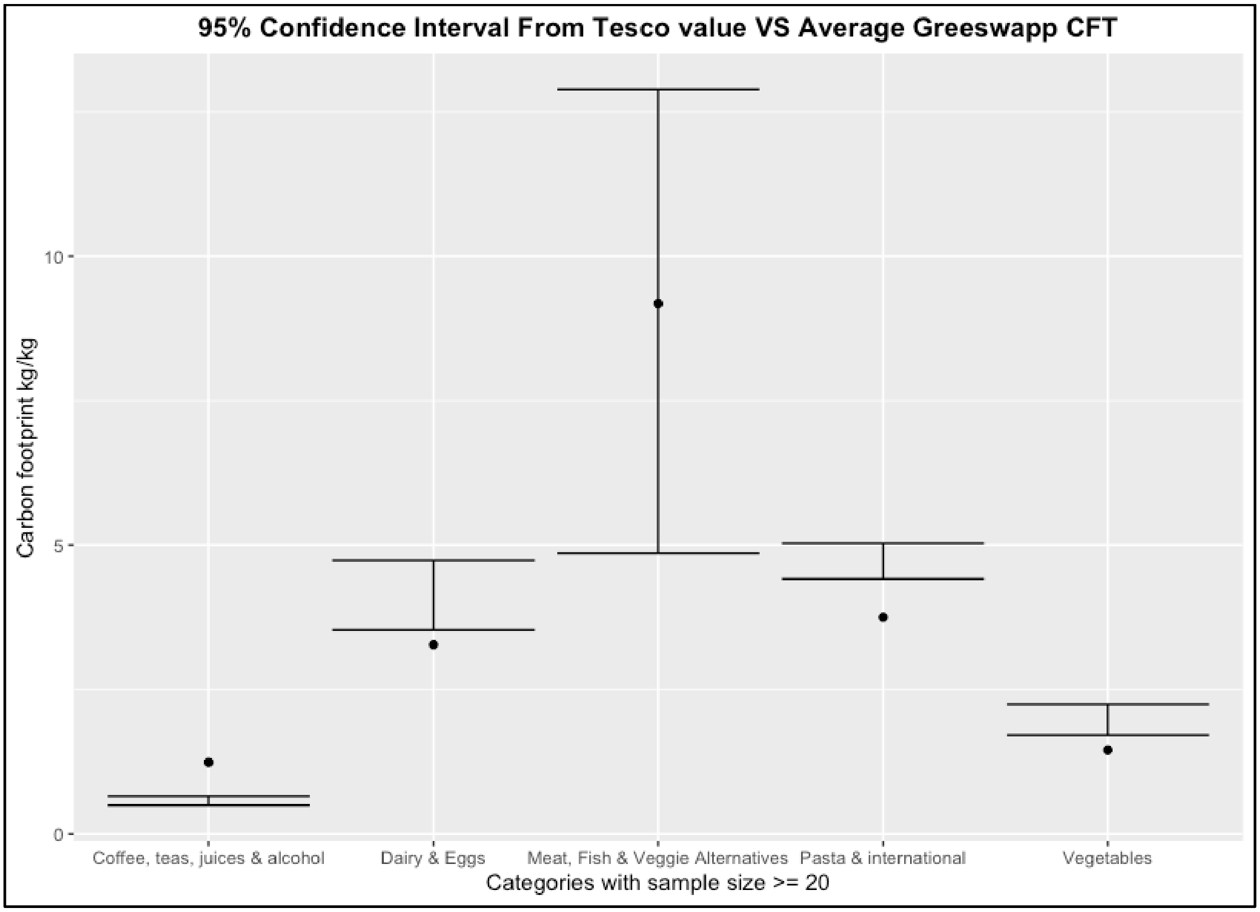


Figure 8, Filtered 95% confidence intervals created from Tesco products are shown in ranges, and GeenSwapp's average carbon footprint estimations at category level are shown in dots.

Discussion and Conclusion:

In addressing question 1, it seems that, on the whole, GreenSwapp's average carbon footprint estimation is not significantly different from Tesco values at product type, subcategory, and category level in general. Additionally, at category level, the average carbon footprints as provided by two frameworks are more similar than at the other two resolutions.

For question 2, there are some identifiable differences in the GreenSwapp estimations, compared with Tesco products at the product type and subcategory levels, specifically for the following classes: pasta and mushroom products. At category level, average carbon footprint of several major GreenSwapp categories (like Coffee, tea, juice & alcohol) fall only slightly outside the interval generated from the Tesco products.

For differences observed in mushroom products, 1) the major reason is caused by inconsistent system boundaries between two frameworks. Since mushroom is defined as an ingredient product according to GreenSwapp, its carbon footprint is collected from third party sources, specifically, MyEmissions. MyEmissions adopts a cradle to gate system boundary, and life stages like transportation to consumers, consumption, and disposal are not included. On the other hand, Tesco includes those stages, which leads to higher carbon footprint values. This is indeed a major limitation to the research design, which will be discussed in the limitation section. 2) To keep exploring other factors that may add to the differences, aside from farm energy and fossil fuels, compost (the process of preparing mushroom substrates) materials and transportation are also major sources of greenhouse gas emission for mushroom productions (Robinson et al., 2019). Common input materials used for compost include peat moss, straws, gypsum, and manure. However, the average transportation distance of obtaining peat moss is almost 10 times as much as obtaining straw (Robinson, 2014). Meanwhile, carbon emission varies based on the compost methods. For instance, tunnel composting emits twice the ammonia emissions than windrow composting (Robinson, 2014). Those are the sources of variation that could explain the observed differences. Although the exact compost process used for the mushrooms in the Tesco report is not specified, we did find out that Monaghan, one of Tesco's main mushroom suppliers, utilizes tunnel composting on rye of straw with poultry and horse manure to create substrate (Monaghan website), which could possibly lead to a higher carbon footprint at the farm stage.

For differences observed in pasta products, which are also considered as ingredients and utilize data from MyEmissions, different system boundaries may again be the main reason behind the scene. As to other possible reasons, for wheat products like pasta, the N2O emissions from soil, production of fertilizers, and processing of pasta contribute the most to its carbon footprint estimation (Sundberg & Hansson, 2010). Among those, N2O and fertilizers are the main factors that are associated with great uncertainties. For instance, planting wheat on organic soil versus mineral soil can have quite different N2O and CO2 emissions (Sundberg & Hansson, 2010). However, it is difficult for us to trace down how MyEmission and Tesco report account for such variation at the farm stage, as the information is inaccessible for us. Lastly, for some Tesco's "pasta" products, like "Spaghetti", "Pennoni Rigati", "Tagliatelle", and "Organic Fusilli", they do not have a clear match under GreenSwapp's classification, but rather being classified as "pasta" in general, which could be another source of error.

It is also important to note there may be differences between the two frameworks for other products, subcategories, and categories that we excluded from our comparison due to their limited sample size. Additionally, the boundary issue may still persist, which requires further inspection on the scope of the data sources.

Limitations:

There are quite a few limitations to this comparative analysis between GreenSwapp and Tesco report, which are specified below:

1. One major limitation of our analysis is that, different from Tesco's cradle to grave system boundary, the system boundary for GreenSwapp's method is much more complicated, since the data that GreenSwapp uses come from different sources. For instance, as GreenSwapp's main data sources, Concito utilizes an extended input-output model, and system boundary covers the entire life stages of products by default (Concito background report, 2021), whereas system boundary for Agribalyse is cradle to gate (Agribalyse

Methodology, 2015). Thus, for GreenSwapp, whether the carbon footprint of a basic ingredient considers stages like consumption or disposal mostly depends on under what method the data is calculated. Theoretically, for each ingredient whose carbon footprints are estimated from cradle to gate, we should interpolate its full life cycle carbon footprint based on the contribution from the stages that are included and also omitted. Then, we need to further adjust the estimation for any complex products whose recipe includes such ingredients. Otherwise, it is likely that GreenSwapp's carbon footprint will always be an underestimation, simply due to smaller boundaries. From such underestimation due to the limited boundaries, we cannot infer bad estimation.

2. Aside from the issue of subjective categorization, some subcategories designed by GreenSwapp are not suitable for comparison. For instance, "fish & alternatives", "steak & alternatives", "chicken & alternatives", and "meat & veggie alternatives" subcategories are created with the intention to provide convenient "swap" for the GreenSwapp customers to identify alternative choices for meat products, which tend to have higher carbon footprints. It is very likely that meat products in the Tesco report, when aggregated at subcategory level, will only contribute to the meat products without accommodating for the meat alternatives, hence introducing a biased comparison.

3. In working with the Tesco data, as mentioned in the issue section, even with our assumption, it is possible that the Tesco, in the report, is using unspecified secondary data or unexplained methodologies. For instance, the report does not make clear the percentage of primary data versus secondary data relied on to fill the data gap. Since secondary data is commonly used, it is important to understand the distribution of primary to secondary data to define the "reference", at least relatively, in order to comparatively analyze the dataset and identify inaccuracies. Also, Tesco products are not distributed evenly across product type, subcategory, and category classifications. Certain product types, subcategories, or categories may only contain a few products. Where a classification group has a limited sample size, its calculated average carbon footprint may not be representative of that group in reality. Because these are issues intrinsic to the dataset that we were unable to control, we framed our research questions tailored to the data that was available to us - the Tesco products and report. Lastly, the Tesco report is rather outdated. It is possible that cleaner energy was used in processing and vehicles, and the climate impact stemming from the manufacturing, transportation, and distribution phases were reduced, which was not included in the Tesco report at the time of its publication.

Future Recommendations and Next Steps:

In expanding on or clarifying our research, we recommend that GreenSwapp or researchers take the following next steps:

1. GreenSwapp should establish a standard for data choice and validation. This can be achieved by setting a minimum requirement for the percentage of primary data that is used, where only above such threshold can GreenSwapp include the data into their

database and methodology. To obtain such threshold, GreenSwapp can calculate the average percentage utilization of primary data for all the methodologies that are currently within the GreenSwapp database, and when a new data sources is considered, its percentage utilization of primary data can be compared with such threshold to determine whether or not to include it. Additionally, to better determine the average values used for life cycle inventory, we can apply a weighting procedure to secondary data (Henriksson et al., 2014). GreenSwapp can choose to include all the data sources found. However, it can give more weight to recent studies and data sources as compared to outdated ones. GreenSwapp can also prioritize data sources that utilize a higher percentage of primary data or measure data using similar production and transportation systems in this same way. Those two measures could help define what data is more accurate, at least relatively, in order to combat the uncertainties caused by secondary data.

2. As the GreenSwapp estimation model uses the carbon footprints of individual ingredients to build complex products, GreenSwapp can further explore the sources of difference for ingredient products and complex products separately. This would help prevent inaccuracy in ingredient carbon footprint estimation from cascading to the estimation for complex products.

3. As mentioned in the introduction, some Tesco products are categorized into a single GreenSwapp product type, hence obtaining only one carbon footprint estimation and inducing bias. Therefore, similar to our study, during the process of collecting carbon footprint for a certain product from various sources, GreenSwapp can compile those data points to create a distribution, instead of a single value. With this distribution, GreenSwapp would be able to construct a confidence interval for that product type under its methodology. Since there remains a gap between product type (like tomato) and exact product names (like tomato from different farms, brands, etc), such confidence interval is useful in that it acts like a "tolerance range" to address the resolution differences between product type and exact product names, instead of further dividing product types into smaller classifications.

Objective 2. Exploring the Relationship between Behavioral Science Techniques and Environmental Behavior

Introduction

The U.S. consumer has become increasingly interested in values-based spending, which is defined as financial support of businesses, products, services, and business people that align with one's value system. (Li, n.d.). One study conducted by Mintel reports that 46% of U.S. consumers say "an understanding of how their purchase directly impacts the environment would encourage them to purchase eco-friendly products." (Mintel, 2021). GreenSwapp is in a prime position to be able to fulfill this consumer desire for additional information and transparency around their purchasing decisions.

GreenSwapp's ultimate goal is to better understand how to influence grocery store customers to swap their typical food purchases with similar items that have relatively lower associated GHGEs. Through the course of this project, our team's aim became to find ways GreenSwapp can use behavior change techniques from environmental psychology to lower the carbon footprint impact of their user base by influencing grocery store purchasing behavior. Specifically, GreenSwapp has asked us to look into the use of behavior nudges and choice architecture. Our client also wanted ways to be able to test the efficacy of any behavior change interventions introduced in their web app.

After doing a literature review and consulting with GreenSwapp we arrived at multiple deliverables. The first of these deliverables was a set of interventions based on behavior nudge and choice architecture research that our client could incorporate in its web app. The intention of these interventions, once implemented, is to influence consumers to swap their typical grocery store purchases with ones that have a lower carbon footprint. Our second deliverable was an experimental design that can be used to test the efficacy of behavior change interventions for GreenSwapp. Our final deliverable was a compilation of proposals guiding GreenSwapp's future behavior change efforts.

Understanding Environmental Psychology and Behavioral Nudges

One client-facing and internal goal of this project was to determine how nudges can be used to affect decisions around diet and purchasing of food products. To further understand these behavior psychology concepts, our team performed a literature review.

<u>Habit formation as key to behavior change</u>

For the purposes of this project, it is important for us and for GreenSwapp to understand how habit influences the selection of food. Because people eat certain foods with high carbon footprints, like meat and dairy products, out of habit, it is important for our team to investigate and select nudges and methodologies that either disrupt that consumer's habit of choosing carbon-intensive food or allow him to choose less carbon-intensive foods by making them more accessible through choice architecture.

Understanding the role of habits in consumer behavior is key to being able to influence behavior change. Dr. Wendy Wood, the author of "Good Habits, Bad Habits: The Science Of Making Positive Changes That Stick", argues that we can learn to build good habits and stop bad ones through understanding the psychology of our routines. (National Public Radio, 2019/2019). Studies have shown that using willpower or self control is not necessarily the best way to achieve our goals, especially long term. (National Public Radio, 2019/2019). For this reason, Dr. Wood has focused her research on the influence of habits on human behavior. She explains that habits, once developed, are self-reinforcing because they are automatic and unconscious acts. (National Public Radio, 2019/2019). People will act in the manner they are used to, even where that action is more difficult or strenuous. According to Dr. Wood, the vast majority of our actions are largely determined by repetition or habit instead of through conscious intention. (National Public Radio, 2019/2019).

> *Case Study: Removal of Cigarette Vending Machines vs. Surgeon General Warning*
> *In 1964 the Surgeon General first issued a warning against smoking cigarettes, linking cigarette smoking to lung cancer and heart disease. For several years, cigarette sales did not dramatically decline. It was not until the sale of cigarettes in vending machines was banned that sales were significantly affected. The ban made it more difficult and less convenient for someone to choose to smoke. This case study illustrates that instead of acting on available and credible information, the majority of people act based on autopilot, habit, and factors that influence the convenience or ease of making that choice.* (Vuolo, 2016).

In the aforementioned case study, the Surgeon General warning actually had little effect on people stopping smoking cigarettes, illustrating that many people will continue to habitually act, either disregarding or not consciously considering the information presented to them. Since information alone is often not good enough to break habits, behavior change techniques such as nudges become useful. The ban of cigarette sales in vending machines was an implementation of choice architecture. The ban made the purchase of cigarettes less convenient for smokers, and therefore, disrupted their buying habits, allowing for more smokers to quit smoking.

Behavioral Nudges

Researchers Richard H. Thaler and Cass R. Sustein are largely credited with developing the behavioral psychological theory behind nudges. They define a nudge as follows:

> "A nudge, as we will use the term, is any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid. Nudges are not mandates. Putting the fruit at eye level counts as a nudge. Banning junk food does not." (*Thaler & Sunstein,* 2008).

A key aspect of nudges is that it takes advantage of biases and lapses in human cognition by providing a certain context in which the behavior happens (Goepel, Rahme, & Svanhall, 2015). Using contextual variables and taking advantage of unconscious biases are what makes a nudge different from other interventions as Byerly et al., point out in their 2018 paper comparing the effectiveness of nudges against interventions which target more conscious processing, namely financial incentives and education. In reviewing 160 interventions to compare the two approaches, Byerly et al. in 2018 outline some basic nudge types, including choice architecture, using social norms, and priming.. The study demonstrated that nudges are effective at changing various behaviors including some that fit within our project scope, like consuming less meat.

A person is more likely to repeat an action if it is easy and fun. (National Public Radio, 2019/2019). If people are more likely to act where there are low barriers to entry, utilizing nudges that reduce barriers to the desired action should result in more people adopting the desired act or habit. An experiment conducted to measure sales of a product category varying by shelf placement demonstrated that the relative sales against its product category were higher when located on the middle shelf as compared to the higher or lower shelves. (Sigurdsson et al., 2009). This is an example of choice architecture as mentioned above.

Choice Architecture as a Nudge

Choice architecture can influence a choice by changing how many options are presented, the order in which those options are presented, and how those options are framed. (Johnson, et. al., 2012). Decisions about presenting these elements must be made, but they can be made blindly or made with knowledge about how the design will affect the end user's decision. Our project seeks to explore how choice architecture can be used to influence the user's decision to select a food product with a lower carbon footprint. By understanding the context around and the conditions that may serve to influence a person's decision, those who are able to frame the choice are able to influence its outcome.

The importance of ordering choices and default options.

The architecture of choices can have important consequences. The *order in which choices are presented* is particularly influential, especially when the decision maker is ambivalent about the decision, when the decision is based on difficult-to-obtain or incomplete information (Thaler & Sunstein, 2008).

> *Case study: The 2000 Presidential Election*
> *In Florida, the order in which Presidential candidates appear on the ballot is determined by which party holds the governorship.* (Saunders, 2020). *In 2000, Republican Jeb Bush was the Governor of Florida. Thus, George Bush's name appeared before Al Gore's. Studies have shown that had Al Gore's name appeared first on the ballot in Florida, or even if the order had been randomized on the ballot, in the 2000 Presidential election, Gore would have won the election over George W. Bush.* (National Public Radio, 2022/2022).

Choice architecture can be incredibly influential. This presidential election was one instance where the order of the choices presented had important implications.

When people are presented with complex or difficult-to-understand information, they are more likely to choose either a default option or the option presented first among the options presented. The default option is the option that is chosen for the user when she has not selected an option for herself. (The Decision Lab, n.d.).

> *Case study: Cost of Health Insurance*
> *In a study where users were told to select the insurance plan with the cheapest premium, they were unable to determine based on the policy information and routinely chose the more expensive plan when that plan was the first option presented to them in the menu of options.* (National Public Radio, 2022/2022)

> *Case Study: Default Health Insurance Plan in Pennsylvania and in New Jersey*
> *In Pennsylvania, the default option for those who did not select a healthcare plan was the more comprehensive and more expensive plan. While in New Jersey, the default option was the less comprehensive and less expensive plan. The selection of these default options in each state resulted in less comprehensive and expensive coverage in Pennsylvania and more comprehensive and expensive coverage in New Jersey.* (National Public Radio, 2022/2022).

Health insurance documents are dense and difficult to interpret. Thus, they can serve as prime examples of contexts in which the order and default choice matters. Like health insurance, GHGEs stemming from food products is a topic too nuanced for many to easily comprehend. GreenSwapp needs to be aware of setting the default food product to one with low associated GHGE.

The use of coding and algorithms can also aid in setting the default option.

> *Case Study: Prescribing Generic Drugs*
> *To encourage doctors to prescribe the generic drug over the brand name, study organizers coded the program used to prescribe to default to the generic drug, when the doctor began to type the brand name (i.e. when a doctor began to type "Allegra", the program offered the generic "Fexofenadine". The doctor was still able to choose "Allegra", but the default choice was the generic. This resulted in major savings in health care costs for the patient.* (National Public Radio, 2019/2019).

Within the scope of our project, this generic drug case study could become relevant if GreenSwapp ever returns as an online shopping retailer or works with online retailers. GreenSwapp could employ a coding system similar to that used in the generic drug study to automatically suggest products with lower GHGEs based on the searched product.

Morality of Choice Architecture and Nudges

Based on its manipulative nature, critics wonder whether the use of choice architecture to influence decision making is ethical. Eric Johnson, PhD, believes nudging is ethical when used to guide people in making the right decisions. He states:

> "Choice architecture is there whether we are using it to manipulate or not. Someone is deciding lots of things like what is the default and how many options. There is no such thing as no choice architecture. Just because you have your eyes closed doesn't mean it's not there. So what I think is the more important thing to do is to realize that it exists and to use it to help people make the right decisions."(National Public Radio, 2022/2022).

The ethical question still remains whether it is morally sound to allow an individual developing and implementing a nudge to determine what is unambiguously "right" for all those who are presented with that nudge.

Social Norms and Behavior Change

Social norms were defined by Cialdini and Trost as "rules and standards that are understood by members of a group, and that guide and/or constrain social behavior without the force of laws" (1998). Social norms are encountered every day, and can affect a person's behavior without them realizing it. One theory that explains how social norms guide or constrain behavior is through the process of internalizing, which is when a social norm turns into a personal norm. Personal norms then beget intentions and behaviors. Internalizing occurs when people learn about the values and behaviors of others, typically of those with whom they most closely identify (van der Werff & Steg, 2014). Because social norms can affect our behavior, they are a tool commonly used to incite behavior change through a method called social norms marketing. Social norms marketing utilizes social norms by conveying the values and behaviors of others through short messages in places that the targeted audience can easily come across (Schultz et al., 2007). For example, an intervention to get students at the University of Michigan to recycle more might include a sign up in a dormitory hallway that simply reads "Wolverines Recycle!". Social norm marketing is one of the most popular types of behavioral interventions and has been used for years with success (Schultz et al., 2007).

> *Case Study: Social norm marketing effects on transportation behavior*
> *One study used social norm marketing by simply providing participants information on others' typical transportation use, such as the extent to which others used public transportation, with the hopes of getting people to more frequently use public transportation. The study found that social norm marketing (in this case telling participants other people tended to use public transport) was successful at getting people to significantly reduce their private vehicle use (Kormos, Gifford, & Brown, 2018).*

In order to properly use social norms, it is important to understand that there are different types. Common social norms used in behavioral interventions include descriptive norms or the perception of what is typically done by others, and injunctive norms or the perception of what is considered right or wrong (Reno, Cialdini, & Kallgren, 1993). There are also dynamic norms which convey how people's behavior is changing. One simple way to differentiate dynamic norms from the other two is that they depend on inciting behavior change based on a growing trend or a fad (Sparkman & Walton, 2017). Importantly, these common types of norms have been found to be effective in promoting pro-environmental behavior.

<u>Case Study: Descriptive norms used to influence home energy use</u>
A field experiment done to determine what influences people to conserve energy found that the use of descriptive norms, such as telling participants how much energy most people use, were more effective at getting people to use less energy than other factors such as saving money or for the environmental benefits associated with lower energy use. (Nolan et al., 2008).

In one interesting example, injunctive norms have been found to be effective at preventing environmental theft.

<u>Case Study: Injunctive norms used to preserve a forest</u>
In an attempt to curb theft of petrified wood from Petrified Forest National Park, Park Rangers, using social norms, placed a sign consisting of a picture of a lone person stealing some wood inside a big red circle with a line through it, and a brief statement asking people to refrain from taking the wood to preserve the natural state of the forest. Ultimately it was a successful campaign and significantly reduced the number of people who stole wood from the national park (Cialdini, 2003).

Dynamic norms have also been found to be an effective tool in social norm marketing and can be effective even when contrasted with other social norms.

<u>Case Study: Dynamic norms used to curb meat consumption</u>
A study done at Stanford University found that dynamic norms were not only effective in getting restaurant patrons to buy more meat substitute products, but also did so in the presence of a descriptive norm countering that most people consume meat. (Sparkman & Walton, 2017).

Given the limited space available on GreenSwapp's web app, which will mostly be accessed via cell phone, GreenSwapp should take advantage of the simplicity of social norm marketing as an easy and effective way to nudge its user base to buy greener products. However it should be noted that normative messaging can be ineffective under certain circumstances. For example, descriptive norms in particular have been shown to have the opposite of their intended effect when used improperly. Research done by Schutltz, et al., in 2007 on behavioral interventions using social marketing and descriptive norms found that sometimes these interventions are not effective because a portion of the target audience may not be fit for the particular descriptive norm. Schultz, et al., in the same 2007 paper creates an example to highlight how this happens;

> *"Consequently, a college campaign targeting alcohol consumption might motivate students who previously consumed less alcohol than the norm to consume more. Thus, although providing descriptive normative information may decrease an undesirable behavior among individuals who perform that behavior at a rate above the norm, the same message may actually serve to increase the undesirable behavior among individuals who perform that behavior at a rate below the norm."*

In order to prevent this, the authors suggest creating a message that utilizes both a descriptive and injunctive norm. However, the combining of descriptive and injunctive norms should be done with care. Cialdini in 2003 discussed that messages that combine two norms are ineffective when they fail to promote the same behavior.

For example, the image below created by our team features both an injunctive and descriptive norm for an imaginary anti-littering campaign at a park.

The text is a clear injunctive norm signaling that picking up litter is the right thing to do and, on its own, could be successful in getting people to refrain from littering. However, the included picture of the litter on the ground is a descriptive norm, which signals that it is normal for people to litter. The combination of these two norms, which signal different littering behaviors, could cause people to litter more, and therefore would lead to an unsuccessful anti-littering campaign. However, that same study by Cialdini in 2003 found that when injunctive and descriptive norms are combined in a synchronized way, it can be more effective than an injunctive or descriptive norm on its own. Returning to our example, keeping the text and swapping the background photo for one of a clean landscape or a person picking up litter would make for a very successful anti-littering campaign that properly synchronizes the messages of the two norms.

> *Case Study: Using a combination of Injunctive and Descriptive norms to influence recycling*
> *To study the impact of combining injunctive and descriptive norms, researchers created several public service announcements (PSA) with the hopes of increasing recycling. In the weeks following the broadcast of the PSAs on local television stations, a 25% increase in recycling was observed. (Cialdini, 2003).*

So, for our client, the use of descriptive, injunctive, and/or dynamic norm messaging aimed at swapping high carbon footprint foods with lower carbon footprint foods can be an effective strategy, especially if GreenSwapp combines injunctive and descriptive norms in a way that aligns the messaging. Using social norms marketing as an intervention requires norm messaging to be easily interpreted and accessible by its intended audience while also being thoughtfully worded to promote the desired behavior.

Behavior Change through Feedback

Another technique for behavior change is informational feedback. Examples of feedback we may regularly encounter include screen-time notifications reminding us of the amount of time we have spent using our cell phones, the Netflix "Are you still watching?" message, monthly bank or credit card statements, and household energy bills. In relating feedback to pro-environmental behavior, the term "eco-feedback" was coined, and is described as "information about resource consumption provided back to consumer(s) with the goal of promoting more sustainable behavior" (Sanguinetti, Dombrovski, & Sikand, 2018). While feedback is used in many different ways, research for its use in promoting pro-environmental behavior has mostly been conducted on utility customers in the attempt to get them to consume less energy (Sanguinetti, Dombrovski, & Sikand, 2018). However, there are uses of feedback relevant to GreenSwapp and its business. In a paper published in 2018 by Sanguinetti Dombrovski, & Sikand, researchers found there are three important design dimensions of feedback required for effective implementation in order to change different consumption habits like energy, water, and food. First, the feedback information should be given frequently and close-in-time with the related behavior. So for example, feedback on a consumer's carbon footprint after shopping for groceries should happen shortly after the customer pays. Second, the feedback information should clearly establish to what and whose behavior it refers. The third design element to consider is how the information is displayed. The information should be easy to understand, relevant, and credible. The authors of this study found that using these three elements can be an effective strategy for changing behavior. They explained its success comes from three behavior mechanisms that work together:

> "feedback that is salient promotes attention, feedback that is precise promotes learning, and feedback that is meaningful promotes motivation" (Sanguinetti, Dombrovski, & Sikand, 2018).

There are additional uses for feedback that can also help drive behavior change. For example, it can be very successful when used with other behavior change methods.

> *Case Study: Goal setting with feedback*
> *A study done on energy consumption sought to understand how feedback can influence consumers who have set goals to reduce their energy use. The study found that the group that received feedback on how much energy they and others in the study had used, ended up reducing their energy consumption significantly more than the group that did not receive any feedback (Becker, 1978).*

Another useful tip when using comparison as feedback in conjunction with other behavior change interventions is that it tends to be more effective when the feedback is given in relation to a relevant group rather than to oneself.

Case Study: Feedback disguised as a social norm
In 2012, three researchers set out to determine how feedback could be used to curtail the carbon footprint of a broad range of everyday behaviors, including eating and transportation habits, among others. They found that intermittent feedback given to the participants on how others were doing in terms of lowering their daily carbon footprints was the most effective way to get people to subscribe to a range of environmentally-friendly behaviors (Toner, Gan, & Leary, 2012).

The above case study also found that it was simply the perception of the participants' peers' behavior that caused them to change their own behavior, and they did not take into account any potential shame regarding their own actions. As made clear by the study, the feedback in this case also acted as a descriptive norm by indicating to the participants what is commonly done by others.

Though feedback can be an effective tool for inciting behavior change, it also has limitations. In a paper written by Buchanan, Russo, & Anderson in 2015 found that many times feedback only works for a limited amount of time and depends heavily on user engagement with the feedback. The authors also found that the effectiveness of feedback often depends on the novelty of it, and so many behavioral interventions that use feedback are not always effective solutions for creating long-term behavior change. For our client's purposes, using feedback on their web app can be an effective tool as long as it is used (1) along with the correct design principles, (2) in conjunction with other types of interventions, (3) for short periods of time and/or, (4) in creative and engaging ways.

Incorporating Behavioral Science Principles into the GreenSwapp Application or Business Model - Deliverables

Deliverable 1: Proposed Behavior Nudges to be Implemented by GreenSwapp

Based on the landscape of research regarding pro-environmental behavior and decision making, our team has developed the following list of nudges designed to be implemented either within a grocery store or digitally to influence app users to choose food products with lower carbon footprints:

Choice Architecture
1. Put in a design element such as green arrows or leaves that "point" users to green products suggested in the app.
2. Show any suggested items in the web-app that have a lower impact as brighter in color than their counterparts.
3. Present suggestions in sets of threes and always have a "Green" option in the middle
4. Indicate if there are sustainable foods on a shelf in the shelving signs above the aisles.
5. Partner with grocery store to place items with lower carbon footprint at eye-level
6. Release new applications or initiatives at times when people are more likely to adopt environmentally-conscious behaviors or adopt new habits.

a. Individuals are more likely to contribute to climate-change related funds on warmer days. It may also be the case that people are more likely to engage in environmentally conscious behavior on days that are warmer. GreenSwapp may wish to test this through comparing user behavior on warm days to that on cold days through compiled purchase and/or scan data.
b. People are more likely to adopt new habits, such as eating a diet with a lower footprint, during times of transition or "new beginnings." GreenSwapp should look to launch new initiatives or market its products or services during December and January to take advantage of this phenomenon.

Social Norm Marketing through Descriptive Norms
1. "Environmentalists even make sure their groceries are "green"
2. "Nature-lovers fight climate change with green groceries"
3. "Conservationists swap for green groceries"
4. "Even vegans and meat-lovers agree on buying green."
5. "Green groceries are popular among everyone from birders to botanists."
6. "Friends of the earth buy green"
7. "Eco-activist purchase green groceries"

Social Norm Marketing through Injunctive Norms
1. "Fight climate by buying green"
2. "Green groceries = Healthy Planet"
3. "Climate change is a human rights issue too, so try greener choices today"
4. "Nature gives us a lot, give back by buying green"
5. "Meat alternatives are good for the environment and animal welfare"

Social Norm Marketing through Dynamic Norms
1. "More Environmentalists are buying green groceries"
2. "Eco-activists are starting to fight by buying green"
3. "Nature-lovers are turning to green groceries to lower their Carbon Footprint"

Feedback
1. Greenery that appears as customers scan or purchase green products.
2. After purchase, give customers a digital forest or garden that grows based on their purchases of products with low associated GHGEs.
3. Each time after a user makes purchases, compare products' carbon footprint with his previous shopping records.
4. Small animation and "ding" sound whenever a green product is chosen, scanned, or purchased.
5. After purchasing, customers are shown a beautiful picture of nature, however they only see a portion of the picture and are told as they buy more green products they can see more of the picture.
6. Small trees or flowers next to green products.
7. When showing suggestions, let users know which would lower their carbon footprint the most based on previous shopping trip or trips
8. Add carbon footprint comparison between users that is shown on receipt after every purchase.

9. Prime the user by showing a grocery bag or cart full of "Green" products, or of a scene of nature either at the opening screen or sometime early in the process.

Deliverable 2: Proposed Experimental Design to Test Nudges

GreenSwapp wants to test the effect of nudges, either implemented in its web app and/or inside a grocery store, on grocery shopper behavior. GreenSwapp's intended result and goals of these tests would be:

1. To have grocery shoppers swap high carbon footprint impact food purchases for products with a lower carbon footprint and,
2. To determine which behavioral nudges would most likely lead to this intended result.

Our team has devised a quasi-experimental design for GreenSwapp to test the efficacy of any nudge implemented either on GreenSwapp's web app or within the grocery store itself. The experiment would need to be conducted at a partner grocery store over the course of at least two months. Included are recommendations for sample size, independent variables, dependent variables, and data analysis that should work to test the efficacy of current and future nudge-based behavior change interventions. Also included are ways to alter the experiment in the case that the partnering grocery store has certain requirements that do not allow for the full experiment as outlined to be implemented.

To understand the experiment, it would be beneficial to understand how grocery store customers interact with GreenSwapp's web app. GreenSwapp has developed its own product labels to be placed under grocery store products. These labels feature the carbon footprint of the product, and a color, either green, yellow, or red, that indicates how high the carbon footprint is in relation to similar products. The colors on GreenSwapp's labels are a nudge themselves, so they are accounted for in the following experimental design. The labels also feature a QR code that, when scanned by a smartphone camera, allows the user to view GreenSwapp's web app, containing additional information on the product, including the estimated breakdown of percent of category emissions (i.e. agriculture, transportation, manufacturing, packaging, etc.) and suggestions for similar swappable products.

Research Question

How can GreenSwapp influence its user base to increase their "green" purchasing behavior and lower their carbon footprint when shopping for groceries?

Research Design

Our quasi-experiment will need to run in conjunction with a partnering grocery store for at least two months in order to obtain the necessary amount of data for a proper analysis. Once finished, GreenSwapp will use sales data provided by the partnering grocery store to compare the outcomes of three levels of the independent variable. From this, GreenSwapp will have a better idea of how effective the colors on their labels and the additional nudge messaging within the app are at getting consumers to swap their typically high impact purchases with lower impact ones. The participants will consist of customers at the partnered grocery store. In this design the participants' exposure to the control and treatment variables is not being controlled by the experimenters but instead the exposure is completely random, making it a type of quasi-experimental design called a natural experiment. While quasi-experiments are more prone to effects from confounding variables than true experiments, they have high external validity and allow for GreenSwapp to be confident that if the experiment finds a nudge to be effective, it will continue to be effective if GreenSwapp decides to expand its use across similar grocery stores.

The first level of the independent variable will be the control group and consists of grocery store products without the GreenSwapp climate label. The treatment groups will consist of the second and third levels which will respectively consist of grocery store products with GreenSwapp's climate label and grocery products with GreenSwapp's label and an additional nudge within the app. The second and third levels will be operating at separate times over a period of at least 30 days each, inside the partnering grocery store. While the 30 days of sales data for the treatment groups will come from the period of time that they are operating, the control group's sales data can come from any time before the treatment groups were in the grocery store.

The labels and the additional nudges are separate groups in order for GreenSwapp to be able to understand if the nudge they wish to experiment on creates additional behavior change when used with the labels and if the labels themselves are effective, since they are also a nduge. Only testing the nudge GreenSwapp is looking to test in the app and comparing it to a control group can be done if necessary, but the results of such an experiment would be seriously affected by the colored labels.

In outlining this experiment, we have used some of the nudges suggested above, based on the request of our client. Specifically, we will use social norm marketing as the example of the experiment's additional, in-app nudge. In this case, the nudge will either be a descriptive, injunctive, or dynamic norm that appears as a short sentence or phrase next to the grocery store product's name, and it will change between the three messages randomly each time the application is opened via the QR code.

It should also be stated that it is not necessary to place GreenSwapp's climate labels next to every product in the grocery store. Instead we suggest selecting a certain section, sections, or group of products, such as all of the milk products or the pasta section, to outfit with climate labels. This will take less time and require fewer resources than using the entire store. Additionally, certain aspects of the experiment can not be fully flushed out until GreenSwapp has partnered with a specific grocery store. Therefore this outline will refer to the products in the experiment as the "section". For future reference, the products chosen should be a thoughtful mix of products that could all be swapped with one another. For example, a customer would not be likely to swap sliced deli ham with filet mignon. If desired, different groups of products can also be used such as different types of bacon and different types of pasta, but the analysis should be done distinctly for each type as it only works among products that could all be swapped for each other.

In terms of the data analysis, GreenSwapp sorts foods into three categories of low, medium, and high impact in relation to that food's carbon footprint. Once the sales data is collected on each individual product, the data should be separated into those three corresponding impact categories. The analysis will compare the sales data of individual groupings across the three levels of the independent variable. For example, low impact foods' sales performance data during the control group phase will be compared to low impact foods' sales performance during the first treatment group phase, when they have GreenSwapp's labels but no additional in-app nudge.

Target Population/Sampling

The target population for our experiment would be GreenSwapp's user base, which comes from consumers who shop at grocery stores with which GreenSwapp has partnered or will partner. The sampling of these individuals would be considered simple random sampling because every shopper has an equal chance of coming in contact with the nudges. The experiment will measure daily sales performance and then average that performance over a set period of time. To ensure a statistical minimum and meet the central limit theorem, the length of the experiment should be at least thirty days for each treatment group. While the data collected for the control group should be over the same amount of days, it can be collected from any month prior to the experiment. In selecting this prior month, GreenSwapp should attempt to account for and control a variety of variables that may influence the purchase of certain products over others. For instance, if the experiment runs from March through April and November through December is selected as the prior months, the products purchased for those two periods of time may differ widely based on holidays, temperature, and area population changes, among other factors.

Independent Variables

As discussed before, this experiment has three levels to the independent variable. The first is the control group that receives no behavioral nudge intervention. The other two are the previously-described treatment groups. See below for suggested nudges to include at the third level of the independent variable.

1. All the products in the desired section (control group)
2. All products within the desired section with GreenSwapp's labels (first treatment group)
3. All products within the desired section with GreenSwapp's labels and randomly appearing normative messages, including (second treatment group)
    a. "Green groceries are popular among everyone from birders to botanists!" (Descriptive Norm)
    b. "Nature gives us a lot, give back by buying green" (Injunctive Norm)
    c. "More people are starting to prioritize the Earth by buying Green" (Dynamic Norm)

Dependent Variables

In order to figure out whether the nudges meet our clients needs, we have included three measures for the dependent variable. First, while the data on the control group can be collected at any time, to repeat, it should consist of a time frame that happened before customers were exposed to the nudges, such as the previous month to the experiment or exactly one year prior. To be more specific, among the chosen section of the grocery store, experimenters should collect data on each individual product's daily sales across all levels of the independent variable. The sales data gathered should reflect the number of units sold rather than monetary sales, as different prices of different products might skew the results. Once sales data are collected, the products and their data should be assigned to one of three groups that correspond with the correct placement in GreenSwapp's carbon footprint impact categories (low, medium, and high). Total daily sales across all products should also be calculated in order to be able to find the percentage that each impact group's sales contributes to the total. To further elaborate, each impact group's percentage make up of total sales should be calculated for every day, and then averaged for each level of the independent variable. For illustration purposes, experimenters should be able to say that sales of, say, low impact meat products on average made up x% of the total daily sales for all meat products during the control group phase, and y% of the total daily sales for all meat products during the 1st treatment group phase. The average daily percentages will be compared to see if there are significant differences between the control, the first treatment group, and the second treatment group. Using percentages instead of simply using the average total sales will help account for any changes in overall sales that might affect the results.

Furthermore, in working with and speaking with our client, we have learned that grocery store operators and managers often are concerned that adding GreenSwapp's climate labels and other in-store services will cause an overall decrease in sales. Potential future online retail partners will likely have the same worry. In addressing this concern, we recommend tracking the daily total sales of the desired section or sections of the grocery store that is being used in the experiment and then finding the daily average over the course of the experiment in order to compare between the treatment and control groups. In doing so, GreenSwapp could more confidently answer this client concern by presenting pilot studies or data to grocery stores that demonstrate its services are not tied to a drop in general sales.

A third variable that might affect the results is how consistently the customers scan GreenSwapp's labels. Customers may stop scanning or never scan the labels to begin with. If scanning is inconsistent, customers will not have the opportunity to see the nudges within the app. GreenSwapp will need to determine if the experiment results reflect an ineffective message or an unencountered nudge due to lack of scan frequency. Either of these results will further GreenSwapp's understanding of how people interact with its labels. Thus, our team recommends measuring the number of times per day customers open the application and then averaging that out between the treatment periods, which will serve GreenSwapp in better interpreting the final results as well as in understanding how customers interact with their labels.

Recommended Process:

1. Daily sales of each individual product
   a. Each product's data should be grouped into low, medium and high impact groups according to GreenSwapp's LCA data. The percentage that each group's sales make up of the total daily sales should be averaged over the 3 levels of the independent variable.

2. Daily sales of each meat section as a whole
   a. The daily sales should be averaged out for each level of the independent variable.
3. Number of times a day the app is opened via the QR codes (during the two treatment periods only)
   a. The total number of times the app is opened a day should be averaged out over the two treatment periods.

Data Analysis

For our first dependent variable, which is equal to the average percent of total sales for each impact group, we suggest using an ANOVA (analysis of variance) test to determine if there are significant differences between the different means. The output of the ANOVA test will compare all the averages at once to one another and determine if significant differences exist between any of the averages. However, when analyzing the output, certain comparisons should be ignored, while others require attention. The comparisons requiring analysis are going to be between the means of the same impact groups. Meanwhile, the differences in means between different impact groups should be ignored. As an example, the results of the ANOVA will indicate whether the mean of the low impact group during the control phase is significantly different than the mean of the low impact group during the first treatment phase, this is a notable comparison as it is between the same impact group, “low”. However, the ANOVA will also show the difference in means between the low impact group during the control phase and the high impact group during the first treatment phase, this is not between the same impact group, so it should be ignored. . To reiterate, experimenters should look at the impact group’s intragroup comparisons across each level of the independent variable and not intergroup comparisons. These intragroup comparisons are important because the nudges are intended to increase the buying of certain types of products (low or medium) and decrease the buying of others (medium or high), therefore, GreenSwapp should be cognizant of how the percentage makeup of each group changes over the different levels of the independent variable.

Another potentially more organized way to do this analysis would be to run three separate ANOVAs: (1) one for the data sets of the low impact group, (2) one for the medium impact group, and (3) another, for the high impact group. This approach would make it easier to read and interpret ANOVA results, which appear in a very large table.

Either process would be an acceptable approach, as long as the correct comparisons are reviewed. While analyzing the differences in means is strictly between the same impact groups, it should be noted that, for the interpretation of the results, GreenSwapp will need to pay particular attention to how the three groups changed as a whole over the three levels of the independent variable in order to understand how the nudges performed. We further explain this concept in more detail in the “Interpretation of Results” section that directly follows this one.

In analyzing the second dependent variable, experimenters should have three means, the average total sales per day for each phase of the experiment. This data lends itself to an ANOVA, which can be used to test their differences. GreenSwapp should determine if there is a significant difference between the average daily sales between the control and treatment groups.

Lastly, a paired t-test should also be used to compare the average number of times the app was opened per day over the course of the first treatment phase compared to that same measurement during the second treatment phase. Here a paired t-test should be used because only two means of data sets are being compared.

Interpretation of Results

If the ANOVA concludes there are significant differences, it is then crucial to determine the direction of that significant difference, which will indicate whether people bought significantly more low impact foods during the second treatment group phase as compared to the control group phase. Some questions that may arise from the interpretation of these results may include:

1. Is the first and second treatment group's shopping behavior significantly different from the control group in a way that indicates consumers are swapping higher impact foods for lower impact foods?
2. Does using the additional social norm messaging significantly change shopping behavior in that same desired way when comparing the control and first treatment groups?

If these questions arise during the course of the experiment, they should be answered with the understanding of the data as a whole. In recognizing that there are too many possible answers to the above questions, we will instead focus on those conclusions that are most likely to arise.

To answer the question of whether or not the data indicates a desired amount of swapping is somewhat up to GreenSwapp because there is no definition of successful "swapping". From discussions with our client, however, we are confident that a successful intervention would most likely appear as at least one of the two scenarios depicted in the tables below. These scenarios describe the change in shopping behavior between any one phase of the experiment and any successive phase of the experiment. For example, assuming that all the changes are significant, if Scenario-1, depicted below, is the change between the control group and the first treatment group, GreenSwapp can conclude that its labels nudge shoppers to swap high impact foods for low impact foods. The arrows in the table indicate if the percentage makeup increased or decreased between the two groups, so in Scenario-1, the low impact foods percentage makeup increased between the control and first treatment group while the medium and high impact foods resulted in a significantly smaller percentage makeup. A similar conclusion can be made if Scenario-1 is the outcome of comparing the first and second treatment groups, concluding that the additional social norm nudges are effective at nudging consumers to swap high impact for low impact products when used in conjunction with the labels.

Scenario-1

Impact Group	Low	Medium	High
Direction of Percentage Change	↑	↓	↓

Scenario-2 below depicts a very similar outcome except that the percentage share of the medium impact products either significantly increases or has no significant change the same between two successive phases of the experiment. The same conclusions as above can be reached if GreenSwapp considers this a successful outcome.

Scenario-2

Impact Group	Low	Medium	High
Direction of Percentage Change	↑	↑ / =	↓

It should also be noted that with any of these scenarios, one of the impact groups significantly changes, but the other two are not found to be significantly different. GreenSwapp could consider this result to be successful or not depending on the criteria it establishes that define "success."

Another possible scenario, one that may not be deemed successful is if medium impact products see a significant percentage decrease, lower impact products see an increase, but higher impact products don't significantly change. While this does still show a positive effect based on the nudge messaging, like in Scenario-2, the result is not ideal. A result like this one might be evidence that those who buy certain high impact products are not affected by appeals to sustainable social norms and perhaps these nudges need to be rewritten to appeal to this demographic, or a new approach needs to be considered. Human behavior is complex so further consulting the behavior change research literature and researching food preferences may be needed if a different outcome is desired. Any situation where high impact products increase their share of the total percentage shows the nudges backfired and actually made customers have what is referred to as a psychological reactance. This phenomenon is not unknown in the field of behavior change when using social norms marketing and usually means the nudges were not designed or written properly (Schultz et al., 2007). There are ways to correct this issue addressed in the Social Norms section above.

Additional Guidance in Conducting the Experiment and Interpreting Results

For brevity and to address the most important and/or likely possible outcomes, we have included guidance to address the additional questions that may arise from the study's potential conclusions.

1. *What if the second treatment group is not significantly different from the first treatment group, but is still significantly different and effective when compared to the control group?*
    a. In this case, the social norm nudges become redundant when used in conjunction with the color coded climate labels. This could happen because customers did not use or stopped using the QR codes, which is something for which researchers should check. If the use of the QR codes was not significantly different across both treatment groups, then they seemingly do not have an additive effect when used with the labels.

2. *What if the second treatment group is simply ineffective at changing behavior when compared to either group?*

  a. If customers use the QR codes the same across both treatment groups, then researchers can conclude that the nudge messages used do not work, AND the labels only work to change behavior for a short period of time, since they are present for both periods, If they did not use the QR codes during the second treatment phase, then the conclusion is just that the labels are not a long-term effective nudge strategy and that customers weren't exposed to the social marketing nudges enough to conclude if they are effective or not.

3. *What is the necessary number of times for customers to use the QR codes in order to start seeing the social norm marketing nudges work?*
   a. It is theorized that an individual being exposed to a social norm message multiple times can increase its effectiveness (van der Werff & Steg, 2014). However, from this experiment, GreenSwapp will not necessarily know how often one individual is exposed to a nudge. GreenSwapp will only understand how often the general grocery store population is getting exposed to the nudge, and there is no scientific indication how much a population needs to be exposed for a nudge to start being effective. This is because most experiments do not have an extra step required for its sample population to be exposed to the nudge - they are usually in a location where subjects can easily come across the nudge (Schultz et al., 2007). GreenSwapp will have to use its own judgment if they feel the number of times the QR codes were used was good enough for the purposes of the experiment.

4. *What if there is a significant decline in sales between the control group and either of the treatment groups?*
   a. If sales data does significantly decrease, it is most likely that a third variable is at play as research has shown that a bad nudge usually results in its audience doing the opposite of its intended behavior, as mentioned previously. In this case, the opposite of the desired outcome is buying more high impact foods, not necessarily buying no products and therefore is not likely caused by the nudges (Schultz et al., 2007).

5. *What if the both treatment groups perform significantly worse when compared to the control group?*
   a. As stated before, this can be evidence that the nudges caused psychological reactance among the customer base (Schultz et al., 2007). Future research on nudges may be needed in order to make better behavior change interventions.

Additional Variables Not Considered

Additional variables that may affect the results of this experiment could include anything that might alter shopping behavior between the different time frames from which the data is collected. The influence of these additional variables may cause higher or lower sales. For example, many religions have different fasting practices where certain types of food are not consumed during certain times of the year, such as meat. Therefore, an increase in low impact meat sales may be due to an increase in consumption of plant based meats as a religious practice and not because of the intervention. Another reason for a change in the types of foods purchased may be explained by the food purchases influenced by the changing of the seasons. People eat differently at different times of the year. The customer base could change drastically one way or the other between two months for grocers located in tourist or college towns. GreenSwapp will need to take care in choosing the points in time to conduct the experiment and the time for which baseline data is established to ensure major differences do not interfere with the experiment results. The factors that could change customers' shopping behavior between the time periods should be discussed with the grocery store, as it would have the best insight in avoiding this issue.

Possible Alterations to the Experiment

Lastly, in the event that the partnering grocery store will only allow a limited amount of time for the experiment to be completed, the experiment design can be altered to include only the control and one of the treatment groups. In this case, paired t-tests should be used instead of ANOVAs to analyze the data because there are only two sets of means to compare. Also, if something similar to the second treatment group is used and compared to the control group, it should be noted that any outcome could be attributed to the labels instead of the in-app nudges because the labels are a nudge too. To avoid this, GreenSwapp could use labels with no color, but we recognize that this is not how GreenSwapp intends for its labels to operate in grocery stores.

Next Steps: Recommendations for Future Behavior Change Efforts

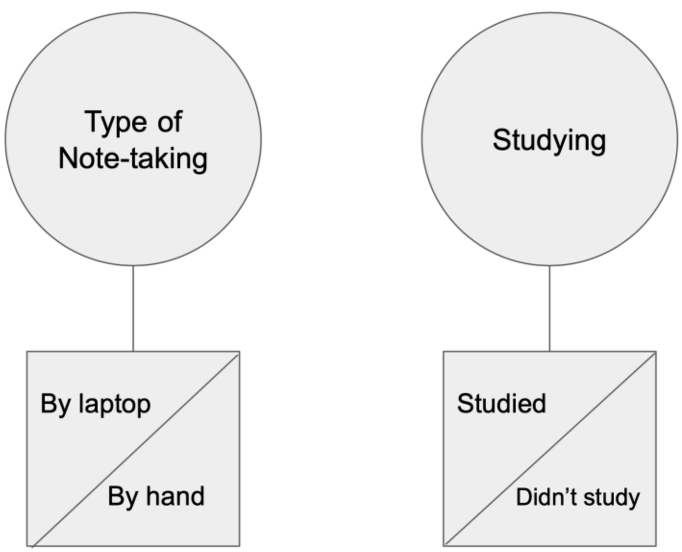
Already included in our deliverables is a list of nudges that GreenSwapp can use in their app, and test using the experimental design to gain an understanding of what will work best for the company moving forward. Our client also was interested in additional suggestions and ideas for behavior change efforts they may implement further into the future in order to have the most positive impact on consumers' carbon footprint.

<u>Future Experiments</u>

To begin, while the included experimental design is useful, fairly simple, and effective, it does have some downsides. For example, understanding how two behavior change interventions interact can not be done in the above design. Through use of a factorial design, GreenSwapp can test multiple nudges at once and understand not only how effective they work on their own but also how they work together. Using this design would allow GreenSwapp to understand what nudges when used together compliment one another to increase the desired behavior more than when used on its own. Factorial design can also help aid experimenters in understanding which nudges when used together do not increase the desired behavior, making the combination either redundant, or lead to decrease in the desired behavior. Practically, it would work well to aid GreenSwapp in understanding which nudges pair best with its color-coded climate labels. Factorial designs are a bit more complicated and time consuming to implement, analyze, and understand. However, as GreenSwapp expands their use of nudges, becomes better at conducting experiments, and begins working with additional researchers, this could be a streamlined and effective strategy to test their behavior change interventions. Below is an example of a fairly simple factorial design in action.

One of the defining attributes of factorial designs is that they have more than one independent variable, each with more than one level. In the most simple form of this is a 2x2 design, there are two independent variables, each with two levels. A study done in 2019 by Morehead, Dunlosky, & Rawson on the effects of different types of note-taking and studying on test performance illustrates 2x2 designs quite well. This study replicated a previous study performed in 2014 that used a more traditional experimental design to understand the difference between the two methodologies. The original study by Mueller and Oppenheimer in 2014 had one independent variable, note-taking, with two levels, by laptop or by hand. The two groups, note taking by hand and note taking by laptop were then compared on how well they performed on a test. In the end, with this design, researchers were able to determine whether there were differences between taking notes by hand compared to via a laptop on test performance.

The Morehead, Dunlosky, & Rawson study expands on this by adding another independent variable, also with two levels, forming a 2x2 design. The first independent variable, note-taking, is the same as in the original experiment, with the two levels being note-taking (1) by laptop or (2) by hand. The second independent variable is whether the students studied for the exam, with the levels set as (1) yes - studied, or (2) no - did not study. Below is an illustration of Morehead, Dunlosky, & Rawson's 2x2 design that includes the two independent variables and their two levels.



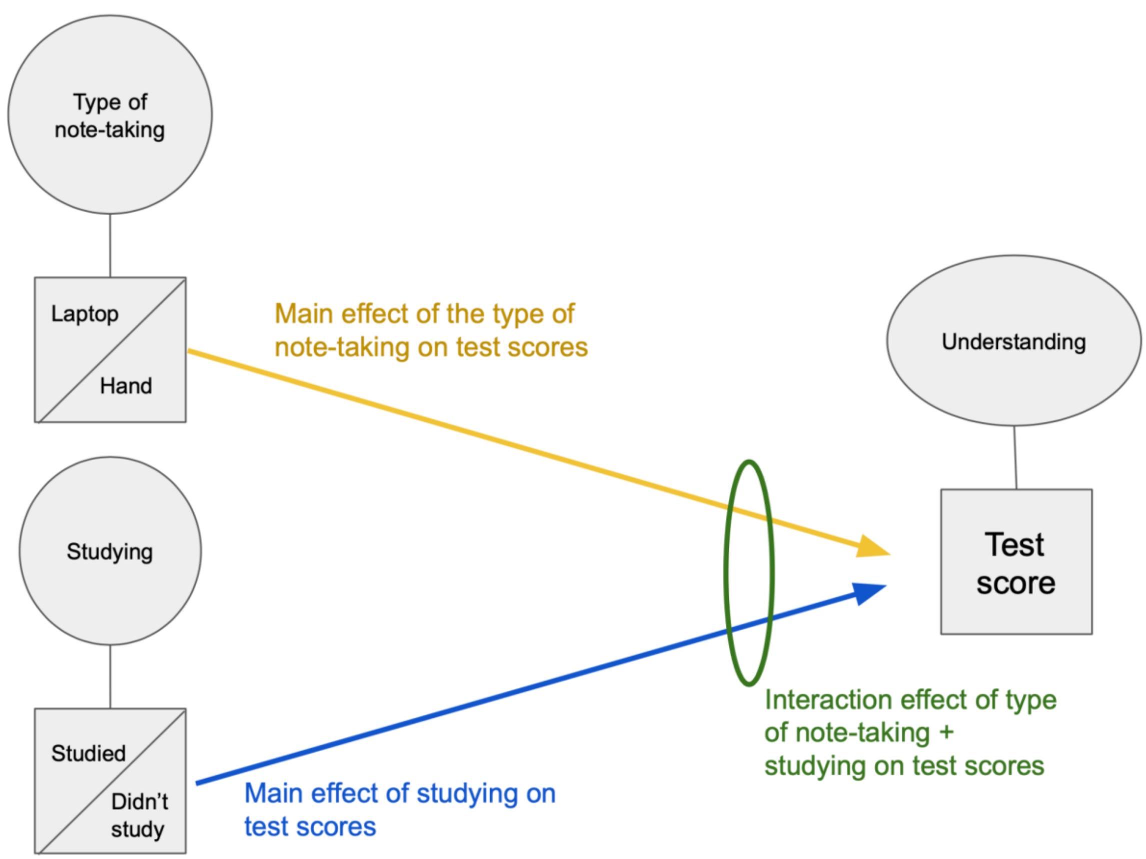
Instead of two groups like in the original design by Mueller and Oppenheimer (2014), this experiment has four groups:

1. Studying after taking notes by hand
2. Not studying after taking notes by hand
3. Studying after taking notes by laptop
4. Not studying after taking notes by laptop

By adding the second independent variable with two levels, the authors were able answer several questions:

1. Are test outcomes affected by the type of note taking an individual performs?
2. Are test outcomes affected by whether an individual studies?
3. What is the combined effect of the type of note taking an individual performs and whether or not they studied on test outcomes?

The first two questions are called main effects, which are a measure of the effect that each independent variable has on the dependent variable by itself. Note that the dependent variable, test scores, is the same for both independent variables. This design also allowed the authors to understand interaction effects. Interaction effects are the combined effects of (1) the type of note-taking someone did and (2) whether or not that person studied on test results. Below is a figure depicting the independent variables, the dependent variable of test scores, the main effects and the interaction effects.

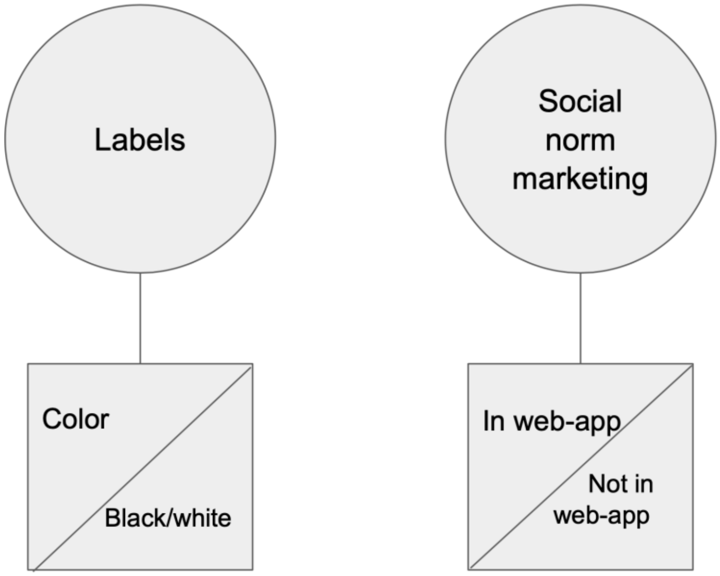


As for the results, a 2x2 design's interaction effects are often conveyed in a table. Using the results from the cited study, we created the table below. The numbers in the boxes are the average scores the participants received on the test, which was not scored on a 100-point scale, although the higher number indicates better understanding.

	Note-taking by laptop	Note-taking by hand
Studied notes	18.3	25.6
Did not study notes	20.6	19.4

While this study focused mostly on the interaction effects, the authors could have highlighted and discussed the main effects if desired. The main effect of how different types of note-taking affects test score performance can be understood by essentially ignoring whether or not someone studied. For example, the authors could find the average test scores for laptop note-taking across both the “studied” and “did not study” groups and compare that to the average test score for note-taking by hand across both the “studied” and “did not study” groups to see which group type of note-takers performed better on the test.This is essentially what the original study by Mueller and Oppenheimer in 2014 did, but they never took into account the second independent variable of studying. The reverse is also true, the researchers could understand if studying or not affects test scores by looking at its main effect. Furthermore, when analyzing their data, the researchers for this study simply found the averages for test scores and looked for significant differences between these averages of each level of the independent variable. See the table above for reference. GreenSwapp could use factorial design similar to the above study to test whether multiple nudges work more effectively alone or when paired.

What could a factorial design potentially look like for GreenSwapp? Our original experiment design could be transformed into a factorial design with a few alterations. Below is a diagram of how the independent variables could be used in a 2x2 factorial design to test behavior nudges. Here the independent variables are types of labels and social norm marketing. The types of labels are GreenSwapp’s typical color-coded climate labels and a black and white one. The other independent variable is the use of social norm marketing, with the two levels being (1) customers receive the social norm marketing in the web-app and (2) customers do not receive the social norm marketing in the web-app.



The four groups to be compared in this design would be as follows:

1. Color labels with social norm in the web-app
2. Color label without social norm in the web-app
3. Black/white label with social norm in the web-app
4. Black/white label without social norm in the web-app

For this type of design, it is more important for GreenSwapp to focus on the interaction effects, since doing so would demonstrate how well the behavior change interventions of colored labels and social norms worked on their own and with one another.

<u>Additional Approaches to Implement Effective Behavior Change Interventions</u>

While nudges are an effective strategy for sustainable behavior change efforts and work well with the functionality of GreenSwapp's web app, there are many different types of behavior change interventions that GreenSwapp could be taking advantage of. Many other types of interventions are more effective at changing behavior than nudges in regard to both the extent to which a particular behavior changes, and how long the behavior remains changed. These more effective types of strategies often urge those targeted by the intervention to be active participants in changing their own behavior. Examples include having people set their own goals, work in teams, and actively reflect and learn, among other techniques (Staats, Harland, & Wilke 2004). While nudges use unconscious heuristics to drive behavior change, these methods require active subject participation to be successful (Schubert, 2017). GreenSwapp has informed our team that it has tried to use more involved behavior change strategies, such as goal-setting, in the past, but had difficulty obtaining enough participants to actively participate.

Given this barrier to using more effective interventions, our team's recommendation is to look into creative ways to get consumers involved and engaged in their own behavior change efforts. One example could be creating a subscription service that provides behavior change interventions to consumers interested in changing their shopping habits, such as wanting to shop more sustainably, ethically, or healthily. Executing this proposal would require a lot of time and resources, but there is precedent that it can work. The company stickK uses this basic strategy to help people form desired and/or stop undesired. (*StickK Commit*, n.d.). It provides a wide range of behavioral interventions to its customers looking to change their habits. GreenSwapp could attempt something similar by instead focusing on shopping behavior to get their user base involved and expand to include potentially more effective interventions. Though implementation of this behavior change application would require additional resources and market research to determine the viability of the idea, it could help GreenSwapp to greatly expand its impact on sustainable consumers' shopping behavior and potentially add an additional stream of revenue for the company.

Conclusion

Several factors that influence a consumer's decision making processes include, (1) the consumer’s perception, (2) his or her skill and knowledge, (3) the consumer’s motivation, and (4) the physical or social environment at the point of purchase (Stávková et al., 2008). When choosing among products with different carbon footprints, consumers will first perceive the information provided to them, which, in this case are the different carbon labels and food carbon footprint estimations (i.e. factor 1). They then will need to process such information based on their understanding of carbon emissions (i.e. factor 2), realizing that there are substitutes for their desired products with lower carbon footprints, and that such carbon footprints make sense. Up to this point, although consumers will not scrutinize the carbon footprints estimated for every single product, the range of estimations provided to them should be reasonable, which is why we compared GreenSwapp’s estimation with other sources and proposed several measures to address uncertainty. The list of behavior change techniques and the nudge experiment address motivation (i.e. factor 3) and situational factors (i.e. factor 4). By making changes to the purchasing environment, for instance, implementing nudges or other behavior change techniques, we are able to influence motivation, and thereby shift purchasing decisions. In summary, the two sections of our analysis can impact several factors regarding consumer choice, fit decently into this flow of decision making, and direct consumer behavior towards a trajectory that is beneficial for the environment.

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Appendix A

Project Database: Comparing Methodologies - SEAS Masters Project
https://docs.google.com/spreadsheets/d/1yxj6f-fe9FMSx78V_G0ZCrPKrYhsE-JQiAWLlLbRbMU/edit?usp=sharing

Appendix B

Capstone Presentation Slides to begin on the next page

INCENTIVIZING A LOW-IMPACT DIET: An Analysis of Food Product Datasets and Behavior Change Techniques

Project Team: Hang Chen, Valerie Fritts, Brett Pickett, and Tianyi Zhang

Advisor: Martin Heller, PhD

Client: Ajay Varadharajan, CEO of GreenSwapp

PROJECT AND PRESENTATION ROADMAP

01

ISSUE AND IMPACT

An introduction to the issue and impact driving our research

02

LCA DATA COMPARISON

An overview of our research question, methodology, conclusions, and suggested next steps

03

EXPLORING BEHAVIOR CHANGE

A run-through of the list of nudges and experiment design based on our literature review

18 GT CO2e

⅓ of global anthropogenic GHG emissions can be attributed to the food and agriculture sectors. The typical American diet needs to change to effectively address climate change.

CLIENT BACKGROUND AND PROJECT IMPACT

GreenSwapp is …

An online-subscription-based grocery tracking platform that seeks to aid companies and consumers in tracking, reducing, and offsetting their climate impacts.

Our project aims to…

Incentivize consumers to choose diets with lower CO_2e through a comparative analysis of two food product LCA databases and relevant persuasive behavior change techniques.

Compare and Assess GreenSwapp Food Carbon Footprint Estimation based on Tesco LCA Data

Life Cycle Analysis and Issues in LCA Work

OVER RELIANCE ON SECONDARY DATA

Which is potentially of lower quality or with unclear boundaries

LACK OF UNIVERSALLY-USED METHODOLOGIES

Makes it difficult to understand, when comparing LCA product data, whether the methodologies used were similar enough for a valid comparison.

DATA SOURCES

GreenSwapp Database

Database consisting of (1) compiled carbon footprint data from varying sources, like Concito, Agribalyse, and others and (2) GreenSwapp's estimated carbon footprint of complex foods based on the individual ingredients making up those complex foods

Tesco LCA Report (2012)

A compilation of processed-based cradle-to-grave LCAs, specific to products sold by Tesco, a large grocery store chain operating in the UK.

RESEARCH QUESTIONS

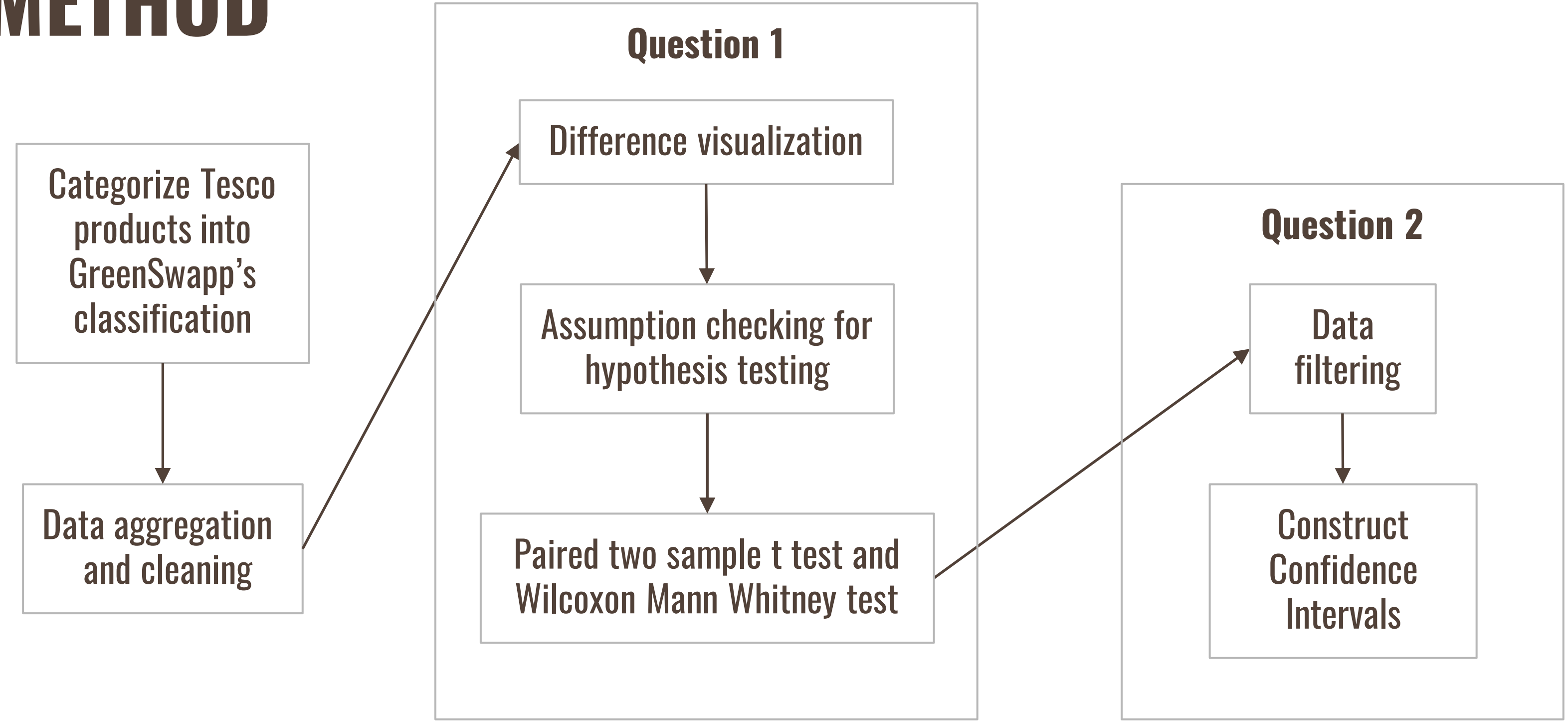
Question 1: Are the average carbon footprints calculated from the GreenSwapp and Tesco values significantly different from one another at the product type, subcategory, and category level?

Question 2: Considering the sample size and distribution of each class (i.e. product type, subcategory, and category) in the Tesco report, where do GreenSwapp's estimations show a difference or gap?

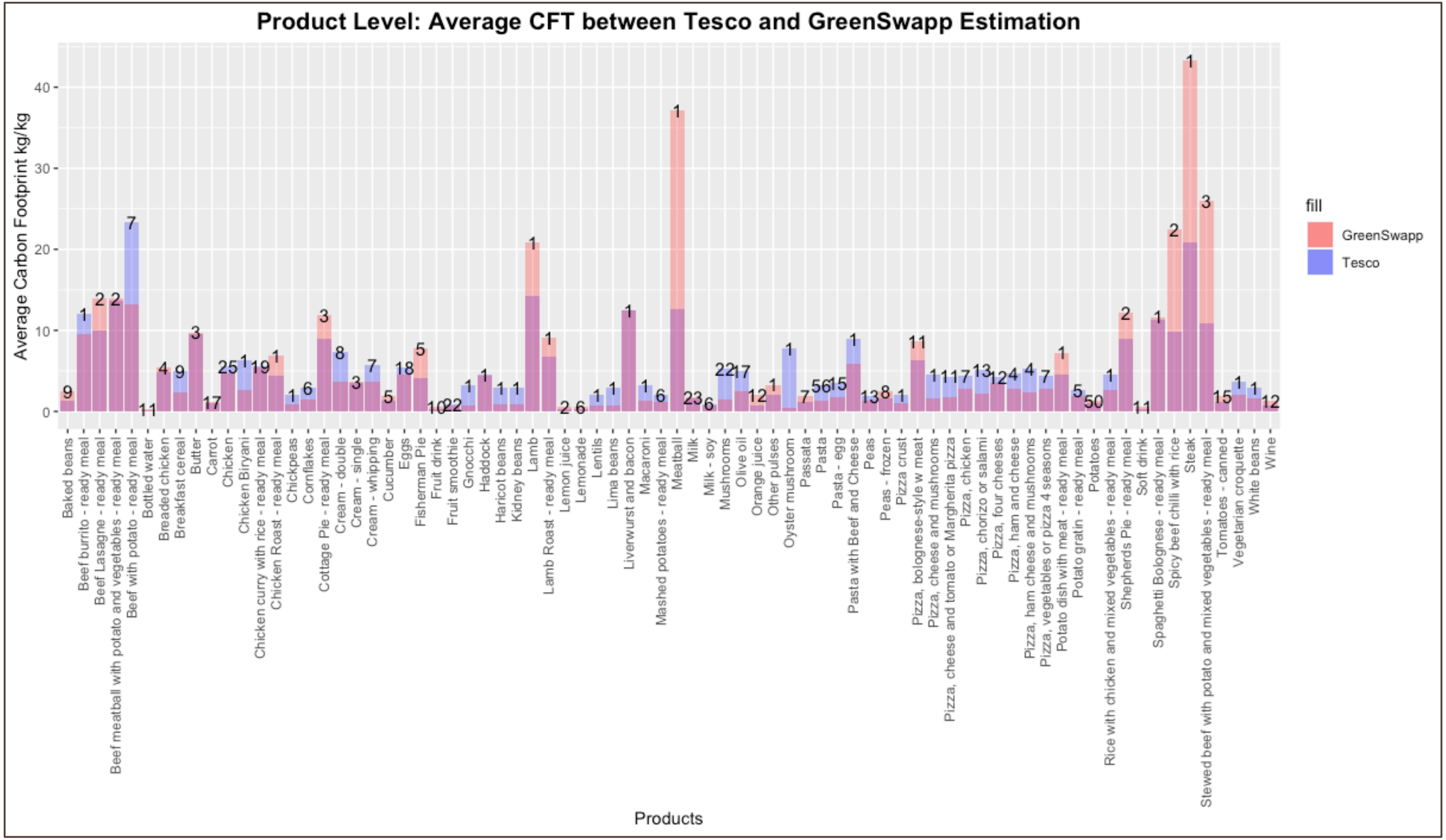
Assumptions:

1. Tesco LCA data is more customized.
2. Customizable LCAs and project-specific data are ideal to produce a better estimate than that based on the standard available information (Inti & Tandon, 2021)

METHOD

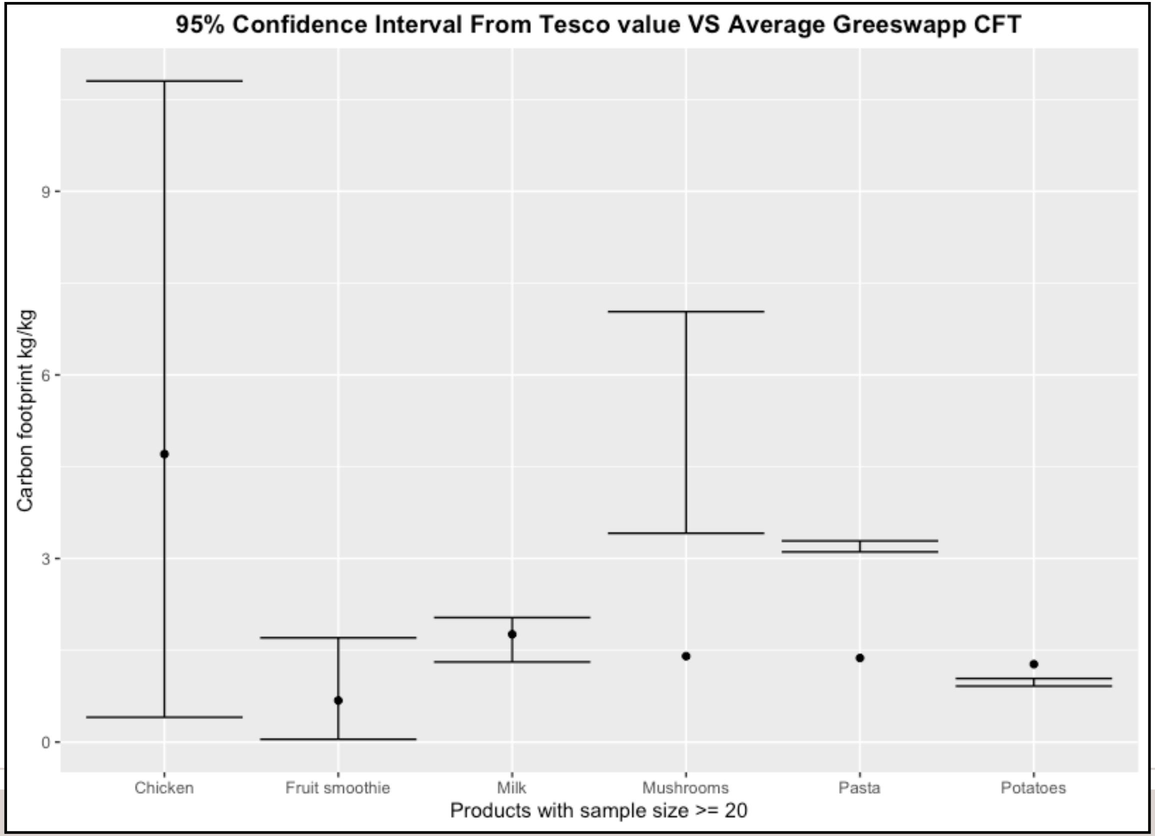

Categorize Tesco products into GreenSwapp's classification
Data aggregation and cleaning
Question 1
Difference visualization
Assumption checking for hypothesis testing
Paired two sample t test and Wilcoxon Mann Whitney test
Question 2
Data filtering
Construct Confidence Intervals

Results



Product Level: Average CFT between Tesco and GreenSwapp Estimation
Average Carbon Footprint kg/kg
Products
fill
GreenSwapp
Tesco

Results



```
        Paired t-test

data:  compareM$LCA and compareM$GS
t = -0.65364, df = 75, p-value = 0.5153
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -1.5365349  0.7773233
sample estimates:
mean of the differences
             -0.3796058
```

Findings

Not Significantly Different

In general, the two frameworks did not significantly differ in carbon footprint, on average.

Significant Difference at Product Type Level

At the product-type level, the GreenSwapp estimation for mushroom and pasta products significantly differ when compared to the Tesco values for such products.

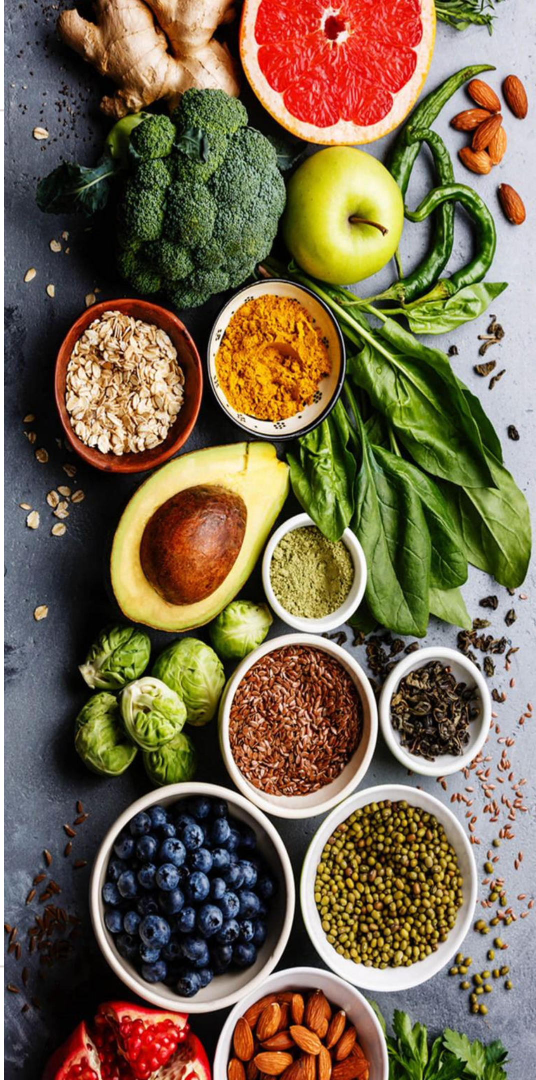
Oversights and Limitations

Our Methodology

1. Using different boundary conditions between two frameworks
2. Some of GreenSwapp's categories are not well-suited for comparison (e.g. "Meat and veggie alternatives)

Data Quality

1. Unknown to what extent the Tesco report uses primary data
2. Tesco products are not evenly distributed within the GreenSwapp categories
3. Outdated data



Recommended Next Steps for Carbon Footprint Estimation Efforts

01

Establish a standard to validate data quality.

02

Identify sources of difference in carbon footprint estimation for simple ingredients and complex foods products separately.

03

Construct a confidence interval, as determined by GreenSwapp, at the product type level.

Exploring Behavior Change

Overview

Data potential
Looking for LCA data applications

Values
Consumers buy based on values (Li, n.d.)

Eco-friendly food
Knowing impact would change how they shop (Mintel, 2021)

Leveraging data
Influence consumers to buy “greener” foods

Behavior Change Literature Review

Habits

Habits often act as a barrier to new behaviors (National Public Radio, 2019/2019)

Need intervention

Information is not enough despite intentions (National Public Radio, 2019/2019)

Behavior Change Techniques

Choice Architecture

Using design to change behavior

(Thaler & Sunstein, 2013)

Social Norm Marketing

Understanding how others behave/believe

(Cialdini & Trost, 1998)

Feedback

Relevant response to a behavior

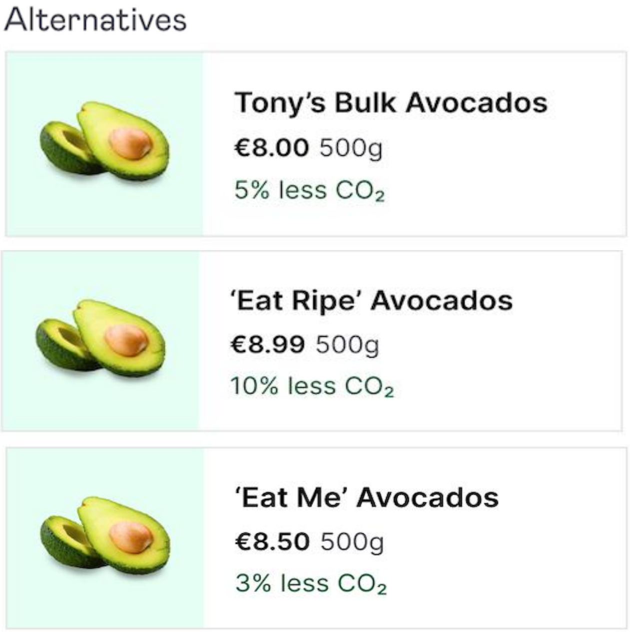
(Sanguinetti, Dombrovski, & Sikand, 2018)

Nudges for GreenSwapp

Choice Architecture

Present suggestions in sets of 3, with the product with the lowest carbon footprint in the middle.

(Valenzula & Raghubir, 2009)



Nudges for GreenSwapp

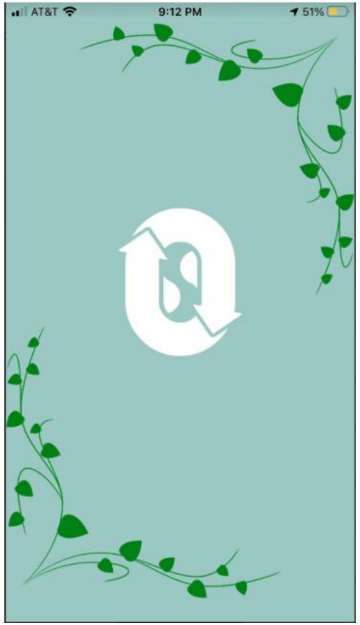
Social Norm Marketing

“Green groceries are popular among everyone from birders to botanists”

Nudges for GreenSwapp

FEEDBACK

Give feedback by having some kind of greenery such as flowers, vines, or trees that appear whenever customers interact with a “green” product



Experimental Design Overview

- Be able to understand effectiveness of nudges
- Partner with Grocery Store for implementation
- Compare change in Sales data over 3 time periods.

VARIABLES

Independent Variable

Behavioral Intervention (3 levels):

- Time-1, Control Group
- Time-2, GreenSwapp Labels
- Time-3, Labels and Additional Nudge

Dependent Variable

Percent of Products Purchased that were

- High impact
- Medium impact
- Low impact

POSSIBLE RESULTS

1. Increase in Low Impact food purchasing, decrease in Medium and High impact food purchasing
2. No one measure of Success
3. Possible Pushback from Consumers (Schultz et al., 2007)

NOTES ON THE EXPERIMENT

1. Quasi-Experimental Design
2. High External Validity
3. Vulnerable to Confounding Variables

Recommended Next Steps for Behavior Change Efforts

- More ambitious experimental designs
- Look for new ways to engage consumers
- Expand use of behavior change efforts

Putting it all Together

IN THE END

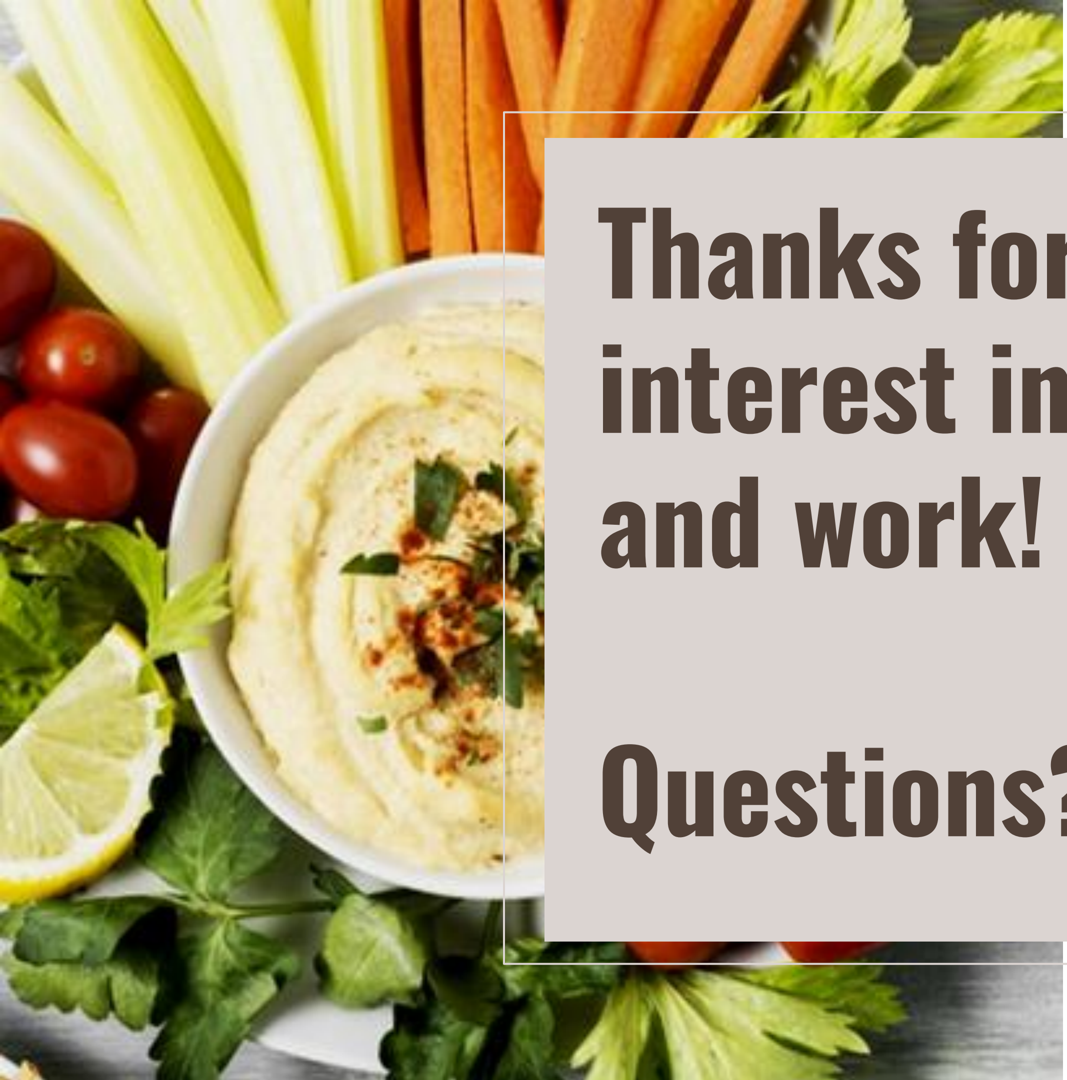
Common factors that influence decision making (Dietrich, 2010):

Next Step 1

1. Past Experience
2. Thinking Patterns Based on Observations and Generalization

Next Step 2

3. Escalation of Commitment.



Thanks for your interest in our project and work!

Questions?

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