Optimizing the Perfect Burrito: An Algorithm for Balancing Cost and Environmental Sustainability in Food Sourcing

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1 Introduction

The global food supply chain presents a fundamental challenge to balancing economic and environmental costs. While producers optimize for profit margins, consumers demand transparency in understanding both the economic and environmental impacts of their food choices. Beyond ingredient sourcing information, ingredient choices themselves significantly impact both metrics - meat products typically generate higher emissions and cost more compared to plant-based alternatives.

Current research in food supply chain optimization primarily serves corporate interests, focusing on producer profits while meeting minimal sustainability requirements. Despite growing consumer awareness, existing models and tools provide limited actionable information about how ingredient choices and sourcing decisions affect both sustainability and pricing.

2 Problem Definition

We propose the Burrito Builder, addressing the bias towards the producer with an interactive platform that enables consumers to optimize their food choices based on both cost and environmental impact. The Burrito Builder allows users to create virtual burritos while visualizing global ingredient origins. By focusing on a popular food item with multiple ingredients, our platform transforms complex supply chain decisions into accessible choices.

The Burrito Builder presents twelve common burrito ingredients: tortilla (wheat), beef, chicken, pork, cheese, sour cream (milk), rice, beans, lettuce, onions, tomatoes, and avocado. It then finds the optimal sourcing countries for these ingredient choices across two primary objectives selected by the user: minimizing the total ingredient cost and minimizing the total environmental impact, subject to the user's budget constraints. Through the buyer's desire to minimize the price, production costs by the vendor will also be minimized.

$Let:$

$I = \{i_1, i_2, \ldots, i_{12}\}$	set of ingredients
$C = \{c_1, c_2, \ldots, c_m\}$	set of possible countries
$b \in \mathbb{R}^+$	user's specified budget
$h \in C$	user's location

For ingredient $i \in I$ and source country $s \in C$:

$$Cost(i, s, h) = FoodCost(i, s) + TransCost(s, h)$$
$$Env_{Impact}(i, s, h) = FoodImpact(i) + TransImpact(s, h)$$

Subject to:

1. Total Cost Constraint:$\sum_{i \in I} Cost(i, s_i, h) \leq b$
2. Supplier Availability:$s_i \in C$
3. Location Constraint: $l \in C_{import}$

The optimization seeks to minimize both total cost and environmental impact.

3 Literature Survey

Current research in food supply chain optimization reflects multiple challenges, primarily focusing on producers' profits, as shown in Banasik et al.'s [1] waste management model and Abbasian et al.'s [2] perishable food networks. Environmental concerns, when addressed as in

Rossi et al.'s [3] "traveling stock" model, typically serve business efficiency rather than consumer choice. Transportation presents significant challenges, with Nakandala et al. [4] highlighting complexities in fresh food networks and Barbosa et al. [5] demonstrating consumer behavior's impact on efficiency, particularly affecting protein supply chains [6].

Environmental impact measurement adds complexity, from Akhter and Sofi's [7] IoT and machine learning solutions to Tundys and Wisniewski's [8] focus on short food supply chains. Yadav et al. [9] identified persistent challenges in balancing sustainability with practical constraints. Consumer behavior research by Dedehayir et al. [10] identified gaps between stated environmental values and actual choices, confirmed by Moreno-Sandoval et al.'s [11] social media analysis and broader consumer food data system research [12].

Current optimization approaches, particularly simple weighted methods [1], fail to capture these complexities. While NSGA-II [13, 14] offers potential solutions, its application to consumer-facing decisions remains unexplored.

4 Method

4.1 Key Innovations

Our approach presents four primary innovations in food supply chain optimization. We invert traditional producer-centric optimization by empowering consumers' to make informed decisions. While NSGA-II has been used in supply chain optimization before, applying it to real-time consumer choice creates a new paradigm for informed decision-making.

Our new, game-like interface design informs customers about the cost and environmental impact of their ingredient choices. The map reinforces that food is sourced from countries around the world, and the environmental impact score reflects the implications of this sourcing.

We paired Google Analytics with our interface, which tracks consumer purchasing decisions. The supplier can learn users' price sensitivity vs environmental preferences, identify market segments (eg, eco-conscious consumers willing to pay more, and help businesses make informed inventory and sourcing decisions. The market research that businesses can do alongside other cost factors inform their decisions, which changes the supply change, thus creating a feedback loop.

4.2 Data Pipeline

Three main sources form our dataset:

1. UN Comtrade Database: Product trade information between 127 countries, including kilos, costs, and transportation modes.
2. Clark et al.'s [15] dataset: Calculated the environmental impact of foods across comprehensive environmental indicators.
3. MIT Climate Portal Freight Transportation [16] data: Provides transportation emissions by weight and transportation mode.

4.3 Data Processing

4.3.1 Data Filtering

We filtered the Comtrade database for 12 primary burrito ingredients, identified through 23 unique HSCodes. The initial query for the complete year 2023 yielded 76,532 rows across 47 columns. After removing redundant and irrelevant columns, we retained 14 essential features for our analysis.

We eliminated importing countries with incomplete cost information, reducing the dataset from 128 to 27 countries and 19,616 rows. We then calculated cost per kilogram for each ingredient, removing entries with missing weight data and outlier costs exceeding 200 USD/kg (figure 1), which accounted for 23 entries. We refined sourcing countries by removing non-country specific data. This thorough cleaning process resulted in a final dataset containing 17,457 rows.

4.3.2 Product Cost Calculation

Using Chipotle's serving sizes (oz), we standardized ingredient portions, creating a consistent basis for further analysis.

Cost calculations required careful adjustment to reflect market realities. We added a $0.75 adjustment per ingredient to better align with retail prices (table 2). To validate our approach, we simulated 1,000 burritos per source country, which achieved our target average burrito cost of $10, adjusted up from an initial $5 .

We did not include overhead and profit costs, which would vary from country to country and be more aligned to real-world pricing.

4.3.3 Environmental Impact Calculation

Environmental impact combines production and transportation emissions. Production emissions use Clark's method, scaling environmental attributes (land use, GHG emissions, eutrophication, scarce water usage) from 1-100 and adjusting for per serving impact.

For transportation emissions, we consolidated transportation modes into four primary categories: road, sea, air, and rail. A Random Forest classifier using scikit-learn incorporated features including cost per kilogram, encoded country codes, and encoded ingredient types. This approach proved particularly effective for predicting road and sea transport modes, though it showed lower accuracy for less common modes like rail and air (figure 2).

The final calculation incorporated country distances, MIT emission data per transportation mode, and standardized serving sizes from Chipotle's website (table 1). In line with Clark's argument[15], we applied an 80-20 weighting split between production and transportation impacts respectively (table 3). The resulting scores were normalized based on maximum possible burrito configurations (table 4).

4.3.4 Data Completion

Data completion posed a final challenge, as six countries lacked data for up to two ingredients each. We assigned sources based on primary global exporters of those ingredients, maintaining data completeness while minimizing potential distortions in the analysis.

4.4 Algorithm Implementation

Our implementation of NSGA-II evolved from simpler approaches. Initially, we employed a single-objective algorithm minimizing weighted averages of cost and environmental impact. The objective function was:

$$f(x) = w_1 \cdot \frac{\text{Cost}(x)}{\text{Costmax}} + w_2 \cdot \frac{\text{Impact}(x)}{\text{Impactmax}}$$

where w_1 and w_2 are weights assigned to cost and environmental impact. While Banasik et al [17] cautioned against this approach due to limited solution diversity, it provided initial insights into cost-emissions interactions. After testing an enumerative approach that proved computationally prohibitive, we implemented NSGA-II to simultaneously optimize:

$$\text{Minimize: } f_1(x) = \text{Total Cost}, \quad f_2(x) = \text{Env. Impact}$$

The algorithm generates 50 random solutions within budget constraints and evaluates them using dual objectives:

- $f_1(x) = \text{Total Cost}(x)$, including production and transportation expenses
- $f_2(x) = \text{Environmental Impact}(x)$, considering emissions

Solutions are ranked through non-dominated sorting: solution x dominates y if it performs at least as well in all objectives and strictly better in at least one objective.

Diversity is maintained through crowding distance:

$$d_i = \sum_{k=1}^{m} \frac{f_k(x_{i+1}) - f_k(x_{i-1})}{\max(f_k) - \min(f_k)}$$

The algorithm evolves solutions through tournament selection, crossover, and mutation (10% probability) for 50 generations. Future iterations could explore Zhang, Qingfu and Li's MOEA/D algorithm [18], which decomposes multi-objective problems into scalar subproblems for higher-dimensional efficiency, or Zitzler, Laumanns and Thiele's SPEA2 [19], which ensures a well-distributed Pareto front through its strengthened Pareto approach, enhancing scalability and diversity.

4.5 User Interface

An example of the User Interface is the Appendix, figure 3.

Users begin by selecting their location and ingredients, and setting their maximum budget. The system generates a Pareto front visualization showing solutions within these constraints. An interactive slider enables exploration of cost-environmental impact trade-offs, with selected solutions displayed on the graph.

A global map highlights the user's location with a bold outline and ingredient source countries in color fill. click functionality provides detailed cost and emissions information. Below, users see their burrito's final total cost and emissions score, with low/medium/high impact qualifiers, and can explore alternatives before submitting their selection to Google Analytics.

4.6 Google Analytics

We integrated Google Analytics' Event Tracking API with our D3.js visualization to capture user interaction data, allowing us to track click events and user burrito parameter patterns through custom event listeners (figures 4, 5). This approach creates a feedback loop between consumer decision-making and supply chain practices, as the intention is for supply chain managers to use the information from the Burrito Builder to inform their decisions. As consumers gain greater awareness of the cost and environmental impact of their food choices, their purchasing decisions shift accordingly, enabling them to support options that align with both their budget and sustainability goal.

4.7 Challenges and Limitations

Our implementation faced several key challenges. Using static 2023 product cost data, while necessary for initial development, limits real-time accuracy. Noted by Barbosa et al. [5], consumer food supply chains are inherently dynamic; prices and availability change frequently.

Transportation emissions calculations presented another challenge. While Nakandala et al. [4] provides a framework for calculating fresh food transportation costs, ingredients often travel through multiple transportation modes. Our current implementation simplifies this by using the primary transport mode, potentially affecting accuracy.

User behavior introduces additional uncertainty. Similar to findings in salmon supply chain optimization [6], self-reported consumer preferences may not align with real purchasing decisions. Our "I want this burrito!" button provides valuable data, while requiring statistical adjustment to account for self-reporting bias.

5 Experiments/Evaluation

5.1 Algorithm Performance Testing

5.1.1 Test Cases

Based on our literature review, we expect certain patterns: meat products should show higher environmental impact scores than vegetables [15], and nearby countries should generally have lower transportation emissions unless their production costs significantly outweigh transportation benefits [3]).

To validate our algorithm, we created a non-optimization function to deliver all possible results given a list of ingredients, home country, and budget. We designed three test cases with known optimal solutions.

1. Single ingredient tortilla in Luxembourg, budget=20
2. Burrito with tortilla and chicken in Colombia, budget=20
3. Burrito with tortilla, chicken, and cheese in Madagascar, budget =20

Tests generate brute-force solutions for comparison with Pareto Front and verify correct source country mapping. For each combination, it calculates total cost and environmental impact, checks budget constraints, and finds Pareto optimal solutions.

For each test case, the Burrito Builder interface aligns with this function: countries selected are aligning with the proper cost and impact per ingredient 5. The interpretability of the testing method provided conclusive evidence that the optimization algorithm is working correctly.

Testing limitations reinforced the need for optimization. The function's time complexity of $0(n^k)$ (n = possible sources per ingredient, k = ingredients) plus O(m²) for Pareto front dominance checks made brute-force testing computationally prohibitive beyond 4 ingredients.

NSGA-II outperforms the brute-force iterative method by finding multiple solutions in one run. This lets users explore the balance between cost and environmental impact more effectively, especially with complex data. Each point on the Pareto front shows a unique optimal trade-off, helping users make informed decisions.

5.1.2 Visualization testing

We tested our Burrito Builder with three burrito profiles across 27 countries: a simple burrito (beef/cheese), middle-ground option (chicken/cheese/sour cream/lettuce/rice), and "the works" (all ingredients).

Starting at \$9.00, we tested the feasibility of each burrito type and decreased the cost until the burrito was not possible. We then increased the cost until a steady state was reached.

As a pricing guideline, the minimum cost for constructing a burrito was approximately 75% of the number of ingredients in dollars (e.g., a burrito with 6 ingredients would cost around \$4.50). Because each ingredient's cost was derived from Comtrade dataset values, the final totals showed slight variations from this estimation - for instance, \$4.55 instead of exactly \$4.50. This aligned with our pricing strategy incorporating calculated offsets from Comtrade data, providing a realistic cost model that balanced both the number of ingredients and their individual market values.

While burrito construction was possible in all test countries, geographic disparities emerged. Smaller, less economically developed countries offered fewer solutions, likely due to limited global supply chain connections. Isolated countries showed higher baseline costs, with Iceland reaching \$11.30 for "The works" burrito, presumably due to high transportation costs and limited supply options.

Pareto Front variations typically showed \$2.00 cost ranges and 2-point impact score variance, reaching 7 points in some cases. This met our expectations from data processing, as ranges within ingredients are smaller than between ingredients. Beef consistently showed the largest environmental impact increase ($\sim$ 30 points), with pork ($\sim$12 points) and chicken ($\sim$8 points) following, though cost increases varied. This suggests the environmental impact of 4oz beef is nearly tenfold that of 4oz beans.

5.2 User Feedback

Upon completing the first iteration of the interface, we tested with family and friends for initial reactions. We then asked a broader group of users to use the Burrito Builder, collected data through Google Analytics, and sent a survey with 10 statements covering usability, enjoyment, and environmental awareness before and after using the tool. The full questions can be seen in table 6 and responses in figure 6.

At the time of writing this paper, we received only 25 responses, which is too small for conclusive results.

5.2.1 Interface Design and Usability

Initial user reactions revealed confusion about the purpose of the game, spurring inclusion of light explanations at each step. They also expressed confusion about the Pareto Front Visualization, leading to the addition of a non-technical explanation.

Users also struggled with understanding environmental impact measurements, prompting the addition of low/medium/high impact indicators.

Our survey shows that 83.3% of users found the interface intuitive (figure 7a), showing consistent positive feedback regardless of users' prior environmental awareness. Over 95% found the experience enjoyable or somewhat enjoyable (figure 7b), creating an effective foundation for the tool's educational mission.

5.2.2 User Engagement

The Burrito Builder transformed users' understanding of food sustainability. Prior to using the application, fewer than half of users (42%) reported having a solid grasp of their food choices' environmental impact. Similarly, only about a third (33%) actively considered the trade-offs between environmental impact and cost in their food decisions (figure 8).

To control for existing environmental bias, we included in our survey the last statement: "I care about the impact of my food choices" (Q10). We separated the responders into two categories: those who care about the impact of their food choices, and those who do not. Further experiments could place Q10 as the first question, before considering changes in attitude.

For each question, we used chi-squared tests to determine if there is a significant relationship between how people answered that question and whether they answered Yes or not to Q10. The most dramatic difference between these groups appeared in overall awareness change, where environmentally conscious users were 3.67 times more likely to report increased awareness with strong statistical significance ($p < 0.001$) (figure 9). For considering cost versus environmental trade-offs after using the tool, conscious users were 2.2 times more likely to engage in such considerations ($p < 0.01$). A similar pattern emerged in food source awareness, with conscious users 2.2 times more likely to maintain this awareness after using the tool ($p = 0.05$).

Encouraging findings are from examining how both groups changed through their interaction with the Burrito Builder. While environmentally conscious users consistently showed stronger engagement, the tool's basic usability and educational impact transcended this divide. Navigation ease showed minimal difference between groups (1.26x difference), and post-use environmental understanding showed the smallest gap (1.12x difference), suggesting the tool successfully reaches and educates users regardless of their initial environmental awareness.

6 Conclusion

The Burrito Builder web application demonstrated success in its goal of increasing user awareness and engagement with their food choices. By creating an intuitive, enjoyable interface, we've built a platform that delivers complex sustainability concepts to a broad audience. The success of our optimization algorithm, combined with a positive user experience and educational impact, positions the Burrito Builder as a model for future sustainability education tools.

Two key limitations affect our results. The most significant is that as a game-like platform, users have no incentive to make honest choices. Additionally, time constraints prevented thorough collection and analysis of Google Analytics data, which could have provided valuable insights into user behavior and preferences.

Looking forward, opportunities for expanded use exist. Partnership with food ordering apps could incentivize users to make real decisions when their money is at stake. Google Flights' "low emissions" option demonstrates how consumers can be empowered to make sustainability-conscious choices, even at a higher cost. Our challenge lies in translating this model to food systems, where supply chains are slower to adapt and producers are driven by their bottom line.

The optimization algorithm could be expanded to include additional factors beyond cost and environmental impact, such as allowing users to select specific countries of origin based on labor practices or other ethical considerations. These enhancements would strengthen the platform's ability to promote conscious consumer choices in food systems and beyond.

7 Work Distribution

Work was distributed equally among members:
Irish Olynyk: Poster design compilation, Google Analytics, product and transportation emission research
Richard Lepkowicz: Dataset cleaning, JSON development, standardized impact cost metrics
Dawei Lin: Algorithm development in D3, visualization implementation, test cases
Hannah Pavlovich: D3, html, and visualization implementation, written compilation
Paul Telford: Algorithm and execution of test cases, meeting notes

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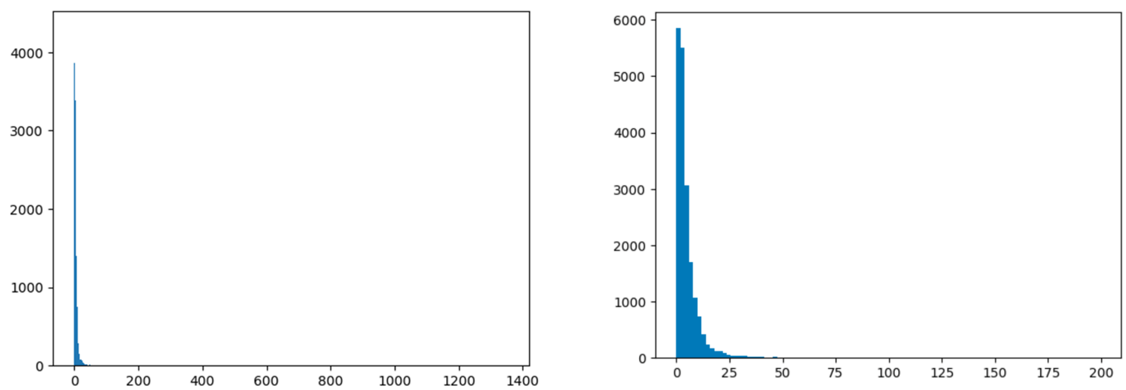
Appendix

Ingredient	Serving Size (grams)	Serving Size (Kg)
Rice	113	0.113
Beans	113	0.113
Chicken	99	0.099
Beef	99	0.099
Pork	99	0.099
Onions	57	0.057
Shredded Cheese	28	0.028
Lettuce	28	0.028
Tomato	99	0.099
Salsa	57	0.057
Avocado	113	0.113
Sour Cream	57	0.057
Tortilla	76	0.07

Table 1: Ingredients



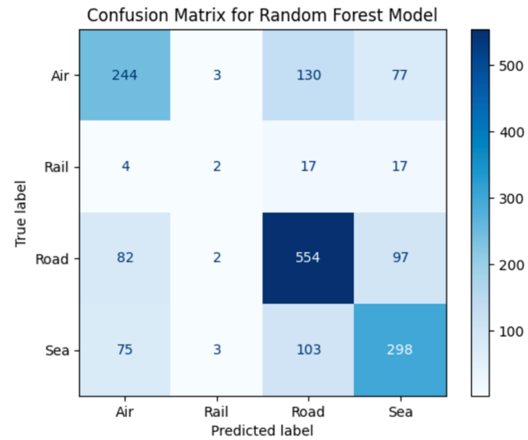
(a) Full Data Set

(b) Filtered Data Set, outlier cost products removed

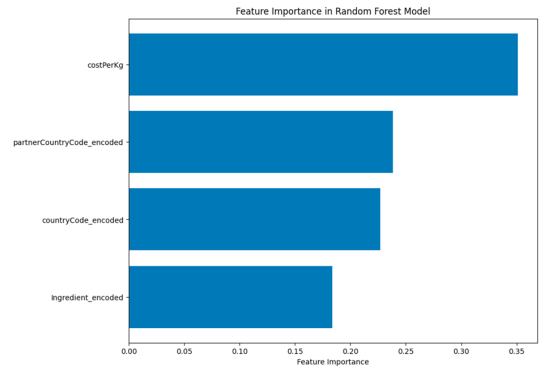
Figure 1: Histogram of product costs (USD/kg)

	Cost Per Serving
count	17457
mean	0.44
std	0.86
min	0.00
25%	0.14
50%	0.25
75%	0.45
max	20.24

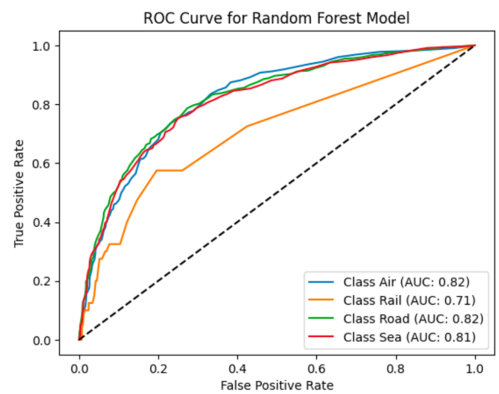
Table 2: Cost per serving



(a) Confusion Matrix



(b) Feature Importance



(c) ROC Curve

Figure 2: Random Forest Model Images

	Transport Emissions
count	17457
mean	0.431
std	0.755
min	0
25%	0.025
50%	0.066
75%	0.368
max	4.273

(a) Transportation Emissions, Raw Data

	Production Env Impact
count	17457
mean	2.944
std	2.567
min	1.064
25%	1.28
50%	1.741
75%	4.46
max	11.901

(b) Production Environmental Impact, Raw Data

Table 3: Raw Data Production and Transportation Impact

Ingredient	Normalized Production Impact	Normalized Transport Impact
Beef	1.142	0.387
Beans	0.133	0.426
Chicken	0.308	0.383
Avocado	0.134	0.468
Lettuce	0.035	0.092
Onions	0.059	0.22
Pork	0.432	0.369
Rice	0.535	0.436
Salsa	0.371	0.236
Shredded Cheese	0.121	0.108
Sour Cream	0.245	0.151
Tomato	8.143	0.383
Tortilla	0.118	0.285

Table 4: Normalized Production and Transportation Impact

Country	Cost	Impact
Algeria	0.77	3.11
Ireland	0.95	3.08
Belgium	1.01	3.02
Luxembourg	1.06	2.97

(a) Tortilla in Luxembourg

Tortilla Source	Chicken Source	Total Cost	Total Impact
Canada	USA	1.74	12.70
Peru	USA	1.75	12.41
Costa Rica	USA	1.96	12.31
Israel	USA	2.03	12.24

(b) Chicken burrito in Colombia

Tortilla Source	Chicken Source	Cheese Source	Total Cost	Total Impact
South Africa	France	United Kingdom	3.28	16.31
Comoros	France	United Kingdom	3.29	15.69
Comoros	France	Belgium	3.37	15.69
Comoros	France	South Africa	3.38	15.64

(c) Chicken and cheese burrito in Madagascar

Table 5: Cost and Environmental Impact Analysis for test cases

	Survey Question Text
1	Navigating the website was easy.
2	I had fun building my burrito.
3	Did you think about where your food came from prior to using the website
4	And after?
5	Did you have an understanding of the environmental impact of your food choices prior to using this website?
6	And after?
7	Did you think about environmental vs. cost trade-offs in your food decisions before using this website?
8	And after?
9	I am now more aware of the impact of my food choices after using this website.
10	I care about the impact of my food choices.

Table 6: Survey Questions

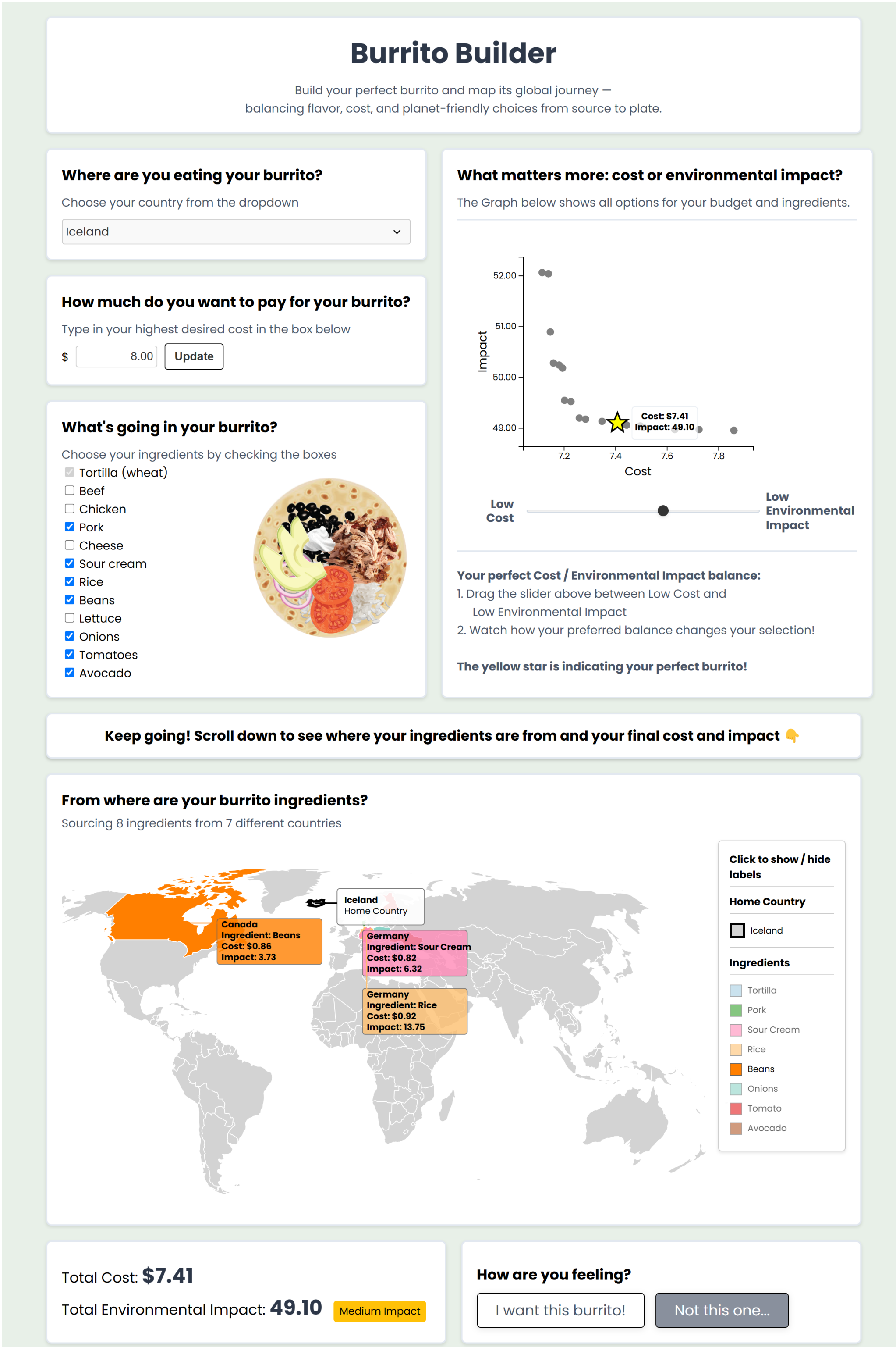


Figure 3: Burrito Builder Website Interface

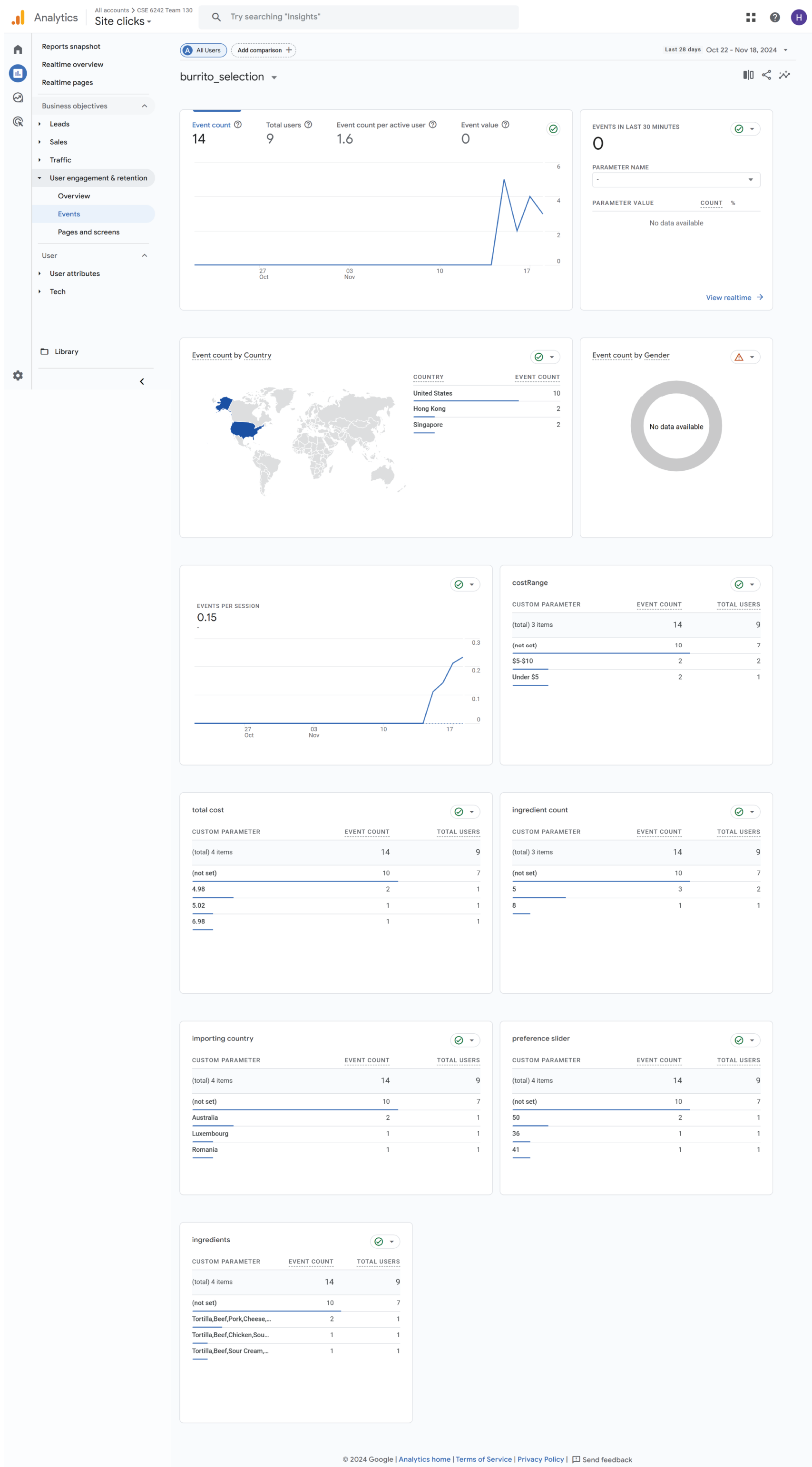
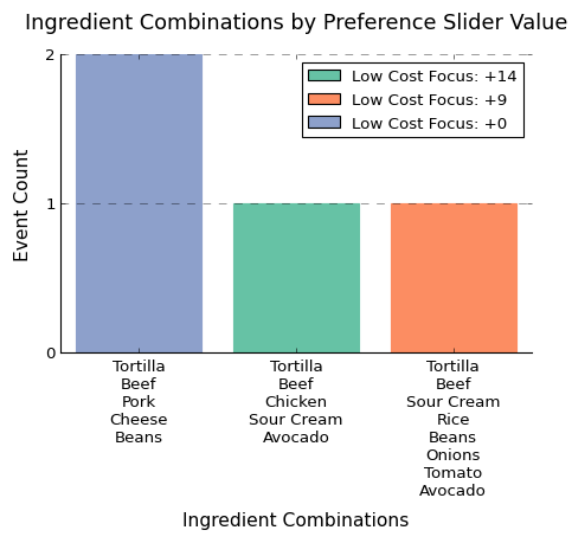


Figure 4: Google Analytics Interface



An example using Google Analytics' collected data:
Figure 5: Ingredients and the user's selection in the preference slider are marked and can form events. Low Cost Focus: +14 indicates the user preferred low cost 14 points more than the center balance.

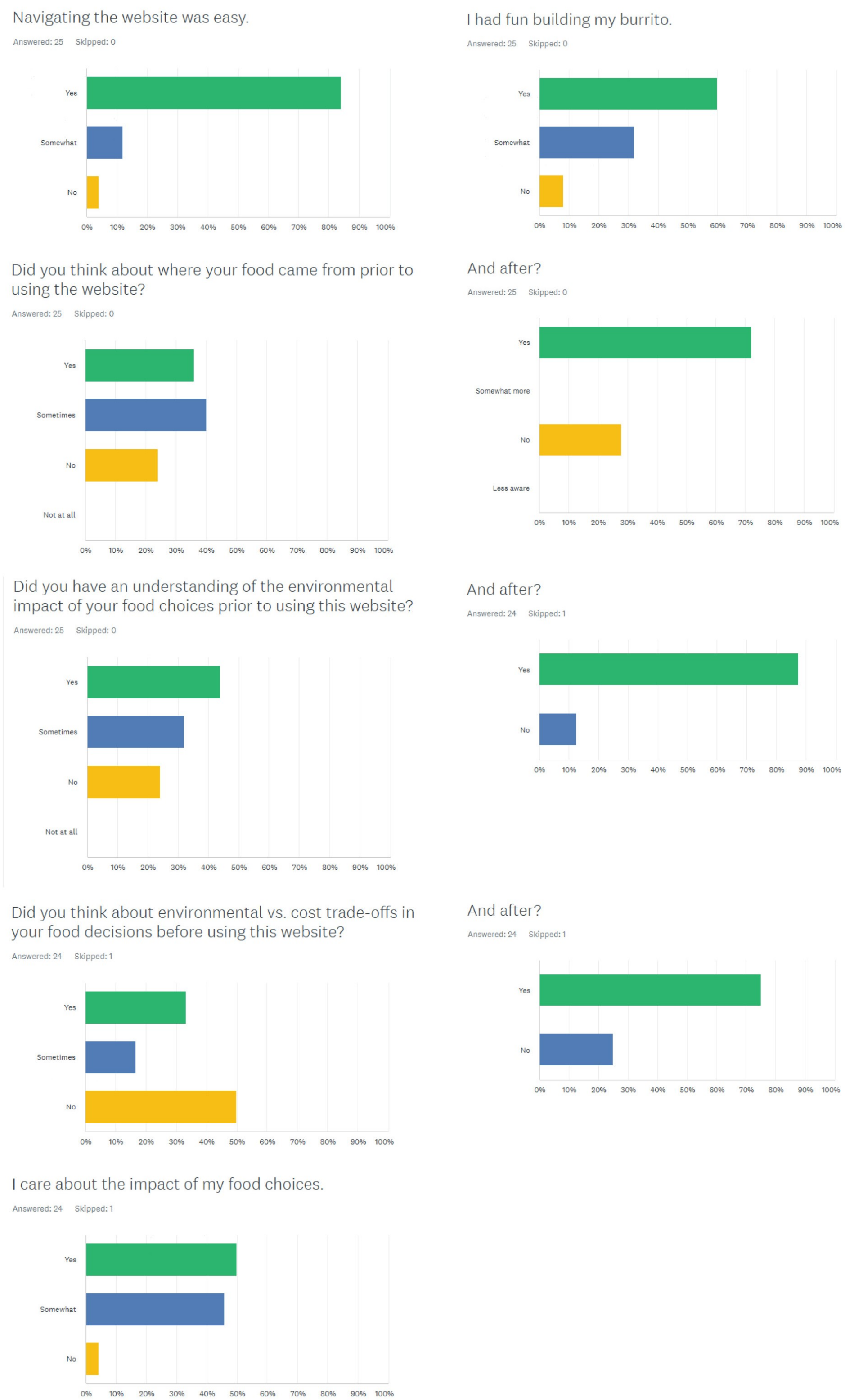
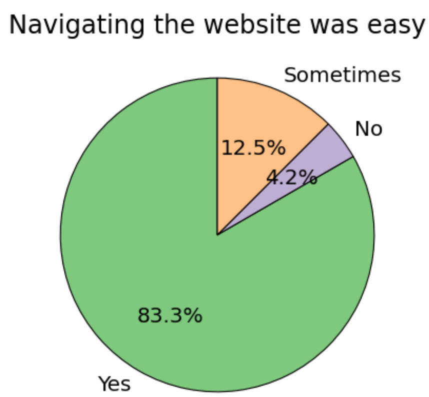
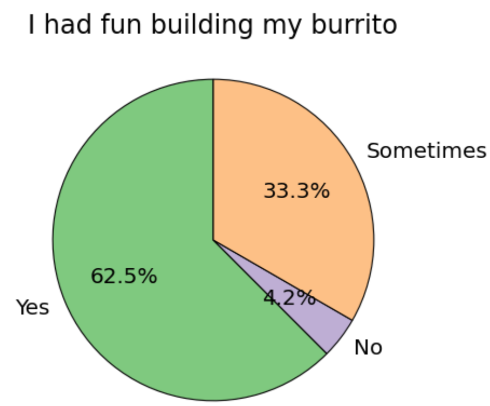


Figure 6: Survey Results



(a) Navigating the website was easy



(b) I had fun buiding my burrito

Figure 7: Measurements of User Engagement

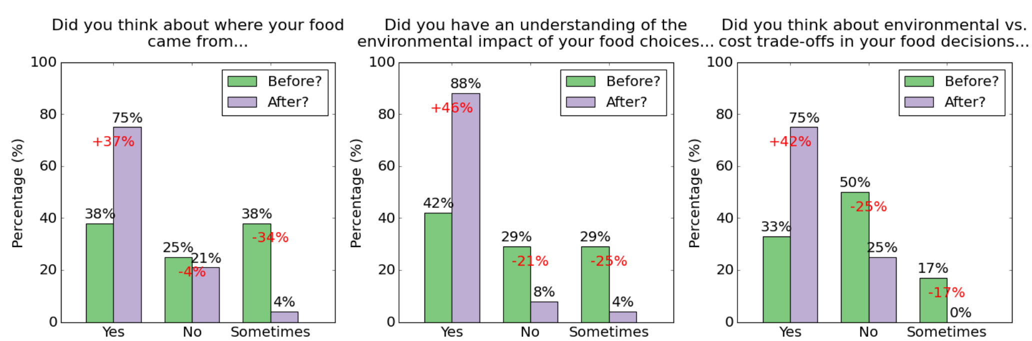


Figure 8: Overall Change in Awareness

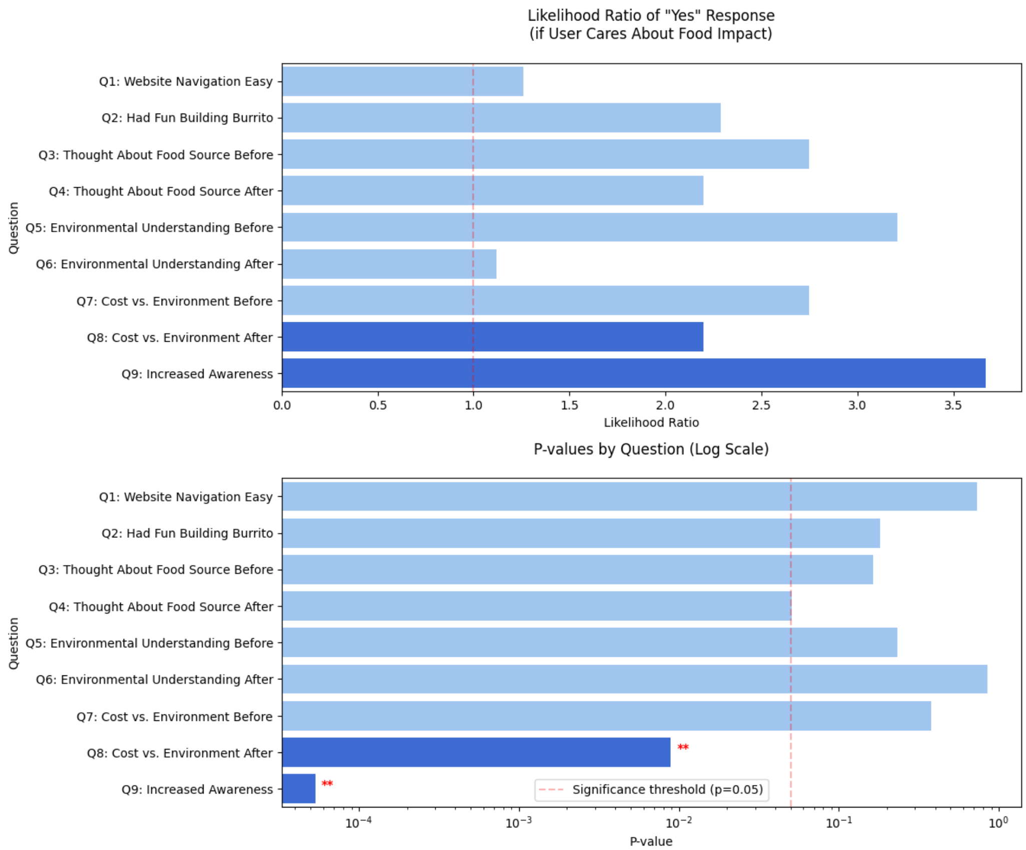


Figure 9: User Responses by Care for Food Impact