

Personalized Carbon Emission Recommender System: Project Design Report

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Abstract

This report presents the design of a personalized carbon emission recommender system aimed at helping adults (aged 18–60) reduce their daily greenhouse-gas footprint. The system delivers five tailored, low-carbon suggestions per session—spanning dietary swaps, transportation alternatives, and home energy tips—via a mobile or web interface. We employ a hybrid recommendation framework that integrates content-based filtering, collaborative filtering, knowledge-based constraints, and context-aware adjustments. In addition, a large language model (LLM)–powered conversational assistant allows users to query their estimated emissions and receive real-time explanations. Two core datasets (food life-cycle emissions and transport mode CO factors) form the structured knowledge base, with an online fallback for missing entries. We propose a two-phase update strategy (real-time profile updates and nightly model retraining) and evaluate the system along both algorithmic (Precision@5, Recall@5, NDCG@5, coverage) and user-centric (click-through rate, acceptance rate, satisfaction survey) metrics. A small user study is outlined to assess practical effectiveness and user satisfaction.

1 Introduction

Climate change mitigation requires individual action as well as systemic change. Everyday choices—what we eat, how we travel, and how we use energy at home—contribute significantly to global greenhouse-gas emissions. However, many individuals lack clear, personalized guidance on lowering their carbon footprint. Traditional recommender systems focus on products or media, but do not account for environmental impact.

In this project, we design a novel recommender system that integrates carbon-impact data directly into its ranking and suggestion process. Our target users are tech-savvy adults motivated to reduce emissions, who interact with the system through a mobile

app or web dashboard. Each session presents five actionable recommendations—such as “swap beef for lentils” or “take the bus instead of driving”—and records simple feedback (Accept / Not Applicable) to refine future suggestions.

To achieve this, we develop a hybrid recommendation framework combining:

- **Content-Based Filtering (CBF)** using feature vectors for emissions savings, cost, and effort;
- **Collaborative Filtering (CF)** on implicit user feedback to capture latent preferences;
- **Knowledge-Based Rules** to enforce dietary, budgetary, and diversity constraints;
- **Context-Aware Adjustments** that factor in time, weather, and user schedule.

A secondary module uses a large language model (LLM) to answer natural-language queries about carbon estimates, falling back to a web-search API when local data are insufficient.

2 Scope

We plan to develop a system that helps individuals (aged approximately 18–60) reduce their personal daily carbon footprint through tailored, actionable suggestions. Typical users are environmentally conscious adults who are comfortable using digital platforms. The system will be delivered via a mobile application or web dashboard and will provide five personalized low-carbon recommendations per session. These recommendations will span diet (for example, “swap beef for tofu”), transportation (for example, “bike instead of drive”), and home energy use (for example, “turn down the thermostat by 1°C”).

Our intended user base consists of tech-savvy adults motivated by climate change concerns and open to modifying their daily habits. Upon launching the app for the first time, users will complete a brief onboarding questionnaire that captures dietary preferences (e.g. vegan, omnivore), typical commute modes (e.g. car, public transit), living situation, and weekly budget constraints. This metadata will seed each user profile, enabling immediate content-based recommendations prior to accumulating sufficient interaction data for collaborative filtering.

During normal use, the interface will present exactly five carbon-reduction suggestions at a time. Users may click **Accept** if they intend to follow a tip, or **Not Applicable** if it is irrelevant or infeasible. Accepted tips will be recorded to update the user’s affinity profile in real time, while skipped items will serve as negative signals. This feedback loop will drive both online profile refinement (e.g. Bayesian updating of content-based vectors) and nightly batch retraining of the collaborative filtering model (e.g. matrix factorization).

To meet the requirement of near-instant response, all inference will execute in memory or via optimized vector stores, targeting latency under 500 ms per recommendation request.

An extended, LLM-powered conversational assistant will allow users to ask free-form questions such as “How much CO did I emit by eating a beef burger today?” or “Is taking the metro better than driving 10 km?” In handling such queries, the assistant will first attempt to detect intent and entities (e.g. “beef burger”, “taxi ride”) and lookup emission factors in our local datasets. If no match is found, it will invoke an online search API (for example, OpenLCA or DEFRA) to retrieve a high-confidence estimate, then provide a dialogue-based explanation (for example, “Beef produces methane during cattle digestion and land-use change”). This conversational module will enhance both interactivity and transparency, empowering users to understand and trust each recommendation.

3 Datasets

The recommender system relies heavily on two curated datasets that form its foundational knowledge base, enabling accurate emission estimation, suggestion generation, and user-query interpretation. Each recommendation, carbon estimate, and LLM-powered response draws directly from these resources. If a user query cannot be resolved within this local knowledge base, the system will escalate to an online retrieval module powered by a large language model with web access, ensuring both completeness and reliability.

3.1 Food-related Carbon Emissions Dataset

We adopt the *Environment Impact of Food Production* dataset, published on Kaggle by user `selfvivek`. The dataset is available at <https://www.kaggle.com/datasets/selfvivek/environment-impact-of-food-production>. It provides life-cycle greenhouse-gas footprints for approximately 43 food items, with breakdowns by production stage. Key fields include `Food_product` (e.g. beef, lentils), `Category` (plant-based or animal-based), `Total_emissions_kgCO2e_per_kg`, and stage-specific metrics such as `Land_Use_Change`, `Animal_Feed`, `Farm`, `Processing`, `Transport`, and `Packaging`. Water-use metrics (blue and green water withdrawals) are provided where available. In our system, this dataset serves as the authoritative source for all diet-related emission calculations. For example, a 200g beef burger corresponds to $0.2 \times 59.6 \approx 11.92\text{kg CO}_2\text{e}$, after which the system can recommend a 200g lentil patty ($0.6\text{kg CO}_2\text{e}$) to highlight a net savings of approximately $11.3\text{kg CO}_2\text{e}$. Because emissions are reported per kilogram, we normalize serving sizes to kilograms and attach confidence scores to each estimate. Items lacking complete subfield data or representing uncommon foods are flagged for online retrieval fallback.

3.2 Vehicle CO₂ Emissions Dataset

For transportation emissions, we use the *Vehicle CO₂ Emissions Dataset* provided on Kaggle by user `brsahan`. The dataset is available at <https://www.kaggle.com/datasets/brsahan/vehicle-co2-emissions-dataset>. It catalogs numerous vehicle models with specifications (make, model, engine size), fuel consumption rates, and CO₂e emissions per kilometer. This dataset enables the system to estimate emissions from user-reported trips; for instance, a 10km drive in a representative petrol car (0.192kg CO₂e/km) translates to 1.92kg CO₂e. As this dataset focuses on private vehicles, we plan to supplement it with publicly available factors for buses, trains, cycling, and walking from sources such as DEFRA or the U.S. EPA when those modes are encountered. Default assumptions are applied for missing occupancy or fuel-type details, and any anomalies are flagged for user clarification.

3.3 Unified Knowledge Base and Online Extension

Together, these two datasets form the core structured knowledge base of the system, supporting direct emission lookups, LLM query parsing, recommendation generation and ranking, and impact estimation for user-logged behaviors. If the LLM fails to resolve an entity—such as a rare food product or novel transport mode—it will trigger an external retrieval strategy: issuing web searches via the LLM’s browser plugin, parsing authoritative environmental reports (e.g. Ecoinvent, DEFRA), and returning summarized answers with source attribution and confidence scores. This two-tiered approach—structured local data augmented by on-demand external lookup—ensures scalability, transparency, and completeness, which are key to a trustworthy AI-powered carbon advisory system.“

4 Literature Review

Recommender systems have increasingly been applied to sustainability domains. Kalisvaart et al. [1] proposed a carbon footprint-aware recommender for e-commerce that reranks product suggestions based on item-level CO₂ impact, demonstrating that environmental performance can be optimized alongside traditional relevance metrics with minimal loss in accuracy. This reranking strategy is directly relevant to our project’s approach of filtering and scoring dietary and transport suggestions by emission reduction potential. In a similar vein, Han et al. [2] introduced *CarbonKit*, a framework that tracks individual carbon emissions and provides personalized behavior-change feedback across domains such as energy use and transport, underscoring the feasibility of emission-aware recommendation in everyday contexts.

Apps such as Oroeco, CO2Hero, and JouleBug have explored the intersection of sustainability and personalized behavior change. Oroeco maps financial transactions to es-

estimated CO₂ footprints and suggests low-carbon alternatives, CO2Hero gamifies climate challenges to promote actions, and JouleBug offers practical tips — including transport-related changes like modifying driving style, planning trips, or substituting car trips with public transit or biking. These platforms validate the importance of contextual personalization (e.g. location, weather, habits) and simple feedback mechanisms (e.g. accept/skip) in sustaining user engagement and driving real-world impact.

Recent research on urban mobility and green transportation recommender systems has emphasized user-centered routing, behavioral personalization, and carbon awareness. Zhang et al. [3] presented a green mobility recommender that adapts transportation suggestions based on user behavior logs and carbon impact data, integrating emission-aware route planning that favors walking, biking, or shared modes when feasible. Similarly, the SmartCityMobility project by Alonso-González et al. [4] demonstrated that personalized mobility recommendations — combining user preferences, mode availability, and sustainability indicators — significantly increased adoption of low-carbon travel options. These studies support our system’s focus on realistic, impactful daily transport alternatives.

Hybrid recommendation systems combining content-based filtering, collaborative filtering, knowledge-based constraints, and context-aware adaptation have proven effective in behavior-change contexts. Our system adopts this multi-layer approach:

- **Content-based filtering (CBF)** matches low-carbon suggestions (e.g. “take metro”) to user profile attributes such as budget, diet, and preferred commute time.
- **Collaborative filtering (CF)** uses binary feedback (Accept/Skip) to model behavior similarity across users and suggest actions likely to be accepted.
- **Knowledge-based rules** enforce hard constraints (e.g. exclude meat for vegetarians, avoid suggestions exceeding budget).
- **Context-aware logic** adjusts suggestions based on temporal and situational cues (e.g. indoor activities during rain, avoid cycling tips at night).

This layered hybrid strategy is inspired by energy-efficiency recommender research [6] and health personalization studies [5], both of which emphasize real-time adaptability and domain-specific constraints.

5 Methods

We plan to implement a comprehensive hybrid recommendation framework designed to promote low-carbon lifestyle actions. The system will integrate multiple paradigms—content-based filtering, collaborative filtering, knowledge-based constraints, and context-aware

adjustments—augmented by a conversational carbon estimation module. In each session, users will receive five personalized, actionable suggestions tailored to their profile, preferences, and real-time context.

5.1 Content-Based Filtering (CBF)

In the content-based module, each suggestion will be encoded as a feature vector, for example

$$f_i = [\text{CO}_2_saved, \text{cost_change}, \text{effort_level}, \text{category_dietary}, \text{category_transport}, \dots].$$

User profiles will be constructed from onboarding questionnaire responses and behavioral logs:

$$f_u = [\text{diet_preference}, \text{transport_mode}, \text{budget_level}, \text{mobility_constraints}, \dots].$$

We will compute the relevance of suggestion i to user u via cosine similarity or dot product between f_u and f_i , after normalizing each feature. This approach will ensure that recommendations align with the user’s explicit sustainability goals and constraints.

5.2 Collaborative Filtering (CF)

We will maintain a sparse binary interaction matrix R in which

$$R(u, i) = \begin{cases} 1 & \text{if user } u \text{ accepted suggestion } i, \\ 0 & \text{otherwise.} \end{cases}$$

To uncover latent user-item relationships, we plan to apply Bayesian Personalized Ranking (BPR) for implicit feedback and Weighted Alternating Least Squares (ALS) for matrix factorization. The predicted acceptance score will be

$$\text{CF}(u, i) = \langle \mathbf{z}_u, \mathbf{z}_i \rangle,$$

where \mathbf{z}_u and \mathbf{z}_i are the learned latent vectors. This component will capture indirect behavioral signals and enable discovery of novel, yet relevant, suggestions.

5.3 Knowledge-Based Constraints

To guarantee feasibility and relevance, we will enforce domain-informed rules. For example, suggestions involving meat will be excluded for vegetarian users, items exceeding a user’s weekly budget threshold will be omitted, and no more than one suggestion from

the same category will appear in each batch. These constraints will act as hard filters, ensuring that all delivered tips respect personal values and practical limits.

5.4 Context-Aware Adjustments

We will refine scores based on situational context. Time-of-day factors will prevent outdoor activity tips at night; real-time weather data will suppress walking suggestions during rain; and weekday versus weekend status will prioritize grocery or meal-planning tips on shopping days. Formally, each candidate’s score will be multiplied by a context modifier:

$$\text{score}_{\text{total}} \times = \text{context_boost}(u, i),$$

thereby aligning recommendations with real-world routines.

5.5 Hybrid Scoring and Ranking

The final hybrid score for suggestion i and user u will be computed as

$$\text{score}_{\text{total}} = w_1 \text{CBF}(u, i) + w_2 \text{CF}(u, i),$$

followed by constraint filtering and context adjustment. The top five items by score will then be returned. The overall procedure is outlined in the pseudocode block below.

```
for each user u:
    candidates = all_suggestions
    for each item i in candidates:
        cbf_score = similarity(f_u, f_i)
        cf_score = CF_model.predict(u, i)
        score = w1 * cbf_score + w2 * cf_score
        if violates_rules(u, i):
            score = -inf
        score *= context_modifier(u, i)
    recs = top_k(candidates, 5, by=score)
    present(recs)
```

The weights w_1 and w_2 will be tuned via pilot testing or learned from feedback logs.

5.6 Conversational Carbon Estimation (LLM-assisted)

In addition to batch recommendations, we plan to integrate an LLM-powered conversational layer (e.g. GPT-4) to handle ad-hoc user queries such as “What’s the carbon impact of eating salmon and taking a 15km taxi ride today?” This module will (1) parse

natural-language queries to identify activities, (2) perform emission lookups in the internal datasets, and (3) fall back to web search or LCA APIs if entries are missing. This interactive capability is intended to enhance transparency and user trust.

5.7 Justification and Suitability

This planned hybrid architecture balances multiple strengths: content-based filtering will provide relevance from day one; collaborative filtering will leverage community patterns for novelty; knowledge rules will ensure feasibility; context adjustments will make suggestions practical; and the LLM module will fill gaps and educate users. Together, these components will deliver a scalable, real-time system that addresses cold-start, personalization, and transparency requirements in promoting low-carbon behaviors.

6 Evaluation

We plan to evaluate the effectiveness of our carbon-reduction recommender system through a two-layer framework that examines both algorithmic performance on historical data and practical usability in live interactions. At the model level, we will assess predictive accuracy by conducting offline experiments wherein each user’s interaction history is split into a training period (the first 70% of chronological interactions) and a test period (the remaining 30%), or alternatively by using leave-one-out validation when timestamps are unavailable. For each user, we will generate top-5 recommendations and compute Precision@5 (the fraction of accepted items within those five), Recall@5 (the proportion of a user’s total accepted items that appear in the top five), NDCG@5 (which rewards high-ranked accepted items via a logarithmic discount), Hit Rate@5 (the percentage of users with at least one accepted suggestion in their top five), Coverage (the fraction of all items that appear in any user’s top-5 lists), and MAP (mean average precision across users). We will prioritize Precision@5 and NDCG@5 to maintain user trust in recommendation relevance, while monitoring Coverage and Recall@5 to ensure diversity and completeness. This offline evaluation will validate that our hybrid scoring—combining content-based and collaborative filtering with knowledge rules and context adjustments—yields accurate and varied suggestions before live deployment.

At the system level, we will measure real-world engagement and satisfaction by analyzing live interaction logs and conducting a small-scale user study with 10–20 volunteers. In this study, participants will complete the onboarding questionnaire, receive five suggestions per session over two to three days, and mark each suggestion as “Accept” or “Not Applicable.” From these logs, we will calculate Click-Through Rate (the ratio of clicked or accepted suggestions to total suggestions shown), Acceptance Rate, and Skip Rate. We will also derive the Novelty Ratio (the fraction of accepted suggestions that the user has

not seen before) and the Exploration Rate (the acceptance rate for less-popular items). Upon completing the study, participants will respond to a Likert-scale survey covering perceived usefulness, alignment with personal goals, and learning outcomes, as well as a question about whether the suggestions felt sufficiently varied. This combination of quantitative metrics and qualitative feedback will capture both objective performance and subjective user experience.

Finally, we plan to validate system performance against real-time requirements by deploying a two-phase architecture. In the offline phase, collaborative filtering models will be retrained nightly, embeddings will be precomputed, and content-based profiles will be updated. In the online phase, we will apply hybrid scoring, enforce knowledge-based rules, and incorporate context modifiers over a prefiltered candidate set, using a fast approximate nearest-neighbor search (e.g. Faiss) to ensure latency under 500ms for generating five recommendations. By integrating both algorithmic and human-centered evaluations, our framework will rigorously and practically demonstrate the recommender’s ability to guide users toward sustainable daily choices.

Dimension	Evaluation Type	Metrics
Model Accuracy	Offline (historical data)	Precision@5, Recall@5, NDCG@5, MAP, Coverage, Hit Rate; session-based split
User Experience	Online interaction	CTR, Acceptance/Skip Rate, Novelty Ratio, Satisfaction Survey, Diversity Feedback
System Efficiency	Performance benchmarking	Real-time latency (<500ms), Hybrid scoring, Batch + Online integration

Table 1: Overview of evaluation dimensions, evaluation types, and key metrics.

7 Conclusion

In this report, we have outlined the design of a personalized carbon-reduction recommender system that integrates content-based filtering, collaborative filtering, knowledge-based constraints, and context-aware adjustments to deliver five actionable suggestions per user session. By leveraging two curated datasets—food life-cycle emissions and vehicle CO₂ factors—and augmenting them with an LLM-powered conversational module, the system can both recommend low-carbon behaviors and answer ad-hoc queries with high confidence and transparency. Our proposed two-phase update strategy (real-time profile updates and nightly model retraining) balances personalization with computational efficiency, ensuring sub-second response times.

We have also presented a comprehensive evaluation plan covering both algorithmic performance (Precision@5, Recall@5, NDCG@5, MAP, Coverage) and user-centric measures (CTR, acceptance rate, novelty, satisfaction surveys), to be validated through an

informal user study. This framework promises to guide individuals toward more sustainable choices in diet, transport, and energy use, while remaining extensible for future enhancements such as multi-modal transport support, gamification, and integration with external carbon markets.

References

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