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EcoLife: A Gamified Mobile Application for Integrated Student Lifestyle Management and Carbon Footprint Tracking with AI-Driven Personalised Insights

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***Abstract*—College students often have irregular sleep schedules, poor eating habits, low physical activity and too much screen time. Many are also unaware of the carbon emissions linked to their daily travel, food choices and electricity use. Most existing apps focus on these issues separately. Fitness and habit trackers focus on health, while carbon calculators do not consider students' health or academic routines. This paper presents EcoLife, a cross-platform mobile application with four main modules: (i) a lifestyle tracker for sleep, diet, exercise, study and screen time; (ii) a carbon emission calculator for transport, food and energy; (iii) an AI-based personalised insights engine that combines supervised machine learning with rule-based recommendations; and (iv) a gamification system where users earn points by completing healthy and eco-friendly tasks. These points can be exchanged inside the app for non-material rewards such as streak freezes, task-skip passes and break tokens. The system uses Flutter, Node.js/Express, MongoDB, Firebase and a Python scikit-learn service. It also uses the Carbon Interface API to obtain standardised emission factors. EcoLife is aligned with United Nations Sustainable Development Goals 3 (Good Health and Well-being), 4 (Quality Education) and 13 (Climate Action). This paper explains the system requirements, architecture, data model, carbon accounting model, machine learning pipeline, reward system, privacy considerations and four-phase implementation plan. It also proposes a pilot evaluation protocol. The project is currently at the design stage, so no experimental results are claimed.**

Keywords—mobile health, carbon footprint, gamification, student well-being, sustainable development goals, recommender systems, behaviour change, Flutter.

I. Introduction

A. Background and Motivation

University students face academic pressure while developing habits that can affect their health and daily routines over the long term. A large multi-country study conducted as part of the World Health Organization World Mental Health Surveys found that about one-third of first-year college students screened positive for at least one common mental disorder [1]. Sleep is also linked to academic performance, with studies of undergraduates finding an association between sleep patterns and learning outcomes [2]. Research has also linked evening screen use to later bedtimes and shorter sleep [3]. Together, poor sleep, an unbalanced diet, long periods of sitting and heavy device use can affect both student well-being and learning.

Students' everyday choices also have an environmental impact. Food systems account for about a quarter of global greenhouse gas emissions, although the impact differs greatly between food types [4]. Research on individual climate actions suggests that choices such as living without a car and eating more plant-based foods are not always given enough attention in public guidance or education [5]. The IPCC has also highlighted the potential of changes in diet, transport and energy use to reduce emissions [6]. However, students may find it difficult to understand how everyday activities, such as taking a bus, choosing a meal or using air conditioning, contribute to CO_2-equivalent emissions.

B. Problem Statement

The problem was identified through personal observation, informal discussions and surveys with college students, along with a review of the United Nations Sustainable Development Goals (SDGs) [7]. Four main gaps were identified:

1. An imbalance between academic work and daily habits can contribute to burnout and poorer mental well-being.
2. Students may not know how much carbon they generate through transport, food and electricity use.
3. Most existing applications focus either on fitness or emissions and do not address students' specific needs.
4. There is a lack of personalised, AI-driven guidance that considers health and environmentally friendly behaviour together.

An informal survey suggested that more than 70% of students had poor lifestyle habits, including irregular sleep, an unhealthy diet and limited exercise. This figure is an early observation by the authors and is not based on a rigorously sampled study. The pilot study planned in Section VIII will assess these habits more systematically.

C. Objectives

The main objectives of this work are to:

1. design one mobile application that tracks lifestyle habits and carbon emissions through a simple daily workflow;
2. provide personalised and explainable suggestions that consider both health benefits and emission reduction;
3. include a gamification system where points can be exchanged only for in-app privileges rather than physical rewards;
4. support campus-level awareness through anonymised and aggregated data; and
5. align the application with SDG 3, SDG 4 and SDG 13.

D. Contributions

This work makes five main contributions: (1) a set of requirements and an architecture for a student application that combines health and carbon tracking; (2) a transparent carbon accounting model designed around student activities; (3) a recommendation approach that combines guideline-based rules with machine learning and can provide suggestions from the first day; (4) an in-app reward system with safeguards against misuse; and (5) a proposed protocol for evaluating the system through a pilot study.

E. Organisation of the Paper

The rest of the paper is organised as follows. Section II reviews related work, and Section III explains the connection with the SDGs. Section IV presents the system requirements. Section V describes the architecture and data model. Section VI explains the scoring methods, carbon model and machine learning pipeline. Section VII presents the gamification design. Section VIII covers implementation and evaluation. Section IX discusses privacy, ethics and limitations, while Section X concludes the paper and lists future work.

II. Related Work

A. Health and Fitness Tracking Applications

Health applications are common, but keeping users engaged over time remains difficult. A national survey of mobile phone users in the United States found that although many people had downloaded health apps, a considerable number had stopped using them because data entry was burdensome or they lost interest [8]. Patel et al. describe wearables and trackers as tools that can support behaviour change, rather than cause it on their own; collecting data is often not enough without suitable motivation [9]. A systematic review also found that gamified health apps mainly use goal setting and self-monitoring, with less use of social features and personalised feedback [10]. Apps such as MyFitnessPal and Google Fit track calories or activity, but they do not provide carbon emission estimates or focus on students' needs.

B. Carbon Footprint Calculators and Eco-feedback

Eco-feedback systems make resource use visible so that people can make better-informed choices. Froehlich et al. explain that this feedback should be timely, practical and connected to user goals [11]. General tools such as the WWF footprint calculator estimate household emissions, often through long questionnaires. They are not designed for daily logging and do not combine health tracking with student-specific categories. The Carbon Interface API provides standardised emission estimates for developers, but it does not provide its own user interface or behavioural guidance [23]. A review of games and applications for climate action found that gamified sustainability tools may be useful, although evidence of long-term behaviour change is still limited [12].

C. Gamification

Gamification means using game design elements in settings that are not games [13]. Hamari et al. reviewed empirical studies and found that gamification often has positive effects, but results depend on the context and users [14]. A field experiment found that badges can increase user activity [15]. Sailer et al. showed that different game elements can support different psychological needs. For example, badges and leaderboards can support competence, while progress graphs and meaningful stories can support other needs [16]. This is consistent with self-determination theory, which identifies autonomy, competence and relatedness as important for intrinsic motivation [17]. For this reason, EcoLife uses in-app privileges linked to users' routines instead of external prizes that could reduce their own motivation.

D. Behavioural Foundations

The Fogg Behaviour Model suggests that behaviour occurs when motivation, ability and a prompt come together [18]. EcoLife applies this idea by keeping daily logging simple, providing points as motivation and sending reminders at suitable times. Social comparison can encourage behaviour, but Schultz et al. identified a boomerang effect in which people performing above average may move closer to the group norm [19]. EcoLife therefore includes personal progress and group-relative ranges instead of relying only on rank. Habit formation also takes time. One real-world study reported a median of 66 days for behaviour to become automatic, with considerable variation between individuals [20]. This supports the use of longer streaks and forgiving features rather than penalising users for missing a single day.

E. Research Gap

Table I compares the main features of the existing tools reviewed for this project.

TABLE I. Comparison of Existing Tools and EcoLife

Tool	Lifestyle habits	Carbon tracking	Student-centric	AI personalisation	Gamification
MyFitnessPal	Yes (calorie)	No	No	Limited	Limited
WWF Carbon Calculator	No	Yes (annual estimate)	No	No	No
Habitica	Yes (generic habits)	No	Partial	No	Yes (RPG)
Google Fit	Activity only	No	No	Limited	Limited
Carbon Interface API	No	Yes (developer API)	No	No	No
EcoLife (proposed)	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

The tools reviewed do not combine daily health tracking, daily emission tracking, student-specific features, personalised insights and an in-app reward system in one place. EcoLife is designed to address this gap. The table is based on the authors' initial review of the tools and should be checked against their current versions before publication.

III. Alignment with the United Nations Sustainable Development Goals

The 2030 Agenda defines 17 Sustainable Development Goals for global action [7]. EcoLife is designed to support three of these goals.

TABLE II. Mapping of EcoLife Features to SDGs

SDG	Relevance	EcoLife features
SDG 3: Good Health and Well-being	Student physical and mental health	Sleep, diet, exercise and screen-time tracking; burnout and unhealthy-streak alerts; micro-break and diet reminders
SDG 4: Quality Education	Health and sleep influence learning; sustainability literacy	Study-versus-sleep balance monitoring; exam-season mode; educational carbon facts and eco-challenges that build sustainability awareness
SDG 13: Climate Action	Reducing emissions and raising climate awareness	Daily CO_2e calculation; greener commute and meal suggestions; campus-level emission trends for green initiatives

The connection with SDG 4 is indirect. EcoLife does not deliver formal teaching, but it supports conditions that can help students learn, such as rest, routine and well-being. It also aims to improve environmental awareness, which is part of education for sustainable development. This distinction helps keep the stated contribution within the project's actual scope.

IV. System Requirements

A. Functional Requirements

- FR1 Authentication: support email and OAuth2 sign-in, with JSON Web Tokens (JWT) used for session management.
- FR2 Habit logging: allow users to record sleep times, meals, exercise minutes, study hours and screen time each day, with reminders.
- FR3 Carbon calculation: estimate CO_2e emissions from travel mode and distance, meal composition and electricity use.
- FR4 Insights: provide personalised daily and weekly suggestions and briefly explain each recommendation.
- FR5 Gamification: provide points, levels, badges, streaks, leaderboards and an in-app reward store.
- FR6 Dashboard: show trends in health score, emissions and points.
- FR7 Institution view: provide coordinators with anonymised, campus-level summaries.
- FR8 Data control: allow users to request an export or deletion of their personal data.

B. Non-functional Requirements

- Usability: daily logging should normally take less than two minutes. Presets, quick-select options and values from the previous day will reduce data entry.
- Performance: screen transitions should take less than one second, and API responses should take less than two seconds on typical mobile networks.
- Offline support: users should be able to enter logs without a connection and synchronise them later.

- Security and privacy: use encrypted connections, hashed credentials, minimal data collection and consent-based analytics.
- Scalability: use stateless backend services that can scale horizontally.
- Accessibility: provide readable contrast, scalable text and indicators that do not depend on colour alone.

C. Target Users

The main users are hostel students, whose food and electricity use can be tracked; daily commuters, whose travel contributes to emissions; students during exam periods, who may need help balancing study and sleep; and institutional coordinators who use aggregated insights.

V. System Architecture and Design

A. Overview

EcoLife uses a layered client-server architecture, outlined in Fig. 1:

- Presentation layer: a Flutter mobile application built from one Dart codebase for Android and iOS [21].
- Application layer: a Node.js/Express service that provides REST endpoints and a real-time channel for notifications and leaderboard updates.
- Data layer: MongoDB stores habit and emission records, while Firebase provides authentication and push messaging [22].
- Intelligence layer: a Python service uses scikit-learn [24] for prediction and recommendations and is called through an internal API.
- External service: the Carbon Interface API provides standardised emission estimates [23].

Fig. 1. EcoLife architecture: Flutter client → JWT-protected Express API gateway → MongoDB, Firebase, the machine learning service and the Carbon Interface API. A scheduler handles reminders and nightly model runs.

The initial proposal considered a web interface, but the current design focuses on a mobile app. This is more suitable for daily logging, push notifications and offline use. Flutter was selected for these reasons. A separate React-based web dashboard may be added later for campus coordinators.

B. Technology Justification

TABLE III. Technology Choices and Rationale

Layer	Technology	Rationale
Mobile client	Flutter (Dart)	Single codebase for Android and iOS, reusable widgets, strong community
Backend	Node.js + Express	Asynchronous, event-driven I/O suited to frequent small writes and notifications
Database	MongoDB	Schema-flexible documents for varied habit, food and transport data
Auth and messaging	Firebase, JWT, OAuth2	Managed sign-in and push notifications; stateless API authorisation
ML	Python, pandas, scikit-learn	Mature tools for tabular prediction and evaluation
Emission data	Carbon Interface API	Standardised, externally maintained emission factors
Deployment	Vercel (API) with managed MongoDB	Simple, scalable hosting for a student project

The technology scores shown in the initial presentation (8 to 9 out of 10) were subjective estimates by the team and are not treated as evidence in this paper.

C. Data Model

The main MongoDB collections and their key fields are listed in Table IV.

TABLE IV. Core Collections

Collection	Key fields
users	userId, email hash, course/year, residence type (hostel/commuter), consent flags, createdAt
habitLogs	userId, date, sleepStart, sleepEnd, mealEntries[], exerciseMinutes, studyHours, screenHours, mood (optional)
emissionLogs	userId, date, transport[] (mode, km), foodItems[], energyUse (device, hours), totalKgCO2e
pointsLedger	userId, timestamp, eventType, points, balanceAfter
rewards	rewardId, name, cost, weeklyLimit, effectType
redemptions	userId, rewardId, timestamp, status
insights	userId, date, suggestionId, rationale, accepted (bool)

The points ledger is append-only. This makes it possible to audit transactions and recalculate balances, and can also help identify misuse.

D. Key Workflows

1. Daily logging: the user opens the app or follows a reminder, checks the prefilled values and submits the entry. The app stores the log locally, synchronises it with the API and receives updated scores and points.
2. Carbon calculation: the API converts each logged activity into kg CO_2e using the model in Section VI-B. It uses the Carbon Interface API where supported and falls back to cached emission factors if the service is unavailable.
3. Insight generation: a scheduled nightly task calculates the features, runs the models and stores ranked suggestions for the user's feed the next morning.
4. Redemption: when a user selects a reward, the API checks the available points and weekly limits, records the transaction in the ledger and activates the reward.

VI. Methodology

A. Habit Scoring

Each day, the system calculates a Health Score from 0 to 100 using four weighted sub-scores: sleep, activity, diet and digital balance. The targets are based on published guidelines. The National Sleep Foundation recommends 7 to 9 hours of sleep per night for young adults [25]. The WHO recommends 150 to 300 minutes of moderate-intensity physical activity per week for adults [26]. Each sub-score uses a piecewise-linear scale: users receive the highest score within the target range, while the score decreases as values move outside it. Sleep consistency is also considered by measuring the standard deviation of bedtime over the previous seven days, since regularity matters in addition to total sleep time.

$$\text{Health Score} = 0.35 \cdot S_{\text{sleep}} + 0.25 \cdot S_{\text{activity}} + 0.25 \cdot S_{\text{diet}} + 0.15 \cdot S_{\text{digital}}$$

The weights are initial settings chosen by the authors and can be adjusted after the pilot. The Health Score is intended to motivate users and is not a clinical measure. EcoLife does not diagnose medical conditions.

B. Carbon Accounting Model

Daily emissions are estimated in kg CO_2e by adding three components:

$$E_{\text{total}} = E_{\text{transport}} + E_{\text{food}} + E_{\text{energy}}$$

- Transport: $E_{\text{transport}} = \Sigma\, d_m \cdot EF_m$, where d_m is the distance travelled using mode m (walking, cycling, bus, metro, auto-rickshaw, two-wheeler or car), and EF_m is the emission factor per passenger-kilometre.
- Food: $E_{\text{food}} = \Sigma\, q_i \cdot EF_i$, where q_i is the quantity of food category i, such as rice, pulses, dairy, eggs, poultry or mutton, and EF_i is its life-cycle emission factor. Differences between food categories are supported by the life-cycle analysis reported by Poore and Nemecek [4].
- Energy: $E_{\text{energy}} = \Sigma\, P_k \cdot t_k \cdot EF_{\text{grid}}$, where P_k is the appliance power rating in kW, t_k is its usage time in hours, and EF_{grid} is the grid emission factor in kg CO_2e per kWh. For shared hostel rooms, the estimated emissions are divided by the number of occupants.

Emission factors are stored in a configuration collection so they can be updated without releasing a new app version. If the Carbon Interface API supports an activity, its estimate is used [23]. Otherwise, the system uses a selected table of factors from published national or life-cycle datasets and records the source for each factor. Since factors vary by country, region and vehicle, results are shown as estimates with an uncertainty note. Specific factors are not listed

in this paper because they still need to be selected and cited during implementation; including unverified values could be misleading.

To make the results easier to understand, the app presents each estimate in a familiar comparison, such as the emissions equivalent of a short bus ride. It also shows the user's trend against their own average for the previous seven days.

C. Personalised Insights Engine

The personalised insights engine combines rules and machine learning. This hybrid design addresses the cold-start problem, where a new user has no history for the system to learn from.

Stage 1: Rule-based recommendations (from day one). Rules based on published guidance can suggest an earlier bedtime when a sleep target is missed, a short walk after a long study session, or a lower-emission meal after a high-emission meal is logged. Each suggestion includes a short explanation so the user can understand why it was made.

Stage 2: Supervised prediction (after enough data is available). The system builds daily feature vectors from sleep duration, bedtime variation, exercise minutes, study hours, screen time, meal categories, commute mode and distance, E_total, current streak, day of the week and an exam-period flag. Two prediction tasks are planned:

1. Adherence classification: predict whether the user will meet the next day's sleep and activity targets (binary classification).
2. Emission regression: estimate the next day's E_total using the planned commute and recent behaviour.

The candidate models include logistic regression as a baseline, along with Random Forest [27] and gradient boosting, implemented with scikit-learn [24]. The models will be compared using cross-validation. F1 and ROC-AUC will be used for classification, while mean absolute error will be used for regression. Tree-based models are considered because they support mixed feature types, can work with small tabular datasets and provide feature-importance information.

Stage 3: Recommendation ranking. Candidate actions are ranked according to their predicted benefit, effort and the user's previous acceptance, following ideas from content-based and hybrid recommender systems [28]. The priority score is defined as:

$$\text{Priority} = a \cdot \text{HealthGain} + b \cdot CO_2\text{Saved} - c \cdot \text{Effort} + d \cdot \text{AcceptanceLikelihood}$$

The parameters a, b, c and d can be adjusted. The user can choose a health, climate or balanced focus, which changes the weights. To avoid overwhelming users, the app shows three suggestions per day. Accepting or dismissing a suggestion is recorded and can later be used as a training signal.

Training data. Since real user data is not yet available, the first models will use synthetic data generated from the guideline-based rules with added noise. The models will then be retrained using data collected with consent during the pilot. Synthetic data will be used to test the pipeline, not to claim real-world accuracy. This limitation will be stated in the evaluation.

D. Exam-Season Wellness Mode

When users enable exam-period mode, the app monitors the ratio between study hours and sleep hours. If a configurable threshold is exceeded for several consecutive days, the app flags the pattern and suggests short breaks, hydration and simple meal reminders. This feature supports the link between well-being and learning under SDG 4.

VII. Gamification Design

A. Design Principles

Based on the studies reviewed in Section II, the design follows five principles: (1) reward effort and consistency rather than extreme results; (2) let users choose their own goals to support autonomy [17]; (3) show levels and progress to support competence [16]; (4) keep rewards within the app so external prizes do not replace intrinsic motivation; and (5) avoid rewards that work against the health goals the app is meant to support.

B. Earning Points

Users earn points by completing defined tasks. Daily limits are used to reduce attempts to exploit the system.

TABLE V. Illustrative Point Rules

Task	Points	Daily cap
Complete the daily log	10	1
Meet the sleep target	15	1
Meet the activity target	15	1
Choose a low-emission commute (walk, cycle, bus, metro)	10	1
Log a plant-forward meal	10	2
Accept and complete a suggested action	5	3
Complete a weekly eco-challenge	30	1 per week
7-day streak bonus	25	1 per week

The point values in Table V are initial settings and will be adjusted during the pilot to keep the reward system balanced. Points are given for completing tasks and recording them honestly, not for achieving extreme values.

C. Levels, Badges and Leaderboards

Users advance through levels, such as Seedling, Sapling, Tree and Forest, as they earn lifetime points. Badges mark milestones, including a first plant-forward week, a 30-day logging streak or a week of zero-emission commutes. The leaderboard provides personal-best, friends/hostel-group and campus views. Based on the findings of Schultz et al. [19], the campus view focuses on percentile ranges and improvement rather than absolute emissions alone. This is intended to avoid discouraging users with poorer results or pushing high performers back towards the average.

D. Redeeming Points for In-App Privileges

EcoLife allows points to be used only for rewards inside the app, rather than gifts or vouchers. These rewards provide users with an occasional break from reminders and their own goals, without adding material incentives.

TABLE VI. Redeemable In-App Rewards

Reward	Effect	Illustrative cost	Safeguard
Streak Freeze	Protects a streak for one missed day	40	Max 2 per month
Skip Pass	Excuses one daily task without penalty	30	Max 2 per week; never for sleep alerts during exam mode
Lazy Day Token	Pauses all reminders and goals for 24 hours	60	Max 1 per week
Cheat Meal Pass	Logs one indulgent meal with no score penalty	25	Max 2 per week
Snooze+	Extends reminder snooze to 3 hours	15	None
Cosmetic Unlocks	App themes, avatar items, badge frames	20–100	None

The reward limits are intended to prevent users from avoiding the health goals too easily. Each privilege has a usage cap, and the app does not allow rewards to hide concerning patterns, such as several nights of very short sleep. In those cases, it shows a supportive check-in instead. By reducing pressure rather than adding more tasks, the reward system is also designed to avoid making the app another source of stress.

E. Anti-abuse and Fairness

Daily caps, an append-only ledger, checks for unrealistic entries (such as 24 hours of sleep) and rate limits help reduce false logging. Since rewards have no monetary value outside the app, there is less financial incentive to cheat. Streaks are also designed to be forgiving, considering that habit formation takes time and differs between users [20].

VIII. Implementation Plan and Evaluation Protocol

A. Phased Roadmap

The project is planned in four development phases. The estimated effort is divided as follows: habit tracking (30%), carbon calculator (25%), AI insights (22%), gamification (13%), and authentication and deployment (10%).

TABLE VII. Development Phases

Phase	Deliverables
1	User authentication and habit logger (sleep, diet, exercise, study, screen time); local storage and sync
2	Carbon calculator with transport, food and energy modules; Carbon Interface API integration
3	Machine learning model for personalised suggestions; dashboard with trends
4	Gamification layer (points, badges, leaderboard, redemption store); integration, testing and deployment

The source code is planned to be maintained in a public GitHub repository and updated as development continues. At the time of writing, the prototype had not yet been built, and implementation will start from scratch.

B. Testing Strategy

Unit tests will cover the health scoring and carbon calculation formulas. API tests will check authentication, input validation and ledger consistency, while widget tests will cover the main Flutter screens. Manual testing is planned on at least two Android devices and one iOS device. Load tests will simulate multiple users submitting daily logs around reminder time.

C. Pilot Study Design

A four-week pilot involving around 30 to 50 volunteer students, including hostel residents and commuters, is planned, subject to institutional approval and informed consent. Participants will be asked to consent to anonymised analysis. The study will consider the following research questions:

- RQ1—Usability: Is the application easy to use? This will be measured using the System Usability Scale [30] and the median time needed to complete a daily log.
- RQ2—Engagement: How often do users log their activities, and how does retention change over four weeks? Measures will include logging rate, daily active users and streak length. Where feasible, engagement will be compared between periods with and without gamification features.
- RQ3—Behaviour: Do sleep regularity, activity minutes and self-reported emissions change between week 1 and week 4? Paired comparisons will be reported with effect sizes and confidence intervals.
- RQ4—Model quality: How accurately do the models predict adherence and emissions? Evaluation will use F1, ROC-AUC and MAE with cross-validation, along with the acceptance rate of recommendations.
- RQ5—Reward economy: Is the reward system balanced? This will be assessed through redemption frequency for each reward, point-balance distribution and participant feedback.

A four-week study with one participant group cannot establish causality. Any changes will therefore be reported as associations. A larger controlled trial is planned as future work.

IX. Discussion

A. Privacy, Security and Ethics

The app handles sensitive information about sleep, diet and daily movement. To limit data collection, it does not require continuous location tracking; users enter or select their travel distance. Data is encrypted in transit, passwords are not stored in plain text, and institutional dashboards show only aggregated and anonymised results with a minimum group size to reduce the risk of identifying individuals. India's Digital Personal Data Protection Act, 2023 sets requirements for consent, purpose limitation and data erasure. The design therefore includes consent screens, data export and account deletion [29]. The app is not intended for users under 18 and does not make medical diagnoses. If a user repeatedly reports very poor sleep or low mood, the app provides supportive messages and directs them to campus counselling services rather than sending more gamified prompts.

B. Limitations

- The system depends on self-reported entries, which may be affected by memory errors, social desirability bias and user fatigue.
- Carbon estimates are approximate because emission factors vary by region and context. It is also difficult to estimate each student's electricity use in shared hostel rooms.
- The initial models use synthetic data, so their real-world accuracy will remain unknown until the pilot is completed.
- The effect of gamification depends on the context and may decrease over time [14]. A four-week pilot may also show novelty effects.
- The point values and scoring thresholds are based on heuristics and will need to be adjusted.
- The comparison with existing applications is based on the authors' feature review and may change as those products are updated.

C. Potential Impact

If the system works as intended, it could help students maintain more regular sleep, be more physically active and choose options with lower emissions. It could also give institutions anonymised information about campus well-being and sustainability trends. These aims relate to SDG 3, SDG 4 and SDG 13. Long-term engagement remains a key risk, so the design focuses on quick logging, forgiving streaks and in-app rewards that students may find useful.

X. Conclusion and Future Work

This paper presented the design of EcoLife, a gamified mobile application that brings student lifestyle tracking and carbon footprint estimation together in one platform. It combines a habit tracker, a carbon calculator, a hybrid rule-based and machine learning insights engine, and a points system that can be used for in-app privileges such as streak freezes and skip passes. The design aims to address the separation between existing tools and support SDG 3, SDG 4 and SDG 13. The proposed architecture uses Flutter, Node.js, MongoDB, Firebase and a Python machine learning service. Development is planned in four phases, followed by an evaluation using the proposed protocol.

Future work will include building the prototype and conducting the pilot study, selecting regional emission factors, adding wearable and calendar integrations for passive data collection, testing reinforcement-learning-based nudges, developing a web dashboard for campus coordinators, and running a larger controlled study across several institutions to assess long-term behaviour change.

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