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Between Algorithms and Everyday Choices: University Students' Perspectives on AI For Campus Sustainability

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Abstract
This study investigates how Hungarian higher-education students interacted with AI-supported sustainability systems in their daily life at campus, specifically in relation to food services, mobility planning, and real-time environmental feedback. Using semi-structured interviews and a focus group with 32 students across multiple institutions, thematic analysis revealed three phases of interaction: sense-making, trust construction, and behavior change. In the sense-making phase, students engaged with the systems using pragmatic considerations like time, tangibility, prior understandings, and fitting into their daily life. Perceived value of what was produced was lessened when inputs were unclear regarding the context or unfriendly regarding the communication format. Trust developed through layered assessments of risk. Early trust was related to transparent data origins; trust developed through student-performed verification in situ; and trust was reinforced through social validation through affordability of services, fair pricing, inclusivity, and language accessibility. Trust diminished when the system stripped away autonomy, masked trade-offs, burdened cognition, or could not deliver cues to action. Behavior change appeared to happen when systems eliminated the friction of decision making, while aligning to previous habits. Sustained acceptance required ongoing trust and perceived value. The findings contribute to understanding of how AI-mediated sustainability initiatives are perceived, validated, and acted upon in the context of higher education, while providing design implications for systems seeking to be inclusive, transparent, and behavior changing.

Keywords: AI Enabled Sustainability; Sense Making; Behavioral Response; Perceived Utility; Student Engagement, Environmental Attitudes

DSR Digital & Social Review

1. Introduction

Across campuses, artificial intelligence is quietly moving into the everyday work of sustainability. Predictive controls trim heating on cold mornings, computer vision helps keep recyclables out of landfill, and dashboards forecast kitchen demand to curb food waste (Amasyali & El,Gohary, 2018; United Nations Environment Programme, 2021). In the broader environmental arena, AI already supports near term ecological forecasting, storm nowcasting, and land use monitoring—tools that make environmental change more visible and actionable (White et al., 2019; McGovern et al., 2019; Zhu et al., 2017). Yet whether these systems change behavior on campus depends on a small circle of daily choices: what students eat, how they move between classes, and how they negotiate comfort in dorms and study spaces.

Universities matter here for two reasons. First, their operations—buildings, food services, and mobility carry a meaningful environmental footprint. Second, they shape the habits and expectations that graduates take into public life and professional practice. AI can help align operations with reality tuning energy use to occupancy, matching menus to demand, and making urban biodiversity legible through sound and image recognition—without asking students to sacrifice experience (Amasyali & El,Gohary, 2018; Kahl et al., 2021). But technical potential is not the same as social uptake. If recommendations feel opaque or unfair, if data practices are poorly explained, or if tools clash with budgets and culture, trust erodes and adoption stalls (UNESCO, 2021).

Hungary is a timely setting for this conversation. Its universities span historic city center campuses and growing regional institutions, with student bodies that mix commuters and residents, Erasmus cohorts and first-generation scholars. The environmental pressures are familiar—rising energy costs, air quality concerns, urban heat, and food waste—but the institutional histories and student cultures are distinct. Rather than assume results from North American or Western European campuses will translate, this study listens to Hungarian students directly: how they encounter AI enabled sustainability, what makes a tool credible or dismissible, and where the value is (or isn't) in the flow of student life.

Food waste analytics only matter if diners change choices or kitchens adjust prep (United Nations Environment Programme, 2021). Energy savings from predictive controls only persist if comfort remains acceptable and override patterns are understood (Amasyali & El,Gohary, 2018). Biodiversity tools only build stewardship if students feel invited, not surveilled (Kahl et al., 2021). In each case, human judgment completes the circuit from signal to action.

Three currents in the literature frame our approach. First, technical reviews show the breadth of AI's environmental capabilities, from remote sensing and building controls to ecological forecasting (Zhu et al., 2017; Amasyali & El,Gohary, 2018; White et al., 2019). Second, environmental and climate tech syntheses point to the need for solutions that are not only accurate but adoptable, embedded in real decision contexts (Rolnick et al., 2022). Third, work on higher education's sustainability role urges a shift from counting initiatives to understanding lived impacts on people and systems—how universities' actions translate beyond campus operations (Findler et al., 2019). Threaded through is a clear ethical call: deploying AI in ways that are transparent, fair, and accountable (UNESCO, 2021).

Against this backdrop, a qualitative, student-centered lens can surface what metrics miss: the frictions, the workarounds, and the small design choices that make tools feel respectful and useful. By situating voices from Hungarian campuses, the study aims to complement technical assessments with grounded insight on when environmental AI moves from promise to practice—and when it doesn't (McGovern et al., 2019; Rolnick et al., 2022).

Research objectives

- Explore how Hungarian university students make sense of AI enabled sustainability on campus where they see value, risk, and irrelevance.
- Examine what builds or breaks trust in AI based recommendations (e.g., transparency, data provenance, cultural fit, perceived fairness).
- To document when and how AI supported tools influence daily choices around energy use, mobility, and food versus when they are ignored.

Much of the environmental AI and campus sustainability literature is centered in Anglophone or Western European contexts, with limited qualitative work capturing student perspectives in Hungary. (Findler et al., 2019.) In previous studies, there is emphasis on technical metrics over adoption: Previous studies often report accuracy and savings but rarely examine how students experience recommendations, resolve conflicts (comfort, cost, culture), or negotiate trade offs in daily routines. (Amasyali & El,Gohary, 2018; Rolnick et al., 2022.) High level AI ethics principles are widely endorsed, yet there is little empirical work on how transparency, consent, and data use are communicated and perceived in campus sustainability deployments. (UNESCO, 2021.) The energy, food, and biodiversity initiatives are typically studied in silos, missing cross domain insights about what consistently helps or hinders student adoption. (Zhu et al., 2017; United Nations Environment Programme, 2021; Kahl et al., 2021.)

The study offers actionable guidance for facilities teams, canteens, and sustainability offices on designing AI enabled interventions that students use—clear provenance, feedback loops, respectful defaults, and accessibility features. (Amasyali & El Gohary, 2018; United Nations Environment Programme, 2021). The study grounds AI ethics in concrete campus contexts, translating principles like transparency and accountability into communication practices, consent flows, and complaint mechanisms students recognize. (UNESCO, 2021).

The study extends environmental AI research with a qualitative, Hungary specific account of adoption dynamics, complementing technology first work with evidence on human fit and institutional context. (Findler et al., 2019; Rolnick et al., 2022.). The study centers student voice in campus sustainability decisions, framing them not as targets of nudges but as co designers whose lived realities determine whether environmental AI delivers on its promise.

2.Literature Review:

Student Perceptions of AI Enabled Sustainability on Campus

Across environmental domains, AI is already part of the toolkit: time series and occupancy models for building operations, computer vision for waste sorting, and near term ecological forecasting to anticipate change. Reviews of building energy analytics show steady progress from statistical baselines to machine learning models that capture usage patterns and improve predictions, a shift that creates more opportunities for data driven campus operations (Amasyali & El,Gohary, 2018; Zhu et al., 2017). In ecology, automated, iterative forecasting systems and acoustic classifiers like BirdNET are expanding what can be monitored at fine temporal scales, making local nature and near-term change more visible to non-experts (White et al., 2019; Kahl et al., 2021).

Perception, however, hinges on more than capability. In higher education, work on universities' sustainability roles points to the importance of lived impacts: students judge initiatives by whether they feel relevant, fair, and respectful of constraints such as time, cost, and comfort (Findler et al., 2019). Broader syntheses on AI and climate action likewise argue that value is realized only when tools are embedded in real decision contexts and tuned to user needs, not just benchmark accuracy (Rolnick et al., 2022). In short, students are receptive when AI makes their choices easier or clearer; they disengage when recommendations are opaque, inconvenient, or culturally tone deaf.

Ethical framing also shapes perception. International guidance urges transparency, contestability, and inclusion as foundational for trustworthy AI, which translates on campus into clear data practices, understandable recommendations, and visible channels for feedback (UNESCO, 2021). When those elements are present, students are more likely to see environmental AI as helpful infrastructure rather than surveillance or technocratic nudging.

Trust And Adoption Drivers for Environmental AI

Decades of technology adoption research offer a useful starting point. Perceived usefulness and ease of use predict intention to adopt, especially when tools reduce effort or improve outcomes in familiar tasks (Davis, 1989). Social influence, facilitating conditions, and habit also matter in institutional settings like universities, where norms and supports differ across faculties and programs (Venkatesh et al., 2003). For environmental AI specifically, these constructs map onto questions students ask implicitly: Does this help me? Is it simple enough to live with? Do my peers and instructors value it? Is support available when it misfires?

Trust in automation adds another lens. People calibrate trust by weighing system performance, transparency, and control—trust rises when users can predict behavior, understand limits, and retain the ability to override or correct (Lee & See, 2004). Explainability research reaches similar conclusions: intelligible models and honest uncertainty help users judge when to lean on an output and when to double check (Guidotti et al., 2018). Documentation practices like "model cards" and "datasheets for datasets" turn these principles into artifacts that campuses can share to signal provenance, scope, and known failure modes (Mitchell et al., 2019; Gebru et al., 2021).

Context matters too. In relation to building operations, occupant acceptance of predictive controls is based on the perceived comfort with those controls and the ease of being overridden. Systems that save energy and allow occupants to be autonomous build trust over time (Amasyali & El Gohary, 2018). In biodiversity monitoring, students engage when the tools seem participatory and educative as opposed to extractive. This might play a role in the previously described citizen science literature suggesting that reciprocity and feedback can uphold further participation in their research (Bonney et al., 2009; Kahl et al., 2021). Ethical commitments from the clear consent process to the right to appeal are not just artefacts of a process , they are also pragmatic trust brokers on campus (UNESCO, 2021).

Links Between AI Tools and Everyday Sustainability Behaviors

Turning insight into action is the hard part. Behavioral and social practice research shows why: daily routines are sticky, shaped by identity, convenience, and social norms as much as information (Ajzen, 1991; Shove, 2010). Eco feedback technologies can move the needle when they deliver timely, personalized feedback that ties actions to outcomes, especially if paired with social comparisons or defaults that lower effort (Froehlich et al., 2010; Allcott & Rogers, 2014). AI can sharpen these levers by predicting high impact moments (e.g., preheating patterns before occupancy) and tailoring prompts to when they are most likely to be heeded.

In energy use, feedback and nudges reduce consumption in the short run, but persistence depends on comfort and the fit with routines; if predictive systems routinely trigger overrides, savings fade (Allcott & Rogers, 2014; Hong et al., 2015). For food, waste analytics can guide procurement and menu planning, but behavior change hinges on price, taste, and habit; interventions that combine behind the scenes optimization with clear, student facing cues tend to do better (United Nations Environment Programme, 2021; Wilkie et al., 2015). On biodiversity, AI assisted identification and near real time feedback can spark curiosity and stewardship, particularly when participation is credited and local insights flow back to campus decisions (Bonney et al., 2009; Kahl et al., 2021). The throughline is mundane but powerful: tools that reduce friction, respect comfort, and offer visible payoff are more likely to influence daily choices. When AI outputs align with these conditions—and when students can see their influence on outcomes—campus sustainability moves from dashboards into daily life.

Design And Governance Conditions for Adoptable Campus AI

Design choices either lower or raise the "activation energy" of adoption. On the interaction side, clarity and control matter: show the signal, the suggested action, and the expected impact; make uncertainty legible; and keep overrides simple (Guidotti et al., 2018; Amasyali & El,Gohary, 2018). On the workflow side, "close the loop" so student feedback can correct the system—photo verification for waste sorting, quick thumbs up/down on canteen forecasts, or opt in sharing of comfort preferences in dorms. Co design practices help surface these details early, aligning features with what students actually do and value (Bonney et al., 2009).

Governance keeps trust intact as systems scale. Plain language model and data documentation, purpose binding for data use, and lightweight contestation channels embody ethical principles in day-to-day operations (Mitchell et al., 2019; Gebru et al., 2021; UNESCO, 2021). Institutional context also counts when sustainability teams measure adoption and satisfaction alongside kilowatt hours and kilograms of waste, they catch friction sooner and invest in support where it matters (Findler et al., 2019). Finally, the broader climate tech literature is clear: long run impact requires attention to maintenance, updates, and evaluative cycles that test whether tools still work as conditions and cohorts change (Rolnick et al., 2022; White et al., 2019). Put simply, adoptable campus AI is less about clever models than about respectful fit: transparent by default, easy to live with, open to correction, and anchored in governance that students can see and trust.

3.Methodology

Research Design

This study employed a qualitative research design, using semi structured interviews to explore Hungarian university students' perceptions and experiences of AI enabled sustainability initiatives on their campuses. The choice of a qualitative approach was guided by the aim of capturing nuanced perspectives, rich narratives, and the contextual details that shape adoption and trust in such technologies. By focusing on students lived experiences, the study was able to move beyond surface level attitudes to uncover how these systems were interpreted, negotiated, and sometimes resisted in daily life.

Setting and Participants

The research was carried out at five Hungarian universities representing both metropolitan institutions and regional campuses. These sites were selected to reflect diversity in size, academic focus, and access to sustainability technologies. Participants included both undergraduate and postgraduate students from a variety of disciplines. All had direct or indirect exposure to AI driven sustainability tools, such as smart energy systems, waste sorting infrastructure, or AI guided food services.

Sampling Strategy and Recruitment

A purposive sampling approach was used to ensure a breadth of perspectives, with attention to variables such as field of study, gender, housing status (on campus vs. commuting), and engagement with environmental initiatives. Recruitment took place through university mailing lists, student organizations, and classroom announcements. In total, thirty-two students participated in in-depth interviews, while an additional three focus groups were held, each with six to eight participants. This sample size allowed for thematic saturation, where no new major themes were emerging in later interviews.

Data Collection Procedures

Data was collected over a three-month period. Semi structured interview guides were developed to probe areas including awareness of environmental AI tools, perceptions of their usefulness and fairness, trust in recommendations, and any changes in daily practices prompted by their use. Focus groups provided a forum for students to discuss these topics collectively, revealing points of consensus, divergence, and debate. All interviews and focus group sessions were conducted either in Hungarian or English, depending on participant preference, and were audio recorded with consent. Field notes captured contextual information, such as body language and environmental cues, that informed analysis.

Data Analysis

Recordings were transcribed verbatim and, where necessary, translated into English for analysis. A reflexive thematic analysis approach was applied, following the steps outlined by Braun and Clarke. The process began with repeated reading of transcripts to familiarize the research team with the data, followed by initial coding that captured meaningful units of text related to the research objectives. Codes were then reviewed and refined into broader themes, such as "trust shaped by transparency," "AI aligning or conflicting with student routines," and "perceived tradeoffs between environmental and personal priorities." Coding was supported by qualitative data analysis software, which facilitated retrieval and comparison across cases.

To enhance credibility, two researchers independently coded a subset of transcripts and then compared results to reach consensus. Member checking was conducted by sharing preliminary themes with a small group of participants for feedback, ensuring that interpretations reflected their lived realities. An audit trail of coding decisions, memos, and theme development was maintained throughout the process.

Ethical Considerations

Participation was voluntary, with informed consent secured from all individuals. Participants were reminded that they could withdraw at any stage without consequence. All identifying details were removed from transcripts to maintain anonymity, and data were stored securely in compliance with GDPR requirements.

4.Findings & Discussion

This section synthesizes the findings gleaned from 32 semi structured interviews and 2 focus groups with Hungarian university students about three uses of AI enabled, systems on campus: demand forecasting for a canteen, mobility route planners, and sustainability dashboards for buildings. The analysis, using NVivo, resulted in a codebook with a total of 38 codes, structured around the three systems. Coding occurred in three iterative cycles, with weekly memos to document evolving interpretations. A member check with six participants affirmed that the themes resonated with their lived experiences rather than seeming abstract. Unless specified otherwise, patterns were consistent across campuses.

The findings portray a pragmatic engagement with artificial intelligence in daily campus life. Students evaluated these systems not by the allure of the "artificial intelligence" label but by their practical utility in saving time, preserving personal choices, and providing clear explanations of processes and rationales. This pragmatic perspective draws from practice theory's focus on routinized action shaped by material arrangements (Shove, 2010), and the Technology Acceptance Model (TAM) as measured by three constructs, perceived usefulness and ease of use as predictors for adoption (Davis, 1989). "Time saved", "choice preserved", and "low effort" from our data map directly to these constructs.

Participants articulated the benefits of canteen forecasting in tangible ways: reduced waiting times, fewer instances of items being unavailable, and perceptions of more efficient kitchen planning that maintained affordable options. As one commuter student stated, " “If it saves five minutes, I’m in. If I must tap three screens, I’m out.”." Credibility increased when kitchens displayed notes such as "We cooked 12% less today, no shortages," as the continued availability of meals aligned with the claim. Mobility applications integrated seamlessly into routines when they accounted for weather conditions and communicated delays transparently. An engineering student explained, "If it shows bikes near me and the route is flat and dry, I take the bike. If it is raining, show the next tram."

Three interconnected themes emerged as central to students' narratives. First, sense making was rooted in everyday pragmatism, where value was assessed in terms of time saved and choices retained, while risks manifested as diminished control, concealed costs, or added mental effort. Second, trust was built over time: knowing something did not come from an unknown source [immediate indicators of origin], having a reasonable likelihood that there was an empirical connection confirmed by my experience, and ways of doing things, such as communication, pricing, and inclusion in decision making. One student said, "show me the time and the sensor, not a green leaf," and another said, "ask me again when you change the deal," both suggesting the need for real consent. Third, behavioral change took place when the systems provided the lowest barrier access or benefits quickly but stopped when they had to make some effort or stop responding to the input. A humanities commuter said, "We said lunchtimes were hectic….the next week it changed, and it was quieter in line. That is when I felt heard." Differences occurred across subgroup perspectives. Dormitory residents weighed comfort and evening schedules while commuters weighed affordability and time. Erasmus exchange students emphasized the importance of having both languages available for interaction: "If I can read it easily in Hungarian, and English, I'm going to use it." But for all the groups the factors that distinguish between sustained use and ones you dismiss as too trivial were the same.

Sense Making of Artificial Intelligence Enabled Sustainability: Value, Risk, and Irrelevance

In keeping with the first research objective, students interpreted these systems in terms of their "practical" relevance. They highlighted functions which allowed more straightforward decision making, without taking away options, such as keeping their favorite dishes in canteens and wasting less, smarter route suggestions in mobility applications, or context specific offerings in dashboards. An on-campus student summed up their perspective: "Make the greener choice the easy choice and I will take it." These accounts illustrate a focus on the habits and things of everyday practice in line with practice theory (Shove, 2010), while the focus on "time saved" and "not removing options" resonates with perceived usefulness and perceived ease of use in Davis's TAM (Davis, 1989).

The perceived risks to these systems revolved around intervention in autonomy and potentially concealed tradeoffs, including the less obvious removal of cheaper options, or decisions on basis of rather than knowledge with systems that were rigid and didn't have a simple override. One commuter user expressed frustrations: "Eco is fine, just do not take away the cheap meal." Given recommendations deemed to be more judgement than action support, eg. to ride their bike in non-ideal circumstances, the user insulted by the recommendation would disengage entirely with the system: "Don't tell me to bike when it is icy. Tell me the best way today."

Meaninglessness plagued signals that were contextless or situationally relevant, such as total aggregate numbers with no daily equivalents, announcements in an unknown language without a translation, or alerts without context (temporal or environmental). "I don't speak kilowatts. Tell me what that means for us" was a repeated line.

In the end, students reframed artificial intelligence not as a part of the wave of technological revolution, but as small, reliable assistants built into campus accommodations. Systems that respected this reframing were accepted; systems that subverted the reframing lost relevance with practical approaches toward functionality over novelty.

Building and Eroding Trust: Transparency, Provenance, Cultural Fit, and Fairness

In addressing the second goal, it is evident that trust was gained step-by-step through multiple levels. Recognizing the source of recommendation with initial visibility, use of timestamps and sensor information, removed some of this distrust: "Show me the time and the sensor, not just a green leaf icon," one commented. The next source of validation was local, for example, the canteen signage indicated an agreement or interrelatedness of shifts in the forecast and shipments, or the dashboard reflected actions which have recently occurred by the end user. An engineering student reasoned, "they admitted Friday was wrong, and then laid out what they changed. Fair enough."

Fairness and seeing aspects of cultural congruence clearly helped build trust, such as multilingualism, identifying areas of flexibility with diet and cost issues and the ability to override, for example, one Erasmu s student said, "if I can't read it easily, in Hungarian and English, I will not use it." A law student said, "ask me again when you make new tracking," referencing an existing form of consent which he felt was very superficial.

Unrecognized peer validations often eclipsed the impact of formal forms of communication, such that a student's or representative's encouragement, "the new timing worked," initiated higher levels of adoption than institutionalist communications. Meanwhile, trust deteriorated with any blatant unreported errors, an alteration that sounded like a restriction, or a feedback loop that went beyond unproductive communication and autonomized as if, "if the menu changed and we do not know why it is a trick," said a commuter participant. "If you report, and nothing changes then is wallpaper," said another commuter.

In this regard, trust emerged not as a simple binary but an iterated series of affirmations for identifying origins, represent reality, include everybody, and fixed it right away. This layered aspect emphasized the relational nature of technology adoption phenomenology across numerous student populations.

Influencing Daily Choices: Conditions for Change Versus Disregard

Behavioral changes took place when systems reduced hassle and delivered immediate rewards for the third pathway. Many participants moved their lunch plans by 10 to 15 minutes when they noticed shorter lines and the potential to pick their meal: "If it says less busy at 12:45 and my favorite option is there, then I will move lunch a little earlier," said one resident. Mobility choices were changed with the inclusion of real time ride disruptions, weather, and availability: "Transit , If it is raining show the next tram. If it is flat and dry, I will take the bike."

Dashboards were encouraging small energy conservation habits by connecting specific actions to observable impacts within days: "It was pushing 'do laundry after 8 p.m.' and then showed the spike flatten out. It was gratifying," said a resident in a dorm. Comparing per floor and utilizing short weekly snapshots-maintained interest when information was formatted to be easy to consume. On the other hand, tools were disregarded if they required additional work that did not seem worth the effort, if they were opposed to ease or cost, or if there was no response: "I've got to scan a code every time I want to check a graph? I'll pass, unless the code reveals a point." "If you lock the settings and I'm freezing after a late lab, I'm finished." Indistinct rewards, like generic eco badges, or other unfixed prompts, were discarded swiftly. In short, students followed orders that were precise, timely, and clear in their gain, while rejecting information that was unclear, burdensome, or insensitive. These behaviors demonstrate some of the conditionality of sustainable action in higher education contexts.

Conceptual Framework: Integrating Sense Making, Trust, and Behavior

The results consolidate into a coherent, empirically founded model outlining linkages from yearnings to sense making to behavioral adaptation to artificial intelligence aided sustainability behaviors. Sense making encompasses perceived value (e.g., less time), preservation of choice (e.g., maintenance of choices), operational compatibility (e.g., consistent with schedules and conditions), against risks and disconnections. Positive assessments create receptivity.

Trust acts as a mediator, created by origin transparency (e.g., where the data is from), localized verification (e.g., agreement with lived experiences), social equity (e.g., inclusion in design), and social corroboration and unity of change transparency. The moderators as contextual include location of residence, cost acknowledgement, language access, or environmental preferences.The behavioral outputs will depend on decreasing degree of friction, presented benefits, and immediate and responsive feedback, which will ultimately promote sustained integration or dis adoption. At the narrative level, when the recommendations made are relevant to a learner's everyday life, and emerge from a demonstrated trustworthiness, then the outcomes will be positively directed change when they are easy and provide benefits; this is otherwise relevant or worse, disuse.

This practice model provides actionable recommendations to campus administrators: make it fit routine, provide clear sources, and provide rapid feedback loops to increase adoption. The last step is to have authentic consent and equitable options if you are to keep this educational practice model legitimate. One participant summed it most effectively when they said, "Help me help you, make it easy, show me it works, and I will stick with it." Future research could iteratively test this educational practice model in diverse sustainable contexts to refine clarity around human artificial intelligence interactions for sustainability efforts.

Conceptual Framework: Students' Engagement with AI Enabled Campus Sustainability Systems

The adoption of AI enabled sustainability tools for Hungarian university students is a multiple step process—sensemaking first, trust second, and then behavioral consequences last. The independent variables IV describe how students understand, interpret, and make sense of the tools in their lived experience. The mediators illustrate how many layers of trust there are. The dependent variables DV illustrate the end state of behavioral change or disengagement. Contextual moderators describe the relationship between the components while allowing students to individualize their presence and experience given that students may approach all components differently.

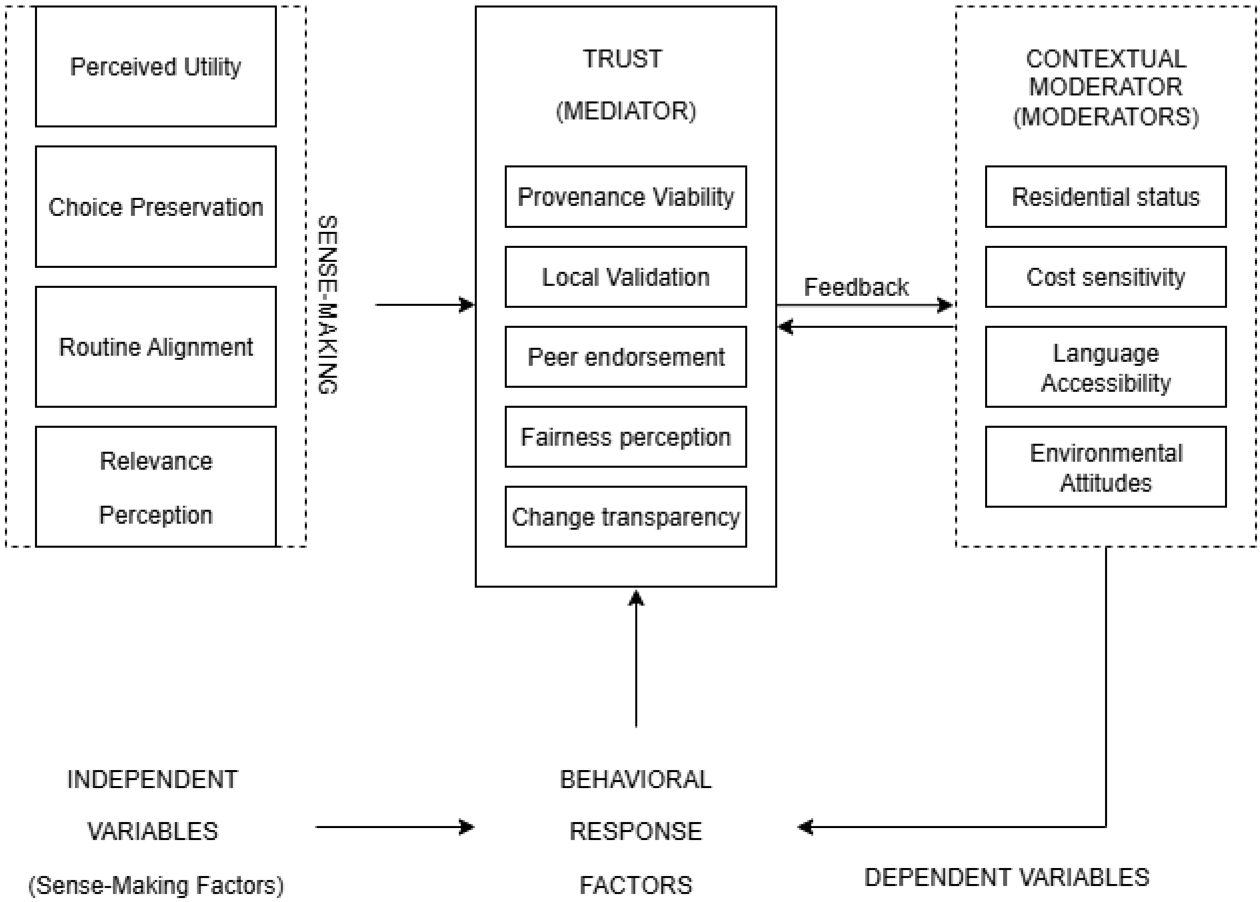

Figure 1: Students' Engagement with AI Enabled Campus Sustainability Systems

The diagram titled "Students' Engagement with AI Enabled Campus Sustainability Systems" offers a straightforward visual to understand how Hungarian university students interact with technology designed to enhance campus sustainability, such as apps for predicting canteen crowds, planning travel routes, and tracking energy use in buildings. It's broken into three key parts that flow together, with some additional factors that shape the process. On the left, the "Sense Making Factors" box lists students' initial thoughts, including whether the tools save time (Perceived Utility), keep their favorite choices available (Choice Preservation), fit their daily routines like weather aware routes (Routine Alignment), and feel relevant rather than confusing (Relevance Perception). These first impressions kick things off. In the middle, the "Trust" box acts as a bridge, showing how trust builds through clear info sources (Provenance Visibility), real life proof (Local Validation), friend endorsements (Peer Endorsement), fair design for budgets and languages (Fairness Perception), and honest updates (Change Transparency). This trust then leads to the "Behavioral Response Factors" at the bottom, where students use the tools if they're easy (Friction Reduction), show quick wins like shorter lines (Immediate Payoff), and respond to feedback fast (Feedback Responsiveness).

The arrows connect these stages, with a feedback connection from behavior back to trust, where the positive encounters increase trust and negative encounters decrease trust. To the right is a "Contextual Moderator" box with factors related to campus living and commuting (Residential Status), financial constraints (Cost Sensitivity), language needs (Language Accessibility), and environmental sensibilities (Environmental Attitudes) that change how the process happens for students. In summary, and together, this map will help campus teams design tools that are congruent with student lives that will help build trust and promote usage with realistic and inclusive approaches.

Implications

The takeaways lead us to a clear and direct conclusion for campus teams: assistive technologies fit with students' lives and trust would follow naturally. Students welcomed systems that provided efficiencies with time savings, let them continue to use their regular choices and provided simple classical instructions on what to do. Canteen forecasting should retain students' cheap staples with peaks and troughs of busy consulting; mobility tools should acknowledge weather and not hide delays; dashboards should take the hard data that deals with buildings and turn it into a simple, local action to a positive outcome fast. Trust built up and through built in and incremental, tangible demonstrations of trust Timestamps and data sources that students could view, owning up to mistakes and making changes within days, and notifications in simple bilingual messaging. Ideally, peer voices (e.g., class representatives, student union representatives) will help more forward in messaging than generic emails.

Campus governance and operations need to work together on this. Treat consent and feedback as key features—check in with students when new features are added and provide an easy, visible way for them to report issues and see results. Assign specific people to own each system so fixes happen quickly and updates reach students where they use the tools, not hidden on a website. Track how many students adopt the tools and how satisfied they are, alongside metrics like waste or energy use—what gets measured gets looked after.

When buying or managing these tools, prioritize clear requirements like "show where info comes from at a glance," bilingual options, and responses within a week. Choose tools that blend into existing student apps to reduce hassle and test them with students beforehand through co design sessions to match campus life before launching widely.

Limitations

This study relied on interviews and focus groups with 32 students from various Hungarian universities. While the group includes diverse disciplines, housing situations, and backgrounds, it's not big enough to generalize to everyone. Smaller schools or vocational colleges might have different views, and we didn't include staff perspectives. The stories students shared were based on memory and self-reporting, so some details might be skewed by how they wanted to sound or what they remembered. We captured just one term, so we couldn't see how trust or use might shift over a longer time or with seasonal changes. Also, we focused on three specific tools—canteen forecasting, mobility apps, and sustainability dashboards—leaving out others like dorm energy controls or waste sorting tech that came up but weren't explored deeply. As we rely on self-reported behavior, we may underestimate the unobserved or unconscious influences on the use of our tools. Furthermore, most of the year will have systematic seasonal variation, particularly for the mobility (weather), and energy (heating/cooling cycles) tools, which means a single term window cannot possibly capture all the seasonal factors affecting usage.

Future Directions

To advance the understanding of student engagement with campus sustainability systems, future research should adopt a mixed methods approach to rigorously test and refine the proposed framework. Initially, qualitative follow up interviews with a broader sample of students could deepen insights into evolving perceptions, complemented by a structured survey targeting key constructs—perceived utility, transparency, fairness, and ease of use. This survey should be designed to assess predictive relationships with long term adoption rates, with stratified analyses comparing dormitory residents and commuters. Where ethical consent is obtained, integrating anonymized usage data with survey responses would enable a robust comparison of self-reported behaviors against actual system interactions, enhancing the validity of findings.

Experimental field studies are recommended to evaluate practical interventions tailored to student contexts. Within canteen contexts, there can be randomized controlled trials that would compare the healthiness of modifying communication approaches, either using visual instructions to inform students for off-peak times or communicating healthiness using arguments that explain the menu changes. The outcome measures could be queue times, sales distribution, and student satisfaction (e.g., surveys) before and after an intervention. For mobility tools, similar A/B comparison tests could be accomplished in different weather scenarios. A typical user could receive a neutral travel suggestion OR an eco-alternative. Route selection and feedback measures would also be considered. For sustainability dashboards: longitudinal experimentation methods would compare prompts for behavior change with raw data visualizations, with outcomes of behavior change (e.g., laundry logging after 8pm, or remembering to switch off a device) tracked over a period of weeks. We would incorporate self-report measures and automated logging as available for outcomes.

Exploring trust repair dynamics provides exciting prospects. Longitudinal case studies could track participants' use of a new system and how initial failures could be addressed through clear expressions of regret and taking corrective action, employing a mixed methods approach (e.g. interviews, sentiment analysis of participant feedback) to identify triggers for participants beyond which repair will be difficult. A participatory design approach should also clearly involve groups historically marginalized in design processes, such as students taking a class at a university, those who are nonnative speakers of English, students living on a budget, and/or students with dietary restrictions or needs, to better assess language accessibility, price point, and availability of options, while co developing educational content that iteratively uses participants' input to shift the system defaults.

In conclusion, to further increase generalizability, work needs to be conducted at other campuses in Central and Eastern Europe, that have different institutional context and technologies, for example, energy management for dormitory buildings, smart bins for waste. There might be a variety of contexts showing variation but still meet evaluation criteria, is the system incorporated into everyday practice, it is easy to articulate, it offers resonance for student voice? Positive evidence might be demonstrated of the framework's capacity to uncover scalable behavior change and lead the way to the investment in participatory, context sensitive sustainability projects.

5.Conclusion

Students judged these campus tools through a practical lens: they saw value when the tools saved time and kept choices fair, felt risky when they took control or added hassle, and ignored them when the language was too abstract. Trust came from clear explanations, local proof, and fast, honest fixes—often boosted by peers and bilingual support. They changed their habits when the tools made things easy and showed quick wins, but stopped if they required extra effort, ignored feedback, or quietly limited options. The message is simple: make the greener choice the easiest one, be open about how it works, and respond quickly when students chime in. When students feel respected, as users, payers, and partners, these tools become part of their routine, not just another screen to ignore.

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