Improving Acceptability of Energy Efficiency Recommender Systems Through HCI Design

Hayet Hammami and Yacine Ghamri-Doudane
L3I Lab
University of La Rochelle
La Rochelle, France
e-mail: {hayet.hammami | yacine.ghamri}@univ-lr.fr

***Abstract*—Energy efficiency recommender systems are increasingly introduced in workplace environments, yet their adoption remains challenging due to acceptability issues, such as lack of trust, intrusiveness, and limited user control. While Human-Computer Interaction (HCI) design principles for recommender systems are well established, their application in shared professional contexts remains underexplored. This paper reports an empirical investigation through two successive studies: (1) an exploratory co-design workshop with corporate employees, and (2) a two-phase evaluation in a university setting, including an acceptability study using medium-fidelity and video prototypes followed by a hands-on evaluation of a functional mobile application (SmartLR). Across these studies, we examine how HCI design elements, such as notification strategies, transparency mechanisms, and personalization features, shape user trust, perceived control, and short-term acceptability in professional settings. The results highlight recurring design trade-offs related to notification intrusiveness, automation, transparency, and cognitive load. Based on these findings, we propose five practical HCI design guidelines for energy-efficiency recommender systems in workplace environments.**

Keywords-HCI design; Recommender Systems; Energy Efficiency; Workplace Environments; User Centered Design; User Acceptability.

I. INTRODUCTION

Recommender Systems (RSs) are increasingly used to support energy efficiency in buildings and workplace environments by providing occupants with personalized recommendations based on sensor data and contextual information [1][2]. Unlike consumer-facing recommender systems, workplace energy RSs primarily operate in shared spaces, rely on continuous environmental sensing, and often offer limited direct personal benefit to individual users. Beyond algorithmic accuracy, adoption also depends on user acceptability, trust, and perceived disruption to everyday work activities.

Prior research in Human-Computer Interaction (HCI) has identified several factors that influence the acceptability and use of recommender systems, including perceived usefulness, ease of use, transparency, and user control [3]–[5]. These dimensions have been widely studied in domains such as e-commerce, media recommendation, and smart home systems [6]–[8]. However, their applicability to workplace energy recommender systems remains insufficiently understood. In professional contexts, users must reconcile energy-saving recommendations with productivity demands, privacy concerns related to environmental sensing, and the collective nature of decision-making in shared spaces, which fundamentally shapes system acceptability [9][10]. Indeed, most existing work on energy-related recommender systems has focused on algorithmic approaches, system architectures, or quantified energy savings [11]–[13]. While some studies examine user engagement and feedback mechanisms [14][15], fewer investigate how concrete interface design choices influence acceptability during early and medium-term adoption phases, particularly as systems evolve from conceptual prototypes to deployed applications. Understanding how user perceptions change across increasing levels of system fidelity is therefore critical for designing recommender systems that can be meaningfully integrated into workplace environments.

This paper presents an empirical investigation of a workplace energy efficiency recommender system conducted through two successive studies. First, an exploratory co-design workshop to surface user expectations, concerns, and perceived adoption barriers. Second, a two-phase study: the first phase employed medium-fidelity and video-based prototypes to examine initial reactions to alternative interface designs following comparative evaluation approaches [16][17]. The second phase examined user experience with a functional mobile application in a workplace setting, focusing on usability, trust, and perceived effort.

Rather than proposing novel interaction techniques, in this work we synthesize five design guidelines grounded in our findings in a setting where recommender systems are often ignored. Our findings reveal recurring design trade-offs specific to workplace environments, such as balancing notification intrusiveness with awareness, automation with perceived user control, and transparency with cognitive load. By articulating these tensions, the paper provides practical insights for researchers and practitioners designing recommender systems in organizational contexts, particularly those addressing sustainability goals.

This paper is structured as follows: Section II reviews related work on HCI design principles and recommender systems. Sections III, III-C, and III-D present our empirical investigation, results and discussion. Finally, Section IV concludes with a summary of contributions and defined limitations of our work.

II. Related Work

In this section, we review related work on HCI design in recommender systems, with a focus on energy efficiency RSs. We structure the review in two parts: (1) a general overview of recommender systems; and (2) HCI design in recommender systems, which are central to our case study. We synthesize gaps, and position our work within the intersection of these two domains.

A. Overview of Energy Efficiency Recommender Systems

According to [2], Recommender Systems (RSs) are *classified as information systems that primarily focus on information retrieval tasks*. They are initially designed for content personalization based on explicit or implicit user preferences. RSs for energy management have emerged as a critical domain, especially in the context of smart buildings [2][11][13]. These systems typically leverage Internet of Things (IoT) sensor networks to monitor environmental conditions (temperature, humidity, occupancy, lighting), analyze user behavior and occupancy patterns, and generate recommendations for energy-saving actions [18]. For example, such systems may recommend opening a window when humidity becomes too high, turning off lights in unoccupied rooms, adjusting blinds according to sunlight, or modifying heating and cooling settings when temperature exceeds comfort thresholds. While much of the literature focuses on the functioning and algorithmic performance of RSs, comparatively little attention has been paid to their interface design. Indeed, HCI considerations remain secondary in this literature, most studies focus on prediction accuracy, optimization efficiency, or energy outcomes, with interface design treated as an implementation detail rather than a research variable.

In this work, our focus lies on the HCI aspect, specifically, how HCI design influences trust, acceptability and acceptance of these systems, key factors of their adoption and success. A comprehensive taxonomy of energy saving RSs can be found in [2]. This gap persists in recent work, e.g., while DigiGuide [19], and the user-centered recommendation system based on a Pareto-efficient optimization algorithm presented by Cipollone et all. [20] represent technical sophistication, neither reports on user interface design, usability testing, or acceptability factors.

B. HCI Design in Recommender Systems

Because RSs are largely unidirectional delivering recommendations rather than soliciting input, user interaction is often limited. As a result, maintaining engagement and fostering trust requires thoughtful interface design. In this context, different researchers explored how reflective interfaces can influence user behavior in energy consumption contexts [9][21]. Different factors influencing user's acceptability and acceptance have been examined, including perceived usefulness, ease of use, trust, and social influence. Each of these can be shaped through HCI strategies. For example, T. Schwartz et al. demonstrate how interfaces that encourage users to reflect on their personal data can lead to more conscious and sustainable energy use [10]. Their findings highlight the importance of providing users with meaningful feedback and actionable insights. Indeed, users are more receptive when systems provide data that encourages reflection. The impact of interface design is further supported by Swearingen and Sinha, who show that navigation and layout significantly influence user satisfaction, more so than aesthetics or algorithm quality [6]. Hammami et al. reach similar conclusions in HCI evaluation studies, reinforcing the need to prioritize interface clarity over aesthetics [17]. Tintarev et al. emphasize the importance of explanation and transparency in RSs [8]. Their work shows that users are more likely to trust and follow recommendations when they are provided with clear, contextualized justifications. Similarly, Falconnet et al. [22] investigate how message framing affects user beliefs, system attitudes, and behavioral intention, demonstrating that well-framed and justified messages enhance engagement and decision making speed. Indeed, tailored messaging within RSs can significantly enhance user engagement and satisfaction. This study demonstrates the critical role of transparent and contextually appropriate communication in improving user experience. In a broader HCI perspective, Wang et al. [23] use the UTAUT model to analyze acceptance factors such as performance expectancy, effort expectancy, and social influence. They underline the importance of contextual adaptation and community perception in fostering adoption, while also highlighting the need for further research into how specific HCI elements affect these variables.

Finally, HCI for sustainability (also called Sustainable HCI) has long investigated how interface design can promote pro-environmental behavior [14]. Sustainable HCI has produced extensive knowledge on eco-feedback, but workplace energy recommender systems, which combine recommendation algorithms with feedback interfaces, remains underexplored. Empirical studies of deployed systems in shared professional environments are a few. Our work responds to this gap by exploring the HCI design of energy efficiency focused RSs in workplace environments.

1) HCI and Trust in Recommender Systems: Trust is a well-established determinant of recommender system success [9]. Research has identified multiple trust antecedents: transparency and explainability (users trust systems when they understand recommendation rationale) [8]; perceived competence (recommendation accuracy and relevance) [24]; privacy assurance (clear data handling policies); and user control (ability to override or customize) [7]. Explainability must be personalized and context-adaptive. Chromik and Butz [25] articulate design principles for explainable user interfaces (XIA), emphasizing adaptation to users' evolving cognitive states and expertise levels. However, these advances remain concentrated in domains such as e-commerce, healthcare, and generic AI decision-making; application to energy efficiency or workplace sustainability contexts is minimal. Little work examines how transparency, control, and privacy perceptions operate in shared workplace environments where users receive recommendations but derive no direct personal benefit.

2) Workplace Specific HCI Challenges: Workplace environments impose distinct HCI challenges for recommender system adoption [26][27]. Most relevant challenge is notification fatigue, recent work on novel notification modalities (e.g., pneumatic shape-changing smartwatch backs) demonstrates efforts to combat alert fatigue, but remains in early prototyping stages and untested in workplace contexts. Also, privacy and surveillance sensitivity is a very important challenge. In shared spaces, users are acutely aware of data collection and monitoring [7]. Unlike e-commerce where data sharing is implicitly traded for personalization, workplace sensing raises concerns about performance evaluation and autonomy infringement. These concerns are amplified when occupants are passive data providers rather than active participants in system governance [3]. While workplace HCI challenges are increasingly recognized, e.g., new ISO standards [28] and Industry 5.0 frameworks [29], empirical research validating design solutions through deployed systems and standardized evaluation frameworks is lacking.

To summarize, while RSs for energy efficiency have made significant progress, their success depends heavily on HCI design. Despite considerable advances, several critical gaps remain in the literature. First, while algorithmic performance has been extensively studied, the impact of specific HCI design elements on long-term acceptability and engagement is less understood, particularly in workplace contexts where motivations differ from consumer applications. Second, though the benefits of transparency and explanation have been established, optimal approaches for delivering this information remain unclear. Our study builds on this literature by examining how HCI design choices could impact acceptability and acceptance of RSs in workplace environments.

III. Empirical Investigation

Building on the research gaps identified in the literature, this section presents our empirical studies conducted across two workplace environments. Our studies directly address the need to better understand how specific HCI design elements influence user acceptability and engagement with energy efficiency recommender systems. In particular, we explore how interface design, notification strategies, and interaction patterns shape users' willingness to accept and adopt such systems in professional contexts.

Our research was conducted as part of two ongoing projects with similar goals but distinct implementation contexts: BuildOn and Smart Campus, presented below. The first study, exploratory in nature, was conducted in a corporate setting through the BuildOn project [30] using a co-design focus group approach. The second study took place in our university through the Smart Campus project [31] , involving iterative user-centered design and evaluation of a functional mobile recommender system. Together, these studies offer comprehensive insights into user expectations, interaction patterns, and trust factors that shape system acceptability and engagement across different professional environments.

TABLE I. Overview of the empirical studies and project phases

Study	Project	Purpose
Study #1	BuildOn	Exploratory co-design workshop to identify user expectations, preferences, and adoption barriers.
Study #2	Smart Campus - Phase 1	Acceptability evaluation using medium-fidelity and video prototypes.
Study #2	Smart Campus - Phase 2	Hands-on evaluation of the functional SmartLR mobile application.

We structure this section as follows: subsection III-A presents the first study, subsections III-B, III-C, and III-D present the SmartLR system used in the Smart Campus project and the two studies related to this project.

A. Study #1: Co-Design Focus Group (BuildOn Project)

To ground our research in real user needs, we conducted an exploratory study as part of an ongoing European project (BuildOn), which aims to design recommender systems for indoor environmental quality optimization in office buildings. This initial study employed a co-design approach involving employees from a corporate office environment (EDF R&D Paris) to understand user expectations and concerns before developing functional prototypes.

1) Methodology and Participants: The co-design focus group involved 12 occupants of the EDF R&D office building in Paris, including engineers, researchers, and project managers. An open invitation email was distributed to employees working in the building, and the 12 participants who volunteered to take part were included in the workshop. No participant selection or sampling procedure was applied as the objective was to capture diverse workplace perspectives related to comfort, energy use, and daily interaction practices in office environments. Participation was unpaid and based entirely on voluntary involvement.

The workshop was facilitated by the author as part of the BuildOn research project. Before the session, an EDF R&D executive introduced the BuildOn project objectives and remained present during the workshop. The co-design activities were then moderated by the author, who guided discussions, asked follow-up questions to better understand participants' design choices and reasoning, and coordinated the different collaborative activities.

The session followed a structured co-design and design thinking format lasting approximately three hours. Activities included presentation of usage scenarios, collaborative brainstorming, group discussions, and interaction blueprinting exercises centered on future energy recommendation services. Participants worked in small groups to propose interface ideas, discuss positive and negative aspects of potential solutions, and present their final concepts to the other participants. The workshop relied on presentation slides, whiteboards, handwritten notes, and participant-generated mockups.

Qualitative data collection combined direct observation, handwritten notes, photographs of participant-produced mockups and collaborative boards, and spontaneous verbal feedback shared during discussions and presentations. During group presentations, participants explained and justified their proposed interaction designs, while the author documented recurring concerns, expectations, and design rationales.

Qualitative feedback was analyzed using an exploratory thematic approach. Notes, participant comments, and workshop artifacts were reviewed iteratively to identify recurring expectations, usability concerns, interaction preferences, and perceived adoption barriers. Emerging observations were progressively grouped into broader themes related to system acceptability, user control, personalization, and communication preferences. This exploratory analysis aimed to identify key interaction principles and acceptance factors to guide subsequent design phases of the recommender system.

2) Key Findings: Workshop notes and participant discussions were systematically documented and then analyzed using an exploratory thematic approach to identify recurring expectations, preferences, and adoption concerns related to workplace energy recommender systems. Several recurring themes emerged from participant feedback, which fell into two main categories: essential features for acceptability ("must have") and potential adoption barriers ("must avoid").

a) Essential Features:

- **Personalization:** Ability to customize thresholds based on personal comfort preferences.
- **Contextual Information:** Connection with external weather conditions and forecasts.
- **Positive Reinforcement:** Messages that congratulate users for energy-friendly behaviors, periodic challenges, or gamified comparisons between offices.
- **Advisory Tone:** Recommendations framed as suggestions rather than commands.
- **Comparative Feedback:** Options to compare performance with others or against historical data.
- **Bi-directional Communication:** Ability to report discomfort or override recommendations.

b) Adoption Barriers:

- **Mobile Notifications:** Users strongly rejected smartphone alerts, anticipating they would be quickly ignored or disabled.
- **Lack of Control:** Systems that offer recommendations without allowing user adjustments.
- **Absence of Visual Signals:** Participants preferred ambient visual indicators (such as LED-based signals) over text-only interfaces or push notifications.

Participants also emphasized the importance of bi-directionality in interactions. Being able to report discomfort, signal absences, or override incorrect recommendations when context is missing (e.g., "*I am feeling cold despite the system saying the temperature is optimal*") was seen as essential for maintaining a sense of agency. These insights underline a recurring tension in workplace recommender systems: users may accept passive systems only if they retain control and can understand or challenge the system's reasoning.

In summary, this initial study highlighted interaction principles essential for designing acceptable recommender systems in workplace environments. It confirmed that transparency, personalization, and perceived control are critical to foster trust and engagement.

B. The Smart Campus Project

Smart Campus is an ongoing initiative on our university campus aiming to reduce energy consumption through context-aware, sensor-driven recommendations delivered to building occupants via a mobile application (named SmartLR). The SmartLR system continuously monitors indoor conditions using IoT sensors installed in staff offices and shared spaces. These sensors collect real-time data on temperature, humidity, presence, and lighting, which are processed to generate energy-saving recommendations. The system targets a wide range of university users—including faculty, administrative staff, and PhD students—encouraging behavior change without disrupting daily routines.

We conducted a two-phase study within this project to investigate how different HCI design elements influence users' willingness to engage with such a system. To ensure a user-centered approach, we adopted an iterative evaluation process spanning two complementary phases:

- **Phase 1 – Early acceptability evaluation:** Participants were introduced to the system through medium-fidelity prototypes and video scenarios. We aimed to explore their initial reactions, concerns, and expectations, and to identify HCI elements likely to affect acceptability (e.g., interface clarity, feedback granularity, perceived control, notification strategies).
- **Phase 2 – Acceptance evaluation:** Based on Phase 1 findings, we developed a functional mobile application and tested it with a new group of participants. This phase focused on real-time interaction, mobile usability, and the role of trust and personalization in shaping user engagement and long-term adoption.

Both studies were conducted on campus and involved 32 participants in total (15 for the first study and 17 on the second study), covering a diversity of roles in the university. The next two sections detail the methodology and findings from each study.

C. Study #2 - Phase #1: Early Acceptability Evaluation

This study evaluates the acceptability of our recommender system (SmartLR) prior to deploying the full app. We focused on how different HCI design approaches influence user perceptions and willingness to engage with energy-saving recommendations in workplace settings. By examining initial reactions to different interface designs, we aimed to identify key factors that enhance or inhibit system acceptability.

1) Protocol: The evaluation session began with a brief introduction to SmartLR, explaining its functionality, the role of IoT sensors installed throughout university facilities, and its mobile application as the primary interface for user interaction. This introduction aimed to familiarize participants with how the mobile app delivers energy-saving recommendations, and its intended benefits.

Participants were presented with three different prototype designs of the mobile application, each illustrating a unique design approach. Following this, they viewed two short video demonstrations simulating real-world interactions with the system. These videos highlighted typical user interactions, showcasing how SmartLR offers recommendations and how users respond to notifications for energy-saving actions through their smartphones. This experimental approach builds on prior HCI evaluation research, which supports the use of multiple design alternatives and video-based evaluation to enhance feedback quality and user engagement. Research has shown that *"testing many is better than testing one"*, as comparative evaluations help users express their preferences and usability concerns more effectively [16][17]. Moreover, using video alongside paper prototypes, as noted by Hammami et al. [32], allows participants to visualize system interactions more clearly, leading to more detailed feedback.

2) Participants: We recruited 15 voluntary participants through internal laboratory messaging and direct email invitations sent to colleagues and administrative staff within the university. No compensation was provided. Participants were drawn from diverse professional backgrounds, including researchers (PhD students, postdocs, and research engineers) and administrative staff. While demographic data such as age were not collected, the participant pool ensured representation across different roles within the university.

3) Prototype Elaboration: To evaluate the impact of different HCI design elements, we developed different design prototypes of the SmartLR mobile application. These prototypes were designed to explore variations in interface layout, interaction flow, and visual hierarchy.

a) Paper Prototype: The paper prototypes were medium-fidelity mockups created in Figma and printed for the session. We created three different interface designs of the mobile application, each with a distinct layout while maintaining the same core functionalities. The three prototype designs are presented in Figure 1.

The design prototypes included key system features: weather information to contextualize recommendations; room identification; room status displaying sensor readings for temperature, humidity, and lighting conditions; and a menu icon providing access to additional system functions (contents not detailed at this stage).

Each prototype contained two different UIs, representing two distinct system states: normal and alert. The normal state shows the system's standard operation when environmental conditions are stable: temperature and humidity within optimal ranges, and lighting conditions aligned with occupancy. The alert state is triggered when conditions deviate from optimal

Figure 1. Three alternative interface designs tested for SmartLR in the first phase of Study #2

ranges, such as excessive temperature/humidity or lights left on in unoccupied rooms, prompting corrective action recommendations.

b) Video Prototype: In addition to the paper prototypes, we created two short video simulations to demonstrate user interaction with SmartLR using the mobile application. The first video lasted 52 seconds, while the second lasted 1 minute and 20 seconds. Each scenario illustrated a different context in which SmartLR provides recommendations and how users respond to system notifications through their mobile phone.

*c) **Scenario 1: High Humidity Alert**:* In the first scenario, a person works in their office with the blinds open, door and windows closed, and the light on, maintaining an ideal temperature. They receive a notification on their phone that the room's humidity is high and a prompt is given to ventilate it. The individual then opens the windows and the door to ventilate the space, following the system's recommendation, and later resumes work. After a short while, they recheck the humidity status on their phone using the application.

*d) **Scenario 2: Unnecessary Lighting**:* The second scenario depicts a person working in their office under normal conditions: blinds open, door and windows closed, and light on. Upon preparing to leave, the individual turns off their computer, gathers their belongings, and exits the office forgetting light on. After leaving, they receive a phone notification advising them to turn off the light to conserve energy. This scenario emphasizes the system's ability to prompt users to save energy even if they forget to perform actions themselves.

The combination of paper and video prototypes allowed participants to evaluate both static interface designs and interactive system behavior, ensuring a comprehensive assessment of usability, clarity, and effectiveness in real-world contexts.

4) Data Collection: To collect user feedback, we employed two complementary methods: semi-structured interviews and a questionnaire based evaluation. Initially, participants engaged in an interactive feedback session (the interview). We used a whiteboard to visually categorize feedback into three columns: *Likes*, *Dislikes*, and *Suggestions*. Participants shared their thoughts directly on the whiteboard using pens or post-it notes. This method captured both qualitative and quantitative feedback, providing diverse insights into user preferences and responses. To enhance feedback depth, we asked participants to think aloud during the evaluation, capturing real-time reactions. Sessions were audio recorded to ensure comprehensive documentation of all feedback.

After the interview, participants completed a structured questionnaire based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model [4]. To clarify the relationship between the questionnaire and our research questions, the questionnaire items were grouped into four constructs derived from the UTAUT model. Items related to perceived usefulness of SmartLR for supporting energy efficiency and workplace comfort were associated with Performance Expectancy (RQ1). Items related to ease of use, clarity of interaction, and usability were associated with Effort Expectancy (RQ2). Items reflecting the perceived influence of colleagues and the organizational context were associated with Social Influence (RQ3). Items related to confidence in the system's recommendations and data handling were associated with Trust (RQ4). In addition, separate items captured usage intention and overall evaluation of the application.

Qualitative feedback collected during these individual sessions was analyzed using an exploratory thematic approach. Feedback from think-aloud observations, interview responses, and whiteboard annotations was reviewed and grouped into recurring themes related to usefulness, usability, aesthetics, and privacy concerns.

5) Research Questions: Our study explores how different HCI design elements influence user experience with the SmartLR mobile application. We explored four specific Research Questions:

- **RQ1 (Performance Expectancy):** Users who perceive the system as beneficial for their work and energy efficiency will be more likely to adopt it.
- **RQ2 (Effort Expectancy):** Users who find the system easy to use will be more likely to adopt it.
- **RQ3 (Social Influence):** Users who perceive a positive social climate around SmartLR will be more likely to integrate it into their routines.
- **RQ4 (Trust):** Users who trust the system's accuracy, privacy, and reliability will be more likely to adopt it.

6) Results:

a) Qualitative Results: We collected 149 feedback during interviews: 63 Likes (42%), 22 Dislikes (15%), and 64 Suggestions (43%). The high proportion of suggestions indicates constructive engagement, with users actively contributing to system improvement rather than merely criticizing existing features.

Feedback was categorized into four dimensions:

- **Utility:** 85 comments (57%) – Users appreciated the ecological focus and real-time environmental measurements. Suggestions focused on personalization (customizable thresholds) and visualization of environmental impact.
- **Usability:** 37 comments (25%) – Concerns emerged regarding notification frequency, with users expressing preference for non-intrusive alerts that would not disrupt work.
- **Aesthetics:** 19 comments (13%) – Minor feedback on visual design elements.
- **Privacy and Security:** 8 comments (5%) – Exclusively categorized as Dislikes or Suggestions, indicating potential trust barriers. Users raised questions about data storage duration, location, and access permissions.

Users expressed strong interest in gamification elements (badges, weekly reports, office competitions) to make energy-saving behaviors more tangible and engaging. This aligns with research by Mendez et al. [15] and Chatzigeorgiou et al. [14], which demonstrates how gamification strategies promote long-term engagement with energy-saving systems.

Notably, participants did not express strong preferences for any single interface design among the three prototypes. Instead, they identified useful or problematic elements across all versions, providing valuable guidance for our final design decisions.

b) Quantitative Analysis: The questionnaire contained 16 items rated on a 5-point Likert scale from "Strongly Disagree" (1) to "Strongly Agree" (5). We analyzed participants' responses by calculating mean scores for each construct and interpreting them with respect to the corresponding Research Questions:

- **Performance Expectancy (RQ1):** 4.0 – Users recognized the system's potential benefits for energy efficiency.
- **Effort Expectancy (RQ2):** 4.4 – Perceived ease of use was rated highest.
- **Social Influence (RQ3):** 3.4 – Workplace norms showed limited influence on adoption intention.
- **Trust (RQ4):** 3.8 – Moderate confidence in data handling and recommendation accuracy.
- **Usage Intention:** 3.9 – Positive willingness to adopt the system.
- **Overall Application Evaluation:** 4.2 – Generally positive perceptions.

These findings suggest that perceived usefulness (RQ1), ease of use (RQ2), and trust (RQ4) were all positively perceived by participants and may play an important role in shaping acceptance of the system.

7) Discussion: This study provides critical insights into factors influencing early acceptability of energy efficiency recommender systems in workplace environments. Key implications for the interface design in such systems include:

1) **Prioritize intuitive, low cognitive load interfaces:** The high Effort Expectancy score (4.4) suggests that usability

is an important factor, though not sufficient alone to guarantee adoption.

2) **Implement transparent data handling practices:** Privacy concerns, while representing only 5% of feedback, were exclusively negative, indicating that clear explanations and GDPR compliance are necessary to maintain trust.
3) **Demonstrate concrete benefits through visualization:** Users requested features showing energy savings and environmental impact, confirming that tangible feedback motivates sustained engagement.
4) **Balance notification frequency:** Concerns about disruptive alerts underscore the need for well-timed, non intrusive notifications in workplace contexts.
5) **Offer personalization options:** The strong demand for customizable thresholds and display preferences reinforces that perceived control is critical for user acceptance.

D. Study #2 - Phase #2: Acceptance Evaluation

Building on insights from phase 1, we developed a fully functional version of SmartLR to conduct a hands-on evaluation of the system in a controlled workplace-like setting. This second phase shifted from hypothetical scenarios toward direct interaction with a working application, allowing us to examine how the HCI design principles identified during the acceptability evaluation influenced usability, trust, perceived effort, and user engagement during realistic usage situations. While phase 1 focused on anticipated acceptability based on prototypes, phase 2 explored user experience through supervised interaction with the functional application.

1) Protocol: User tests were conducted using a fully functional mobile application on a provided Android smartphone. The session began with a brief introduction to SmartLR, after which participants were given time to freely explore the application's features and interface. During this exploration period, we simulated environmental changes to trigger alert conditions, generating notifications that participants could respond to in real time. This controlled evaluation approach allowed us to observe reactions to system alerts and assess how intuitively users navigated the interface when prompted to take action. Although the evaluation took place in a supervised setting, the interaction scenarios were designed to reproduce realistic workplace situations, with participants seated at office desks while interacting with the system. The main SmartLR application interfaces used during testing are shown in Figures 2, 3, and 4. The home screen features several key elements: Current weather conditions displayed prominently. University branding for institutional context. Profile access for personalization. Real-time sensor readings (temperature, humidity, presence, lighting). Alert indicators when measurements exceed thresholds. And navigation menu for accessing additional features.

Based on phase 1 of the study, we implemented several enhancements:

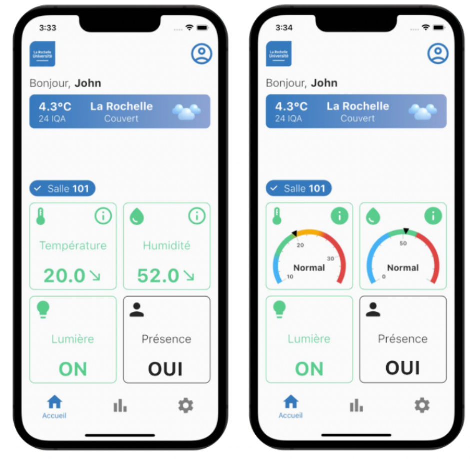

Figure 2. SmartLR home screen showing normal conditions with sensor readings

Figure 3. SmartLR home screen with alert notification for high humidity

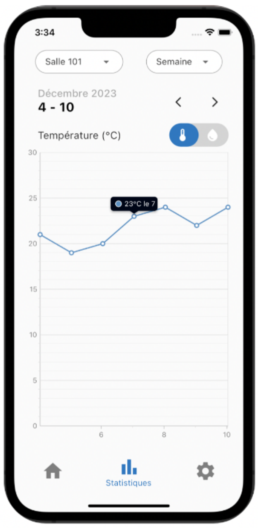

Figure 4. SmartLR statistics page displaying historical environmental data

- **Dynamic indicators** showing temperature and humidity trends (increasing, stable, and decreasing arrows), providing users with proactive awareness of changing conditions. These visual cues allow users to anticipate changes and take preventive actions, such as opening a window or adjusting heating, before reaching critical thresholds.
- **Visual gauges** indicating "normal" ranges for environmental measurements, making it easier for users to interpret data at a glance, a feature particularly appreciated for humidity levels.
- A dedicated **statistics page** (see figure 4) offering historical measurement data organized chronologically, enabling users to track patterns over time and better understand environmental fluctuations.
- **Enhanced privacy protection** through comprehensive GDPR compliance documentation, developed in collaboration with the university's specialized legal services. This included the integration of a formal data protection charter within the application, directly addressing privacy concerns raised during Study #1.

These design decisions directly addressed feedback from the first evaluation, particularly the desire for more personalization options, clearer visualization of environmental data, and transparent privacy controls. The interface prioritized intuitive navigation and minimal cognitive load while providing the detailed information users requested.

2) Participants: We recruited 17 voluntary participants from the same university population as Phase 1 through internal laboratory messaging and direct email invitations sent to colleagues and administrative staff. No compensation was provided. Participants came from similar profiles, including researchers, faculty members, and administrative staff.

3) Data Collection: As in phase 1, we employed a mixed-methods approach combining qualitative feedback through interactive sessions and quantitative assessment through a standardized questionnaire. During the interview, we asked participants to categorize their feedback as likes, dislikes, or suggestions, providing consistent comparison with our first study results.

The questionnaire was modified slightly from Study #1 to include additional items related to expected effort and expanded questions about design aesthetics and privacy perceptions. These additions were motivated by a specific focus on how interface design influences perceived effort and usability. The revised questionnaire maintained the 5-point Likert scale structure from the previous study.

As in phase 1, qualitative feedback collected during these individual sessions was analyzed using an exploratory thematic approach. Participant comments and suggestions were reviewed and grouped into recurring themes related to utility, usability, aesthetics, and personalization.

4) Results:

a) Interactive Feedback Analysis.: We collected 132 feedback which we categorized and quantified. The distribution showed 32% Likes, 30% Dislikes, and 38% Suggestions. Compared to phase 1, we observed a relative increase in Dislikes (from 15% to 30%) and a decrease in Likes (from 42% to 32%). This shift likely reflects the transition from conceptual evaluation to practical usage, where users encountered actual limitations rather than hypothetical capabilities.

We further classified feedback based on the system aspects users commented on most directly. The analysis revealed three main categories:

- **Utility:** 54.3% of feedback. Representative suggestions included adding comparative consumption data between dates, language selection options, and visibility of threshold values on the statistics page. These suggestions reveal users' desire for more personalized and informative features that enhance the practical value of the system.
- **Usability:** 37.4% of feedback. Participants requested highlighting relevant measurements during alerts and praised the overall simplicity and ergonomics of the interface. Comments such as "easy to handle" and "fairly simple and ergonomic" indicate generally positive reception.
- **Aesthetics:** 8.3% of feedback. Only minor comments about color choices, indicating that participants were primarily concerned with functionality and ease of use rather than visual appearance.

A notable pattern in the feedback was the emphasis on personalization. Multiple users requested the ability to customize which measurements appeared on the home screen, highlighting the importance of adaptability in interface design.

b) Questionnaire Analysis.: The questionnaire analysis revealed consistently positive perceptions across all dimensions, with improvements in almost all categories compared to phase 1.

- **Performance Expectancy:** Increased from 4.0 to 4.2, suggesting that hands-on experience with the functional system strengthened users' belief in its utility. This suggests that participants perceived the system as useful and relevant for supporting energy-efficiency practices.
- **Effort Expectancy:** Remained high (4.5 compared to 4.4 in Study #1), confirming that the implemented interface successfully preserved the intuitive usability identified as crucial in our first phase of the study. This result suggests that ease of use was positively perceived and likely contributed to overall system acceptance.
- **Trust:** Showed a slight increase from 3.8 to 4.1, indicating that the privacy controls and transparency features incorporated into the functional application helped address users' data protection concerns.
- **Design:** The addition of a specific Design score (4.5) suggests that visual and interactive elements contributed positively to user satisfaction and perceived usability.
- **Social Influence:** Increased substantially from 3.4 to 3.9, approaching the thresholds of the other factors. This suggests that as users gain concrete experience with energy-saving recommendations, they become more aware of the social and organizational context of their

 ISBN: 978-1-68558-383-5

energy consumption behaviors.

5) Discussion: this second phase of Study #2 provided valuable insights into how users interact with and perceive SmartLR in a functional context, revealing both strengths in our implementation and opportunities for future refinement. The questionnaire results provide encouraging indications regarding the acceptability of the proposed design approach and the relevance of the explored Research Questions. The high Effort Expectancy score (4.5) suggests the importance of usability and interface design in participants' perceptions of the system, demonstrating that our user-friendly interface contributed positively to system acceptability. The increase in Performance Expectancy (4.2) from phase 1 supports RQ1, suggesting that users who recognize the application's practical value may be more willing to adopt it Similarly, improvements in Trust (4.1) and Social Influence (3.9) indicate more positive participant perceptions regarding confidence in the system and its integration within workplace practices.

A recurring theme in user feedback was the desire for personalization. Multiple participants requested the ability to customize displayed measurements on the home screen, highlighting the importance of adaptability in interface design. This preference reveals that even when users appreciate an interface's overall design, they still value the ability to tailor it to their specific needs and preferences.

The functional aspects of the system emerged as particularly crucial to users, with utility related feedback dominating the comments (54.3%). This suggests that while aesthetic considerations contribute to overall satisfaction, the core capabilities and practical benefits remain primary drivers of user engagement. Features that provide tangible evidence of impact, such as comparative energy consumption data, appear especially valuable in reinforcing performance expectations and sustaining motivation.

Based on these findings, we identify several implications for future development:

1) **Enhance personalization options:** Allow users to configure their information displays according to individual preferences and priorities (linked to RQ2).
2) **Provide more concrete visualization of energy savings:** Reinforce performance expectations through tangible evidence of impact (linked to RQ1).
3) **Maintain interface clarity and usability:** Continue to evolve the design while preserving the high standards identified in this study.
4) **Further strengthen trust:** Maintain transparent communication about data handling practices and regular updates on security measures (linked to RQ4).
5) **Develop social features:** Encourage users to share their experiences, leveraging the increased importance of social influence observed in this study (linked to RQ3).

IV. Conclusion and Future Work

This paper investigated how Human-Computer Interaction (HCI) design influences the acceptability of energy-efficiency recommender systems in workplace environments. Through two complementary studies, a co-design workshop in the BuildOn project and a two-phase SmartLR evaluation in the Smart Campus project, we examined how users perceive and react to different interface design choices across early design and hands-on evaluation stages.

The results consistently indicate that short-term acceptability is shaped by perceived usefulness, ease of use, trust, perceived control, and the way recommendations are presented through the interface. In particular, participants responded positively to personalization options, contextualized feedback, and clear interaction mechanisms, while raising concerns about intrusive notifications, insufficient transparency, and limited control over recommendations.

Based on these findings, this work contributes five practical design guidelines for workplace energy-efficiency recommender systems:

1) **Balance notification intrusiveness:** Recommendations should be delivered in ways that support awareness without unnecessarily interrupting work activities.
2) **Enable personalization:** Users should be able to adapt thresholds, displayed information, and notification preferences to their needs and workplace situations.
3) **Provide layered information access:** Interfaces should present essential information first while allowing access to more detailed explanations, sensor values, and historical data when needed.
4) **Visualize impact:** Systems should make the consequences of recommendations more concrete through clear and meaningful feedback on environmental conditions and energy-related effects.
5) **Build trust through transparency:** Interfaces should clearly communicate recommendation logic, privacy-related information, and data-handling practices in order to support user confidence.

Rather than claiming long-term adoption effects, these guidelines should be understood as design recommendations grounded in iterative empirical evaluation of initial user perceptions and reactions. Although these guidelines were derived from the context of energy-efficiency recommender systems, some of the identified HCI considerations, such as transparency, personalization, feedback clarity, and user engagement, may also be relevant to other domains involving persuasive or behavior-change technologies. However, additional studies would be required to validate their applicability beyond the energy domain.

This work has several limitations. First, the studies relied on relatively small participant samples in specific workplace contexts, which limits the generalizability and replicability of the findings. Second, the evaluations primarily captured short-term acceptability and supervised interaction rather than long-term adoption in everyday practice. In particular, the second phase of the SmartLR study involved controlled hands-on sessions with simulated alert conditions rather than a fully naturalistic deployment. Third, the qualitative analyses were exploratory and intended to identify recurring expectations, concerns, and design implications rather than establish predictive or causal relationships.

Future work should extend this research through longitudinal studies in real workplace environments in order to examine sustained use, behavioral change, and long-term acceptance. Additional work is also needed to explore adaptive notification strategies, richer personalization mechanisms, and stronger integration with building management systems. Future investigations could also examine the role of gamification elements, which emerged as a user interest in our studies, while considering the risk of engagement fatigue. Finally, evaluating these design principles in other organizational settings would help assess their robustness beyond the specific contexts studied here.

REFERENCES

[1] F. Ricci, L. Rokach, and B. Shapira, "Recommender systems: Techniques, applications, and challenges," *Recommender systems handbook*, pp. 1–35, 2021.

[2] Y. Himeur *et al.*, "A survey of recommender systems for energy efficiency in buildings: Principles, challenges and prospects," *Information Fusion*, vol. 72, pp. 1–21, 2021.

[3] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS quarterly*, pp. 319–340, 1989.

[4] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS quarterly*, pp. 425–478, 2003.

[5] V. Venkatesh and H. Bala, "Technology acceptance model 3 and a research agenda on interventions," *Decision sciences*, vol. 39, no. 2, pp. 273–315, 2008.

[6] K. Swearingen and R. Sinha, "Beyond algorithms: An hci perspective on recommender systems," in *ACM SIGIR 2001 workshop on recommender systems*, vol. 13, 2001, pp. 1–11.

[7] B. P. Knijnenburg, M. C. Willemsen, Z. Gantner, H. Soncu, and C. Newell, "Explaining the user experience of recommender systems," *User Modeling and User-Adapted Interaction*, vol. 22, no. 4–5, pp. 441–504, 2012.

[8] N. Tintarev and J. Masthoff, "Explaining recommendations: Design and evaluation," in *Proceedings of the 9th ACM Conference on Recommender Systems (RecSys)*, ACM, 2015, pp. 147–150. DOI: 10.1145/2792838.2792841.

[9] E. Glikson and A. W. Woolley, "Human trust in artificial intelligence: Review of empirical research," *Academy of management annals*, vol. 14, no. 2, pp. 627–660, 2020.

[10] T. Schwartz, G. Stevens, L. Ramirez, and V. Wulf, "Uncovering practices of making energy consumption accountable: A phenomenological inquiry," *ACM Transactions on Computer-Human Interaction (TOCHI)*, vol. 20, no. 2, pp. 1–30, 2013.

[11] T. Pinto *et al.*, "Multi-agent-based cbr recommender system for intelligent energy management in buildings," *IEEE Systems Journal*, vol. 13, no. 1, pp. 1084–1095, 2018.

[12] F. Taghvaei and R. Safa, "Efficient energy consumption in smart buildings using personalized nilm-based recommender system," *Big data and computing visions*, vol. 1, no. 3, pp. 161–169, 2021.

[13] R. O. Panizza, S. M. M. Mohammadi, M. Anbia, and M. Nik-Bakht, "Design recommender system for building energy performance," in *Canadian Society of Civil Engineering Annual Conference*, Springer, 2023, pp. 223–236.

[14] I. M. Chatzigeorgiou and G. T. Andreou, "A systematic review on feedback research for residential energy behavior change through mobile and web interfaces," *Renewable and Sustainable Energy Reviews*, vol. 135, p. 110 189, 2021. DOI: 10.1016/j.rser.2020.110189. [Online]. Available: https://www.researchgate.net/publication/343563334_A_systematic_review_on_feedback_research_for_residential_energy_behavior_change_through_mobile_and_web_interfaces.

[15] J. I. Méndez, T. Peffer, P. Ponce, A. Meier, and A. Molina, "Empowering saving energy at home through serious games on thermostat interfaces," *Energy and Buildings*, vol. 263, p. 112 015, 2022. DOI: 10.1016/j.enbuild.2022.112015. [Online]. Available: https://escholarship.org/uc/item/4959v9tf.

[16] M. Tohidi, W. Buxton, R. Baecker, and A. Sellen, "Getting the right design and the design right," in *Proceedings of the SIGCHI conference on Human Factors in computing systems*, 2006, pp. 1243–1252.

[17] H. Hammami, G. Calvary, M. Riahi, F. Moussa, and S. Bouzit, "Comparative evaluation? yes, but with which alternative ui?" In *Electronic Visualisation and the Arts (EVA 2017)*, 2017, pp. 32–1.

[18] M. T. Siddique, P. Koukaras, D. Ioannidis, and C. Tjortjis, "Smartbuild recsys: A recommendation system based on the smart readiness indicator for energy efficiency in buildings," *Algorithms*, vol. 16, no. 10, p. 482, 2023.

[19] J. Ma, R. Yus, and G. Bouloukakis, "Digiguide: A dt-based occupant guiding system for optimizing comfort and energy consumption," in *2025 IEEE International Conference on Smart Computing (SMARTCOMP)*, IEEE, 2025, pp. 9–17.

[20] V. Cipollone *et al.*, "User-centric comfort measurement and energy optimization: A pareto-efficient approach for a personalized recommendation strategy," in *2025 IEEE International Workshop on Metrology for Living Environment (MetroLivEnv)*, IEEE, 2025, pp. 312–316.

[21] B. Xiao and I. Benbasat, "E-commerce product recommendation agents: Use, characteristics, and impact," *MIS quarterly*, pp. 137–209, 2007.

[22] M. Wutz, M. Hermes, V. Winter, and J. Köberlein-Neu, "Factors influencing the acceptability, acceptance, and adoption of conversational agents in health care: Integrative review," *J Med Internet Res*, vol. 25, e46548, 2023, ISSN: 1438-8871.

[23] Y.-Y. Wang, A. Townsend, A. Luse, and B. Mennecke, "The determinants of acceptance of recommender systems: Applying the utaut model," *18th Americas Conference on Information Systems 2012, AMCIS 2012*, vol. 3, pp. 2238–2246, Jan. 2012.

[24] K. Acharya and J. Mikkonen, "Energy usage responsive space and personal mobile devices," in *Proceedings of the 12th international conference on human computer interaction with mobile devices and services*, 2010, pp. 407–408.

[25] M. Chromik and A. Butz, "Human-xai interaction: A review and design principles for explanation user interfaces," in *IFIP Conference on Human-Computer Interaction*, Springer, 2021, pp. 619–640.

[26] M. Chen *et al.*, "Values of user exploration in recommender systems," in *Proceedings of the 15th acm Conference on recommender systems*, 2021, pp. 85–95.

[27] Y. Wang *et al.*, "Surrogate for long-term user experience in recommender systems," in *Proceedings of the 28th ACM SIGKDD conference on knowledge discovery and data mining*, 2022, pp. 4100–4109.

[28] International Organization for Standardization, "Iso standard 88373," 2026, [Online]. Available: https://www.iso.org/standard/88373.html (visited on 05/2026).

[29] R. Hamdani and I. Chihi, "Adaptive human-computer interaction for industry 5.0: A novel concept, with comprehensive review and empirical validation," *Computers in Industry*,

vol. 168, p. 104 268, 2025, ISSN: 0166-3615. DOI: https://doi.org/10.1016/j.compind.2025.104268. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0166361525000338.

[30] BuildON Project, "Buildon project," 2026, [Online]. Available: https://buildon-project.eu/ (visited on 05/2026).

[31] University of La Rochelle, "Smart campus," 2026, [Online]. Available: https://www.univ-larochelle.fr/luniversite/notre-vision/mettre-en-place-un-campus-intelligent-durable-et-responsable/smart-campus/ (visited on 05/2026).

[32] H. Hammami, F. Camara, G. Calvary, M. Riahi, and F. Moussa, "The benefits of combining paper-and video-based prototypes for user interface evaluation," Apr. 2020.