

High School Students' Evaluation of AI-Generated Energy Recommendations: A Qualitative Study of Trust and Decision-Making

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Abstract

This paper examines the way high school students perceive the credibility of AI-generated energy recommendations and also justify how they choose to accept, modify or reject them. A qualitative design was taken and the semi-structured interviews with eight high school students were used. The respondents were asked three cases that concerned the use of washing machines, air conditioners, and energy-saving tips with explanatory details. The data were thematically analyzed. These results imply that the students have taken into account the applicability of recommendations to their domestic situation, the strength of evidence and coherence of explanations. Having knowledge about AI did not mean that participants trusted the specific recommendations. Household routines, comfort, and practical needs were also the factors that students took into account when determining whether to take the advice. Others wanted to get more information or confirmation prior to decision making. These results suggest the relevance of situational context, explanations that can be understood, and evidence in helping the students to evaluate AI generated energy recommendations. The research provides an understanding of the rationale of young users concerning the use of AI in making energy choices.

Keywords: Ai-Generated Energy Recommendations, High School Students, Trust, Decision-Making

Introduction

The need of electricity is not only a problem that requires attention of households, communities, and energy systems but also necessitates the daily life. Nevertheless, domestic electricity demand is largely differentiated by day to day activities, utilization of appliances as well as personal habits of energy management. This has led to smart meters and home energy management systems being important technologies in this evolution. AI-enabled meters can record electricity consumption and provide information that helps users understand their energy usage patterns. By providing this information in an easily accessible format, consumers will be able to determine the time of peak usage and think about ways to limit unnecessary

consumption (Samancioglu et al., 2026). Energy feedback can be consumption records, estimated cost, comparison of usage over the various periods, and personalized recommendations. Energy information provision however does not necessarily imply that the users will comprehend and act on the recommendations. Another aspect that users must take into account is the credibility of the advice they are being given, its applicability to their situation, and its practicality.

Users can use AI suggestions in cases where they have confidence in the system to produce valuable and credible data. However, they might place their trust in inaccurate recommendations-or reject useful ones-due to misunderstandings regarding the purpose or limitations of the suggestions. Provision of clear explanations that facilitate users in understanding the rationale behind certain recommendations is one of the factors that determine trust. In contrast, in the case of uncertainty in system performance, this kind of explanation might result in excessively relying on AI advice as well. Thus, the right trust means the ability to consider the recommendations depending on the evidence (Papenkordt et al., 2026). Explainable AI research focuses on the relevance of explaining AI recommendation and AI trust research focuses on the relevance of letting users judge AI recommendation appropriately instead of simply adhering to it (Henrique and Santos, 2024; Teixeira et al., 2025). These views are complementary and the knowledge of an explanation and trusting a system may not automatically prove whether a given recommendation is right and appropriate in a given household. In home energy management, users may therefore need to consider the information supporting a recommendation, whether the proposed action is feasible, and whether other factors explain the household's electricity consumption. How high school students make these judgments about AI-generated energy recommendations remains an important question.

Credibility judgments might not be enough to describe the decision of users. A suggestion can be very believable, yet still be denied due to being unrealistic. Users on the other hand, might hesitate to accept a suggestion but may be more open to them after reviewing more details. Information verification becomes thus pertinent to the question of how the users evaluate recommendations. They can either relate the advice to what they already know, search more information or demand a more detailed explanation of the advice first before making a decision to act. The past studies of AI-assisted decision-making have investigated the utilization of AI guidance by people, yet the connection amid perceived credibility, verification, and practical limitations needs to be investigated in particular decision-making circumstances (Grawitch et al., 2026). These processes can be understood to explain the acceptance, modification and rejection of recommendations by users instead of looking at adoption as the only meaningful product.

This is a problem that deserves special attention of high school students. In spite of the fact that adolescents can experience AI tools both in school and in their daily life, their knowledge of AI does not always mean that they can recognize the validity of specific recommendations and that they will accept the advice as suitable to their context. When it comes to household energy, students might have to evaluate the supporting data, determine whether they need additional verification, and think about whether a proposed course of action should fit into the family routine and needs (Massagony et al., 2026). All these factors can prompt them to react to suggestions that seem believable. Nevertheless, the existing body of knowledge

regarding the concept of household energy feedback and AI-aided decision-making lacks a comprehensive description of how high school students can unite these factors to make decisions related to taking AI-generated energy advice.

To fill this gap, the current research analyzes the judgment of the high school students on the AI-generated energy recommendations on three associated dimensions including credibility evaluation, information verification, and applicability in practice. A combined look at these dimensions can help give a more in-depth insight into the way students approach advice and describe the actions that they intend to take (either accepting, changing or refusing). The research questions are:

RQ1: How do high school students evaluate the credibility of AI-generated energy recommendations?

RQ2: How do high school students explain their decisions to accept, modify, or reject AI-generated energy recommendations?

Literature Review

AI-Generated Energy Recommendations in Home Energy Management

The consumption of electricity has emerged as a major field of study in the management of home energy due to the influence of the technical system and human behavior. The digital energy management systems and smart meters offer data on electricity consumption, approximate expenses, and variations in energy demand to enable users to discover ways to cut on unnecessary electricity use. Nonetheless, the fact that energy data is available does not necessarily translate into the more efficient utilization of energy; the users need to understand this information and evaluate the relevance of the suggested measures to their particular situation.

A review of residential energy feedback research by Samancioglu et al. (2026) indicates that energy feedback takes various forms, and even similar feedback methods can yield different results across different research contexts. This observation indicates that the value of energy information will be determined by its presentation, when it is served and the manner in which users perceive it. Moreover, smart meters systems also offer high-frequency consumption data, which allows users to discover their consumption habits and reflect on ways to make some changes in their daily routine. According to studies conducted by McIlvennie et al. (2020), it is essential to comprehend how the functionality of the system is related to the household users and the outcomes associated with energy. Also, AI-powered systems can recommend minimizing non-essential use at peak times or encourage users to look into appliances that cause high energy usage. Findings from Oonk et al. (2025) demonstrate that, in the contexts evaluated, combining economic and environmental persuasive information increased user acceptance of recommendations. This indicates that the content and explanations accompanying energy recommendations can influence user reactions.

The optimization of AI-based energy recommendations, as a result, brings up concerns that do not solely pertain to technical optimization. Although a system may point to a possible energy-saving step, it remains up to the user to decide which advice to trust, whether it is doable and suitable or not. Explainability and trustworthiness are crucial considerations when applying artificial intelligence to energy-related issues. To conclude, the current studies have confirmed the significance of feedback on energy, individualized recommendations and

explanations. Nevertheless, the technical part of the energy recommendations generation is quite different in comparison with the human part of the energy recommendations interpretation. The research problem that this study explores is how high school students rate AI-generated energy recommendations and why they describe the choices they make using AI-generated energy recommendations.

Trust and Credibility in AI-Assisted Decision-Making

The issue of trust is fundamental to human-computer interaction because users often need to determine whether to put their trust in the information produced by systems the inner mechanics of which may not be entirely visible. Trust in this research can be defined as the readiness of a user to consider computations of AI-generated energy as credible enough to use it in the decision-making process. Credibility assessment in particular, is the user evaluation of the credibility of a recommendation; that it is trustworthy, reasonable, and well-founded.

In the article by Henrique and Santos (2024), the authors talk about the importance of not necessarily accepting useful systems or recommendations without a good reason, and not necessarily doubting AI outputs without a good reason, which are under- and over-trust, respectively. Reasonable compatibility of expectations with capabilities and limitations of the system is needed with appropriate trust. The perception of the capabilities of the system, the quality of the available information, the transparency of the recommendations, and the previous experience of the user with AI are the factors that affect trust. A recommendation can be viewed as more valid in the context of household energy, when it mentions recognizable consumption patterns or offers a clear explanation of the rationale behind the proposed action. Moreover, explainability is an essential part of the process; explanations can make users comprehend why a recommendation was made and the information behind it. Studies by Papenkordt et al. (2026) show that the idea of explanations does not always lead to trust and can make users accept AI suggestions blindly; they introduce design principles that are meant to motivate users to be involved in and evaluate AI suggestions more critically instead of simply accepting it. Credibility is to be judged by the grounds that user gives their judgment, not by deduction that can be made by the fact that explanations are given. In this research therefore, trust is considered as a user judgment but not a direct measurement of system performance.

Information Verification and User Decision-Making

Users can reflect on the evidence they have, whether the recommendation is backed by appropriate information and whether the action, which is suggested, fits their particular case. Information verification, in turn, can be viewed as a helpful construct that can be used to comprehend the reaction of people to AI-generated recommendations. Verification, in this paper, is the process through which users evaluate how credible or relevant the AI-generated energy recommendations are. This includes comparing recommendations against information provided in the scenario, requesting explanations, identifying missing details, and so forth.

The explanation design determines the interaction between users and AI suggestions. Papenkordt et al. (2026) underline that the explanations must be given in such a way that they provoke profound thinking and do not turn into a routine. In like manner, a review by

Henrique and Santos (2024) underscores the larger problem of the compatibility of user trust and AI abilities. Together these studies indicate that decision-making of users cannot be gauged by simply whether a recommendation is adopted; the reasoning process that goes into the decision adopted is also critical. Verifying the status of a recommendation in energy management can be done by examining the accuracy and completeness in relation to available electricity consumption statistics. There are also practical constraints of decision-making. Comfort, day-to-day activities, appliance needs, and preferences of their households are directly connected to household energy use. Thus, users may accept a recommendation, adjust it to suit their needs, or reject it. These reactions can be an indication of different ratings on the credibility, relevance, feasibility, and the personal priorities of the user to the recommendation. Therefore, this study examines the decisions and explanations articulated by the participants.

Research Gap and Conceptual Framework

There are three areas of research that are identified in the literature review. To begin with, household energy feedback studies have investigated the effect of the format and content of the energy information on the comprehension of electricity use among the user (Zhao & Huh, 2026). Second, explainable energy recommendations studies have emphasized the need to have explanations and personalized information in AI-based energy management systems (Teixeira et al., 2025). Third, the study on human-computer interaction has highlighted the necessity of proper trust to AI because explanations do not always result in proper decision-making (Henrique & Santos, 2024). Collectively, these studies underscore the significance of the quality of information, its explainability and trust. Nevertheless, they do not elaborate on how users integrate credibility considerations, information validation, and practical considerations in reacting to certain energy recommendations. Studies on AI trust tend to be more broadly studied, typically concentrating on decision-making, whereas energy feedback studies tend to concentrate on consumption, system design, or behavioral consequences. More studies are thus required to know how these factors interrelate with certain application situations.

This is a lack that is especially pertinent to high school students. Even though young people are likely to experience AI-generated information both at school and in daily life, the knowledge of AI does not always presuppose the way the young people consider personal recommendations. Under home energy circumstances, students can also reflect on the possibility of convincing evidence to support a recommendation, the possibility of not having all the information necessary about the situation and consider whether the recommended action is appropriate to their routines and needs of the family. Nevertheless, the reviewed literature fails to provide a complete explanation of how high school students take into account these factors in combination with each other when assessing AI-generated energy recommendations and choosing the way to react to them.

To fill these gaps, the current paper explores three associated dimensions of analytics credibility analysis, information verification, and applicability in practice. Credibility assessment is the aspect of how students should evaluate the credibility and validity of AI-generated advice. Information verification relates to the process of checking the information by the students to find the supporting evidence, to compare the recommendations and available information, or to find more confirmation. Practical applicability deals with the issue

of whether the suggested actions are applicable to the household routine, and comfort levels, as well as family needs. Decision-making is concerned with the manner in which students elaborate on their plans to accept, amend or dismiss suggestions. A combination of these dimensions can be used to understand why a recommendation can be perceived as credible by students and ignored.

The research does not presuppose that the higher trust, the higher the acceptance and that verification always results in higher trust. Neither does it presuppose that the credibility assessment, information verification, and applicability are in a predetermined order. A recommendation could be perceived as true by the students but then they dismiss it as being impractical. They can also wish to find out more in evidence without getting more trustful. This study comparatively analyzes these judgments and the reasons behind them and evaluates how high school students perceive AI-generated individual energy recommendations and negotiate the relationship between perceived credibility and information verification, on the one hand, and practical constraints of everyday life, on the other.

Methodology

Research Design

The research design adopted in this study is qualitative since it examines the perceptions that high school students have towards AI-generated energy recommendations. The research focuses on students' perceptions of the recommendations' credibility, their trust in AI, and the reasons underlying their decisions to accept, modify, or reject these recommendations. Given the aim to examine students' explanations and decision-making processes, a qualitative approach is appropriate. Semi-structured interviews were used to collect the data; this approach will guarantee that the main questions will always be posed and make it possible to explore the particular answers of each participant in a more profound way.

Participants and Sampling

Purposive sampling will be used to recruit eight high school students. No previous experience in AI or electrical engineering is needed, and the participation is voluntary. The sample includes students with varying levels of familiarity with AI tools, facilitating the identification of commonalities and differences in how they evaluate AI-generated information.

Research Materials and Scenarios

The main research content would be composed of three brief scenarios in the form of texts that are based on AI-generated recommendations of energy use. These are scenarios that outline common scenarios in regard to the use of electricity in homes. The first scenario presents an AI recommendation to use the washing machine during periods of lower electricity rates. The given scenario is to find out whether the students find the recommendation credible and what kind of information they need in order to make sure that it is applicable. The second scenario presents a recommendation to adjust the air conditioner temperature to reduce power consumption, but provides little to no explanation. Such a scenario analyses how students would respond upon getting the reasons behind a recommendation being unclear and also explores the possibility of whether not being told to them influences how they evaluate the credibility of the recommendation. The third situation offers a suggestion on how to decrease the use of certain gadgets with the details on the

possible energy or financial savings. This scenario explores whether explanatory information influences students' judgments and identifies what further evidence they deem necessary before accepting the recommendation. Such situations are meant to make the participants think about various issues such as: is the recommendation credible, is the foundation of the recommendation clear enough, do they need more information, and would they take up the recommendation themselves.

Data Collection Procedure

Data were collected through one-on-one semi-structured interviews. The interviews were based on eight main questions, which are separated into three parts. The first question aims to gauge the participants' familiarity with AI tools and their prior experience with AI-generated recommendations. Questions 2 through 4 explore issues of credibility and trust, including participants' assessments of the recommendations' reliability, the evidence required to evaluate them, and the impact of explanatory information. Questions 5-8 focus on the decision-making process, including the acceptance, modification, rejection of the recommendations; consultation, non-consultation of other sources of information; the practical considerations that can change the decisions; and changes that can alter the decisions. The duration of each interview will be around 15-20 minutes. The researcher introduced the purpose and procedure of the study and then the participants read through the three scenarios and comment on how they reacted to them. The interviews taken place in three phases. To begin with, the respondents specify their knowledge of AI tools and suggestions on saving energy. Second, they assess the situations and explain their verdicts concerning credibility. Third, they specify whether they would or would not accept the recommendations, make changes or reject them and provide reasons behind their decisions. The interviews were transcribed and audio-recorded with the due permission. The participants were given a code (S01-S08) to identify them in the analysis and reporting stages. Any personally identifiable information were removed from the transcripts.

Data Analysis

Interview data were analyzed using thematic analysis. The approach help to determine common trends in the process of students assessing AI-generated energy recommendations. There are six stages in which the analysis were done. First, the researcher familiarized with the data by reading the transcripts multiple times. Secondly, initial coding was done on meaningful statements. Third, the corresponding codes were divided into possible themes. Fourth, these themes were examined by the researcher on the data of the interviews. Fifth, all themes were well defined and named. Lastly, the researcher summarized the results. The analysis procedures can be left open to the surprising revelations. Transcripts, codes, and themes were organized using spreadsheets by the researcher.

Ethical Considerations

The researcher determined the ethical approval requirements that could be applied before data collection and sought permission of the corresponding institutions or schools. The participants were given a clear information about the purpose of the study, the interview process, voluntary character of the participation, and the purpose of the data. They still had the right to refuse to answer any questions and may withdraw out of the study in line with the stipulations in the approved research protocol. The privacy of the participants was ensured by the pseudonyms and deletion of the personally identifiable information.

Results

The chapter includes a thematic analysis of the evaluation of AI-generated energy-saving recommendations by high school students. The discussion focuses on three domestic energy scenarios with reference to the time of using a washing machine, changing air conditioner settings, and the assessment of energy-saving recommendations with explanations. The analysis focuses on students' judgments, information needs, and the rationales behind their decisions.

Evaluating the Credibility of AI-Generated Energy Recommendations

In the case of washing machine, the students were required to think about whether it would be beneficial to turn on the washing machine at a particular time and save household electricity costs. As Student 1 remarked, "I have to find out whether electricity is really cheaper to our household during that period." Such is the way students learn to differentiate between the recommendations, which appear to be plausible and those, which apply to their own households. Any possible financial gain of switching to electricity consumption will depend on the rate plan the household is subscribing to; time-of-use plans have different rates across the day, whereas fixed-rate plans have the same price, irrespective of the time of the day. Other students expressed similar views regarding the importance of credibility assessment.

Knowledge of AI tools can also assist students to learn to deal with them, but it does not mean that they trust all the recommendations. Student 6 said that he uses AI to help him with his studies, but this does not mean that he accepts the information given on the use of electricity without questioning. This proves that the knowledge of AI can be associated with a prudent approach to particular suggestions. The personal experience of the use of AI tools is not necessarily the guarantee of confidence in all the results obtained; participants can be ready to use AI at the same time questioning the validity of the recommendations.

Concerning AI-generated suggestions on how to change the air conditioner settings to achieve optimal performance, which did not provide enough explanation, students believed that the recommendations did not have a good rationale or have actionable information. As Student 3 remarked, "I want to know why changing the temperature would help. Otherwise, I can't tell if the recommendation is suitable for our household." This emphasises the problems associated with insufficient explanation which makes the participants doubt the recommendation, and the reasoning behind it, or how the advice applies to their home. While some students might seek further explanation, others might evaluate the recommendation based on their existing knowledge or practical experience. The research question addressed whether explanatory information, as well as estimates of possible energy or cost savings, had any changes on the judgment of students. Student 8 stated that the explanation helped him to better comprehend the situation, but he still did not understand how the savings were computed. This is where the difference between knowing of a recommendation and seeing the evidence of the same comes in. Although an explanation can make the students understand the course of action suggested, it still does not eradicate all uncertainties.

Decisions to Accept, Modify, or Reject Recommendations

Students admitted that it would be possible to reduce costs by running the washing machine during off-peak hours, but still considered the proposed times to be inconvenient. As Student

7 mentioned, "I could use the washing machine later on, as long as electricity is cheaper depending on the schedule of our house." This shows that the ultimate decision of whether to accept a recommendation or not depends on its credibility and compatibility to the day-to-day activities of the house. Students also indicated that they would consider factors such as air conditioning comfort levels and the needs of other family members.

Students would want to find further details (e.g., to check their electricity plan, ask their family members, compare the information provided by others, or have the AI assistant clarify the information) before making a decision on whether to apply AI-generated recommendations. According to Student 4, "I would prefer to check our electricity plan and compare it to that offered by the AI." This indicates the verification strategies of the students; they did not accept the advice immediately, but put it in contrast to the relevant information about the house.

Student 2 commented, "I would take into account the suggestion, though I would change the time to fit the schedule better to fit my family." This indicates that students did not dismiss the intent behind the AI-generated advice but preferred to tailor the proposed actions to their family's needs and daily routines. Their reactions provide emphasis on the significance of practical considerations in the decision-making process and emphasize the distinction between evaluating the potential value of a recommendation and making a decision, whether to implement it as it is presented. This also brings out the joint impact of perceived usefulness and practical applicability on the decision-making intentions of students towards AI-generated energy recommendations.

Discussion

The results show that the students find the appropriateness of the recommendation to the real-life situation of the household, evidence used to support it, and the explanation understandable. Their evaluation will be dependent on whether the action that is recommended is reasonable in the described context. Responses of students indicate that the applicability of energy recommendations is one factor that can make them credible. This observation is consistent with those of Samancioglu et al. (2026) on the variety of the presentation and use of energy information. The interactions between smart home energy management systems, the users of the household, and energy-related outcomes are also examined by McIlvennie et al. (2020), which forms the basis of comprehending the necessity of providing energy information in context. In addition, the research demonstrates a difference between the general plausibility of a recommendation and its contextual credibility; students might doubt a recommendation as being applicable to their situation instead of just accepting a recommendation by its rationale. What sounds like a reasonable suggestion, may not have enough evidence to support a particular decision. Besides, being acquainted with AI does not necessarily make people trust AI; students were still apprehensive about AI suggestions even when they were familiar with the tools. Henrique and Santos (2024) discovered that proper trust assumes users to take into account the dependability of a particular output instead of depending on the overall familiarity with the system. Though students saw the usefulness of AI, they were still unsure about the validity of certain energy suggestions. They were ready to apply AI to certain tasks, but their decision made was determined by the information given along with their interpretation of the circumstances and their thought of the outcomes of taking the advice. The findings did not,

however, show that students who were more familiar with AI were more or less critical. Lastly, students were inquisitive about recommendations when there was little or no explanation as to why a certain action was recommended to cut down on the use of electricity. While explanations helped students understand the recommendations, they did not necessarily convince them of the recommendations' reliability. This relates to Rahman et al. (2026) and the importance of explanations in encouraging users to evaluate recommendations rather than simply accepting or rejecting them.

The results show that the decision-making of students does not rely on the evaluation of the credibility of the recommendation only, but also the possibility of the proposed actions to correspond to the everyday activities of the household and its practice. People may still feel that even when they do not apply a recommendation directly as it is proposed, it is something that could be helpful. This result is consistent with the general view suggested by McIlvennie et al. (2020) that energy choices in households occur in the framework of everyday life and real-life situations. Household routines, comfort levels, and family needs can influence students' anticipated responses; even when students deem an energy recommendation reasonable, they may question its convenience or feasibility. The findings also show that practical applicability has an effect on whether students will implement recommendations as they are. Furthermore, the findings suggest that students may seek additional information, engaging in a deliberative process before deciding whether to adopt AI-generated energy recommendations. Strategies employed by students include reviewing their electricity usage plans, comparing recommendations with other information, consulting family members, and requesting clearer explanations. It is a discovery that can be echoed by the difficulty that Henrique and Santos (2024) find in the integration of user trust in AI systems with the real capabilities of the systems. The results reveal a link between information verification and decision-making: students may seek information due to uncertainty, and the information obtained can shape their interpretation of the recommendations. Understanding students' interpretations is crucial to comprehending their decision-making processes, and the findings indicate a willingness among students to consider modifying recommendations to better suit their household needs.

Conclusion

This paper explores the credibility of the AI-generated energy recommendations among high school students and the reasons why they believe these recommendations are credible or not. The results suggest that students rely on the appropriateness of recommendations to the real-life situation in their households, the evidence provided and understandability of the descriptions in their assessments. The results also show that familiarity with AI does not imply that students will trust all AI-generated recommendations. In case of no explanation of the recommendations, students want to know the logic behind the recommendation. Even when explanations and estimated energy savings are provided, students remain skeptical about the basis for these estimates. Furthermore, the findings reveal that students' intended decisions depend on practical considerations alongside their judgments regarding the credibility of the recommendations.

These results contribute to the understanding of AI trust by clarifying how students evaluate specific recommendations, rather than relying solely on their general familiarity with AI tools. Students can be able to identify the value of AI and at the same time doubt the sufficiency of

a particular suggestion. Trust cannot be regarded as agreement *per se*; students might perceive a recommendation as credible and fail to implement it because it failed to correspond to his or her own reality. The research also brings out the difference between giving an explanation and giving sufficient evidence, a simple explanation might not decrease the users concerns. Explanations must be easily understandable and address the specific questions users have about the recommendations. Additionally, the results highlight the significance of the domestic context in deciphering AI-produced energy suggestions. Students ask themselves whether the recommendations regarding energy usage saving will be applicable to their everyday lives and the needs of their households, which proves that energy value stems not only from its prospective benefits but also even from its applicability.

This study also has certain limitations. First, the sample size is small. Second, while three scenarios were used, they did not fully replicate the complexities involved in using actual home energy management systems. Moreover, the research is based on perceived credibility and decision making processes, which implies that it is not able to find out whether the judgments of students should be consistent with the real accuracy or effectiveness of the recommendations. Lastly, the research uses qualitative thematic analysis to determine trends in the answers of the participants; this approach is not intended to establish a causal connection between the familiarity with AI, quality of explanations, information verification, trust and decision outcomes.

Suggestions for future research are provided below. To begin with, the following studies might use a broader sample of students that belong to different schools and cultural backgrounds. Second, the reaction of students to energy management interfaces closer to actual real-world applications might be explored in the future. In addition, the connection between explanation and validation could be analyzed in more detail by new studies in the future. Also, it may be possible to perform future research on how students assess the technical situations, which underlie energy-related recommendations. Lastly, further studies may expand the scope to actual behavior to determine whether users will accept recommendations, adjust them to fit their own situations, or ignore them, and to differentiate these reactions (and actual changes in electricity consumption).

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