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Leveraging Humanized Performance Labeling to Drive Sustainable Building Choices

Azadeh Omidfar Sawyer * and Sanaz Saadatifar

School of Architecture, Carnegie Mellon University, Pittsburgh, PA 15213, USA
* Correspondence: asawyer@andrew.cmu.edu

Abstract: Climate change is a pressing global challenge, significantly influenced by human actions. Considering that buildings account for approximately 40% of total US energy use in the United States, this study examines how humanized energy labeling can influence home buyers' preferences, shaping total energy demand and usage. "Humanized energy and carbon data" refers to the simplification of complex energy metrics into accessible formats for non-expert audiences. By presenting energy data in a user-friendly manner, this approach aims to empower consumers to prioritize energy-efficient buildings, consequently driving demand for sustainable practices in the building sector. To test this approach, a survey of 163 participants was conducted. Participants were presented with six building façade designs in two rounds: one without energy, carbon, or utility cost data, and the second with comprehensive performance information. Results revealed that 77.3% of participants shifted their preferences after reviewing energy-related data. Furthermore, the study found consistent impacts across demographic groups, highlighting the broad applicability of humanized labeling. These findings confirm the potential of humanized energy labeling to influence housing decisions, driving demand for sustainable practices in real estate. By empowering consumers with accessible information, this approach contributes to mitigating climate change while fostering informed decision-making in the housing market.

Keywords: environmental consciousness; green consumption behavior; real estate sustainability; building performance labeling; humanized energy data; carbon emissions

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Academic Editors: Mojtaba Parsaee and Hing-Wah Chau

Received: 22 July 2024
Revised: 15 April 2025
Accepted: 19 April 2025
Published: 27 April 2025

Citation: Sawyer, A.O.; Saadatifar, S. Leveraging Humanized Performance Labeling to Drive Sustainable Building Choices. *Architecture* **2025**, *5*, 30. https://doi.org/10.3390/architecture5020030

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1. Introduction

When individuals consider purchasing or renting a new home, their focus often centers on location, costs, and size, frequently overlooking operational costs, environmental impacts, and sustainability aspects. However, with buildings responsible for approximately 40% of total US energy consumption [1,2], the choices made in housing have broader implications for sustainability and our collective future. This growing emphasis on sustainable living and environmental consciousness underscores the need for consumers to prioritize energy-efficient decisions in the real estate market [3–5].

Despite this, many prospective homebuyers or renters lack access to or understanding of the energy-related costs associated with their decisions. This oversight can lead to financial strain when energy bills exceed expectations and undermines efforts to promote energy-efficient housing. Platforms such as Zillow provide valuable property details, yet energy-related metrics, such as utility costs or carbon emissions, are rarely highlighted [6]. Previous research has demonstrated that energy efficiency labels can significantly influence consumer behavior by presenting meaningful and contextually relevant information in real

estate listings [7–9]. Studies also suggest that energy ratings and clear labeling designs can motivate household investments in efficiency and shape housing market dynamics [8–10]. These findings underline the importance of making energy-related information accessible to consumers to facilitate informed decision-making [11].

Beyond real estate, labeling practices in other industries have shown success in guiding consumer behavior. For example, calorie labeling has encouraged healthier food choices [12–14], while ingredient transparency in cosmetics has empowered consumers to select eco-friendly products [15–18]. These examples illustrate how clear, accessible information can shift market demand and encourage sustainable practices. However, the real estate sector has yet to fully leverage labeling strategies to promote energy-efficient choices, especially during critical moments when housing options are being evaluated.

Building on this body of research, our study investigates whether providing energy performance data, in the form of user-friendly, humanized energy labels, can influence consumers' preferences when presented with different building designs. Specifically, we explore the potential of simplified energy metrics to inform decision-making when consumers evaluate housing options, such as façade design choices, before purchase. By offering actionable energy information tied to design features, this approach addresses a critical gap in real estate sustainability practices.

This study seeks to answer the following question: Can the integration of humanized energy, cost, and environmental data influence consumer choices and promote sustainability in the real estate market? By equipping consumers with accessible energy information, we hypothesize that demand for energy-efficient buildings will increase, driving environmentally responsible practices in the building sector and fostering informed decision-making. This approach has the potential to align consumer behavior with sustainability goals, contributing to climate change mitigation [19–21].

2. Methodology

This section outlines the methodology used to investigate the impact of humanized performance labeling on participants' decision-making and building preferences. The study integrated perspectives from both design experts and individuals without specialized knowledge to ensure the findings' broad applicability. Ethical approval was obtained from Carnegie Mellon University's Institutional Review Board (IRB). Data collection occurred between 1 and 20 September 2020, yielding 166 responses. Of these, 163 participants who completed all survey questions were included in the analysis. The survey instrument was created and administered using Qualtrics, an online survey platform.

2.1. Survey Design and Procedure

The survey aimed to evaluate how qualitative and quantitative data influence decision-making in façade selection. Previous research indicates that individuals prioritize aesthetics over performance data when evaluating building designs [22,23]. To address this gap, the study provided participants with performance data in a user-friendly format alongside visual representations of façade designs.

2.1.1. Façade Design and Performance Analysis

Six diverse façade designs for a high-rise residential building were developed using Rhinoceros 3D [24]. The designs varied by glazing and shading configurations: "100% glass", "100% glass with louvers", "100% glass with Voronoi shading", "30% glass", "30% glass with louvers", and "30% glass with Voronoi shading" (visual representations in Figure 1). Each façade design was analyzed using Cove.tool, a performance modeling

platform, to generate quantitative data on energy consumption, carbon emissions, and utility costs [25]. This ensured that participants evaluated realistic performance metrics.

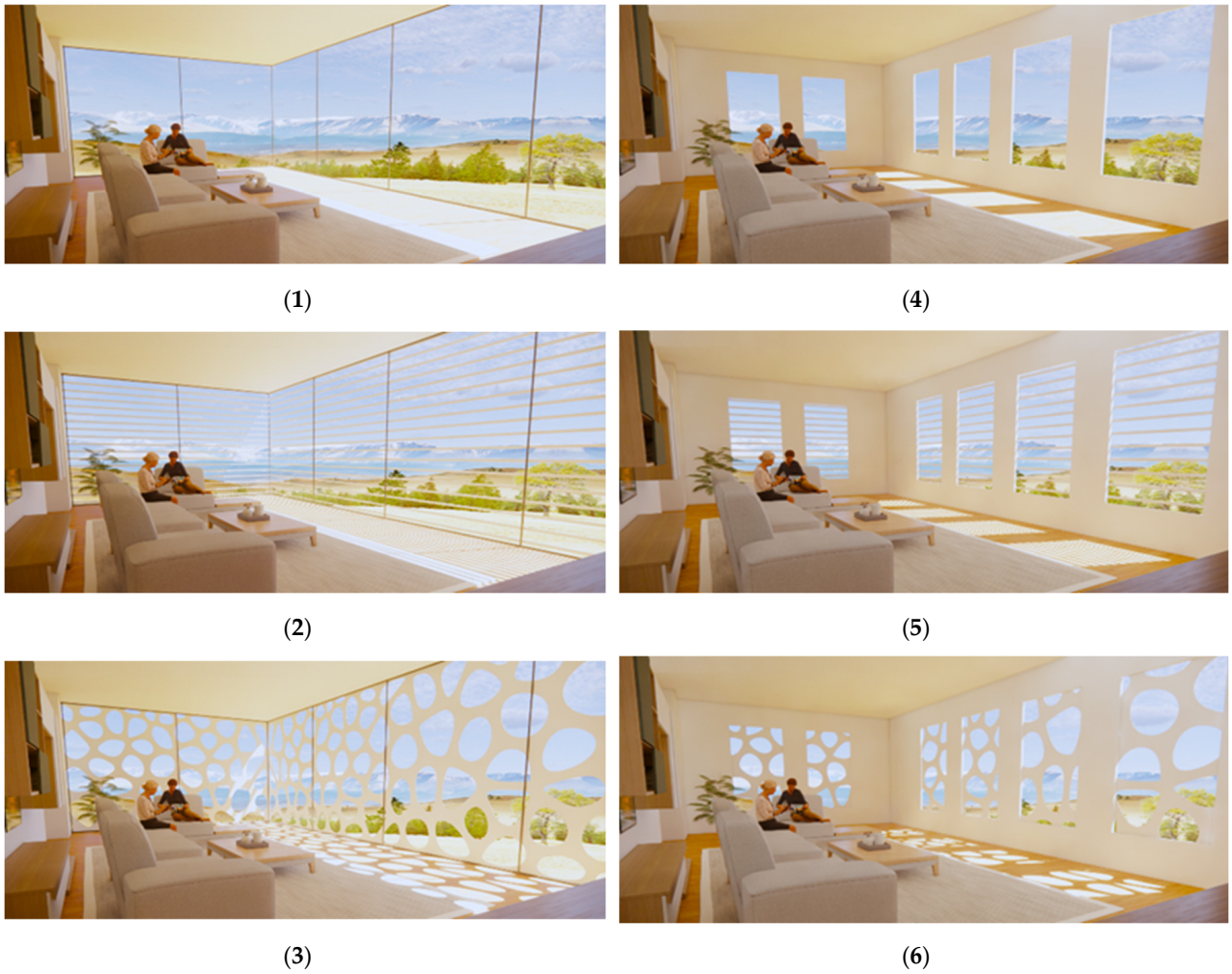


Figure 1. Six façade systems with different shading strategies: (**1**) 100% glass with no shading pattern, (**2**) 100% glass with simple louvers (80% void ratio), (**3**) 100% glass with voronoi shading pattern (60% void ratio), (**4**) 30% glass with no shading pattern, (**5**) 30% glass with simple louvers (80% void ratio), (**6**) 30% glass with voronoi shading pattern (60% void ratio).

2.1.2. Survey Phases

The survey consisted of two main phases:

1. Phase 1 (Qualitative Data Only): Participants selected their preferred façade design based solely on visual aesthetics (Figure 1).
2. Phase 2 (combined Data): Participants re-evaluated the same façade designs, this time with accompanying performance labels presenting energy, carbon, and cost metrics (Figure 2).

Participants were instructed to base their decisions on both aesthetic and performance considerations in Phase 2. Feedback on influential factors was collected to better understand how participants weighed qualitative versus quantitative information.

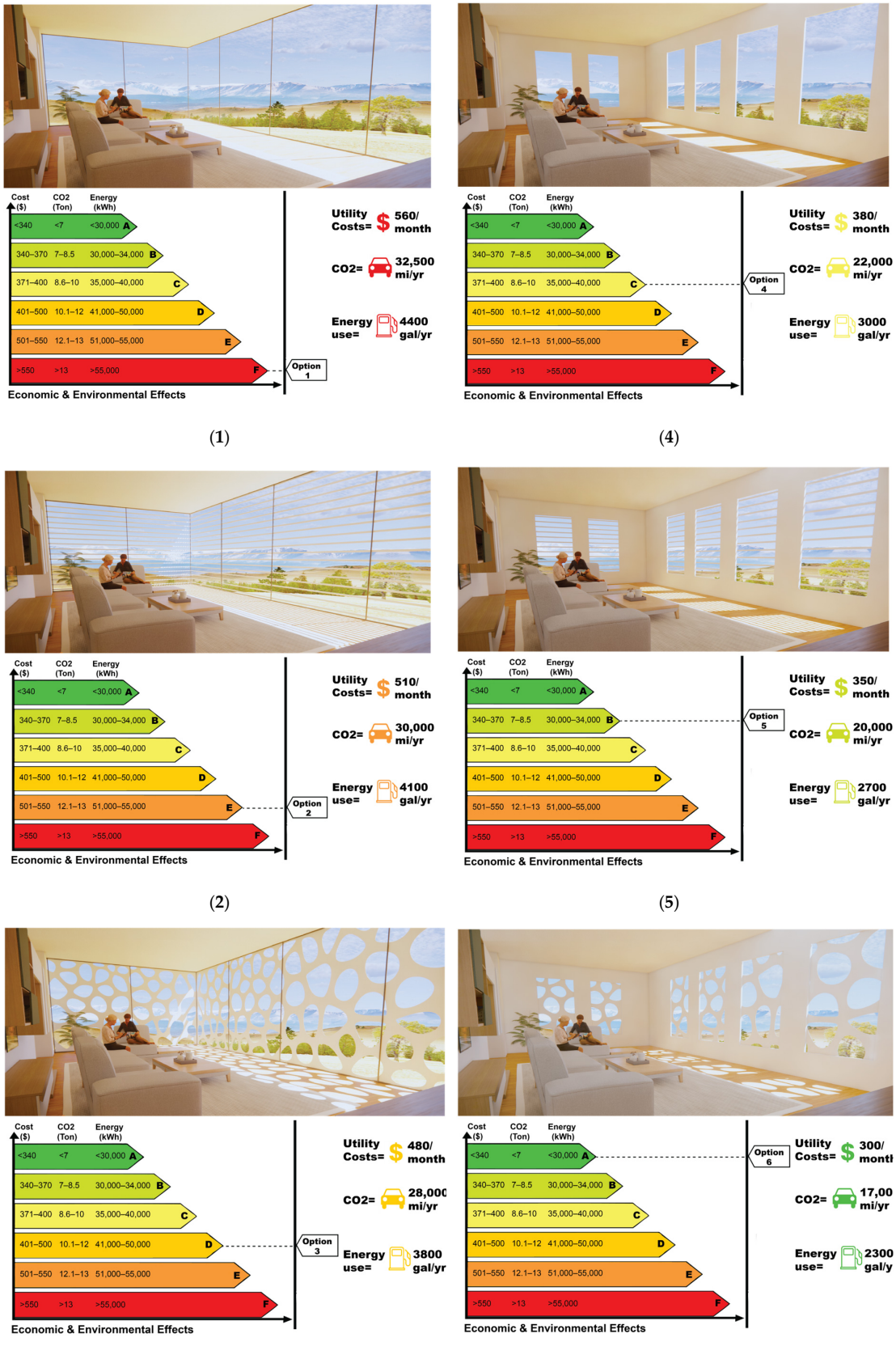


Figure 2. The same six façade systems as Figure 1, now with corresponding humanized performance data (Utility Costs, Carbon and Energy use). Figure (**1**) represents the highest energy use, Figure (**2**) corresponds to high energy use, Figure (**3**) indicates elevated energy use, Figure (**4**) reflects moderate energy use, Figure (**5**) shows lower energy use, and Figure (**6**) demonstrates the lowest energy use.

2.2. Participant Recruitment and Quality Control

Participants were recruited through diverse channels, including university mailing lists, LinkedIn professional groups, and industry connections to ensure a broad and diverse sample. The study required participants to be aged 18 or older, with no additional eligibility criteria. Recruitment yielded 166 participants, of whom 163 provided complete data.

2.2.1. Sample Size

An a-priori power analysis was conducted using G*Power (v3.1.9.7) to ensure statistical validity. A minimum sample size of 90 was required to detect a medium effects size (Cohen's d = 0.5) at a power of 0.8 and an alpha level of 0.05 in paired *t*-test. By exceeding this threshold, the study achieved robust statistical reliability and generalizability.

2.2.2. Consent and Privacy Measures

Participants provided informed consent though a digital form outlining the study's objectives and voluntary nature. Data privacy was ensured by anonymizing responses and separating email addresses from survey data. This minimized biases and protected participants' identities.

2.3. Data Analysis

The data were analyzed using quantitative statistical methods to evaluate the impact of performance labeling on participants' preferences. Descriptive statistics were used to summarize participant demographics and initial preferences, providing a foundational understanding of the dataset. Paired *t*-tests were conducted to compare façade preferences between Phase 1 (aesthetics only) and Phase 2 (combined data), assessing whether performance labels influenced decision-making. Additionally, chi-square tests were performed to examine whether demographic factors, such as age, income, and education, affected participants' likelihood of changing preferences. Confidence intervals at a 95% level were applied to ensure the reliability and generalizability of the results.

3. Results

The analysis focused on evaluating how humanized performance labels influenced participants' preferences and identifying the factors driving decision-making.

3.1. Participant Demographics

The study included 163 participants, representing diverse demographic profiles. Among the respondents, 92 were female and 71 were male, with the largest age group being 25–34 years old (60 participants). The majority of participants (105) identified as white, and 106 held graduate degrees. Household income was evenly distributed, with 47 participants reporting incomes of $100,000 or more. Regarding time spent at home, 62 participants reported 9–15 h daily (Figures 3–5).

This diversity ensured robust evaluation of performance labeling across a range of demographics. Statistical analysis revealed no significant differences in the "Information Effect" across gender, age, education, income, or time spent at home ($p > 0.05$), indicating that the provided information had a consistent influence on decision-making across groups.

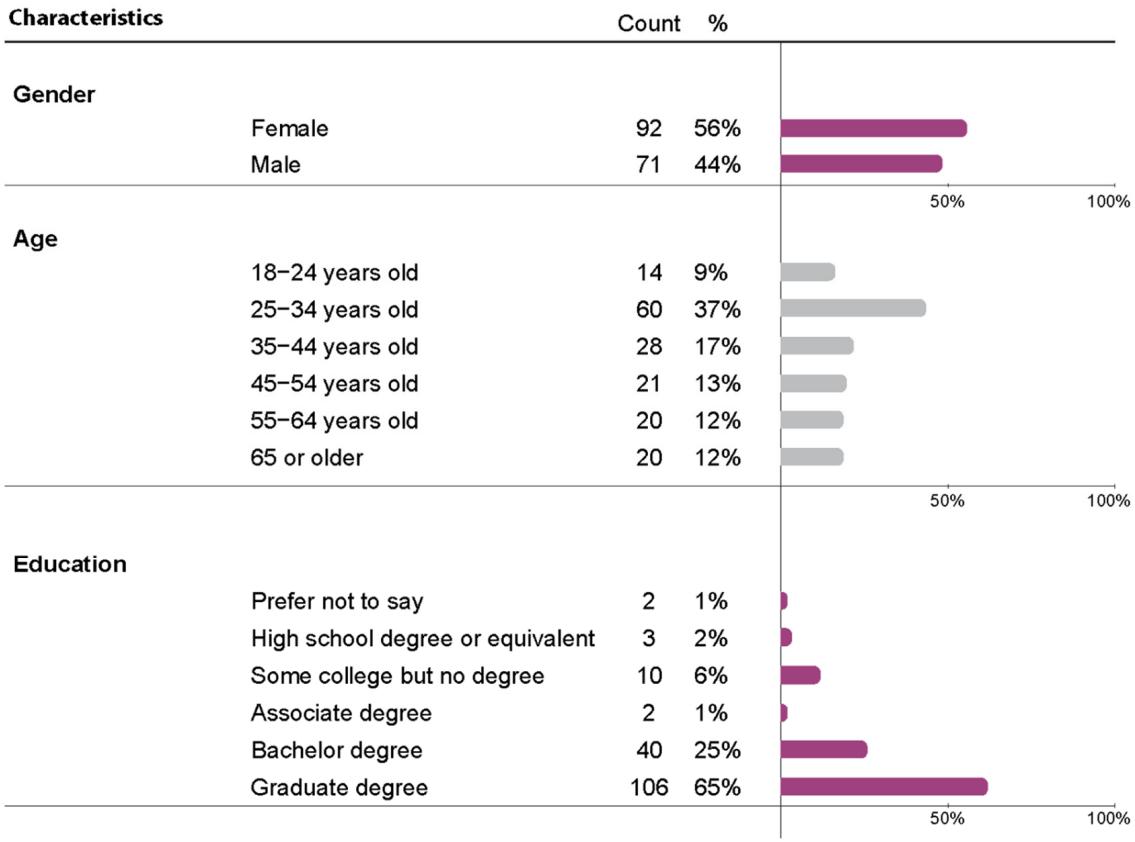


Figure 3. The number of participants among different Gender, Age, and Education groups.

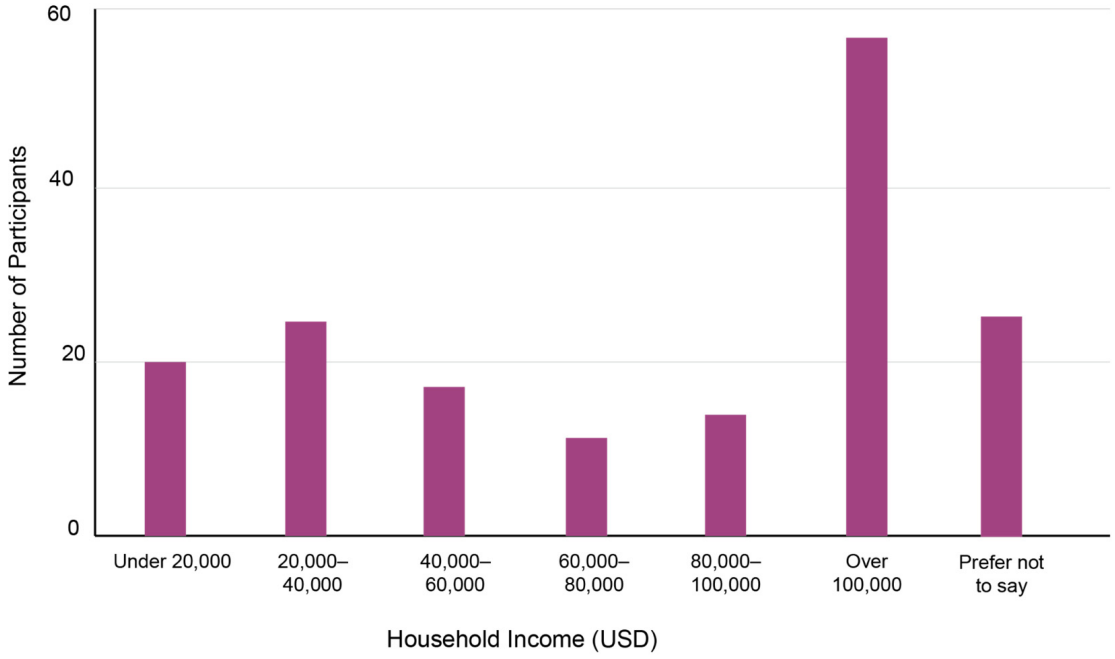


Figure 4. Bar chart representing the number of participants among different Household Income groups.

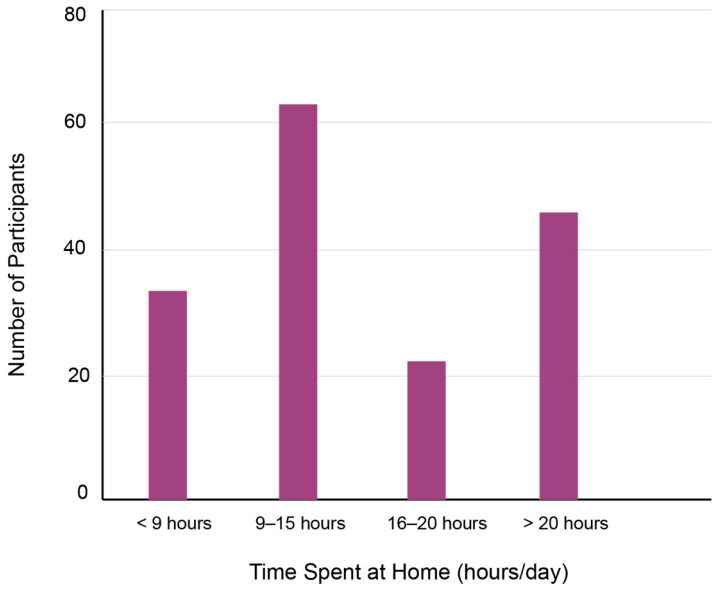


Figure 5. Bar chart representing the number of participants among different Time Spent at Home groups.

3.2. Impact of Information on Preferences

To assess the influence of performance labeling, a paired *t*-test compared participant preferences in Phase 1 (aesthetics only) and Phase 2 (aesthetics + performance labels). The results rejected the null hypothesis of no difference between the two phases (t = 18.306, df = 162, $p < 2.2 \times 10^{-16}$), confirming that performance information significantly impacted decision-making.

Approximately 77.3% of participants (126 out of 163) altered their preferences in favor of more energy-efficient and cost-effective options after reviewing the performance labels. This percentage was calculated from the paired *t*-test results and reflects the significant behavioral shift observed between the two rounds. The visualization in Figure 6 illustrates the differences in participants' preferences across the six façade options in the two phases. The mean difference in preferences between the two phases was 2.34 units (95% CI: 2.09–2.60), reinforcing the reliability of these findings. Notably, 37 participants who initially selected energy-efficient façades maintained their choices, and none selected less efficient options in Phase 2.

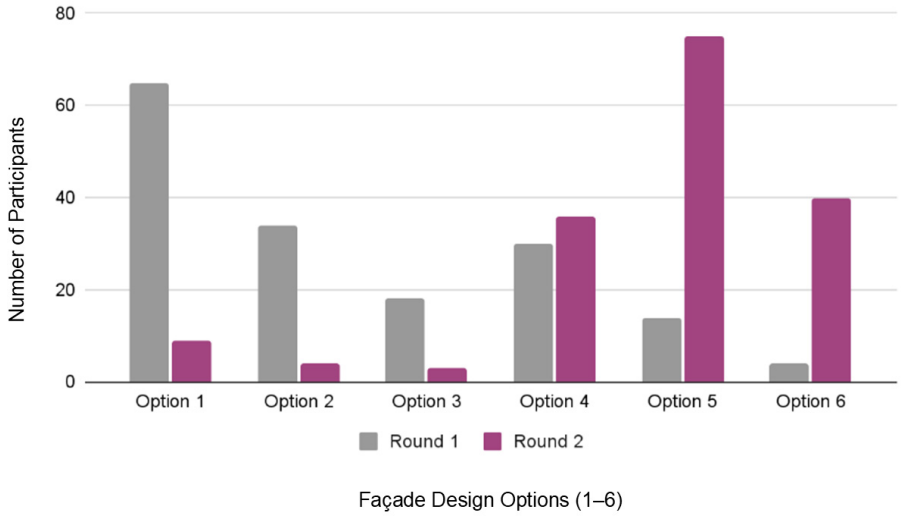


Figure 6. Bar chart comparing the six options' selections in Round 1 vs. Round 2.

3.3. Analysis of the "Information Effect"

To quantify the impact of performance labeling, an "Information Effect" metric was calculated as the difference between participants' Phase 2 and Phase 1 selections. On average, participants' choices increased by 2.34 units, with a standard deviation of 1.63 and a range of 2 units. The most common change was an increase of 3 units, reflecting a strong preference shift toward higher-performing façade designs.

The consistency of the "Information Effect" across demographic groups was analyzed. No significant differences were observed based on gender, age, education, income, or time spent at home ($p > 0.05$), underscoring the universal applicability of humanized performance labels.

3.4. Factors Influencing Decision-Making

Participants ranked factors influencing homebuying decisions, as shown in Figure 7, with the price of the home (88.3%) and the design of the home (86.5%) emerging as the most significant factors. Monthly utility costs ranked third, followed by energy consumption and CO_2 emissions. This ranking reflects participants' general priorities when considering housing options.

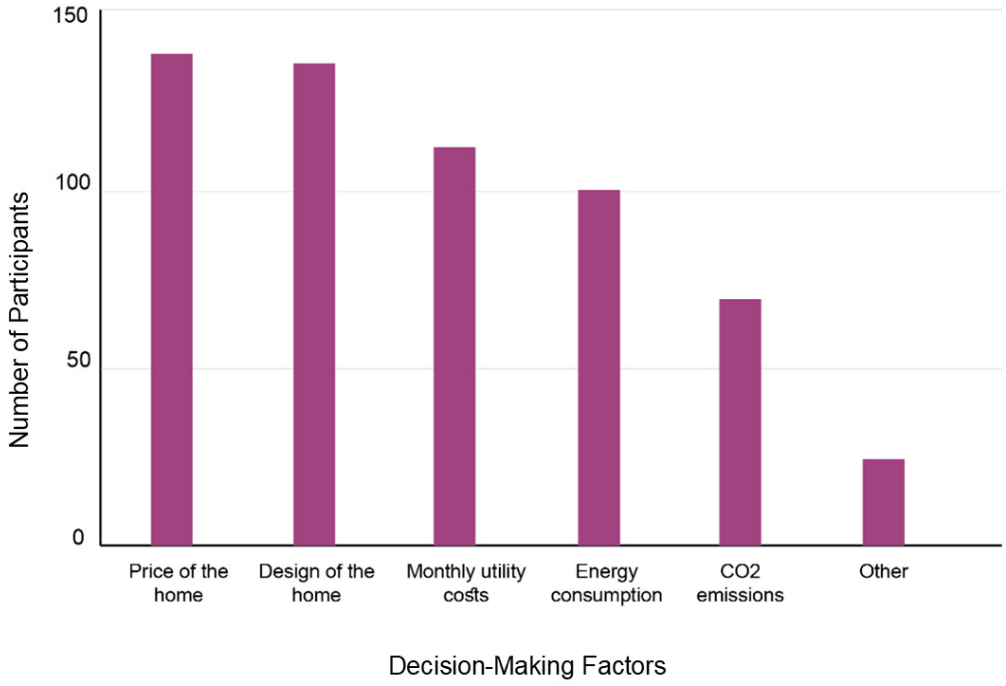


Figure 7. Bar chart representing the factors influencing home buyers' decisions.

However, it is important to note that in this study, the price and design of the home were held constant across both phases. This allowed us to isolate the influence of performance data, such as utility costs, energy consumption, and CO_2 emissions, on decision-making. When participants evaluated options with identical price and design, utility costs became the most influential factor in Phase 2, followed by energy consumption and CO_2 emissions. This shift highlights the critical role of humanized performance labels in shaping decision-making when other factors remain constant.

While CO_2 emissions were considered less significant overall, with 43.5% of participants indicating they influenced their decisions, this finding underscores their relevance in sustainability-focused choices. Qualitative feedback revealed that some participants were less familiar with the implications of carbon emissions compared to utility costs, emphasizing the need for public education to elevate awareness of environmental metrics.

In addition to these quantitative findings, qualitative insights identified other influential factors, including location, neighborhood, materials, and construction quality, as highlighted in a word cloud analysis of responses in the "other" category (Figure 8).



Figure 8. Text cloud showing answers to factors other than the list above.

4. Discussion

This study highlights the importance of humanized energy labeling in influencing housing choices by providing clear, accessible energy-related information to prospective homebuyers. These findings contribute to research on how decision-making impacts climate change mitigation by emphasizing the role of buildings in energy consumption and carbon emissions. Energy-efficient designs not only reduce environmental impacts but also provide financial and quality-of-life benefits, aligning with research across various industries that demonstrates the effectiveness of labeling systems in guiding consumer behavior [7].

The results demonstrate that 77.3% of participants altered their initial preferences after reviewing humanized energy labeling, with no participants opting for less efficient designs in the second phase. This underscores the power of performance information in promoting sustainable decision-making and aligns with studies showing that contextualized information fosters demand for environmentally responsible choices [26]. While energy labeling influenced most participants, its impact on those already inclined toward energy-efficient options was limited, consistent with research suggesting that performance labels often reinforce pre-existing preferences [27].

The chi-squared analysis confirmed that the influence of energy labeling transcends demographic differences, highlighting its broad applicability. These findings suggest that humanized labeling can reduce disparities in decision-making across income and education levels, providing a universal tool for promoting sustainability [28].

While the findings offer valuable insights, several limitations must be acknowledged. The study's reliance on a moderate sample size and online surveys introduces potential biases, including response and selection bias [29]. Additionally, the controlled survey conditions may limit the generalizability of results to real-world settings. Future research should investigate the long-term effects of energy labeling in real-world contexts, where decision-making conditions are more dynamic and nuanced. Additionally, exploring how cultural and social factors influence consumer preferences could provide deeper insights into the effectiveness of labeling systems across diverse populations. Expanding on how

information framing impacts trust and engagement with energy data could further refine the design of performance labels.

These findings reinforce the value of humanized energy labeling as a practical tool for promoting energy-efficient housing choices. By providing accessible, performance-based data, labeling systems can empower consumers to make informed decisions, fostering demand for sustainable practices in the real estate sector.

5. Conclusions

This research highlights the potential of humanized energy labeling to influence housing choices, promoting energy-efficient designs and supporting climate change mitigation efforts. By presenting energy performance, carbon emissions, and utility cost data in an accessible format, the study demonstrated that 77.3% of participants shifted their preferences toward more sustainable options. This research highlights the dual role of energy labeling as a tool for both consumer engagement and broader climate change mitigation efforts. Raising awareness about energy costs and environmental impacts through humanized labels can align individual housing decisions with collective sustainability goals. However, the findings also reveal opportunities to increase the emphasis on carbon emissions in labeling systems, as awareness and understanding of their significance remain limited.

The results further underscore the consistent impact of energy labeling across diverse demographic groups. Regardless of income, education, or other factors, participants responded similarly to the provided information, emphasizing the universal relevance and applicability of performance labels in guiding environmentally conscious decision-making.

By presenting clear and actionable data, humanized energy labeling provides a practical tool for bridging the energy performance gap and advancing sustainable building practices. These systems encourage developers to prioritize sustainability while enabling consumers to make environmentally responsible choices. When addressing global environmental challenges, tools like these represent a meaningful step toward advancing a more sustainably built environment.

Author Contributions: Conceptualization and study design, A.O.S. and S.S.; data collection and analysis, S.S.; manuscript writing, A.O.S. and S.S.; manuscript review and editing, A.O.S. and S.S.; supervision and project administration, A.O.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: This study was conducted in accordance with the guidelines of the Carnegie Mellon University Institutional Review Board and approved under protocol STUDY2020_00000313 (date of approval: 21 August 2020).

Informed Consent Statement: Informed consent was obtained from all participants involved in the study.

Data Availability Statement: Data will be made available on request.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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