

## Article

# Eyes on the Goal! Exploring Interactive Artistic Real-Time Energy Interfaces for Target-Specific Actions in the Built Environment

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**Citation:** Goubran, S.; Cucuzzella, C.; Ouf, M. Eyes on the Goal! Exploring Interactive Artistic Real-Time Energy Interfaces for Target-Specific Actions in the Built Environment. *Sustainability* **2021**, *13*, 1996. <https://doi.org/10.3390/su13041996>

Academic Editor: András Reith

Received: 20 January 2021

Accepted: 8 February 2021

Published: 12 February 2021

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**Abstract:** Current research is focused on sensing and modeling occupant behavior to predict it and automate building controls. Another line of research recommends influencing the behavior of occupants through feedback mechanisms and engagement. Yet, most of the work has focused on pushing occupants to reduce energy consumption over a long time and does not explore the potential to guide users to take specific actions promptly. The study examines a new interface mechanism that aims to solicit immediate and predefined actions from occupants. Building on seminal research in the field, the study uses art visualization to reinterpret social feedback. We test this approach in an immersive interaction space where participants react to artistic visuals to attain predefined settings for three indoor devices. In the 197 interactions recorded, participants' overall actions conformed with the predefined goals. The participants were able to reach all or some of the targets in more than 80%, within an average of less than 30 seconds. We also see that complementing the visuals with textual hints improved the interaction in terms of engagement and accuracy. We conclude that ambient, abstract, and artistic real-time goal-driven feedback is effective in influencing immediate actions. We recommend that guiding occupants didactically has a strong potential for advancing building controls.

**Keywords:** human building interactions (HBI); occupant behavior (OB); feedback (eco-feedback); gamification; energy behavior; immediate actions

## 1. Introduction

Today, a large body of building-related research is focused on collecting, understanding, analyzing, and predicting the behavior of building occupants. Researchers depend on occupants' feedback to investigate indoor environmental quality (IEQ) and the parameters that affect space users' behavior through sensing and monitoring human–building interaction (HBI) or using post-occupancy evaluations. Increasingly, automated controls have been gaining the interest of researchers and building operators as a means for balancing energy efficiency and occupants' comfort. Many scholars have focused their work on understanding human behavior in buildings and modelling and predicting it. We know that occupant behavior (OB) is complex and can be affected by many factors [1–3]. The fact remains that “[our] understanding of occupant behavior and its role in building energy performance remains vague, confusing and inconsistent” [4].

A parallel research direction proposes that influencing OB is needed to sustain energy efficiency improvements and to close the gap between predicted and actual performance [5–8]. Significantly less attention has been given to studying more innovative and interactive feedback mechanisms for occupants. Janda [8] proposes to advance our understanding of building and ecologically related feedback towards a pedagogy, or a form of didactic learning, as suggested by Cucuzzella et al. [9–11]. The seminal work of Ham, Midden, McCalley and others [12–20], published almost 10 years ago, has already proved that both social and ambient feedback are more persuasive mediums for inciting behavior changes and influencing occupants. Yet, most of the available work on feedback interfaces in buildings remains focused on direct data reporting (such as energy consumption metrics or savings metrics) or direct messages (such as red indicators for high usage and green indicators for eco-usage, or text information related to comfort or efficiency), e.g., [21].

Additionally, a common focus for all studies focused on energy feedback in the built environment was overall consumption and specifically energy-saving trends. Today, with the expanding complexity of building systems, energy-metering structures and the dependence of multiple energy sources, building control actions have evolved beyond the single parameter optimization for overall energy savings to incorporate a time-dependent demand response as seen in [22,23]. Thus, there is a need to explore how control interfaces can trigger timely actions whose purposes are less linear.

This study builds on the findings of Ham and Midden [12–20] by reinterpreting social digital agents in the form of digital art that can convey messages aesthetically, symbolically, and in a manner that appeals to the emotions. It also extends the end-goal of human–building interaction towards more complex control objectives beyond simple energy reduction. Specifically, it explores real-time ambient and artistic feedback’s potential to guide users to take precise control actions to reach predefined target levels instantaneously (i.e., in a short amount of time). The paper starts in Section 2 by providing the study’s relevant background, further highlighting its objectives. Section 3 presents the research design and methodology. The detailed results and discussions are presented in Section 4. Finally, Section 5 concludes the study, presenting areas for future investigations.

## 2. Background and Theoretical Foundation of the Work

Occupants’ decisions and behaviors are influenced by various external factors [24], and their priorities and preferences could vary significantly [25]. Paone and Bacher [26] reviewed studies that reported variations of more than 25% in energy consumption due to changes in occupant behavior. Yet, O’Brien and Gunay [1] conclude their review by indicating that many of the contextual factors that influence OB “may not be suitable for mathematical models”. There has been a call to move towards including occupants within the loop of building controls (known as human-in-the-loop controls), which can be achieved through occupancy sensors and measurement of human feedback or HBI [27]. Emerging research in the building controls field is now moving towards occupant centric controls, which uses environmental and HBI data to identify optimal control actions [28]. However, most models assume discomfort as a critical driver for human interaction with building controls.

Research has proved that occupants are willing to accept minor or temporary violations of their comfort if given rewards, compensations, or incentives. Financial incentive has been used to control energy consumption used by electric producers, as explained by [22,23] and supported by research findings, e.g., [29]. Others have explored competitiveness between individuals as means for creating these changes, e.g., [30]. Occupants with pro-environmental beliefs were also shown to accept less than ideal conditions in “green” buildings, supporting their environmental principles [31]. Others, e.g., [32], have shown that occupants’ perception of comfort is highly dependent on their assessment of their level of control; this is in line with the environmental psychology work related to “threat of autonomy” presented by [14]. Thus, focusing only on meeting the

comfort expectations of occupants (through comfort-driven control strategies) while not trying to influence OB could result in increased energy use [33] and in disregarding many important ecological, ethical (related to prioritizing humans and their over nature or resource consumption), cultural/beliefs, and even biological factors [5]. Additionally, it limits occupants' ability to contribute to demand-related control actions, such as controlling energy demand during peaks, responding to specific energy shortages, keeping buildings within self-generated energy, and even meeting carbon budgets.

Published research has analyzed the triggers for OB (e.g., [24,26,34,35]). However, most of the work has been focused on understanding normal or "unsolicited" occupant behavior in built spaces (e.g., [36]). Studies highlight the "Intention-Behavior Gap", which occurs when occupants perform a specific action repeatedly based on habitual patterns rather than on a conscious cognitive intention to perform it [37–40]. A large body of knowledge highlights that feedback mechanisms can change OB in the immediate and medium and long term. Energy metrics provided through apps or displays, such as those reviewed in [41–43], were used to inform occupants about energy consumption and the effects of their actions. The availability of energy feedback systems was also seen as a contextual factor that affects occupants' actions, as proposed by O'Brien and Gunay [1]. While gamification, rewards, and persuasion are proposed as a possible means for achieving positive behavior change, most of the available literature focused on rewarding users based on their energy savings or consumption patterns (e.g., [44–46]).

Jain et al. [41], in their 6-week study, focused on understanding the link between different eco-feedback interface features (such as historical comparison, normative comparison, reward/penalization, and disaggregation or appliance level energy data) and reductions in energy consumptions. They confirmed a link between interface engagement and reduction in energy. Additionally, real-time feedback was reported as an effective means for raising awareness regarding the consequences of occupant action and possibly changing their behaviors [43,47–49]. Based on the concept of persuasive computation, Chen et al. [50] used a virtual object (an aquarium-like environment) that responds to energy consumption data in two university labs over 7 weeks. The virtual aquarium flourished (or not) based on the energy metrics obtained from appliances, including real-time, medium- and long- term indexes [50]. They found that the display system had a significant effect on energy conservation in the test space; i.e., that users reduced the energy consumption in the rooms monitored throughout the experiment [50]. The effectiveness of virtual objects was also proved in a much earlier study by Kim et al. [20] and recently explored in eco-driving behavior [51]. In a 2011 study, researchers developed ambient and artistic feedback displays, which moved beyond traditional bar charts, graphs, or depictive graphics [52]. They reported that abstract representations are suitable for providing occupants with an understanding of energy consumption and enabled a high engagement level with the information [52]. While exploring the representations' design parameters, they did not examine their displays' energy consequences [52].

Yet, in their recent study, Day et al. [53] highlight that exploring new interaction techniques and technologies could offer a wide range of opportunities for the field of control, human–building interaction, and building interfaces.

The majority of studies focused on the medium and long-term consequences of feedback or explored the changes in occupants' energy consumption awareness and/or behavior over a period ranging from days to months (e.g., [21,44,45,47,50,54]). Additionally, the focus of most research remained on overall energy consumption metrics. Additionally, most studies built the game and interaction logic on quantitative data; i.e., by showing direct metrics or translating metrics directly into quantifiable elements such as the number of trees or fish (e.g., [45,50,55]). Very little work explored innovative approaches to providing feedback to occupants (that depended on art, for example) or studied eco-feedback's ability to trigger immediate occupant actions. Additionally, few published works focused on using feedback as a means for soliciting specific or goal-driven control actions from space occupants.

### 2.1. Social, Persuasive, and Ambient Feedback—The Theoretical Underpinnings

The work of Midden and Ham is influential to the topic and presents research areas that remain, until today, solemnly developed upon in building research. In a series of studies published between 2008 and 2014, the researchers explored several key hypotheses surrounding the potential of non-quantitative feedback in guiding occupants' energy behavior. On the first level, they proved that virtual environments and specifically intelligent agent technologies (such as virtual robots or characters), which interactively communicate personally, could enhance supportive systems for attaining energy-related goals [13]. Then, they proved that social feedback, from a virtual robotic agent, has stronger persuasive effects than factual and data-driven feedback and that negative feedback (i.e., evoking valence) was more effective than positive feedback [16], especially in conditions of higher task similarity [18]. They attributed these findings to the fact that quantitative feedback required more cognitive loading than social forms of feedback and that persuasion can happen without directly receiving the user's conscious attention [15]. Finally, they further abstracted their approach to exploring ambient lighting's effect in guiding behavior unconsciously, proving that ambient lighting feedback is a more effective form of persuasion than numerical or factual feedback [17].

McCalley [19] presented the theoretical foundations of these discoveries, grounding the work in a combination of the goal-setting theory, first proposed by Locke and Latham [56], and the feedback intervention theory (FIT), first developed by Kluger and DeNisi [57]. They indicated that have a specific and clear goal could affect performance by (1) directing attention and effort to objective-related activities, (2) energizing individuals to attain the goal, (3) prolonging the effort to reach the goal, and (4) leading to discovery and exploration of task-relevant knowledge. FIT provides clarification that reaching the goals is contingent on providing relevant and goal-specific feedback.

### 3. Research Design and Methodology

Building on the theoretical foundation presented, this paper further extends the nature of feedback interfaces to root it in digital art, inspired by the work of [52]. Here art is seen as an ambient feedback medium that can evoke emotions, communicate messages, or teach lessons and act as social agents. Thus, the approach aims to activate art as an ecological didactic social agent in the built space. In line with the approach of [52], this research does not study the energy consequences of human actions (i.e., savings or changes in consumption patterns). Instead, the research aims to explore if art-based social interfaces can trigger engagement leading to immediate occupant actions. The study explicitly moves away from the broad target of overall energy saving to explore these new interfaces' ability to solicit immediate and predefined actions from the occupant. In this context, the predefined actions are understood as goals that users have to attain, and based on which they are provided feedback, building on [19,56,57]. This approach eliminates the positive belief–action biases reported by [31] and frames this interface's potential as a control strategy fit for more complex control and demand response situations. Specifically, we aim to understand these art-based interfaces' success in terms of soliciting engagement from space users and their effectiveness in triggering them to take specific control actions. Additionally, we study how the interface features could affect the interaction's efficacy and the occupants' ability to attain the predefined control targets.

Thus, the study aims to answer the following overarching research question: Can ambient, abstract, and artistic real-time feedback be an effective way to trigger immediate predefined indoor environment control actions? In addition to the following sub-questions:

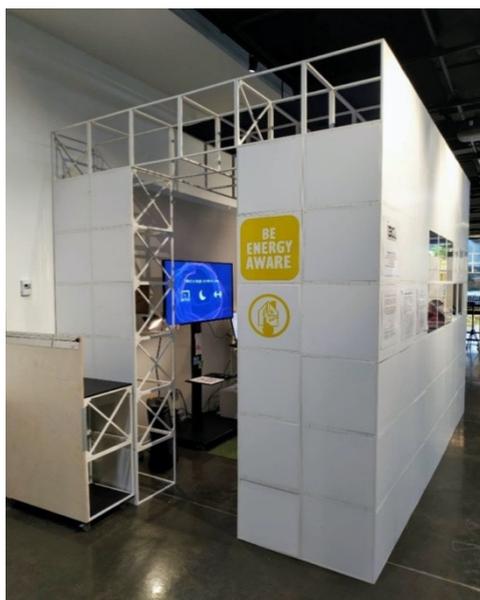
- How do the actions of the users conform with the predefined control goals required?
- How does the difficulty of the actions, in terms of the number of parameters and controls requiring modification, affect the outcomes?
- How does the availability of textual or non-artistic hints affect the outcomes?

We define that *ambient, abstract and artistic real-time feedback* is real-time feedback that is continuously running in the environment (i.e., ambient), abstracted from its quantitative metrics (i.e., abstract), and visually appealing and stimulating (i.e., artistic). *Immediate actions* are occupant actions that take place within seconds or minutes of a trigger or feedback. *Target-specific actions* are defined as equipment- or device-level actions that require occupants to set specific devices (such as heater, fan, or light) to a predefined or target setting.

We design and build an immersive real space where participants can interact with the feedback interface we developed and designed (similar in logic to what was previously used in testing occupants' actions, e.g., [25]). It consists of a room of approximately 1.5 by 2.5 m, modelled as a living room, and with only one entrance. We added an opaque black cover to the room's ceiling to minimize the penetration of direct light. Since the room was located in a university exhibition space, we did not invite participants. Instead, we presented the exhibition visitors with a series of colourful posters and a large active screen so that they would feel compelled to enter the space and play (seen in Figure 1). The experimental room was equipped with 3 types of indoor environment devices relating to 3 different indoor environment parameters, which would have to be controlled by the participants (these were real physical devices):

1. Heating: an infrared space heater (with 3 levels: 0, 1, and 2);
2. Ventilation: a pedestal fan (with 3 levels: 0, 1, and 2);
3. Lighting: two space lamps with 2 separate switches (allowing for 3 levels: 0, 1 lamp, 2 lamps).

We connected each of the 3 devices to non-invasive AC current sensors. We feed the current information into a computer that processed the data in real-time to create corresponding artistic visualizations. We did not alter or centralize the devices' physical and actual controls, which were dispersed around the room. The room was also equipped with a large screen and computer control pad which made up the interactive game components. The large screen size allowed the users to be immersed in the visuals presented. We optimized the space so that there were visible and evident differences in lighting conditions when the lamps were turned on or off in the space.





**Figure 1.** Test room setup fitted with a heater, fan, and two lighting units, the comfortable leather couch and plants, and the interactive control interface.

We designed the interaction with simplicity and clarity in mind. When the participants first enter the space, they are prompted to reset all devices to the zero (0) level, pick up the control pad, and select one of 3 profiles: namely, sleep, exercise, or work. As seen in Table 1, each of the profiles had its specific device target levels, representing varying difficulty levels (discussed in the next paragraphs). The artistic visuals moved between two main states (screenshots seen in Figure 2 considering that the actual game featured non-static, i.e., dynamic, and interactive visuals): (1) a state of harmony, and (2) a state that is out of synch. The difference between the two was designed to be clear, and the visual would progressively approach harmony as the devices' settings converged to the target levels. Based on previous research recommendations [16], the art conveyed negative feedback in the form of uncoordinated and out-of-sync visuals to solicit action. The artwork used in the experiment was dynamic and reacted to the AC current data. It changed in speed, size, color, and general distress based on the current data and profile following an underlying generative code (Inspired by the “Generative Breath” sketch by *elektronaut* on OpenProcessing: <https://www.openprocessing.org/sketch/579102>).



(a)

(b)

**Figure 2.** Sample screenshots of visuals used (showing overall artistic character and the device-level indicators at the bottom right corner) at: (a) harmony state and (b) out of sync state.

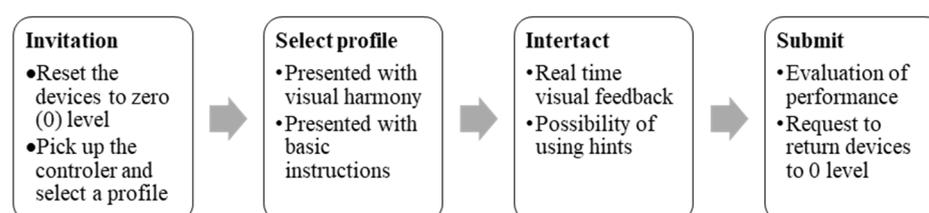
The visuals changed from a “slower” and harmonious rate of animation shown in Figure 2a to a “faster”, more randomized, and distressed rate of animation shown in Figure 2b. While the artwork was visibly different depending on the AC current data and profile, the visuals’ main elements did not change over the study.

**Table 1.** Target levels for indoor parameters in the three designed profiles.

Difficulty	Profile	Target level		
		Heater	Fan	Light
1	Sleep	Level 1	Level 0	Level 0
2	Exercise	Level 1	Level 2	Level 1
3	Work	Level 2	Level 1	Level 2

Once the participant selected a profile, the screen presented the occupants with the harmonious visual for 8 s and explained that they were required to modify the settings (i.e., levels) of the fan, heater, and light to reach this state of visual harmony presented. After this initial 8 s, the visual would go to an out-of-synch state and start to react to the real-time AC current data by changing speed, size, alignment, and/or general distress. The participants would know that the target equipment levels were being reached when the visual moved towards its state of harmony and that they succeeded in setting all parameters when it returned to its full state of harmony (presented in the initial 8 s). A HINT button was made available on the control pad and presented textual hints (for example, “you could try adding more light!”) at any point during the interaction. If the participants pressed the hint button at the harmony level, the interface prompted them with a message indicating that “everything looks just right!”. The language selected was low-controlling language in line with previous research findings [14].

Additionally, and to make the devices’ real-time settings clear, we used small indicators (seen in the bottom right corner of the screenshots in Figure 2) to indicate the devices’ actual levels. Once the users were satisfied with the levels they selected for the devices, they would click on a SUBMIT button, and the interface informed them on the screen if they were successful or not in reaching the target values. This overall game process is presented in Figure 3.



**Figure 3.** Overall interaction process and framework.

Each profile had a slightly different level of difficulty in terms of control actions. The sleep profile only required the heater to be set to level 1 (considered the easiest of the profiles). The exercise profile needed changes in all the 3 parameters, with only one of the 2 light switches having to be modified (considered an intermediate level of difficulty). Finally, the work profile was considered to be the most difficult since participants were required to configure all the 3 parameters, including the 2 separate light switches.

In all the profiles, participants had the free choice to adjust the ventilation (i.e., the fan), heating (i.e., the heater), and lighting (i.e., the 2 light switches), and the visual was affected by the changes in any of the devices in all profiles. The participants were asked to reset all the equipment to their zero (0) level before and after their interaction. The research team also ensured that all devices were set to 0 before and after each interaction, and when not in use. We did not provide the participants with an explanation regarding

the connection between the different devices and the visual (i.e., how the various equipment's current data affected their visual effects). Additionally, the participants were not expected to understand these connections fully. Instead, they were simply expected to discover the device control actions required to get to the desired visual state of harmony. Thus, the visualization tool operated in "a black box" and produced visual outputs that remain complex in their form.

The exhibition space in which the experiment was located operated according to typical Canadian education institution standards of indoor comfort (as per the available standards, [58,59]). To eliminate the individual, values, and psychological action biases reported in previous studies [25,31], the design specifically selected not to shape the required actions around pro-environment (for example, using less energy) or pro-comfort (for example, making the space more comfortable) considerations. The interface did not ask the participants to change the equipment settings so that they would be/feel more comfortable. In fact, some of the participants indicated that most of the goals required led to the space being "less comfortable". Further, there was no clear material reward or persuasion presented to the participants. Instead, the experiment required the participants to react to the visual on the screen and bring it back to a "visual harmony". Thus, it is assumed that the participants' actions were not driven by factors other than the interaction itself. A data filtering system was embedded in the interface code to ensure that all interactions recorded were correct (i.e., ignoring uncompleted interactions and pre-mature submits). The system was designed to record the following data for each case:

- The time and date each interaction started (the timestamp when a profile was selected);
- The selected profile;
- The interaction time in seconds (i.e., how much time until the participant clicked on the SUBMIT button, after the initial 8 s of harmonious visual and instruction presentation);
- The levels of the 3 devices at the SUBMIT moment, ranging for all devices between 0 to 2;
- The number of hints used during each case.

Based on the device levels recorded, the submission's correctness was assessed as follows: (1) If the participant reached all the 3 parameters' target levels, correctness is equal to 3. The submission is considered fully-correct. (2) If the participant attained 2/3 or 1/3 of the parameters' target-levels, correctness is equal to 2 or 1, respectively. The submission is considered partially-correct. (3) If the participant did not attain any of the parameters' target levels (0/3), correctness is equal to 0. Their submission is considered incorrect.

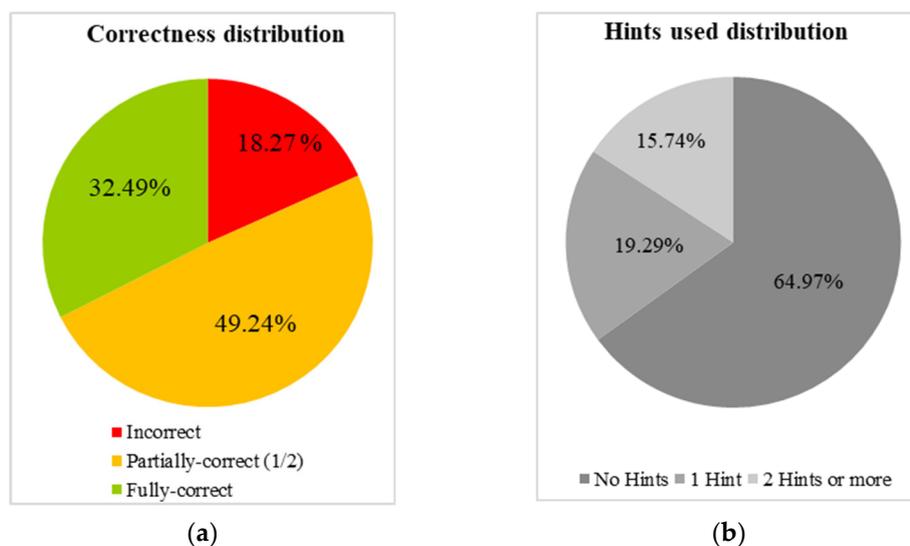
Since the research team was available during the experiment hours, some conversations happened with the participants after they engaged with the interface. These were not part of the study's original design (i.e., no interview was planned or directly integrated into the study); they immersed naturally and were generally initiated by the participants. However, the conversations shed some crucial insights on the interactions' dynamics and substantiated some observations. The study used correlations, rather than regression, to explain the relationship between the interface parameters. This approach is in line with the work's exploratory nature and is based on the fact that the participants were performing those interactions in a simulated environment located in a public space, and the fact that the experiment was not designed as a controlled trial (considered a limitation).

#### 4. Results and Discussion

The experiment was active from the end of October to the end of November 2019 for a total of 30 days. Overall, 197 valid interaction cases were recorded. The general overview of the 197 cases is as follows:

- The average correctness was 1.8 (i.e., in all the cases an average of close to 2 of the 3 correct parameters were submitted by participants), with a standard deviation of 1.1.
- The average number of hints used was 0.7 (median of 0 hints and a mode of 0 hints), with a standard deviation of 1.4 hints.
- The average engagement time was 27.6 seconds, with a standard deviation of 24.9 seconds.

The cases are well distributed across the 3 profiles: 38% of the cases were in the sleep profile, 31% in the exercise profile, and 30% in the work profile. Figure 4 presents the overall results. As seen in Figure 4a, in the most considerable portion of cases, the participants provided partially correct submissions. As seen in Figure 4b, there were no hints used in most cases (more than 60%).



**Figure 4.** Overview of findings: distribution of (a) observed correctness, (b) use of hints.

The participants in this experiment were able to attain all or some of the goals (more than 80% of the time), by modifying up to three independent parameters and four controls, with no earlier (*a priori*) knowledge of the devices' required target levels, nor how their actions affect the artistic visuals, and with no numerical or quantitative energy metrics. They were also able to register a partially correct submission in an average of 24 seconds and fully correct submissions in an average of 36 seconds. Finally, they were also able to reach these outcomes while using minimal assistance, since more than 60% of the cases had no hints recorded. Thus, the results point to the ability of real-time artistic feedback in triggering target-specific actions.

One of the questions that we explore in the discussion is whether ambient, abstract, and artistic real-time feedback adds a significant layer of influence on the other contextual factors guiding normal occupant behaviors (under no discomfort, for example). Following Ozcelik et al. [25], we divide the control actions into thermal (relating to fan or heater), visual (relating to light), and multimodal actions (combining the two previous categories). In the experiment, the sleep profile required thermal-only action (heater), and the two other profiles required multimodal actions. The observed likelihoods of different actions types are presented in Table 2 (separated based on the profile-specific requirements). The most dominant action corresponded to the requirement of each profile group (i.e., either thermal-only in the sleep profile or multimodal in the exercise and work profiles).

**Table 2.** Observed likelihood of no action, visual-only, thermal-only, or multimodal actions.

	Thermal-Only Actions	Visual-Only Actions	Multimodal Actions	No Actions
<b>Sleep profile,</b> thermal-only action required ( <i>n</i> = 75)	<b>46.67%</b>	10.67%	8.00%	34.67%
<b>Exercise and work profiles,</b> multimodal actions required ( <i>n</i> = 122)	4.92%	7.38%	<b>68.85%</b>	18.85%

**Notes:** Required action observed likelihood in bold.

The Kruskal–Wallis test indicated that the difference between the participants' actions in the two profile groups is significant ( $p < 0.001$ ). The independent samples Mann–Whitney U Test revealed a significant difference ( $p < 0.001$ ) between the thermal-only actions, and a significant difference ( $p < 0.001$ ) between the multimodal actions across the two profile categories. As expected, the test revealed no significant difference (at  $p < 0.01$ ) in the visual-only actions. There was also no significant difference (at  $p < 0.01$ ) in the no-actions category across the two profile groups. This shows that a certain number of participants might not take any action independently of the profile and its requirements (the observed likelihood of no action in the 197 cases is 24.87%). Thus, we conclude that occupants' decisions and actions under no discomfort conditions can considerably be influenced by real-time artistic feedback, guiding them to take specific actions according to the predefined goals. These actions contrasted previously reported occupants' actions priorities under no discomfort conditions [25]. In the next sections, we will present several statistical tests to understand further how the participant's choices (relating to profile selection, hints used, and the number of trials) affected their submissions' correctness.

#### 4.1. Correlations between Parameters

We start by investigating the correlation between the different variables of the experiment by using the Spearman's rank-order correlation for the (A) profile, (B) hints used, (C) engagement time, and (D) correctness (results presented in Table 3). The results show a strong negative correlation between the profile and correctness (i.e., the easier the profile, the more correct the submitted answer). The results also show strong positive correlations between the hints used and the engagement time (i.e., the higher the number of hints used, the longer the engagement time), as well as the hints used and correctness (i.e., the higher the number of hints, the more correct the submitted answer). In the next sections, we further analyze the collected data while focusing on the variables with strong correlations.

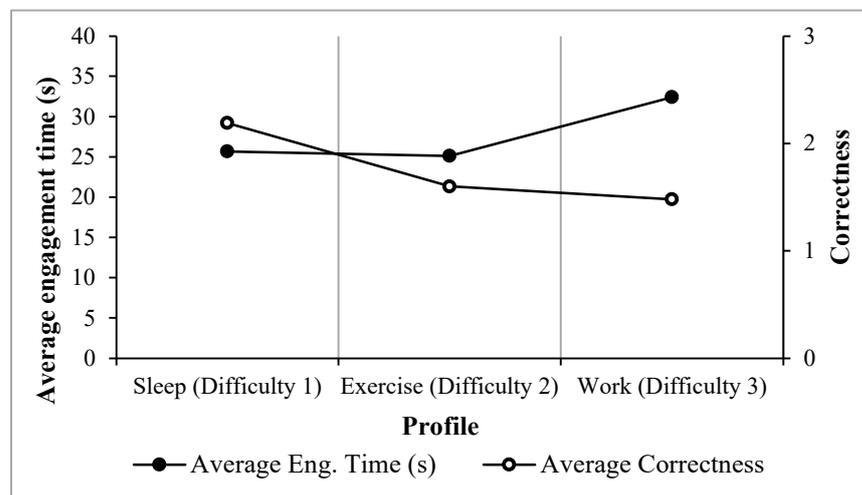
**Table 3.** Correlation between the different variables of the experiment.

		Eng. time (s)	Hints Used	Correctness
<b>Profile</b>	A	0.084	0.049	−0.249
	B	0.2417	0.4940	0.0004 ***
<b>Engagement time (s)</b>	A	-	0.361	0.169
	B	-	$1.81 \times 10^{-7}$ ***	0.0177*
<b>Hints used</b>	A	-	-	0.434
	B	-	-	$1.97 \times 10^{-10}$ ***

A = Correlation coefficient; B = *p*-value (based on Spearman's rank-order correlation); \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

#### 4.2. The Effect of Profile Difficulty

We intentionally designed the experiment's profiles to vary in difficulty based on the number of environmental parameters and the number of controls requiring modification. Figure 5 illustrates that, in general, the more difficult the profile, the longer the engagement time and the lower the correctness.



**Figure 5.** Average engagement time and correctness for the different profiles.

The Kruskal–Wallis test revealed no significant difference (at  $p < 0.05$ ) between the engagement time and hints across the three profiles. We can conclude that the level of difficulty of the profile did not significantly affect participants' on those variables, furthering supporting the fact that the participants did not know the complexity of the profile they selected.

The Kruskal–Wallis test showed a significant difference between the correctness ( $p < 0.001$ ) across the three profiles. Thus, we used the Dunn pair-wise comparison for the correctness across the three profiles (presented in Table 4). The results show that the correctness of submissions in the profiles that required modifying three parameters (i.e., the exercise and work profiles) is significantly different from the profile that required modifying one parameter (i.e., the sleep profile, which required changes only to the heater level). However, there was no significant difference in correctness when a second control requirement for lighting was added (i.e., between the exercise and work profiles). We conclude that the number of environmental parameters to be controlled affected the submissions' correctness, but that the added control complication (i.e., more control actions needed to meet target levels) had no significant effect.

**Table 4.** Dunn pair comparison of correctness in the three profiles

	Sleep (Difficulty 1)	Exercise (Difficulty 2)	Work (Difficulty 3)
Sleep	-	0.0048 **	0.0007 ***
Exercise		-	0.5924

Note: The Kruskal–Wallis test revealed that there is a significant difference ( $p < 0.01$ ) between the profiles used across the correctness groups (i.e., fully correct, partially correct, and incorrect). The Dunn pair-wise comparison results show that there is a significant difference ( $p < 0.001$ ) between the profile selected in the cases with incorrect and partially correct, as well as incorrect and fully correct submissions. However, there is no significant difference in the chosen profile between the cases with partially or fully correct submissions (at  $p < 0.05$ ). \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

Considering that the most common profile for the partially and fully correct submissions was the sleep profile (difficulty 1) and that of incorrect submissions was the

work profile (difficulty 3), we further conclude that the profile difficulty had a significant effect on the correctness of the submissions, with significantly higher correctness when only one parameter is requiring control. This points to the possibility that asking the participants to control one parameter at a time (e.g., dividing multiple parameter problems into incremental single parameter tasks) might yield more correct submissions. Additionally, it shows that the participants responded to the complexity of the goals set by further engaging with the interface, indicating the success of the game strategy in maintaining engagement in line with the goal-setting theory [56].

#### 4.3. The Effect of Hints Used

While the profile difficulty did not affect the number of hints used, Table 2 showed that the hints used are strongly correlated with the correctness (positively) and engagement time (negatively). Table 5 presents the average results related to those variables.

**Table 5.** Average correctness and average engagement time based on the number of hints.

	Average Correctness	Average Engagement Time (s)
<b>0 Hints (<i>n</i> = 128)</b>	1.45 (Std Dev 1.06)	21.81 (Std Dev 21.42)
<b>1 Hint (<i>n</i> = 38)</b>	2.34 (Std Dev 0.80)	32.34 (Std Dev 25.34)
<b>2 Hints or more (<i>n</i> = 31)</b>	2.48 (Std Dev 0.88)	45.39 (Std Dev 27.80)

The Kruskal–Wallis test showed a significant difference ( $p < 0.001$ ) between the engagement time and correctness across the three groups proposed in Figure 4b. The Dunn pair-wise comparison (Table 6) shows that using one hint (as opposed to no hints), resulted in a significant difference in correctness ( $p < 0.001$ ) and engagement time ( $p < 0.01$ ). However, using more than one hint (i.e., two hints or more) did not result in a significant difference in both variables. Thus, we conclude from our experiment that participants who used at least one hint were more likely to submit correct answers and engage with the interface for a longer time. These results confirm the findings of Midden and Ham [12–20] that combining textual and visual feedback could result in more effective social interactions, exhibited here by longer engagement time and more effective outcomes. Considering that the average hints used in incorrect and partially correct submissions are both below one, we further conclude that using at least one hint can significantly increase the submission's correctness.

**Table 6.** Dunn pair-wise comparison of correctness and engagement time based on the number of hints.

	Correctness		Engagement Time	
	1 Hint	2 Hints or more	1 Hint	2 Hints or more
<b>0 Hints</b>	$8.0 \times 10^{-6}$ ***	$5.60 \times 10^{-7}$ ***	0.0062**	$3.0 \times 10^{-6}$ ***
<b>1 Hint</b>	-	0.4642	-	0.0747

**Notes:** The Kruskal–Wallis test revealed that there is a significant difference ( $p < 0.01$ ) between the number of hints used across the correctness groups (i.e., fully correct, partially correct, and incorrect). The results of the Dunn pair-wise comparisons for the two variables indicates that there is a significant difference ( $p < 0.001$ ) between the number of hints used in the cases with incorrect and partial correctness, and partially correct and fully correct submissions. However, there is no significant difference in the hints used between the cases with incorrect or partially correct submissions (at  $p < 0.05$ ). \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

## 5. Conclusions, Limitations and Areas of Future Studies

This article explores how real-time artistic feedback can be an effective way to trigger target-specific occupant action. It presents several contributions to the study of solicited behaviors and the possible role of these highly engaging interfaces as didactic tools in the

built environment [9–11]. The work is built on the goal-setting theory and the FIT [56,57] and develops on their application in the built environment, as seen in McCalley's work [19]. We present a new methodology and approach for soliciting short-term occupant actions. The approach proposes a new form of ambient building interfaces that is engagement focused and interaction driven [53,60,61]. It continues and expands the areas of study proposed in the seminal work of Midden and Ham [12–20], which has been largely ignored in the recent exploration of the topic. The study underscores the important art and design fields that can play a role in developing next-generation building interfaces [62]. The findings also emphasize that building controls research needs to investigate the qualitative triggers to behaviours in the built spaces in more depth.

The results show that with little incentive, people were able to perform complex and precise control actions. The feedback mechanism and interface triggered participants to quickly take these predefined control actions, even if they contradict their comfort. Table 7 presents the study's conclusion (in terms of research and discussion questions, and the findings). In the next paragraphs, we will discuss further the limitations and implications of the research.

**Table 7.** The study's research and discussion questions and the summary of findings.

<b>Research Question (and Sub-Questions)</b>	<b>Conclusions</b>
Can ambient, abstract, and artistic real-time feedback effectively trigger targeted indoor environment control actions?	Yes. In 80% of the cases, participants could make all or some of the required actions for reaching the required devices' target levels.
Can the control goals set ambient, abstract, and artistic real-time feedback significantly guide the actions of users?	Yes. The results show that the dominant participants' actions corresponded to the problem's requirement (being thermal or multimodal), rather than the visual dominance proposed in the literature. Since the control actions are unknown for the participants before their interactions (participants do not have a priori knowledge), the engagement time and hints used are not affected by the difficulty.
How does the required actions' difficulty affect the number of hints used, the correctness of the submissions, and the engagement time?	Yet, we observe that the more difficult the control actions (i.e., the more parameters requiring modification), the lower the correctness. However, the addition of controls (i.e., having multiple control switches for the same parameter) did not significantly affect submissions' correctness.
How does the number of used textual hints affect the correctness of the submissions and the engagement time?	Using at least one textual hint significantly increased the correctness of the submissions and the engagement time. However, using more than one hint did not significantly affect both variables.

The research had some fundamental limitations. This study presented an experimental and simulated HBI environment. Thus, without further validations, our findings are not directly transferable to real building environments. We also do not study the long-term effects of these interfaces. Finally, the research focused on exploring this tool's potential and was not designed as a controlled trial. Based on the design assumptions, certain variables, such as the effect of the artwork dynamism, were not tested independently and might require further investigation. Additionally, in the experiment, the target levels were predefined for all the test periods. In real-building applications, the target levels could be dynamic and informed by external (e.g., weather) and building-related parameters. These points limit the findings to correlations and broad observations specific to the case at hand.

This paper focused on studying if these art-based interfaces can trigger space users to execute precise control actions. We also attempted to push users to take actions that are

not rooted in comfort or energy savings to validate the approach. In the real-building applications, the approach would not be meant to penalize comfort or contradict savings behavior, but rather to moderate between comfort, performance, and environment. Such predefined actions would be geared towards actual energy objectives, including energy savings, demand reduction, emission reduction, responding to energy shortages, keeping buildings within self-generated energy, utilizing energy when available, or even meeting carbon budgets. Nevertheless, this study presents several implications and contributions to energy behaviors and feedback in the built space, which opens new avenues for research.

The next step for this line of work would be to formalize the experimentation to develop models that can predict these interfaces' effectiveness in real occupancy situations. Other lines of development include (1) exploring different visual and user-interface designs, (2) investigating the potential of this mode of feedback in different built spaces (private vs. public, for example), and (3) studying the long-term effectiveness of these interfaces (including its integration in mobile and smart home devices).

In this context, researchers can move away from depending on occupants' knowledge about their long-term energy consumption or savings for changing behaviors, to concentrate on providing them with prompt positive stimuli regarding their short-term energy-actions [63] and on ways to deliver immediate action-reward mechanisms through enticing visuals, interactions, and specific goal-driven mechanisms [13]. Additionally, it shifts our understanding of energy feedback from one-way reporting approaches to a form of coaching (through step-by-step didactic guidance [10], or even to a form of artificial companionship [64,65]). Our experiment shows that giving occupants control while didactically guiding them to make decisions does not translate to an inability to attain target settings for indoor devices, but the opposite might be true. The proposed interface can complement current control devices, ensure the users' involvement and awareness, while also achieving complex control objectives. The potential of these feedback mechanisms offers insights into next generation building interfaces and answers the design gaps identified in recent state-of-the-art reviews [53].

**Author Contributions:** Conceptualization, C.C., S.G. and M.M.O.; methodology, C.C., S.G. and M.M.O.; investigation, C.C., S.G. and M.M.O.; resources, C.C. and M.M.O.; data curation, S.G.; writing—original draft preparation, S.G.; writing—review and editing, C.C., S.G. and M.M.O.; visualization, S.G.; supervision and project administration, C.C. and M.M.O.; funding acquisition, C.C. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research did not directly receive specific grants from funding agencies in the public, commercial, or not-for-profit sectors. However, the researchers would like to recognize the Canadian Social Science and Humanities Research Council's support for their support and Concordia University. Sherif Goubbran would also like to acknowledge the Vanier Canada Graduate Scholarship's support and the Concordia Public Scholar Program.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Data available on request.

**Acknowledgments:** We would like to thank Aya Doma for her excellent assistance and insights on the statistical analysis. We would like to thank Anghelos Coulon for his work on the software design and setup of the experimental interface. We would also like to thank Gabriel Peña for setting up the testing space and providing the experience of sitting in a living room. We would like to thank Anna Waclawek of Concordia University's 4th Space for organizing the Cities event.

**Conflicts of Interest:** The authors declare no conflict of interest.

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