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Research Paper

User engagement for thermal energy-efficient behavior in office buildings using dashboards and gamification

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ABSTRACT

With growing concerns about climate change and increasing energy costs, energy-efficient use of buildings offers an opportunity to decrease CO_2 emissions and costs. The behavior of building occupants plays a significant role in the process of improving this efficiency both for new and existing buildings. In this work, we introduce a suite of web-based software applications that aim to encourage thermal energy-efficient occupant behavior in an office environment under the Living Lab Energy Campus (LLEC) initiative, using the campus of Forschungszentrum Jülich as a demonstration. The applications in the suite allow building occupants to visualize their energy demand and automatically control heating in the offices. Behavior change motivation is provided through the related concepts of gamification and serious games through the evaluation of behavioral energy efficiency reported as *energy penalties*, as wells as through real-time feedback and recommendations. An experiment was designed to test the interventions in a real-world setting, where the focus was on the setpoint temperature and ventilation habits of the occupants. The mean daily energy penalties in the ventilation intervention group was 65% lower than that of its control group (1.66 kWh vs. 4.67 kWh), with even lower penalties in the "activated" subgroup of the intervention group (0.74 kWh). In another test building that considered both ventilation and setpoint temperature, activated offices had 56% lower daily mean energy penalties than the control (1.91 kWh vs. 4.35 kWh), while in the pilot building, the energy penalties in the activated offices was 40% less than that of its control group (1.61 kWh vs. 2.94 kWh). All these effects were statistically significant and with large effect sizes. Furthermore, year-on-year thermal energy savings of about 18% (11.8 MWh) were realized in the pilot building where occupancy-driven heating was introduced.

1. Introduction

In the European Union (EU), the building sector contributes 40% of the energy consumption and over 30% of the CO_2 emissions [1,2]. According to estimations, 75% of the buildings in the EU are energy-inefficient [3]. Within the building sector, occupant behavior has been identified as a key factor in the energy efficiency of buildings and is often implicated in the difference between modeled and actual (post-occupancy) energy consumption of buildings [4–6]. According to the PROBE studies (Post-occupancy Review of Buildings and their Engineering), this difference is usually a factor of two: the actual consumption is twice the modeled consumption [4,7]. Similar results are also reported by other studies. For example, in one simulation study of energy behaviors of office occupants with profiles classified as one of austerity, standard, or wasteful, it was estimated that the wasteful profile can use up to 90% more energy than the standard energy profile in a one-person office, while the austerity profile can use up to 50% less energy than the standard profile [8]. In a related simulation study targeting commercial buildings with energy saving measures (ECMs), the wasteful profile consumed more than twice the energy of the austerity profile when the ECMs are occupant-dependent [9].

Clearly, there is potential for the improvement of energy efficiency in buildings through energy-efficient occupant behavior. However, there are challenges in engaging occupants and triggering behavior change in public buildings. First, building occupants in public buildings are usually indifferent to the energy efficiency of their behavior because they are not conscious of their impact on the energy consumption and are not responsible for the energy costs [10]. Additionally, this

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Nomenclature

Roman Symbols

T_{amb}	Ambient temperature (°C)
T_{base}	Base temperature for calculating heating degree days (°C)
$\hat{E}_{th}$	Estimated thermal demand of building (kWh)
$E^{*}_{th,saved}$	Adjusted thermal energy savings (kWh)
E_{th}	Historical (measured) thermal energy demand (kWh)

Sets

$\mathcal{N}_d$	Set of time points for day d at which ambient temperature is measured for calculating heating degree days

Acronyms / Abbreviations

API	Application Programming Interface
DIN	Deutsches Institut für Normung (German Institute for Standardization)
DSM	Demand Side Management
ECM	Energy Saving Measure
EU	European Union
FZJ	Forschungszentrum Jülich
GUI	Graphical User Interface
HDD	Heating-Degree Days
HMI	Human–Machine Interface
IAQ	Indoor Air Quality
ICT	Information & Communication Technology
IPVMP	International Performance Measurement and Verification Protocol
KPI	Key Performance Indicator
LLEC	Living Lab Energy Campus
MILP	Mixed Integer Linear Programming
NFC	Near-Field Communication
RMSE	Root Mean Squared Error
UX	User Experience

issue of occupant apathy to energy consumption in public buildings is not easily addressed in a top-down, management-initiated and management-sustained fashion in a European country like Germany. Only in the light of the energy crisis occasioned by the Russia–Ukraine conflict was there more assertive drive from government to save energy across the country. In spite of this, occupant behavior still requires more grassroots motivation for its transformation.

Furthermore, typical behavior intervention strategies involve providing energy consumption feedback to occupants through the installation of measurement devices [11]. However, in public buildings the issues of privacy and data security arise, which invariably impose a limit on the extent of such instrumentation, especially in a country like Germany where privacy is taken more seriously than in most other European countries, with supporting structures like the works council and Data Protection Officers serving to protect employees from privacy infringements [12–15]. Also, beyond privacy considerations, the cost of instrumentation in terms of time, effort and finances dictates the granularity of measurements that can be taken. Naturally, effective behavior intervention strategies that have minimal impact on privacy with low cost of instrumentation are preferable, especially when the transferability of such intervention methodologies is paramount.

Considering these challenges in bringing about behavior change in public buildings, in this work we develop and test software applications and tools to support occupant behavior transformation towards improved thermal energy efficiency, whilst maintaining acceptable privacy levels and reasonable instrumentation costs. These software applications enable building occupants to visualize the energy system of the building as well as control the system through a human–machine interface (HMI). Furthermore, the software applications include a *gamification* platform powered by an occupant behavior evaluation system with real-time recommendations, in addition to an accompanying *serious game* with real-world coupling. We then evaluate the real-world effectiveness these deployed systems in influencing occupant behavior. The behavior interventions studied in this work focus on occupant interactions with the heating systems in naturally ventilated office buildings under real-world conditions. This work is incorporated in the Living Lab Energy Campus (LLEC), in which a part of the infrastructure of Forschungszentrum Jülich GmbH (FZJ) is transformed into a testbed for *e.g.* monitoring and control approaches for future building and district energy systems. Our case study consists of a subset of office buildings in FZJ with different years of construction (ranging from the 1970s up to recently completed buildings), which are representative of the office building stock.

2. Background & literature review

The interaction of occupants with the building and its energy system is the focus of several large-scale studies. For example, the DataFEE project[1] focuses on the development of tools and methods for the analysis of the interaction of occupants with buildings. Likewise, Annex 66[2] and Annex 79[3] projects of the International Energy Agency's Energy in Buildings and Communities programme (IEA-EBC), focused on modeling occupants and occupancy, as well as the integration of occupancy in building models. This is because the actions of building occupants affect the energy system of the buildings in one of several ways, including via interactions with the heating, ventilation and air condition (HVAC) systems, and lighting system, and through window operation and electrical appliance use, among others [16]. For thermal energy consumption in naturally ventilated buildings, HVAC operation and window use are strong determinants of energy consumption in the heating season. Reducing the temperature setpoint from 20 °C to 19 °C, for example, can reduce building energy demand by 9%–10% [17,18].

Therefore, in order to address energy efficiency of building occupants, various behavioral intervention projects have been carried out. These interventions take one of several forms, including provision of information through visualization, active feedback through various means of communication, and numerous gamification and serious games studies. One main element for providing information and visual feedback in energy systems is the use of *energy dashboards* [19]. These dashboards provide a Graphical User Interface (GUI) for visualizations regarding energy-related data. Additionally, interactive dashboards provide good User Experience (UX) and encourage interactions with the information being presented. Whilst some studies show that dashboards are beneficial, other studies indicate, however, that visualization alone does not lead to sustainable energy-saving behavior [19,20]. Most studies related to occupant behavior interventions, however, focus on *gamification* and *serious games*.

Gamification is defined as "the use of game design elements in non-game contexts" [21], where game elements are features traditionally associated with games such as leaderboards/rankings, points, and

[1] Available at https://www.ebc.eonerc.rwth-aachen.de/cms/E-ON-ERC-EBC/Forschung/Forschungsprojekte2/Projekte-Nutzerverhalten-und-Komfort/~cviyk/DataFEE/?lidx=1

[2] Available at http://www.annex66.org/

[3] Available at https://annex79.iea-ebc.org/

achievement badges. The popular question and answer suite of sites, *StackExchange*, can be regarded as an example of gamification, since it is a non-game app that features rankings and achievement badges. A *serious game*, on the other hand, is a full-fledged game but whose primary design purpose is to achieve a real-world, non-entertainment goal [21]. An example is a flight simulator game for training pilots, which whilst being entertaining, has the primary goal of helping pilots develop necessary flight skills. Gamification and serious games aim to achieve real-world behavior change by means of an engaging and fun experience, and several studies have used different gamification concepts with the intention of motivating users to take action for enhanced energy efficiency, as outlined next.

In the review by Johnson et al. [22] the authors investigated 25 gamified applications and serious games in the domestic energy consumption sector. The results of the behavioral interventions are classified into four categories: behavioral interventions, cognitive interventions, learning and knowledge acquisition, and user experience. The outcomes of the majority of the studies (17 out of 25) fall into more than one result category. The user experience is the most frequent, followed by cognitive, real-world behavioral, knowledge, then in-game behavioral categories. Across the studies, the results were mostly, but not exclusively, positive. About half of the reviewed interventions explored serious games and the other half explored gamified applications. Among the employed applications were seven mobile apps, nine browser apps and five computer games. While around half of the applications feature integrations with the real world, the others are completely digital.

AlSkaif et al. [23] introduces a conceptual framework based on gamification to effect energy-related behavior change in occupants of residential buildings. The framework proposes a three-step approach: identification of the necessary process of behavior change using a human behavior change model, definition of required components of the intervention, including technical components and game design elements, and finally the elaboration of the framework's potential to address Demand Side Management (DSM) applications such as energy efficiency, self-consumption and demand response. Indeed, the framework can be adapted to office buildings also by considering the energy efficiency target and using gamification, since as discussed earlier, office occupants do not gain direct financial rewards from energy savings, nor can they themselves decide to self-consume. The merit of their approach is that it allows the planning of occupant energy-related intervention programmes, both at the level of the conceptual stages of behavior change the occupant passes through, and the required deliverables for the intervention to provide the necessary support.

OrbEEt (which stands for Organizational Behavior Improvement for Energy Efficient AdminisTrative Public Offices) [24] was a major gamification project aimed at developing "an innovative solution to facilitate public and social engagement to action for energy efficiency by providing real-time assessments of the energy impact and energy-related organizational behavior". A core contribution of this project is the development of the so-called Systemic Enterprise Operational Rating (SEOR), a building performance certification framework based on operational rating, which integrates business processes model, the occupant behavior and preference models, and the physical building model. This rating system can be integrated into a gamification framework for targeting user behavior [25]. In the Germany pilot study, which boasted an acceptance level of 80%, overall energy savings of 17% was reported, broken down into 17%, over 20%, and 7% reduction in the energy consumption for heating, lighting, and other electrical load types, respectively [26]. In another demonstration site, savings of 7–8 % was achieved, with over 90% user acceptance [27].

The EnerGAware project [28] ran from 2015 to 2017 and involved developing a serious game, the Energy Cat game [29]. Pilot studies were conducted in over 50 homes in the United Kingdom. At the end of the interventions, an average electricity saving of 3.46% and average gas saving of 7.48% were achieved, when compared to the baseline period before the interventions, although the savings were not statistically significant [30].

TRIBE (TRaIning Behaviors towards Energy efficiency: Play it!) [31] was a project aimed at enabling behavioral change in occupants of public buildings towards increased energy conservation. The project analyzed energy-related behavior regarding heating, cooling, lighting and electrical appliances in five pilot buildings in two European countries consisting of a public residential building, a university building, and office buildings. A serious game in 3D, called TRIBE, was developed as a mobile app to whose aim was for players to achieve the highest energy savings within the virtual buildings in the game. The winning criterion was that the user achieves 20% energy savings in the virtual building (compared with the original baseline) by year 2020 in terms of the game time progression [32]. In order to measure the effect of *energy efficiency measures* (EEMs), they integrated precompiled building simulations developed using EnergyPlus into an energy simulation engine developed for the game [10]. The baseline was obtained via simulation, since at the time of writing the gamification report, enough data was not available from the installed sensors until the end of the project [32]. In TRIBE, the play space was entirely virtual, and no user actions in the real world were directly accounted for, although the parallel game world that is fed with real data showed the current status of the actual buildings. Nevertheless, electricity savings for two of the buildings were 4% and 9% respectively compared to the baseline [33].

ChArGED (CleAnweb Gamified Energy Disaggregation) [34] is a framework that leverages gamification to reduce energy inefficiency and wastage in public buildings. Central to the idea is the incorporation of the possibility for micro-generation (*i.e.* local energy generation), allowing users to maximize locally generated energy and minimize grid power usage. In the project, the energy consumption-related sensors are augmented with location sensors (Near-Field Communication (NFC) and iBeacon devices) to enhance energy disaggregation [35]. The gamified interface was developed for portable/mobile devices and features social interaction aspects like teams and competitions, as well as individual feedback. However, no results seem to be available for the intervention.

Mindergie [36] was a pervasive game developed in order to foster pro-environmental behavior at the workplace. It ran for four weeks in an academic institution involving 15 participants. Game elements employed were information, action, badges, quiz, activity, and challenge. Additionally, physical rewards were also given. From the results, the users favored the active elements of the game (action, activity) above the informational elements (quiz, information on energy systems). Badges had the least impact, and the authors explain that the nature of the badges (not related to any earned skills) was probably inappropriate for a university environment where skills are highly valued. On the flip side, Mindergie employed game mechanics that were designed to take the users out of their offices/desks to look for clues on the campus, which would not produce sustainable engagement since it detracts from the user's daily work and requires too much effort, although the authors state that the users found them interesting. Also, no quantitative measures regarding energy savings was involved. Finally, the authors point out that a more longitudinal (*i.e.* over a longer time span) study should be carried out.

2.1. Research gap and contributions of research

First, this work attempts to combine several energy interventions that are rarely found occurring in the same work in the literature, including eco-feedback, gamification, and a serious game, whilst providing the possibility for user-defined heating schedules for a subset of the investigated buildings. Since the focus of this work is thermal energy efficiency in naturally ventilated office buildings without cooling, the relevant user behavior comprises window ventilation practices and setpoint temperatures for heating. Secondly, normative feedback is

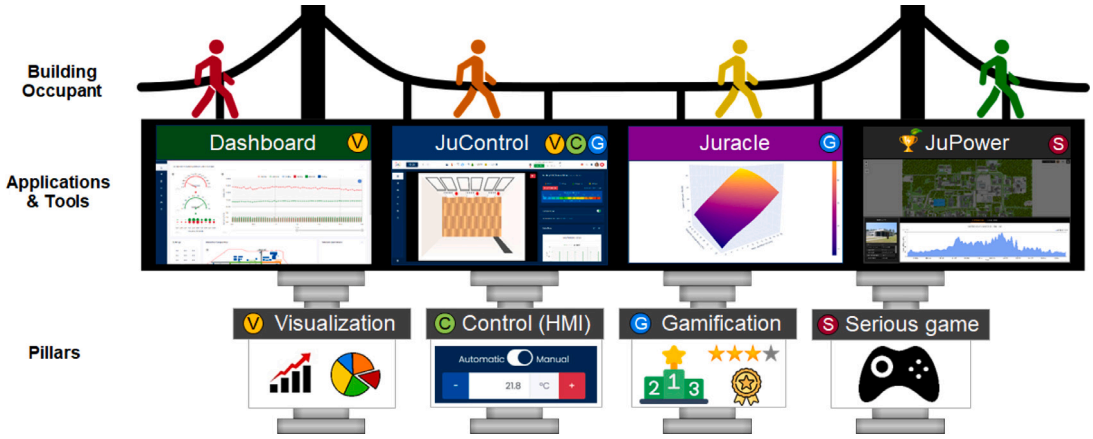


Fig. 1. Behavior intervention narrative depicting software applications built on the conceptual pillars of visualization, control, gamification and serious games, aimed at supporting the transition of building occupants from energy-inefficient to energy-efficient behavior.

provided using a simulation-model—derived *ideal occupant profile*, similar in spirit to the evaluation approach in [37], but unlike most other studies which depend on arbitrary goals [38–40] or peer networks [41, 42].

Subsequently, the developed system then evaluates the energy efficiency of the occupant's behavior with respect to this ideal, which in turn has a built-in guard against overcompensation, *i.e.* an attempt by a user to gain points in the gamification by possibly violating indoor environmental quality (IEQ) standards through unreasonably low temperature setpoints or inadequate ventilation. Furthermore, an experiment is performed involving several instrumented buildings. In addition to the analysis of the behavior evaluation metric, building-level energy savings are also presented for a pilot building over a longer horizon, using a performance metric that takes the influence of weather into account. Finally, unlike in most interventions in the literature, a cost–benefit analysis is performed to estimate the expected payback period for the investment in hardware for the pilot building.

The rest of this paper is organized as follows: Section 3 describes the design and development methodology employed in this work, including a brief presentation hardware setup and the applications developed according to various behavior and energy intervention strategies. Afterwards, Section 4 details the experiment design for testing the system, while Section 5 analyzes the results of the experiments and interventions in general, including effects on occupant behavior, energy savings and payback period analysis for the hardware setup, and user survey feedback. A discussion of the results is presented in Section 6, while Section 7 concludes and provides an outlook.

3. Design & development methodology

The conceptual methodology of this research work is diagrammatically depicted in Fig. 1, which describes the narrative that using the concepts of *visualization*, *control*, *gamification*, and *serious games* as pillars, software applications were developed to help building occupants transition from energy-inefficient to energy-efficient behavior. These software applications together make up the LLEC Energy Dashboard Suite, comprising the *Energy Dashboard*, *JuControl*, *Juracle*, and *JuPower*. A supporting tool named ALICE is used for providing a diagrammatic representation of the rooms as well as for linking sensors and actuators to room-level components like windows and radiators. The sensor and actuator metadata come from a device book-keeping tool named WALDO (see [43]).

The *Energy Dashboard* deals with visualization of heating, cooling, and electrical demand at the building and campus levels. *JuControl* visualizes the state of individual rooms, supports the automatic control of the heating system in the room, and provides the gamification and recommendation platform. *JuPower* is a serious game where players design an energy system for a virtual FZJ campus to minimize CO_2 emissions. Finally, *Juracle* is the behavior evaluation engine that supports the gamification aspect of JuControl. Fig. 2 shows the interactions amongst these applications. In subsequent subsections, the applications are presented in more detail, and their interactions explained.

3.1. Hardware overview

The measurement data processed by the software applications and the associated actuation capabilities are provided by hardware. The hardware setup and the underlying ICT framework, whose general architecture is given in Fig. 3, are only briefly presented in this work, since the hardware details and the reasoning for their selection are already described in related work (see Althaus et al. [44] and Redder et al. [43]). At the building level, most buildings were already equipped with digital meters to measure electricity, heating and cooling demand, *e.g.* for billing purposes. For research purposes, a connection was established between these building-level meters and the research ICT platform for a subset of buildings. In addition, all offices, meeting rooms and kitchenettes in the selected buildings were equipped with commercially available wireless indoor air quality sensors (to measure CO_2 concentration, temperature and relative humidity), window and door status sensors, and wireless smart radiator valves. The sensor network makes use of wireless sensors using the EnOcean protocol. On the other hand, a subset of the selected buildings were already equipped at construction with actuators for shading, lighting and underfloor heating control, as well as push buttons with integrated displays (using the KNX wired protocol). Several software *adapters* for translating between different communication protocols and data formats were developed, as shown in Fig. 3. The MQTT communication protocol, which features a publish–subscribe data transfer model, was used extensively both in the ICT framework and in the developed applications of the Energy Dashboard suite for communication.

3.2. The energy dashboard: Visualization of energy data

The *Energy Dashboard* provides an interface through which employees and visitors of FZJ can gain insight into the energy demand of the campus, thus providing eco-feedback [45]. Via the Energy Dashboard, users can view both historical and real-time heating and electricity data at the campus level as well as for individual buildings, see Fig. 4.

Additionally, the Energy Dashboard shows operation data of so-called *energy demonstrators*, which are proof-of-concept energy systems for generation, conversion, and storage of renewable energy and waste heat. The goal of the Energy Dashboard is to drive user awareness regarding energy systems in general, as well as to improve the public understanding of the represented systems.

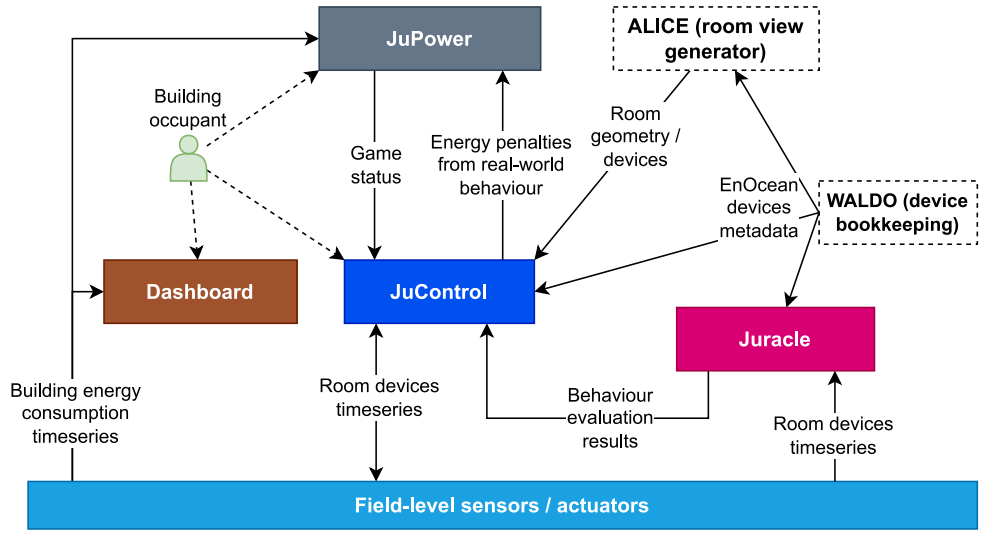


Fig. 2. Simplified overall system architecture showing interactions amongst the components of the Energy Dashboard Suite.

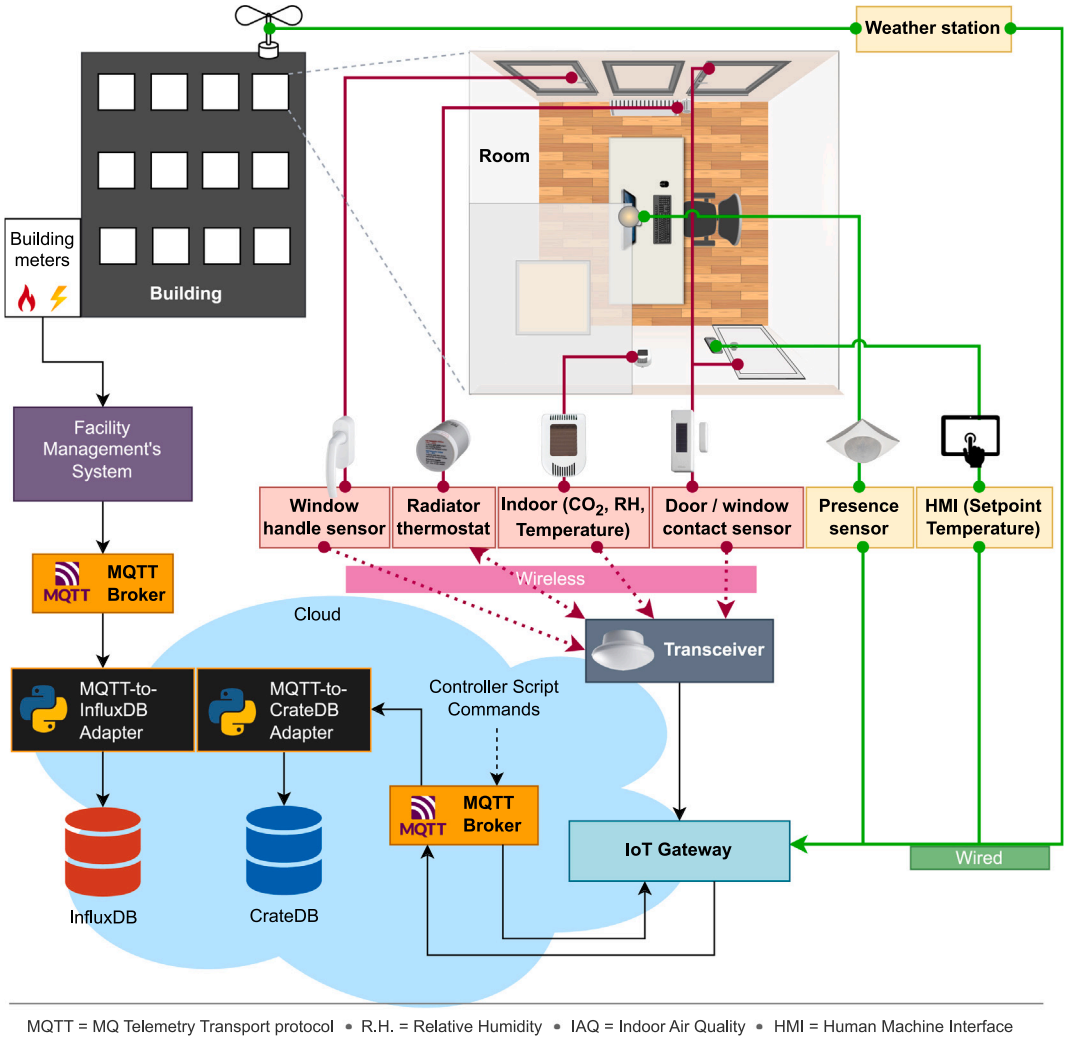
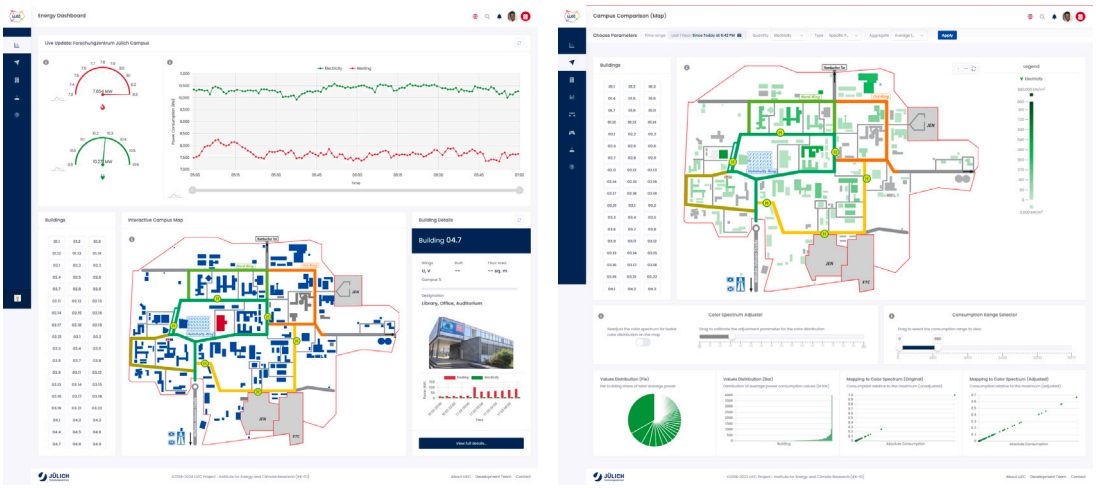


Fig. 3. Hardware architecture and communication protocols for the sensors and actuators used to gather data for the research and to control devices.



(a) Energy Dashboard: Home page

(b) Energy Dashboard: Building comparison page

Fig. 4. Screenshots of the Energy Dashboard. (a) Exemplary building page showing live electricity and thermal demands. (b) Comparison of building thermal demands in a map-based view.

3.3. JuControl: Visualization, control and gamification

JuControl is a web application that deals with *visualization* by providing access to room-level real-time and historical data, including indoor conditions like temperature, CO_2 concentration, relative humidity and luminosity, as well as the state of the windows and doors. It also features a stylized pseudo-3D real-time visualization of the room, which shows window and door status visually (see Fig. 5(a)). The 3D diagrams are generated by *ALICE*, which is both a mini-language and a tool developed within this work for automatically generating geometrical diagrams of rooms, as well as linking the wireless sensors and actuators to room components, in order to support visualization and control. Besides the more detailed visualization of data, *JuControl* also enables users to *control* radiator valves in their room via a web interface, in addition to the physical controls available at the radiators themselves.[4]

To deal with privacy issues that naturally arise with such finer granularity of instrumentation, room-level data is only visible to the occupants of an office if *all* other occupants of the office consent to the data being shown. Thus, JuControl is deactivated for the office by default and only becomes *activated* when all occupants agree to the data policy.[5] The activation system in JuControl automatically emails an activation link to all occupants of an office when the first occupant provides their consent. After all other occupants follow this emailed link and grant their consent, the office becomes available in JuControl. More details about the privacy protection features are discussed in Section 3.7.

3.3.1. Automatic heating control in JuControl

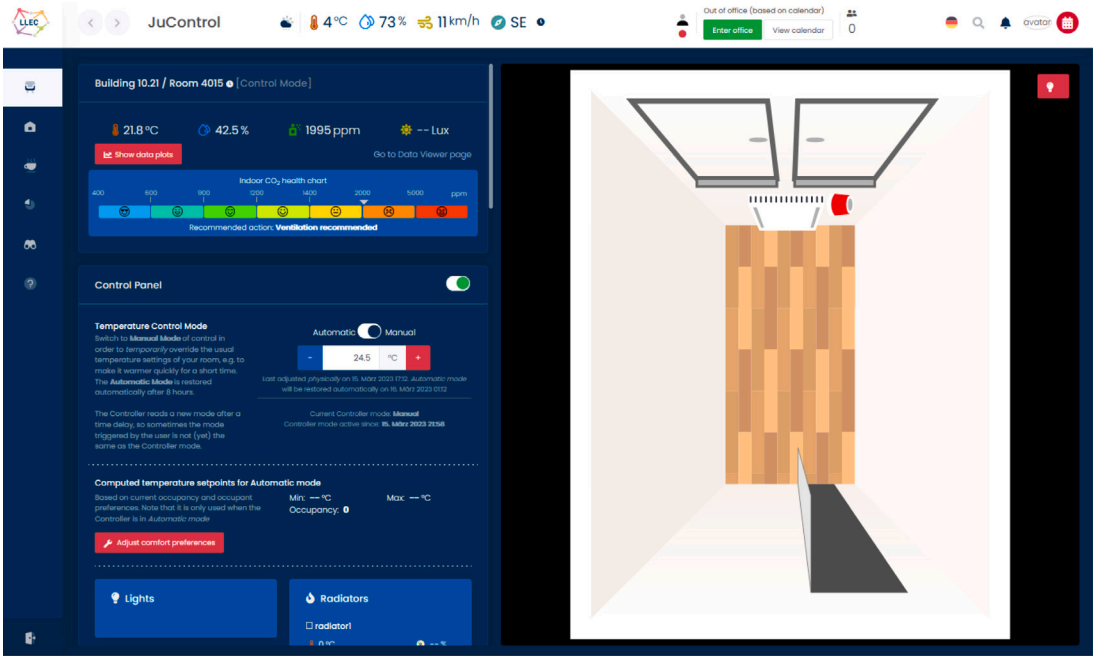
Within the LLEC project, the equipped rooms form a test-bed for testing different innovative control approaches beyond what is reported in this paper, *e.g.* model predictive control-based room controllers. *JuControl* provides the central user interface and persistence layer for the comfort preferences of the room occupants that are taken into account by these control algorithms. (For details regarding the controllers, see Althaus et al. [46].) *JuControl* coupled with a corresponding controller implementing the temperature schedule offers a great deal of savings potential whilst enabling options that go far beyond what was possible with the previous manual adjustment of thermostats, since office spaces are usually only used in a clearly limited time frame. Specifically, via *JuControl* occupants can individually create an own weekly schedule in which they enter their expected presence in the office using a drag-and-drop calendar interface (see Fig. 5(b)), along with their preferred comfort temperature range. Based on the schedules and temperature preferences of all occupants of an office, *JuControl* then derives a setpoint temperature trajectory for the room, which the heating controller queries via an Application Programming Interface (API) and subsequently implements. Thus, heating energy can be conserved by lowering the room temperature to an appropriate level when the office is not occupied, which is often not done by occupants in the manual-control case, for example after working hours and over the weekend. The heating controller also ensures a comfortably warm office before the occupant arrives based on the schedules.

The JuControl calendar was developed separately and without connection to the traditional work-related employee calendar (*e.g.* Outlook), since the latter does not usually include the site of work or of scheduled meetings, *i.e.* whether the employee is working from home or on-site. Hence, it could not be used for office heating. In *JuControl-activated* offices, the JuControl calendar is pre-populated for each employee with a default weekly schedule of 8.5 working hours per day, including a 30-minute lunch break, in order to avoid cold offices in the base case if the employee does not adjust the schedule. Non-JuControl-activated offices are heated based on a fallback value for the temperature setpoint or the setpoint temperature manually specified in the smart radiator valve by occupants. As such, fallback temperature needs to be selected to find a compromise to allow heating up to comfortably warm conditions again after a manual setpoint has been set, this invariably means that in JuControl-activated offices, the controller can fall back to a lower *setback temperature* at night or during periods of no occupancy, unlike in the non-JuControl-activated offices.

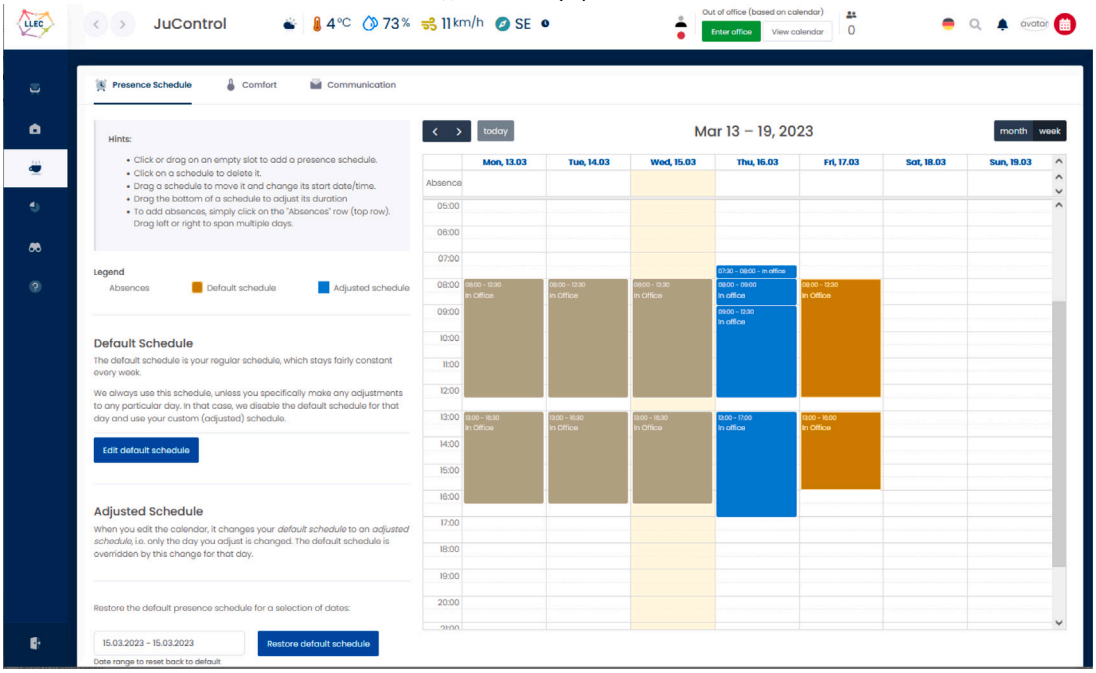
Naturally, an occupant's schedule may not always match the actual presence in the office, for example when the schedule changes temporarily on short notice. For scenarios such as these, the occupant always has the option to switch to "manual control", in which the schedule and the associated desired setpoint temperatures are overridden by the manual setting. Manual control can be triggered via the *JuControl* web interface or by physically operating the thermostats. In both cases, the new user-specified setpoint temperature is then targeted by the heating control. After a maximum of 8 h, the control automatically returns to automatic mode, in which the presence schedule is used once again.

[4] As at the time of writing, underfloor heating is also included in the room heating managed via JuControl.

[5] In a future upgrade of JuControl, some less privacy-critical sections of JuControl will be made available independent of user consent in agreement with the aforementioned stakeholders.



(a) JuControl: Exemplary room view



(b) JuControl: User specific time schedule for the expected presence in the office

Fig. 5. Screenshots of the JuControl. (a) Exemplary room view showing indoor conditions, the heating control panel (left half) and the 3D room view (right half). (b) The JuControl calendar page.

3.3.2. Gamification

JuControl features a gamification section, in which the energy efficiency of occupants' offices is evaluated and ranked based on predefined behavioral patterns related to ventilation habits and indoor setpoint temperatures. The evaluations, which are currently limited to heating demand, are carried out by *Juracle*, a behavior evaluation engine discussed in Section 3.5. The performance metric derived by the evaluation system is an estimate of *wasted thermal energy*, referred to as *energy penalty* in this work. The term *penalty* in this context is as opposed to *reward*, where both terms are commonly used to represent incentive mechanisms for behavior change (*e.g.* in Caton and Greenhill [47] and Ghorashi et al. [48]). The energy penalty is shown to the user scaled to the size of the FZJ campus, with the interpretation of "this is how much thermal energy the campus would *waste* per day if every office behaved like yours". Part of the motivation for this representation was that energy penalty value is transferred to the virtual campus of the JuPower game (see Section 3.4.2).

Social interactions (competitions, teams) have been shown to be key elements of effective gamification [22,49,50]. To this end, gamification in *JuControl* is designed around teams and competition. Groups of offices compete in teams against groups from the same or other buildings. A leaderboard ranks teams based on performance, and within each team, the constituent offices are also ranked. Additionally, the performance of teams is coupled to a serious game *JuPower*, discussed

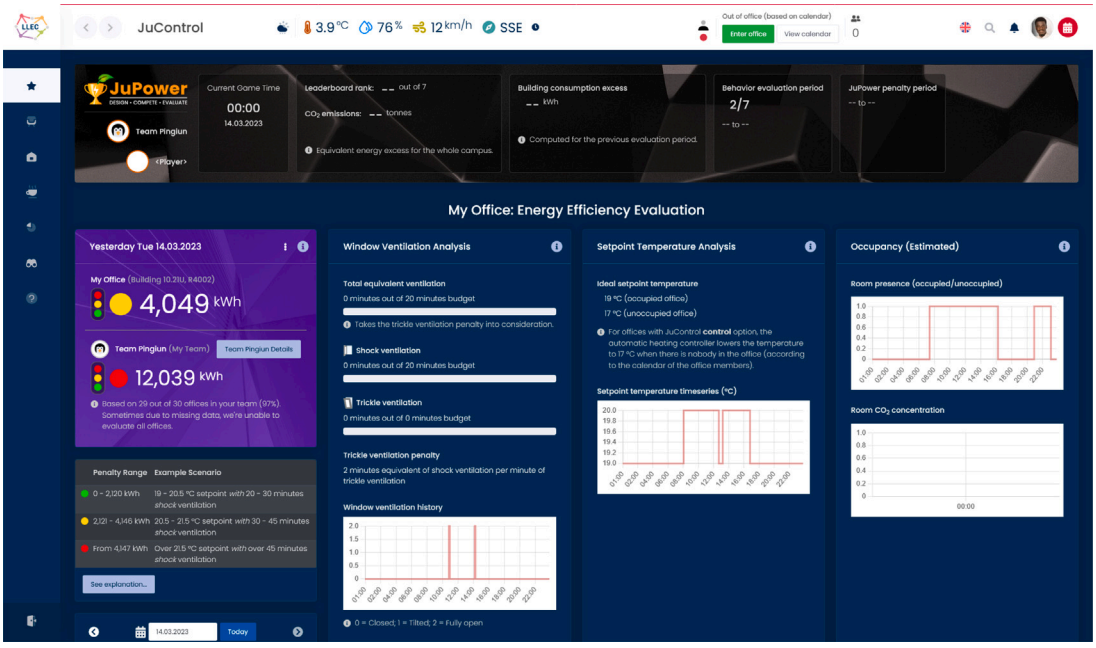
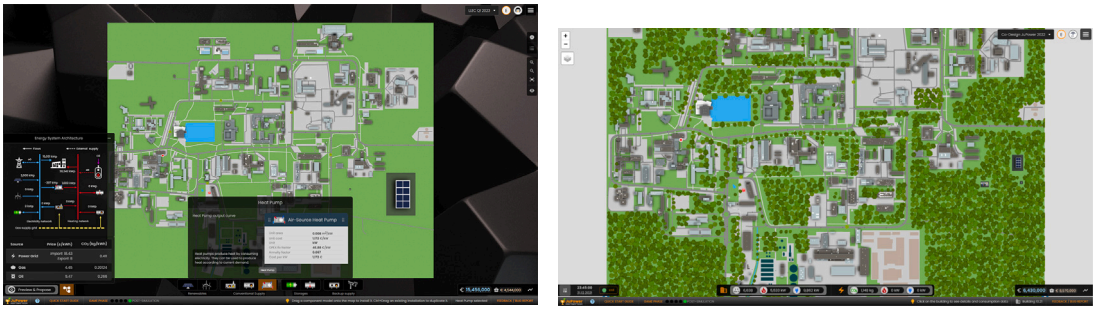


Fig. 6. *JuControl* gamification interface showing integration with a serious game, *JuPower* (top dark bar), and behavior evaluation *energy penalties* obtained from *Juracle*. The charts show the timeseries for the input quantities for behavior evaluation — window state, setpoint temperature, and presence profile.



(a) JuPower design page

(b) JuPower simulation page

Fig. 7. Screenshots of the JuPower serious game. (a) JuPower design page. (b) JuPower simulation page.

more in Section 3.4 below. Additionally, the *energy penalties*, *i.e.* the amount of energy wasted, are translated into a three-color traffic-light feedback system to provide injunctive norms that allow occupants to determine if their performance is relatively good or bad. The *JuControl* gamification interface is shown in Fig. 6 below.

3.4. JuPower: A serious game

JuPower is a *serious game* with the goal of designing an energy system with minimal CO_2 emissions for a virtual FZJ campus. Players compete in teams to collaboratively design an energy system to represent each team, and subsequently the designs are simulated over the course of a game-world year. To support behavioral change, JuPower is linked to the real-world energy performance of the players through the *energy penalties* derived by *Juracle*. This is further explained in Section 3.4.2 below. Screenshots of JuPower are shown in Fig. 7.

3.4.1. Gameplay

A game run consists of *game phases*, each of which provides a defined set of interaction opportunities for the players. In the *design phase*, players design an energy system by installing energy system components on a stylized aerial view of the campus via drag-and-drop. By design, the default energy source for heating in the virtual campus is an oil boiler, with electrical power being drawn from the virtual electricity grid. The aerial map view faithfully mimics the main features of the landscape of the real campus. Each installation of a component requires cash and real-estate, and is subject to the availability of these resources. Players propose their designs to their teams and cast votes to determine which proposed design is adopted for the team. To enhance coordination and communication amongst players within a team, a rich-text chat functionality with mentions is available in the Proposals page. Furthermore, players tag and optionally describe their designs prior to proposing them.

The *pre-simulation phase* follows the design phase. In this phase, the most-upvoted design is automatically adopted for each team. Based on this design, the operation of the energy system over a certain period is projected by computing the dispatch of the components. The dispatch is the result of a Mixed-Integer Linear Program (MILP) optimization problem, solved using the Gurobi™ [51] solver. Afterwards, the *simulation phase* starts, during which various system data and performance indices are shown in "real game-time" as the simulation progresses. The Key Performance Index (KPI) is the accumulated operational CO_2 emissions, and teams are ranked on a leaderboard based on this KPI. Figs. 7(a) and 7(b) below show the design page and simulation page, respectively. The

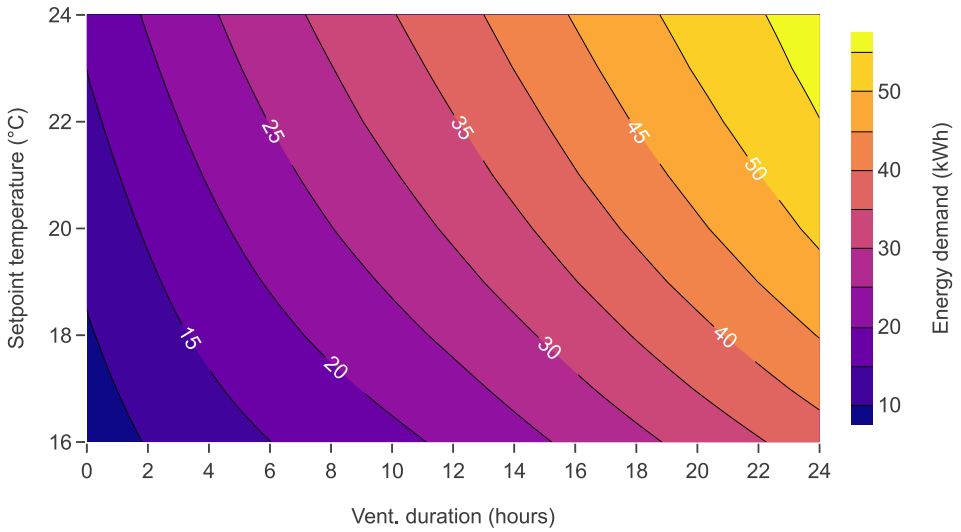


Fig. 8. Energy demand of reference room for the space of window ventilation durations and setpoint temperatures.

post-simulation phase allows players to take stock and reflect on their design choices.

3.4.2. Coupling with real-world behavior evaluation

The real-world wasted energy due to non-ideal behavior, which is computed by *Juracle* as part of the *JuControl* gamification described previously, is transferred to *JuPower* as additional building thermal demand in the game, after scaling the per-team penalty to the total area of the campus. Specifically, for each team, the average weekly energy wasted by offices in the team is added to the thermal demand of the buildings in JuPower for that team. Hence, the term *energy penalty* becomes even more meaningful in this context. This addition of penalties has the effect of increasing the CO_2 emissions in the game through making the buildings less energy-efficient, and by extension worsens the performance of the team's energy system in the game in line with real-world behavior.

3.5. Juracle: Occupant behavior evaluation engine

Juracle is an engine that evaluates the thermal energy-related aspects of occupant behavior based on two criteria: window interaction (ventilation) and room heating (setpoint temperature). First, it defines the notion of an ideal occupant, and then computes the deviation of a given instance of occupant behavior from this ideal. Finally, it expresses this deviation in energy terms (kWh) as wasted energy, called *energy penalties* in this work.

The task of such a behavior evaluation system is to analyze the effects of occupants' direct and indirect interactions with the energy system of the building, such that the output of such an evaluation system indicates the *appropriateness* of such interactions with regard to energy consumption or other relevant key performance index. This evaluation output is ideally graded from positive through a neutral point to negative, depending on if a reward- or penalty-based system (or both) is desired. In essence, such actions and effects are interpreted normatively to indicate if such they are positive (desirable/appropriate) or negative (undesirable/inappropriate). *Juracle* first defines *ideal behavior* in terms of window ventilation style and room setpoint temperature in the heating season, which serves as the basis for evaluating the appropriateness of occupant actions with respect to these two behavior aspects.

In this paper, the ideal setpoint temperature was assumed to be 19 °C for an occupied office, and 17 °C for an unoccupied office. The 19 °C setpoint temperature was chosen to support the then-extant German government policy of 19 °C in office buildings, which was promulgated in response to the energy crises of the last few years, apart from supporting recommendations by the German indoor air quality and thermal environment standard (DIN EN 16798 Standard [52]). On the other hand, the ideal ventilation duration was assumed to be 20 min of *shock ventilation* per winter day during office hours. *Trickle ventilation* during the heating season (in which an occupant opens the window in the tilted state, *i.e.* hinged on the bottom side and only partly open, as is common in Germany), is generally discouraged since it is considered energy-wasteful in Germany; rather, the so-called *shock ventilation* strategy is usually recommended in Germany, where the windows are side-hung and fully open [53–56]. Accordingly, the trickle ventilation style is penalized by the behavior evaluation system, specifically by including an arbitrary *trickle penalty factor* of 2, such that when trickle ventilation is used, the ventilation quota is "consumed" twice as fast as if the recommended shock ventilation was used. By the design of Juracle, therefore, *energy penalties* computed by Juracle only become non-zero when the ideal quotas are exceeded. No compensations are awarded by Juracle if an occupants sets a lower-than-ideal setpoint temperature or ventilates too little, in order to guard against extreme comfort- and/or air quality-violating actions.

Therefore, to evaluate the energy efficiency of an action or state (*i.e.* setpoint temperature level or window opening duration), the *deviation* of the state from the ideal profile is computed. Specifically, the difference between the ideal setpoint temperature and that of the occupant is taken as the *setpoint deviation*, and the difference in ventilation duration is taken as the *ventilation deviation*. Note that these values are always greater than or equal to zero.

In order to convert these deviations into an energy value, a reference two-person office model was developed with which various combinations of window ventilation duration and setpoint temperatures were simulated to determine the corresponding energy demand for the office, and then interpolated over to obtain a surface plot (see Fig. 8). Using this model, the *deviation* of the occupant from the ideal profile energy consumption, called the *energy penalty* in this work, is computed from the interpolation model by taking the difference between the energy consumption at the ideal setpoint and ventilation duration, and the energy consumption at the occupant setpoint and ventilation duration. Specifically, the energy penalty for a given evaluation day for a real-world office, is the sum over the whole day of the instantaneous (minute-wise) difference in energy demand (in kW) between the office operating point (*i.e.* current setpoint temperature and total ventilation duration for the day) and the ideal operating point (*i.e.* the ideal setpoint temperature and the ideal daily ventilation duration). Subsequently, the energy value is normalized by the area of the reference

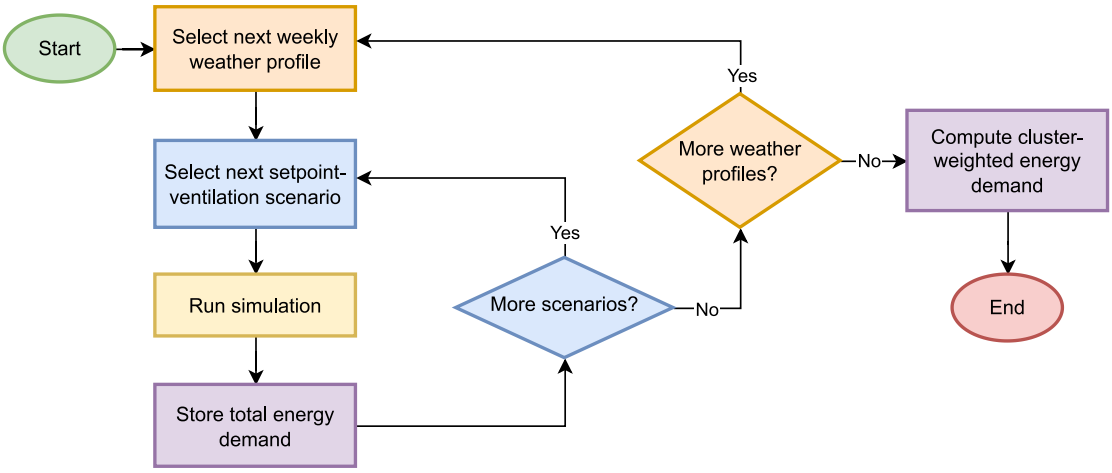


Fig. 9. Flowchart showing how energy demand is derived for the reference office model for different combinations of setpoint temperature and ventilation duration.

Fig. 10. CO_2 health chart developed as a result of feedback from users, in order to understand the values shown.

office model, and then scaled to the size of the real-world office under consideration.

In order to account for weather differences in the development of the model, ambient temperature data for the geographical region for the first three months of years 2021 and 2022 was divided into weeks and clustered. For each cluster, the number of weeks assigned to the cluster was used as the *cluster weight*, while the week with the minimum deviation from the cluster center was chosen as the cluster's representative weekly weather profile. Using the cluster representative profile for each cluster as weather input, the model is simulated for the weather profile to obtain the total energy demand for different combinations of setpoint temperature (ranging from 16–24 °C) and window ventilation duration (ranging from 0 to 24 h per day) (see Fig. 9). This approach of using a model to pre-calculate the effects of energy saving measures is similar to Conserva et al. [10].

3.6. Co-Design process

The energy dashboard suite was developed using a co-design process. By this means, future users of the dashboard were actively involved in the development cycle and feedback and results were collected at several points in the process. A total of four co-design workshops targeting different aspects and developmental stages of the LLEC Energy Dashboard Suite have been carried out, apart from various additional less-structured usability tests. During the co-design workshops, volunteers were granted alpha- and beta-stage access to test the dashboard components and provide feedback on existing features. Furthermore, during the co-design workshop events, potential features and further development concepts were discussed in detail. The results of these four workshops are summarized in the following paragraphs.

3.6.1. Co-Design results: Energy dashboard and JuControl

Beyond the standard requirements for user friendliness, the barrier to on-boarding for the applications should be as low as possible. By following a web-based approach, the applications do not require a separate installation step. Additionally, the responsive design that caters to different device sizes and orientations for the *Energy Dashboard* and *JuControl* made it possible to view these apps on mobile devices and tablets. Furthermore, to ease the burden of password management and mitigate potential security issues related to credentials, we integrated authentication via the institution-wide Shibboleth authentication. Thus, the authentication process was the same for the users as for most other services they access in their regular work.

Again, users expressed the wish to have data shown on a spatial granularity level below the campus or building level, *i.e.* the floor or room level, so that they can reconcile the data to their own contributions. The implementation of this wish was the development of *JuControl*.

Furthermore, given the diverse range of specializations in the campus, it was necessary to not assume a knowledge of energy systems on the part of the users. This meant that all necessary information needed to understand the visualizations were made available in the application. For example, in *JuControl* a health chart is shown alongside the CO_2 concentration for the room, as shown in Fig. 10. This was the result of feedback.

Yet again, whilst the applications are designed to maximize user interaction, users expressed fears about the apps being a distraction from work by requiring too much attention. To this end, a notifications management system was developed that allows users to be notified by email about certain events (*e.g.* when CO_2 concentration is above their defined threshold), or even turn off notifications completely. When the notifications are on, their frequency is throttled.

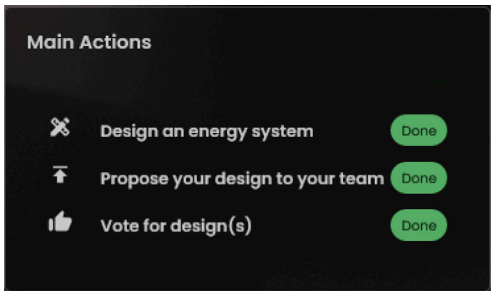


Fig. 11. JuPower screenshot showing main actions and their completion status.

3.6.2. Co-design process for JuPower

For the JuPower game, for which two co-design workshops were conducted, the feedback were received and implemented. In general, the game was well received. Some key aspects are outlined as follows.

First, the game application included a manual that explained the objectives and functionalities in the game. However, multiple test users reported that they found this manual too long and not easily readable, and preferred scan-only help information with relevant information highlighted. In response, we introduced the Quick Start section with selected bold text that summarized the most important points, alongside visual aids like images and illustrations. In the same vein, to reduce the risk of information overload, an *Actions* widget was introduced, which showed the three main steps involved in the gameplay and their completion status (see Fig. 11). Additionally, a short tutorial video of about 15 min was made to introduce the main features of the game, which several participants found helpful.

Secondly, since the game usually runs over several weeks, and each stage of user interaction can be spread of several days, it was helpful to notify users of the game phase transitions and impending deadlines by email. The emails contained the relevant description for the phase, and any actions that were necessary were included as clickable links in the email.

Finally, to reduce the cognitive load required to play the game, we reduced the range of component options available to the player in the design of an energy system, based on feedback. Furthermore, the number of exposed parameters for each component was reduced to the bare essentials, in order to make decision making easier for the players.

3.7. Dealing with privacy and data security

As mentioned in the preceding sections, the issue of privacy requires special consideration in a research work such as this. Consequently, several design decisions were based on considerations for privacy preservation, in addition to factoring in legal and policy limitations. Policy compliance was achieved in collaboration with the data privacy officer for FZJ and the Works Council (*Betriebsrat* in German), with concrete measures including compulsory data privacy course for all developers, data consent forms for JuControl before room-level data is shown to occupants, and anonymous processing of data for research purposes.

On the software application side, three levels of access were defined for room-level data — no access, "view" access, and "control" access. Only authorized personnel had "view" or "control" access to rooms, assigned on a room-by-room basis or for a building. When all occupants of an office agree to the data privacy terms, JuControl is activated in the office as previously mentioned, and all occupants are granted control access to the office. However, the implication of allowing only official occupants of a given office to access room-level data for that office is that JuControl must stay updated regarding office allocations, in case an employee changes office. To deal with this, a script runs periodically on the JuControl server to check for changes in office allocation in the centrally managed facility allocation database of FZJ, and when changes occur that add new occupants to an office, JuControl is deactivated for the office automatically and the new occupants are presented with the data access agreement form. Each data consent that is granted by an occupant is stored for the office for which the user granted it, so that when the occupant moves to a new office, they need to grant consent for the new office separately. Furthermore, the new occupants, on consenting to the data agreement, can only view historical room data which begins at the time-point at which they joined the office. In this scheme also, when an occupant relocates away from an office, they lose access to the data of the office from which they left.

Finally, during the real-world experimental run of the system, the energy evaluation results of offices that are shown in JuControl as part of the gamification system were only available to the room occupants, while aggregated statistics over the rooms in an experiment team were shown at the team level. At the global level, only aggregated team statistics are shown.

Table 1
Building construction data for the buildings of the experiment.

Building ID	Year Built	Num. Floors	Floor Area (m^2)
B-01	1976	2	999.4
B-02	2014	4	2,003.1
B-03	1979	2	1,009.0
B-04	2009	1	701.7
B-05	2014	4	3,309.5

4. Experiment design

To evaluate the effectiveness of the suite of applications holistically, a real-world experiment was run from Mar. 13 to Apr. 28, 2023 (inclusive). The experiment setup consisted of 12 instrumented buildings of various ages and sizes, in which JuControl was enabled. However, for this paper, only a subset of the buildings is presented and analyzed, and they are shown in Table 1 below.

The test rooms were divided into experiment groups, where each group represents a particular combination of experimental variables. Seven experimental variables are incorporated in the design of the experiment, corresponding to features of the deployed system that are enabled or disabled in each experiment group, as follows.

- **JuControl View**: whether or not the measurement data can be accessed in JuControl; enabled for all buildings in the experiment.
- **JuControl Control**: whether or not the heating system in the room can be controlled via JuControl. This requires that the building be equipped with smart radiator valves which are cloud-controllable.
- **Setpoint Temperature Evaluation**: whether or not the setpoint temperature for room heating is considered in the room evaluation.
- **Window Ventilation Evaluation**: whether or not the window ventilation strategy is considered in the room evaluation.
- **Recommendations**: whether or not the office occupants receive real-time recommendations about energy savings. Recommendations were activated after the experiment had already commenced.
- **JuPower**: whether or not *JuPower* game is available to occupants of the room.
- **JuPower Penalty**: whether or not the energy penalties from the evaluation of the office are transferred as demand penalties to JuPower.

A total of 8 experiment groups were created, having features as shown in Table 2. At the same time, offices and buildings are clustered into experiment teams, also shown in Table 2 with the number of offices

Table 2
List of all experiment groups, their associated teams and team statistics, and their associated feature sets.

Feature Group	Team	Building	Employees	Offices	Features in Feature Group						
					View	Control	S.P.[a]	Vent.[b]	Recomm.[c]	JuPower	Penalty[d]
A	T1 T3	B-01 B-02	58 70	39 30	×	×	×	×	×	×	×
C	T2	B-02	33	24	×	×	×	×	×		
E	T4	B-03, B-04	37	20	×		×	×	×	×	×
K	T5	B-05	63	44	×			×	×		
L	T6	B-05	51	44	×						

[a] Setpoint temperature evaluation
[b] Ventilation evaluation
[c] Recommendation
[d] JuPower penalty

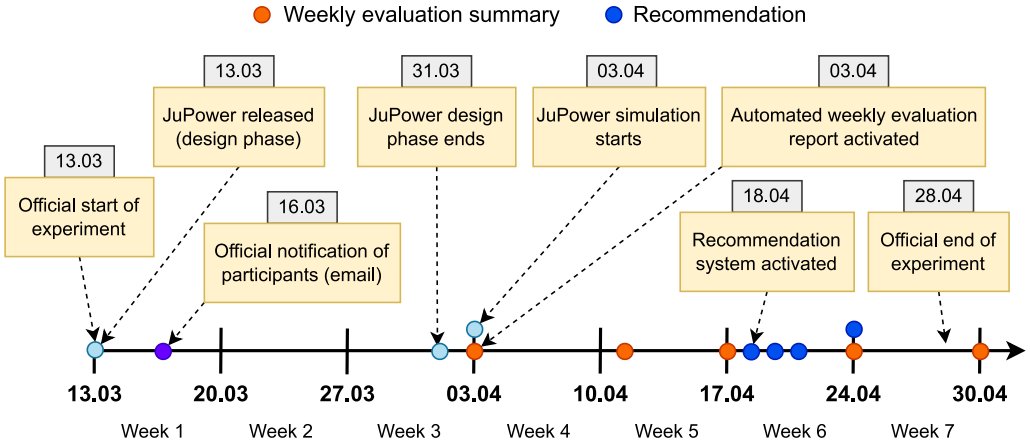


Fig. 12. Timeline of activities related to the experiment.

and number of employees. Several research questions can be addressed by the experiment design, but only the main questions listed below are considered in this work:

- How effective are the behavior intervention measures in improving the energy efficiency of occupant behavior represented by estimates of wasted energy (*i.e.* energy penalties)?
- What additional effect does the JuPower serious game have on improving occupant behavior when coupled with behavior evaluation?
- What are the effects of the occupancy-schedule-based heating on the energy efficiency of the pilot building, Building B-01?

To answer the first question, the null hypothesis that the intervention measures have no effect will be tested based on team daily energy penalties, using Team T5 as the test group, and Team T6 as the control group. Additionally, JuControl-activated offices will be compared to non-activated offices in each of the rest of the teams, namely Teams T1, T2, T3, and T4, respectively. For the second research question, comparing the performance of Team T3 against T2 (both from the same building) should determine if the null hypothesis that the use of the JuPower game made no difference should be rejected. However, as will be seen, this hypothesis could not be tested due to low engagement with the game. Nevertheless, the game is still included in this report, since it was an integral part of the systems, and since there are lessons to be learned. For the last research question, the performance of the pilot building, Building B-01, is compared for the test year with its performance in the previous year using the *energy signature* method (Section 5.4).

4.1. Running the experiment

The experiments officially started on Monday, 13.03.2023 and ran for seven weeks, until the end of Friday 28.04.2023. *JuPower* was also activated at the same time, with the design phase initially billed to end on Friday 24.03.2023 (two weeks after the official start) with simulation to follow on the next Monday (27.03.2023). However, the deadline for the design phase was extended by one week to give more time for users to get registered with the game and get familiarized with its features. Therefore, the simulation phase started a week later on Monday, 03.04.2023. Fig. 12 provides a pictorial timeline of the major activities that were performed regarding the experiment.

4.2. Suspension of evaluation during warm periods

In order to account for the fact that heat losses through ventilation are minimal during warm periods in a day, the evaluation system pauses evaluations when the outside temperature reaches or exceeds 15 °C, since heating may no longer be required. This means that during such periods, the energy penalty is kept at zero. Another justification for the suspension of evaluation in warm periods is that higher ambient temperatures naturally induce longer ventilation durations to achieve air freshness than colder ambient temperatures, since the temperature gradient-driven air exchange rate is lower for smaller temperature differences between room and outside air. In Fig. 13, the distribution of temperature over each day is shown in a heatmap for the period. Several days within the experiment period had long durations (up to several hours) in which the ambient temperature was at or above 15 °C.

4.3. Technical and user issues

Due to technical issues with the installed sensors, several offices were disabled during the experiment, but for the analyzed buildings, the number of offices was small or none. Also, it was planned that the recommendations should be activated at the beginning of the

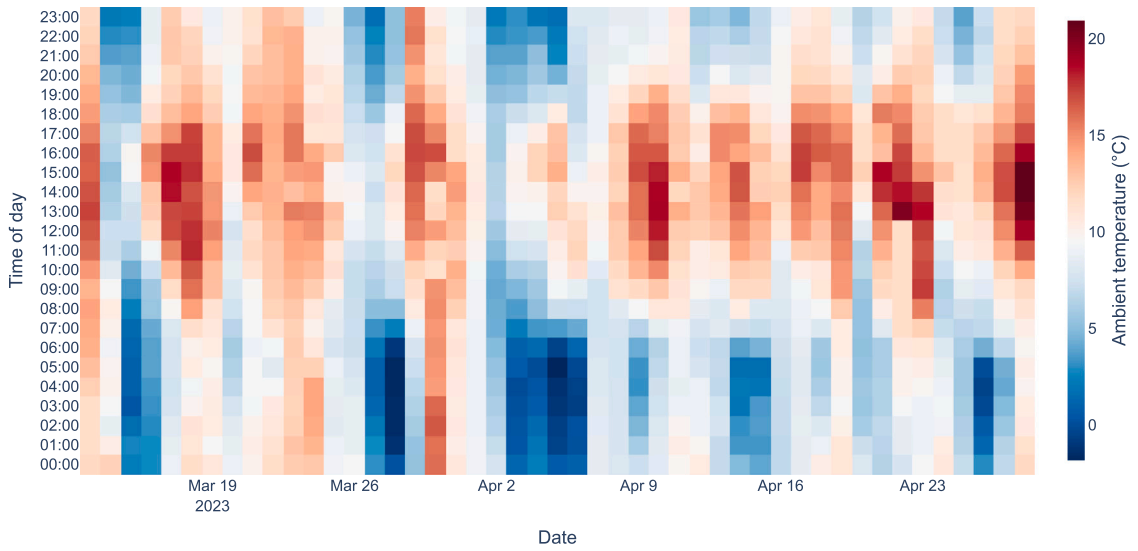


Fig. 13. The distribution of the temperature over each day of the experiment as a heatmap. Evaluation was suspended when ambient temperature is at or above 15 °C.

experiment and were to be sent maximum of once per day per office, the recommendation system did not go online until Week 6 (on 18.04.2023), due to delays in the implementation and testing, and only functioned for four days from Apr. 18 to 20, and Apr. 24, due to a tiny bug in the scheduling logic that remained undiscovered until after the experiment.

Furthermore, in the trial phase before the experiment, the heating controller often did not adequately heat the rooms in Building B-01, leading to dissatisfaction with the system among occupants. One main cause of the poor performance of the controller was the source of the temperature feedback for the smart radiator valve's hardware-integrated controller: the cloud controller sends the setpoint temperature to the local hardware-integrated controller of the smart valve, which in turn provides the actual control functionality to determine the desired valve position. As at the time of the experiment, this hardware-integrated controller was configured to use its closed-loop feedback temperature from the in-built radiator temperature sensor by default, since it does not have access to the room temperature sensor. Due to local heating effects, the temperature measured at the radiator was often 1–2 °C higher than the actual room temperature (as measured by the room temperature sensor on the opposite side of the room), which caused the local hardware controller to stop heating before the room attained the actual desired temperature. Nevertheless, as at the time of writing, the hardware-integrated controller now is provided with measurements from the room temperature sensor to use as feedback temperature.

In order to maintain fairness in the evaluation of setpoint temperature during the experiment, *Juracle* compensated for the heating shortfall by raising the *reference* setpoint temperature for unoccupied offices in the building from 17 °C to 19 °C. This compensation coincided with a corresponding increase of the setback temperature by the heating controller in Building B-01 during unoccupied hours, which was one of the measures taken to ameliorate the problem.

5. Results

In this section, the results of the real-world experiment run are presented covering user engagement with the developed systems, and effectiveness of the behavior intervention measures. Beyond the experiment period, the energy savings and cost–benefit analysis for the pilot building, Building B-01 is presented.

5.1. User engagement

Regarding engagement of employees of FZJ with the LLEC Energy Dashboard Suite in general as at the end of the experiment (28 Apr. 2023), about 1,906 employees making up almost 30% of the nominal staff strength of FZJ had interacted with the system at least once. Out of these, 43.3% (825 employees) have visited it more than once. For JuControl in particular, Fig. 14 shows the timeline for the *activation* of JuControl in offices by occupants (*i.e.* by *all* occupants of each office consenting to the data policy to enable JuControl for their office). Following the initial announcement of Mar. 16, 2023, a total of 27 offices became activated, and in the one week following the announcement date, another 10 offices were activated. Subsequently, further spikes in activations took place on April 3 and 11, in response to the automatic sending of weekly evaluation summary emails by JuControl to all occupants.

By the end of the experiment, 420 users (48.3%) of the approximately 870 potential users involved in the experiment had accessed JuControl at least up to the data policy consent-granting stage. This consists of 283 occupants who accessed JuControl during the experiment, and 137 users who already had access in the preceding trial phases. On the other hand, 82 offices (18.6%) out of the 439 "activatable" offices involved in the experiment were activated in JuControl by the end of the experiment, consisting of 51 offices (11.6%) that were activated during the experiment period itself, and 31 offices (7%) that were already activated during the trial phase prior to the experiment. Here it should be noted that due to the policy of all occupants actively granting consent for activation to occur, in most non-activated offices, only one occupant had failed to grant consent, almost always due to oversight and not by actively declining. In fact, out of the 76 offices that had some occupants who did not click the activation link emailed to them by the JuControl activation system, 63 offices (83%) had only one outstanding consent request that was not acted upon, which prevented the office from being activated. Nevertheless, recommendations and evaluation summary emails were sent to all occupants irrespective of office activation status. Fig. 15 shows the number of activated offices for the teams being analyzed in this work.

5.2. Effectiveness of behavior intervention measures

In order to investigate the effect of the behavior interventions during the experiment, we compare the performance of two teams, Teams T5 and T6, which were drawn from the same building (Building

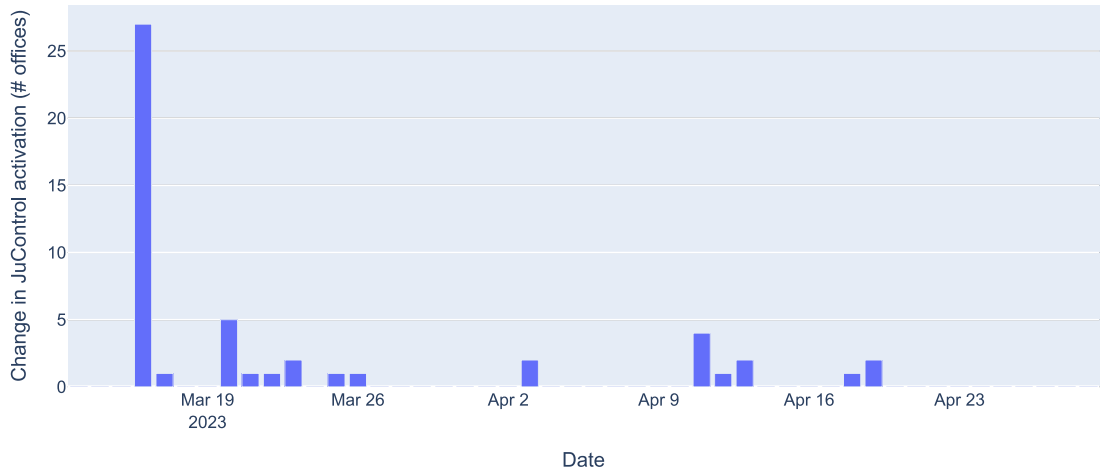


Fig. 14. Timeline of activation of rooms in JuControl by occupants over the experiment period. The plot shows the change in number of rooms activated in JuControl on each day of the experiment.

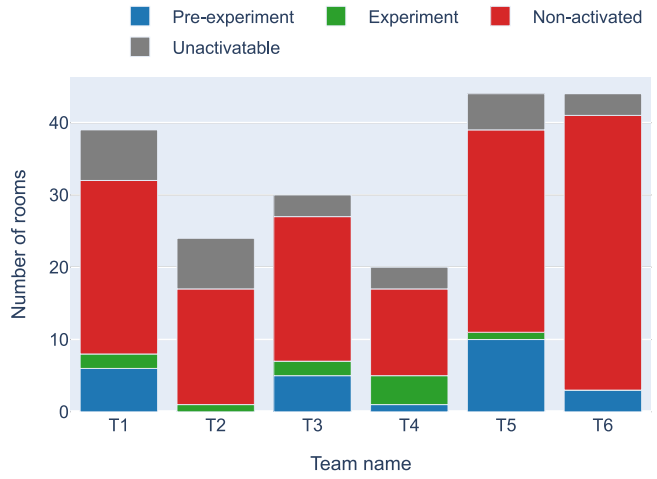


Fig. 15. JuControl-activation of offices across the teams. "Unactivatable offices" are *e.g.* meeting rooms that have no assigned occupants.

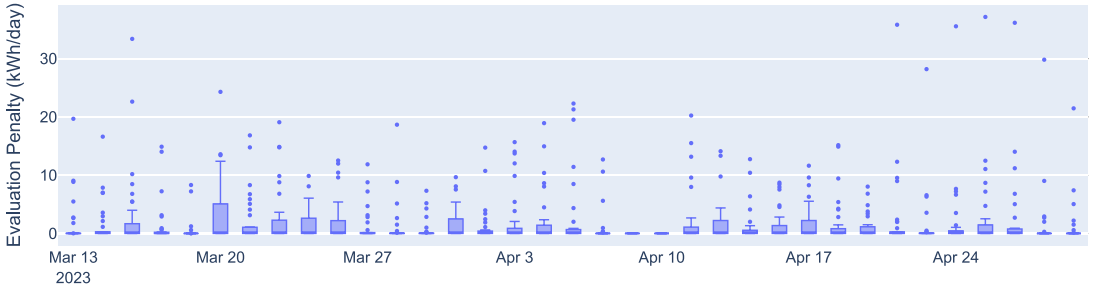
B-05), where Team T5 comprised the lower two floors, and Team T6 the upper two floors (44 offices per team). Whilst Team T5 had *JuControl view* with *ventilation evaluation* and *recommendations* enabled, Team T6 only had *JuControl view* (see Table 2). In Fig. 16, the distribution of energy penalties for Team T5 (Fig. 16(a)) and Team T6 (Fig. 16(b)) are shown in a boxplot. As can be seen, while the energy penalties for Team T5 generally remain low in the last days of the experiment compared to the starting period of the experiment, for Team T6 the opposite is true: the penalties increased at the end of the experiment above the starting case.

Since the daily *energy penalties* in both Team T5 and T6 follow an approximately normal distribution as determined by the Shapiro–Wilk Test (T5: W=0.977, p=.68; T6: W=0.986, p=.93), and have unequal variances (T5: σ^2=0.468; T6: σ^2=2.892), we choose Welch's T-test to determine the statistical significance of the performance difference between the two teams, and then we use Cohen's d to estimate the effect sizes. From the results, the average daily *energy penalty* is significantly lower in Team T5 (μ = 1.659 kWh) than in Team T6 (μ = 4.667 kWh) ($p < .001$) with a correspondingly large effect size (d = 2.27), showing that offices in Team T5 were more energy efficient than those in Team T6.

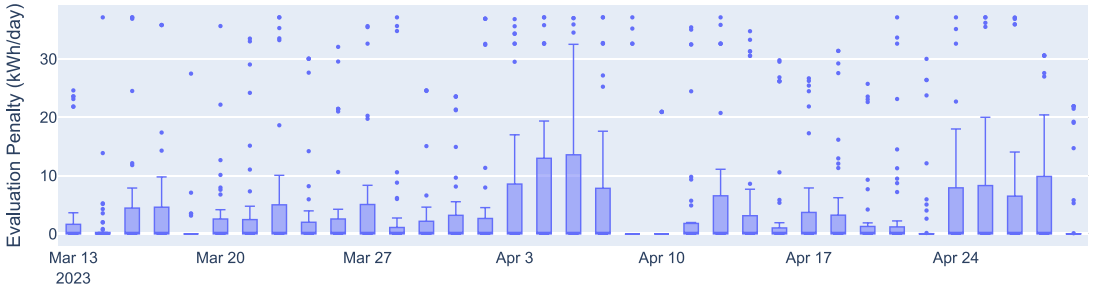
Furthermore, due to the "activation policy" in JuControl, whereby office occupants are only granted access to JuControl and its features after *all* occupants have agreed to the data consent form, only a subset of offices in each team was "activated". Figs. 17 and 18 are composite plots showing the average team energy penalty and number of offices in each JuControl-activation category for Teams T5 and T6, respectively. For each team, the corresponding figure comprises three sub-figures: (a) JuControl activated offices, (b) non-JuControl-activated offices, and (c) all offices, with each sub-figure showing the average team energy penalty (line chart, top), and office counts (bar chart, bottom) for the experiment period. The energy penalty plot (top) depicts the trend in average team penalty over the experiment period, while indicating the traffic-light rating of the penalties (as mentioned in Section 3.3.2). The office-count plot (bar chart, bottom) shows the number of offices in the JuControl-activation category. As can be seen from the figures, for Team T5 (Fig. 17), there were relatively more offices that were JuControl-activated than in Team T6 (Fig. 18), and these JuControl-activated offices had lower penalties than non-activated offices, whilst trying to stay within the "green zone". The initial low energy penalties in Team T6 is an artifact of the nature of the experiment — offices became JuControl-activated throughout the experiment period, and for Team T6, the number of activated offices is too low to be statistically meaningful, and the low penalties can be regarded as coincidental, as the spikes on Apr. 3 and 25 show. Considering Team T5 and analyzing the difference between activated offices (n=9) and non-activated offices (n=24), a significant difference is observed in the average energy penalty with a large effect size, where the penalty is much lower in activated offices (μ = 0.739 kWh) than in non-activated offices (μ = 1.995 kWh) ($p < .001$, d = 1.4).

Extending the analysis to Teams T1 and T3, where all aspects of JuControl were enabled, including setpoint temperature evaluation (Group A in Table 2), a clear difference in performance between activated and non-activated offices is observed in each team, as indicated by the average *energy penalty* scores. Specifically, for Team T1, mean penalty in activated offices is 1.607 kWh, compared to 2.494 kWh in non-activated offices (p=.029). For Team T3, mean penalty in activated offices is 1.907 kWh, compared to 3.817 kWh in non-activated offices ($p < .001$). These results strengthen the hypothesis that access to, and *actual use* of, JuControl contributed to higher energy efficiencies than the base case.

In Team T2, only one office was JuControl-activated, and no penalty was calculated for the office due to a problem with its sensor, so the entire team was non-activated. Since T2 and T3 are in the same building (T2 is the lower two floors, while T3 is the upper two floors), we compare T2 with both activated and non-activated offices of T3. The analysis shows that there is a significant difference and a large effect size in the mean of the energy penalties between T2 (μ = 4.35 kWh)



(a) Team T5 energy penalty distribution



(b) Team T6 energy penalty distribution

Fig. 16. Box plots of the distribution of the energy penalties for offices in (a) Team T5 and (b) Team T6 showing a stronger trend towards energy efficiency improvement (lower penalties) over the course of the experiment for Team T5 than for Team T6.

Fig. 17. Composite plot for Team T5 showing energy penalties and number of rooms in (a) JuControl-activated offices, (b) non-JuControl-activated offices, and (c) all offices.

and *activated* offices in T3 (μ = 1.907 kWh) ($p < .001$, $d = 1.5$), while for T2 compared to non-activated offices in T3, there is no significant difference in the means (p=.201) and the effect size is small ($d = 0.3$).

Finally, Team T4 had the worst performance, with daily mean penalties up to four times that of the other teams. Anecdotal evidence pointed to a fault in the building management system of the larger building in Team T4, Building B-03, in which the heating system could not be regulated and the occupants had to cool their offices by leaving the windows open (Building B-04, the other building in the team, was mainly a lab building with few, hardly occupied offices). There was no difference between JuControl-activated and non-activated offices in this team. Note that the heating in this Building B-03 was not managed

Fig. 18. Composite plot for Team T6 showing energy penalties and number of rooms in (a) JuControl-activated offices, (b) non-JuControl-activated offices, and (c) all offices.

Table 3
Comparison of average daily duration of shock vs. trickle ventilation in Teams T5 and T6 for the entire experiment period, showing that trickle ventilation was the main driver for high energy penalties in both teams, although much more pronounced in Team T6 than in T5.

Team	Shock vent.[a] (minutes)			Trickle vent.[b] (minutes)			Ratio[c] (Trickle:Shock)		
	All[d]	Act.[d]	N/Act[d]	All	Act.	N/Act	All	Act.	N/Act
T5	8.0	9.1	7.6	38.8	15.4	47.5	4.8	1.7	6.2
T6	5.4	14.0	4.7	149.5	39.2	158.2	27.7	2.8	33.5

[a] Mean shock ventilation duration.
[b] Mean trickle ventilation duration.
[c] Ratio of average trickle to average shock ventilation duration.
[d] All: All offices; Act.: JuControl-activated offices; N/Act: non-JuControl-activated offices

by the controller associated with this work.

In conclusion, we can reject the null hypothesis and conclude that the interventions led to behavior change in the building occupants. Specifically, having access to feedback as presented in the developed systems, as well as access to the relevant contextual performance information in JuControl, led to more energy-efficient behavior among occupants, than in the control groups without these features. Also, the willingness to use the provided behavior intervention tools was a key factor in causing positive behavior change. In Section 5.2.1, further discussion is provided regarding the particular occupant behaviors that influenced the performance of Team T5 and T6.

5.2.1. Analysis of ventilation behavior for teams T5 and T6

The relative contributions of window ventilation style (trickle vs. shock) and duration on the energy penalties of Team T5 and Team T6 are shown in Table 3. Note that only the raw ventilation durations are given, without the trickle ventilation penalty. From the data, it can be seen that the use of trickle ventilation is the main factor contributing to penalties, as the daily duration of trickle ventilation is always higher than that for shock ventilation by a wide margin. On average, in Team T5, trickle ventilation is used almost 5 times as long as shock ventilation across all offices (38.8 min vs. 8 min, respectively). For JuControl-activated offices, trickle ventilation is used only about 56% longer on average than shock ventilation (14.6 min vs. 9.3 min, respectively), while for non-JuControl-activated offices trickle ventilation is used almost 8 times as long as shock ventilation (55.7 min vs. 7 min, respectively).

On the other hand, Team T6 tells a more extreme story: across all offices, trickle ventilation is used more than 27 times as long as shock ventilation on average (149.5 min trickle vs. 5.4 min shock), with non-JuControl-activated offices being the major contributors to trickle ventilation, which is used almost 36 times as long as shock ventilation on average (see Table 3). Comparing Teams T5 and T6, the average trickle ventilation usage in Team T6 is almost 4 times that of Team T5 for all offices (149.5 min vs. 38.8 min), while average shock ventilation usage in Team T6 is two-thirds that of Team T5 (5.4 min vs. 8 min), although the values are low in absolute terms. This higher use of trickle ventilation in Team T6 in place of shock ventilation contributed to its high energy penalties.

5.3. Effect of JuPower coupling

In the experiment run, the user engagement with JuPower was insufficient to permit any analysis: out of 465 potential players, only

19 (about 4%) registered on JuPower or played the game. One reason for the low turnout is that the amount of information that the user needed to keep track of was high, considering that JuControl and its gamification aspect were already demanding in terms cognitive effort. Another reason is that the duration of the experiment was short, while the game required more time to get used to. From the users' perspective, reasons for this low turnout are provided by the post-experiment survey in Section 5.5, along with the results of the test runs during the co-design workshop focused on JuPower.

5.4. Analysis of occupancy-schedule-based heating in pilot building

5.4.1. Thermal energy savings

In order to determine the thermal energy savings occasioned by the deployment of automatic heating control in the pilot building, Building B-01, through JuControl, we use the *whole-facility measurement* approach (Option C) of the International Performance Measurement and Verification Protocol (IPVMP) [57], in which energy savings are determined based on utility meters *e.g.* the building level. The whole-building methodology applied in this work is based on the widely used Degree Days approach [58,59], which theorizes that the heating energy demand of buildings is a linear function of the ambient temperature, when the ambient temperature is below a given threshold; above this threshold, called the *balance point temperature*, heating is not required. In particular, we use the building's *energy signature*, which is a three-parameter regression model that relates the historical daily energy demand of the building to the daily mean ambient temperature, to determine the energy savings. The energy signature curve is derived for the building using historical data obtained in the *baseline* period, and using this signature, the expected energy demand of the building in the reporting period is "forecasted". The difference between the forecasted demand and the actual demand in the reporting period is the amount of energy saved.

The three-parameter regression model is of the form:

$$\hat{Y} = \beta_1 + \beta_2 \cdot (\beta_3 - X)^+ \tag{1}$$

where β_1, β_2, and β_3 are the three regression coefficients, $\hat{Y}$ is the estimated daily thermal energy demand (dependent variable, in kWh), and X, the independent variable, is the daily average ambient temperature (in °C). The magnitude of the constant line β_1 represents the base load of the building (kWh), while β_2 is equivalent to the overall heat loss coefficient of the building (in kWh/K), and β_3 is the building's *balance-point temperature* (°C). The $(\cdot)^+$ notation means that the parenthesized expression is set to zero if the result is non-positive. The expression $(\beta_3 - X)^+$ effectively represents the daily Heating Degree Days (HDD) [58,59]. Mathematically, for heating demand, the HDD for a period D consisting of d days, is [59,60]:

$$HDD_{\text{period}} = \sum_{d \in D} \left[\frac{1}{N} \sum_{t \in \mathcal{N}_d} \left(T_{\text{base}} - T_{\text{amb}}(t) \right)^+ \right] \text{(K} \cdot \text{day)} \tag{2}$$

where $\mathcal{N}_d$ is the set of time points of ambient temperature measurements for day d (*e.g.* hourly data of 24 time points), $N = |\mathcal{N}_d|$ is the number of measurements per day, and $T_{\text{amb}}(t)$ (°C) is the ambient temperature at time t in $\mathcal{N}_d$. The *base temperature*, T_{base} (°C) is commonly a standard value for simplicity (for example, 15.5 °C in Europe [61] and 18.3 °C in the U.S.A. [58]). However, T_{base} refers more accurately to the *balance-point temperature* of the particular building under analysis [58,59], and the assumption of a standard value can lead to errors in energy estimation. Nevertheless, for comparing the heating requirements of different weather periods, a standard base temperature is appropriate. A typical energy signature plot is shown in Fig. 19.

The goodness-of-fit for the regression models is usually assessed by the Root Mean Squared Error (RMSE), which estimates the model residuals, and the squared correlation coefficient, R^2, which represents how well the regression model fits the data compared to how well the mean fits the data [60]. Mathematically,

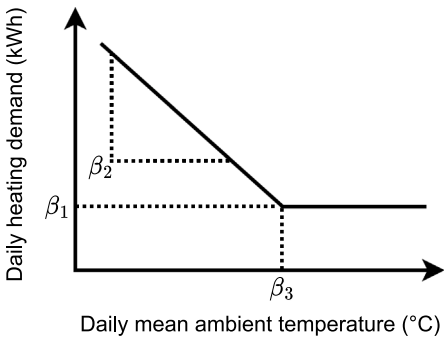


Fig. 19. Shape of the three-parameter regression model representing the building energy signature.

$$RMSE = \sqrt{\frac{\sum (Y - \hat{Y})^2}{n - p}} \tag{3}$$

and

$$R^2 = 1 - \frac{\sum (Y - \hat{Y})^2}{\sum (Y - \bar{y})^2} \tag{4}$$

where n is the number of data points, p is the number of regression coefficients, Y is the set of historical thermal energy demand data points, and $\hat{Y}$ is the model-estimated demand computed from Eq. (1), and $\bar{y}$ is the mean of the historical demands. An R^2 value of zero means that the regression model does not fit the data any better than the mean does, and $R^2 = 1$ indicates a perfect fit between the data and the model.

For the analysis of energy savings in the pilot building, the baseline period is taken to be October 2021 to September 2022 inclusive, prior to the use of the automatic heating controller and before the main experiment, while the reporting period is October 2022 to September 2023 inclusive after the deployment of the automatic controller, and within which the main experiment was run. Applying Eq. (1) to the historical data of Building B-01, we obtain the regression parameters of Eq. (5) below:

$$\hat{E}_{\text{th},d} = 3.21 + 41.86 \times (17.91 - T_{\text{amb},d})^+ \tag{5}$$

where $\hat{E}_{\text{th},d}$ is the estimated thermal energy demand (kWh) for daily mean ambient temperature $T_{\text{amb},d}$ (°C) on day d. Comparing the above equation with Eq. (1), $\beta_1 = 3.21$ kWh, $\beta_2 = 41.86$ kWh/K, and $\beta_3 = 17.91$ °C. Fig. 20 shows the regression line and historical data on the plot of daily energy demand vs. mean daily ambient temperature for Building B-01, excluding weekends.

As previously mentioned, there were issues with the heating controller in Building B-01, in which the desired temperature was usually not attained, especially after weekends and in the early mornings (see Section 4.3). Since the temperature shortfall was about 1.5 K on average, this "shortfall" in supply should be accounted for in the calculated savings by discounting from the savings an estimate of the unmet energy demand corresponding to the shortfall. Specifically, from Eqs. (1) and (5), the dependence of the daily heating energy on temperature is captured by the slope term, $\beta_2 = 41.86$ kWh/K (when ambient temperature is below the balance-point temperature). Hence, the savings in the reporting period with adjustments is as below:

$$E^*_{\text{th,saved}} = \sum_d \left(\hat{E}_{\text{th,d}} - E_{\text{th,d}} \right) - 41.86 \times HDD_{\text{short}} \tag{6}$$

where $E^*_{\text{th,saved}}$ (kWh) is the adjusted thermal energy savings in the reporting period, while $\hat{E}_{\text{th,d}}$ and $E_{\text{th,d}}$ (both in kWh) are the forecasted and historical demand for the d days in the reporting period, respectively. The heating shortfall in terms of heating degree days, HDD_{short}, is estimated for the entire reporting period as follows. From the data, out of about 120 working days in the heating season that

Table 4
Performance comparison of Building B-01 between the baseline period (from Oct. 1, 2021 to Sept. 30, 2022, inclusive) and the reporting period (from Oct. 1, 2022 to Sept. 30, 2023, inclusive). Weekends are excluded from the analysis.

Period	$HDD_{15.5}$ (K · day)[a]	Thermal Demand (kWh)		Difference[b]		Statistics	
		Model	Actual	Abs. (kWh)	Rel. (%)	RMSE (kWh)	R^2
Baseline	1,333.7	71,928.2	71,916.5	11.8	0.016	73.68	0.91
Reporting	1,207.1	66,599.5	54,210.5 (54,838.5[c])	12,388.9 (11,761[c])	18.60 (17.66[c])	–	–

[a] HDD is calculated using EU-standard base temperature of 15.5 °C for standardization purposes, and only for weekdays.
[b] Difference between model-predicted demand and actual demand.
[c] Heating shortfall-adjusted values. See Eq. (6).

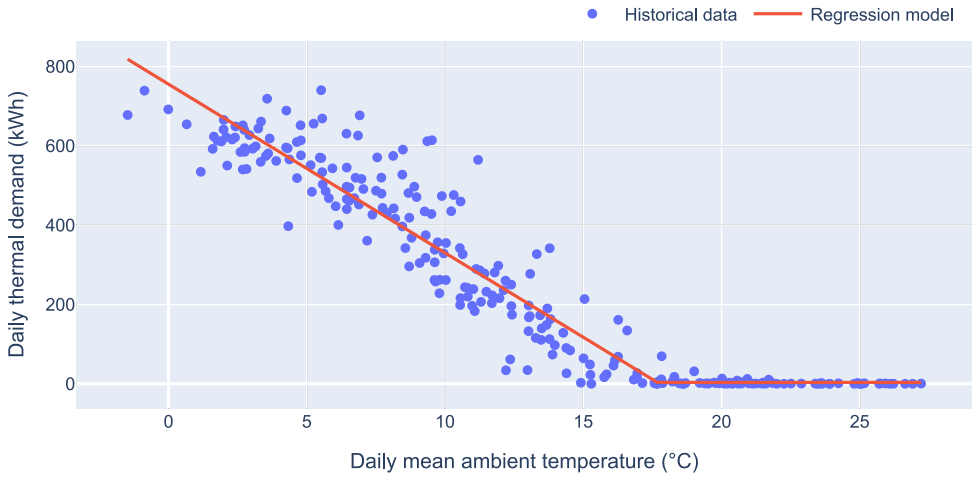


Fig. 20. Three-parameter regression model fitted on the historical data of Building B-01 to derive the energy signature for the baseline period. The data is from Oct. 2021 to Sept. 2022 (inclusive), using weekdays only.

had daily mean temperature at least 3 °C below the building balance point temperature, the first 60 days were affected by this issue. For each day, about 4 h had insufficient heating (1.5 °C below the desired temperature). Therefore, the **total heating shortfall** is estimated as $1.5\ \text{K} \times 60\ \text{days} \times 4/24 = 15\ \text{K} \cdot \text{day}$.

Based on Eqs. (5) and (6), the performance comparison of Building B-01 between the baseline period and the reporting period is detailed in Table 4. As can be seen in the table, the model fits the training data with reasonable accuracy in the baseline period ($R^2 = 0.91$; RMSE = 73.68 kWh). Also, Table 4 shows that the reporting period achieved a savings of 18.6% (about 12.4 MWh) compared with the predicted demand. The heating shortfall estimated as 15 K · day above, would have required $41.86 \times 15 = 627.9$ kWh of additional heating energy, using Eq. (6). Hence, the adjusted total savings is 11,761 kWh, or approximately 17.7% of the predicted demand. The heating shortfall-adjusted savings are shown in parenthesis in Table 4.

To examine how the building energy signature changed between the two periods, the energy signature of the baseline period is compared with that of the reporting period in Fig. 21, showing that the energy savings in the reporting period are as a result of lower thermal demand per unit increase in the associated driving temperature difference (equivalent to HDD) compared to the baseline period ($\beta_2 = 38.4$ kWh/K in reporting period vs. $\beta_2 = 41.9$ kWh/K in baseline period), and a lowering of the balance-point temperature by 1 °C ($\beta_3 = 16.9$ °C in reporting period vs. $\beta_3 = 17.9$ °C in baseline period).

5.4.2. Cost-benefit analysis for instrumentation

For the pilot building, Building B-01, a total of 183 wireless sensors and valve actuators were installed in 38 spaces, costing €23,330 in total (see Table 5). There were no KNX-protocol-based devices in the building. The costs for the installation of sensors and actuators are not considered here, since after the development of a sophisticated workflow for the preparation and installation of these devices, the time required for the equipping further offices is minimal. If only the installation costs are compared with the reduced energy costs due to energy savings which amount to 11.8 MWh, assuming the price for heat of €0.1647/kWh (2022), it would take 12.0 years to fully recover the investment. A few important remarks should be made here. First, only 8 offices were JuControl-activated in the building, meaning that the heating controller managed only these rooms with respect to dedicated user-specific schedules in the reporting period. In a best-case scenario where all offices are activated and occupants specify schedules that are up to 90% in alignment with real presence, the energy savings compared to an uninstrumented baseline would be expected to be above 30%. In this case it would take at most 7.2 years to recover the investment. Indeed, after further consultation with the works council and the data protection officer, in a future upgrade the automatic heating controller would always be enabled, regardless of JuControl activation status. Apart from the energy savings, the installation setup also provides occupants an insight into the indoor air quality and consequently ensures better air quality on average.

As can be seen from the table Table 5, the Indoor Air Quality (IAQ) sensors, and sensors for window/door states account for around 50% and 22% of the hardware costs respectively. In a minimal setup where the detection of ventilation patterns is based on software sensors (*e.g.* based on temperature profile) and the IAQ sensor could be replaced by an EnOcean-based temperature-only sensor (costing approximately €50 instead of €300) the payback period could be reduced to 4.5 years. When switching from EnOcean to LoRaWAN, the IoT gateway and the transceivers could be replaced by a single, significantly cheaper LoRaWAN gateway and the cabling costs would be eliminated. In such a case, the payback period could be decreased further. This effect especially holds for smaller setups with a limited number of rooms like in the pilot building.

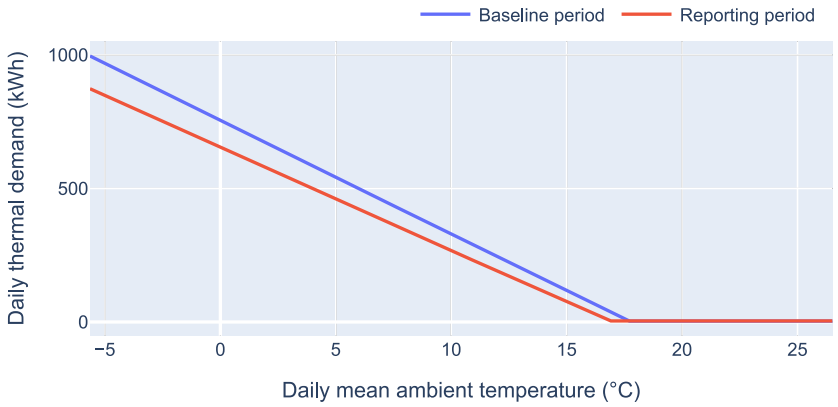


Fig. 21. Comparison of "energy signature" regression lines for baseline and reporting periods for Building B-01, showing reduction in balance-point temperature and slope.

Table 5
Installed device types and their associated purchase costs.

Device Type	Unit Price	Quantity	Total Price
IoT Gateway	€1,500	1	€1,500
EnOcean Transceiver	€120	8	€960
Cabling of Transceivers	€650	1	€650
IAQ multisensor	€300	38	€11,400
Window handle	€70	54	€3,780
Contact sensor	€35	38	€1,330
Valve actuator	€70	53	€3,710
Total			€23,330

5.4.3. Use of JuControl calendar

In this section, an analysis of the usage of the JuControl calendar is presented, specifically the agreement or otherwise between the *predicted* presence of the occupant according to their JuControl calendar schedule, and the real presence of occupants in the office. The terminology used in this analysis to describe the mismatch between the calendar schedule and real presence is akin to supervised learning terminology, where the calendar schedule can be thought as *predicting* the real presence. For example, when the JuControl calendar *predicts* that the office is occupied but it in reality it is not, then this is a *false positive* (see Table 6 for the full terminology).

A sample comparison is shown in Fig. 22 for Apr. 17, 2023, showing a comparable amount of true positives and false positives clustered within the typical working hours, and with true negatives dominating the early mornings and early evenings. In general, an analysis of the frequency of the true/false positives/negatives for these 30-minute buckets across all the experiment dates and all JuControl-activated offices in the building shows that employees were not present in the office as much as their JuControl calendar schedules indicated, with the false positive rate (*i.e.* calendar presence but actual absence) ranging from 25% to over 50%. This trend remained consistent in general throughout the experiment period. There were generally very low false negative rates (periods where the calendar predicted an unoccupied office, but in reality it was occupied). In general, the matches between the calendar schedule and real presence (true negatives + true positives) were almost always above 50% for each day, averaging about 61% for the entire experiment period.

5.5. User survey results

The results of the post-experiment user survey is briefly presented in this section. The survey was carried out between June 20 and October 16, 2023. In total, there were 113 respondents. However, since the questions were programmed to be context-sensitive, meaning that subsequent questions depend on both the previous answers and the experiment features available to the respondent's team, some questions were not shown to all 113 respondents if a qualifying condition for displaying the question was not met.

In terms of frequency of use of JuControl during the experiment period, out of 103 respondents, about half visited only a few times throughout the experiment period (n = 54), although more than a quarter (n = 30) visited JuControl several times per week, while 15% (n = 15) never visited it and less than one-tenth (n = 9) visited it several times a day. When asked about which data they were most interested in, respondents mostly said room temperature (n = 38), which is probably because in winter season, thermal comfort is one of the most important needs for building occupants. This was followed by energy rating of own room (n = 22) and energy rating of other rooms (n = 10). The least common response was CO_2 concentration (n = 3), which seems to imply that indoor air quality was not a priority for most respondents. However, since the question allows selecting only one option, it is possible that CO_2 concentration still mattered to the respondents, but perhaps the novelty effect of having energy ratings, and the more pressing need for thermal comfort, made occupants prioritize those other data over CO_2 concentration.

A number of questions in the survey dealt with user response to evaluations. Regarding evaluation summary and recommendation emails, out of 85 respondents, two-thirds remembered receiving the emails and read them at least once (n = 64), while only one person received but did not read it; the rest did not recall receiving it or did not see the emails (only offices with evaluation or recommendation enabled according to the experiment design had access to this question). Among those who recalled receiving the emails (n = 65), almost half (n = 31) liked the idea and thought the emails were interesting, while more than one-fifth (n = 14) found them annoying and uninteresting. Eleven respondents were indifferent, while the remaining nine found them annoying but interesting. Out of those who found the emails annoying (n = 23), when asked about the *most* annoying thing about the emails, the top response was that the data in the emails was erroneous or inaccurate (n = 9), followed closely by the emails being spam-like (n = 8). Most of the respondents that received the emails claimed nevertheless that the emails were quite or totally understandable (n = 39), and one-third said it was only a little understandable (n = 22). In response to whether the emails affected their behavior in terms of window use and/or heating setpoint temperature, the majority said "No" (n = 39), while the remaining said "Yes" (n = 24), which shows that the option of sending emails is effective to an extent. On the general subject of energy ratings as a means of improving their personal behavior with the assumption that the ratings were "properly implemented", half of the respondents answered that it would only be "a little" effective for them, while more than one-third (n = 23) said "totally" effective or "to a large extent". Eight answered in the negative.

Table 6
Terminology for describing agreement or otherwise between occupant-specified JuControl calendar schedules and real presence, along with the color coding. The terminology is derived by thinking of the calendar schedule as *predicting* the real presence.

JuControl calendar (*predictor*)	Computed real presence	Terminology for *prediction outcome*
Occupied	Occupied	True positive
Unoccupied	Unoccupied	True negative
Occupied	Unoccupied	False positive
Unoccupied	Occupied	False negative

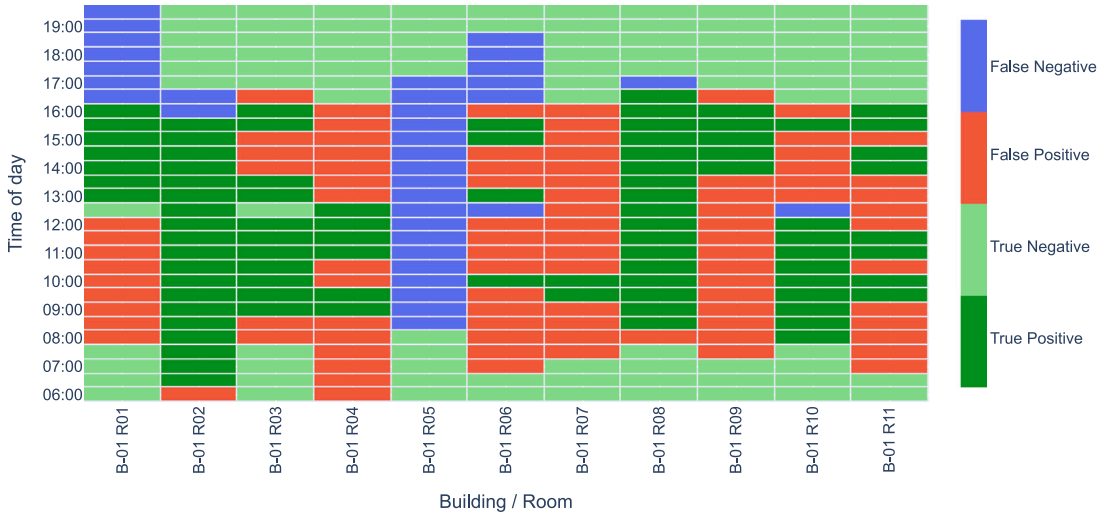
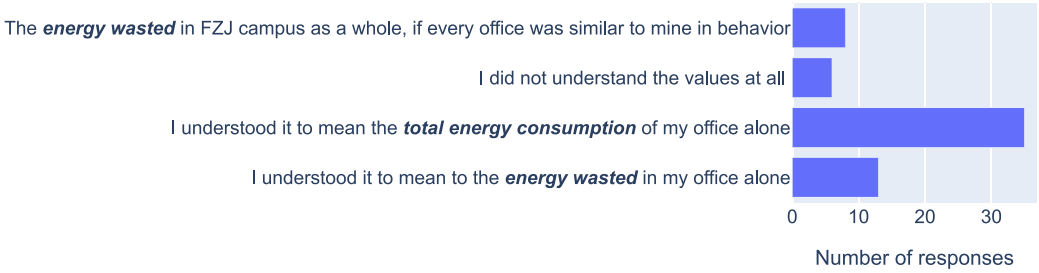
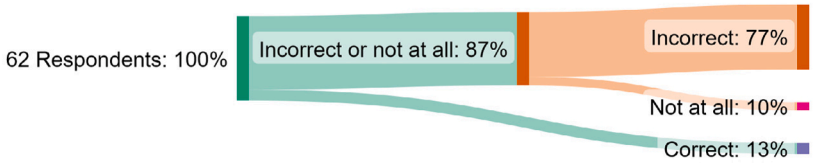


Fig. 22. Comparison of JuControl calendar schedules with real occupancy for offices in Building B-01 for a normal working day (Apr. 17, 2023). Each cell represents a 30-minute period for one office.



(a) Response to survey question



(b) Breakdown of survey response

Fig. 23. Respondents' understanding of energy penalty values. (a) Survey response options and frequency of response. (b) Breakdown of survey responses, showing that most respondents did not understand the meaning of the energy penalties.

In order to further test the respondents' understanding of the energy penalties, occupants were asked to select the option that reflected their understanding, as shown in Fig. 23(a). The responses revealed, however, that energy penalty values were mostly misunderstood (Fig. 23(b)), which implies that the claim of "erroneous or inaccurate" values above was at least partly due to misunderstanding. Indeed, when respondents were asked in a follow-up question about what they felt about the comparison of their performance with that of other offices in their team, the most common response was that they believed something was technically wrong with the comparisons (n = 29), while less than one-quarter said they were motivated to perform better (n = 15). One respondent stated they did not understand the comparison, while the rest selected "No thoughts/I did not notice the comparison" (n = 17). The implication for the User Experience design is that the most natural understanding of "energy rating" among the target audience was energy consumption in *own* office, unlike the *energy-penalty-scaled-to-campus-size* approach that was used in this work, which was inspired by the need to couple the penalties with *JuPower*. Hence, energy rating of own office would have been a better way to present the evaluation results to users. Again, this underscores

the importance of user acceptance tests before deployment of such tools.

As mentioned previously, not enough data was available for any analysis to be performed regarding the effectiveness of JuPower, since the game was hardly played by the users. Only 15 out of 57 respondents registered on JuPower during the experiment period, while the remaining were either not aware of JuPower (n = 19) or were aware but did not register on it (n = 23). Among those who interacted with JuPower, almost three-quarters understood the main idea of the game (n = 11), while others either only partially understood (n = 3) or did not understand (n = 1). It should be noted here that many of the respondents who played JuPower were also already familiar with the game from the game testing period prior to the experiment. Those who did not play the game (n = 27, including some who registered but did not play it) gave the reason for non-participation as being too busy (n = 16), not interested in the game (n = 8), or the game not being useful (n = 3).

Finally, many improvements were suggested by the respondents in the free-text field following the above-analyzed questions. The most recurrent theme was about having more "meaningful" energy values, which relates to the misunderstanding of energy penalty values discussed above. Other themes included fixing sensor and software issues, having a real-world bonus system that rewards top performers, and performance comparison against own office benchmark instead of against other offices. Additionally, the unavailability of German translations for some parts of JuControl (especially the Evaluation/Gamification part) negatively affected more than one-fifth of the respondents (21 out of 96).

6. Discussion

Eco-visualization and feedback has been used widely for engaging building occupants and facilitating energy-related behavior change. Similar to the interactive room in JuControl and its traffic light energy rating system, Francisco et al. [62] tested occupant responses to a building information modeling–based interface that colors zones based on energy consumption. Their results show that such representations lead to improved user engagement, and the 2D version of the interface was more engaging for users than the 3D version due to its simplicity. Regarding the use of energy penalties instead of rewards, Jain et al. [63] suggests that rewards have more positive effects on users than penalties, although they only tested the initial view the user has on logging into their interface (negatively or positively signed reward points). Nevertheless, like in our case study, they find a positive correlation between interaction with their digital platform and energy savings among the participants. Also, since JuControl provided more than mere visualization by including traffic-light-based energy ratings and recommendations, the results agree with existing literature that indicate that visualization alone does not produce behavior change. For example, Peschiera et al. [41] showed that no change in behavior was noticed when occupants of a school dormitory merely saw their energy consumption, as against those that had the consumption compared to either the building or peer network average.

The analysis of performance difference between Teams T5 and T6, both located in Building B-05, showed significant differences and large effect sizes, but the splitting of the building could have introduced a bias, since from the beginning of the experiment, the mean consumption of Team T5 was generally lower than that of Team T6. One possible bias could be that the occupants in Team T5 have a more energy-efficient disposition due to being entirely scientists, while Team T6 is equally split between scientists and management staff. Indeed, analysis of the level of engagement with JuControl and JuPower shows such a skew in favor of scientists, especially those with an energy-related background. Another possible explanation for the bias could be the difference in floor level, where Team T5 occupies the bottom two floors, and Team T6 the upper two floors. Again, a few offices in Team T5 already had informal access to JuControl before the actual experiment announcement, although the sensors in the building were only commissioned the week before the experiment. Nevertheless, the significant differences between JuControl-activated and non-activated offices in Team T5 still proves that, even without the bias, the developed systems had a positive effect among a homogeneous population, as also observed in Teams T1 and T3 respectively. At the whole-building level, since Building B-05 was not homogeneously used for energy saving measures, and the duration of the experiment was short compared to the duration of the entire heating season, the effect of the interventions are negligible on the building thermal demand.

For the whole-building energy savings of nearly 18% realized in Building B-01 for the test year compared to the reference year, previous work indicate similar results, where it has been noted that a significant portion of energy wastage in buildings is due to unnecessary heating or cooling of unoccupied spaces [64,65]. The analysis carried out by Meyers et al. [65] estimates potential energy savings of 14%–20% due to *not* heating unoccupied rooms in homes in the United States, and even further savings with lowering of excessively high temperature setpoints. Becker et al. [66] investigated the energy savings from simulated occupancy-based heating for several thousand households as compared to the real-world energy consumption without a setback temperature. The results showed average energy savings of 9%, with about 11% and 5% of these households being able to save up to 15% and 20% respectively. Interestingly, the 5% with the highest savings potential share similar characteristics with Building B-01 in our study, *i.e.* being old and having rooms that are unoccupied for several hours a day. Furthermore, Iria et al. [67] report electricity savings of 20%, and the review of Zhang et al. [68] estimates energy savings of 5%–30% in commercial buildings, due to occupant behavior change. Additionally, Peng et al. [69] reports savings of 7%–52% in cooling energy in a commercial building by using machine-learning-based occupancy-driven cooling.

Since in Building B-01, the building envelope and energy systems remained the same during the baseline and test periods, the savings can be attributed to more efficient use of the heating system and more efficient building-occupant interactions. Specifically, from the energy signature comparison curve of Fig. 21, the improved performance can be attributed to:

- schedule-based heating and lower setpoint temperatures as demonstrated in the energy penalty analysis of the previous section, which reduces the balance point temperature by reducing the overall thermal demand during office hours but especially during periods of absence, including at night.
- less wasteful ventilation as shown in the previous section, which reduces the overall building heat loss coefficient accounted for by the slope term, β_2 in Eq. (1), as well as reduces the balance point temperature, since the balance point temperature depends on the overall heat loss coefficient.

Note that these savings were achieved despite the fact that just 8 out of the 32 offices in Building B-01 were JuControl-activated and hence had automatic setpoint temperature regulation, indicating more potential for energy saving, from both the user and control perspectives.

Regarding the estimated payback period of 4.5 to 12 years, our results are similar to the 4 to 15 years reported by Iria et al. [67] for electricity savings in a gamified application involving similar instrumentation, where the reported energy savings was 20%.

On the other hand, the low engagement with the JuPower game indicates that the time and cognitive effort required from building occupants in order to engage with any technology-based interventions should be as low as possible, especially in public buildings where the primary use of the spaces is for productive work. This is especially important in interventions that target a generic audience of non-energy

specialists. An alternative approach that could arguably enhance engagement would be to introduce the game as a stand-alone activity where users have time and focus to familiarize themselves with the game and develop their virtual campus energy system. Subsequently, these virtual campus systems can be used at a later point during behavior evaluations. In this way, the attention requirement of the systems is spread over a more manageable time-frame.

The results of the user survey raise interesting points. First, the eco-visualization method of "energy penalty scaled to campus" values in this work proved to be a hindrance to engagement and comprehension. Indeed, the literature shows that the comprehensibility of feedback to users has is a common issue [62,70]. A better feedback would have been "total energy consumption of own office" as indicated by the survey, and it could also have been presented visually in addition to raw numbers [62]. Nevertheless, [70] found that a table-like presentation of energy consumption values and associated costs was preferred by the participants in the study, more than any of the other more visual representations tested. The bottom line seems to be that users prefer "familiarity" to creativity.

Furthermore, the negative impact of the impression that the system is faulty can be seen in the feedback, calling for thorough system testing in addition to user acceptance tests. Finally, even a well-designed system does not have the ability to always positively influence *all* target users, which is corroborated in the literature [70], but generally should influence a significant number of users.

Finally, regarding the scalability of the system and its adaptability to other environments, a limiting factor is the cost of the hardware installation setup. The project does not use any non-publicly available or custom hardware components, basing its ICT backbone on the open-source FIWARE framework (see Redder et al. [43]). Relevant software units are packaged as publicly available repositories, and the developed software is entirely based on open-source software. In JuPower, the mathematical optimization is handled by Gurobi^{TM} [51], a commercial solver. However, JuPower can also use open-source alternatives out-of-the-box. A new version of JuControl is being tested as at the time of writing, which has been redesigned from scratch to abstract away the peculiarities of the FZJ campus and make it more generic for deployment in other places. Furthermore, the new JuControl incorporates in-built desk-booking functionality as the means for tracking occupant location, instead of the fixed-office calendars of the previous version. This means that occupant preferences can be applied to the correct space in a flexible office setting, like in the FZJ campus of nowadays. In summary, while there are adjustments to be made in a new setting, they are not prohibitively expensive.

7. Conclusion & outlook

In this work, a set of software applications, tools, and methods targeting building occupants in public buildings was developed, with the overall goal of improving the energy efficiency of the occupants' behavior within the buildings. These user behavior interventions were developed based on the concepts of visualization, control, gamification, and serious games, and embodied in a set of software applications, namely the *Energy Dashboard*, *JuControl*, *Juracle*, and *JuPower*. The developed systems were holistically tested in a real-world setting for seven weeks using selected buildings of the campus of Forschungszentrum Jülich. By the end of the experiment period, almost 2000 employees had accessed the Energy Dashboard Suite at least once, and about 50% of the 870 employees who were part of the experiment accessed JuControl within or before the experiment period.

The experiments demonstrated that the interventions had largely positive effects on occupant energy efficiency as reflected in ventilation styles and setpoint temperature, especially where the level of engagement with the developed systems was reasonably high. The mean daily energy penalties in the ventilation intervention group was 65% lower than that of its control group (1.66 kWh vs 4.67 kWh), with even lower penalties in the "activated" subgroup of the intervention group (0.74 kWh). In another test building that considered both ventilation and setpoint temperature, activated offices had 56% lower daily mean energy penalties than the control (1.91 kWh vs. 4.35 kWh), while in the pilot building, the energy penalties in the activated offices was 40% less than that of its control group (1.61 kWh vs. 2.94 kWh). All these effects were statistically significant and with large effect sizes. Furthermore, year-on-year thermal energy savings of about 18% (11.8 MWh) were realized in the pilot building where occupancy-driven heating was introduced. Accordingly, a preference for shock ventilation was adopted above trickle ventilation in line with the goals of the interventions, demonstrated by the predominant use of trickle ventilation for offices in the control group, as against the use of shock ventilation in the offices with interventions. Furthermore, the results demonstrated superior energy efficiency in JuControl-activated offices compared to non-JuControl-activated offices as a result of more efficient window ventilation styles in JuControl-activated offices than in non-activated offices. These results reflect the potential that the developed system has to improve energy efficiency when used. Nevertheless, an analysis of the use of the JuControl calendar for specifying planned presence indicates that the occupants did not generally update their calendars to reflect their planned presence, with a tendency towards overestimating scheduled presence in the office.

On the other hand, the level of engagement with the developed systems was shown through data and surveys to be dependent on the user acceptance of the developed systems, especially as a function of the perceived correctness of the behavior evaluation results and the understandability of their presentation. It was not possible to get statistically significant data about the effect of the JuPower game on the behavior of the building occupants, mostly due to the additional time and cognitive requirements of the game on top of the JuControl evaluation system, which many users could not afford within the test period.

Several issues were encountered in the development and testing of the systems, prompting desired improvements such as better publicity, more longitudinal experiments, better system monitoring and fault detection, and more inclusive design methodologies and user testing using *e.g.* co-design approaches. The lessons learned from this work are now being implemented in a future iteration of the experiment (scheduled for the cooling season of late 2024 to early 2025). First, a longer experiment is planned to cover the entire winter season. Secondly, indoor air quality (IAQ) will be the major driver for ventilation recommendations, without considering the window opening style (tilted or fully opened), where the goal is to maintain a healthy indoor CO_2 concentration. This approach is expected to be more acceptable by users since it is more occupant-focused. However, how the resulting energy demand compares with that of control groups without intervention is yet to be seen. Thirdly, the results of real-world energy evaluations as reflected in the JuPower game will be shown in JuControl as the primary eco-visualization, instead of energy consumption or energy penalties. In other words, the energy efficiency of the offices will be directly expressed as how "green" the FZJ campus is, as depicted by JuPower. Naturally, the user is provided with the opportunity to view more details, including estimated energy consumption. Furthermore, the results of the upcoming experiment can be subsequently be compared with data from the preceding year at the building level, where no experiments were run for the same setup. By implication, the design of the experiment will permit the investigation of building-wide energy savings due to interventions.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Dirk Mueller reports financial support was provided by Federal Ministry for Economic Affairs and Climate Action. If there are other authors, they 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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Data availability

Data will be made available on request.

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