Chair for Computer Science 10 (Media Computing and Human-Computer Interaction)

RWTH AACHEN UNIVERSITY

Promoting Energy-Efficient Decisions through Simulation-Driven Gamification

Master's Thesis at the
Media Computing Group
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by
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Abstract

Office buildings account for a significant share of energy consumption, with heating, ventilation, and air-conditioning systems representing a major contributor. While user behavior plays an important role in energy-efficient operation, occupants often lack guidance on how to achieve thermal comfort efficiently. To address this challenge, the DataFEE-App is being developed as a decision support system that aims to motivate energy aware behavior through intrinsic motivation via gamification.

Prior to this thesis, the DataFEE-App existed primarily as a conceptual prototype, providing static recommendations and fixed point allocations that were independent of environmental conditions. As a result, the app lacked a credible basis for fair comparison of user actions and was not suitable for long-term field studies. The goal of this thesis is to extend the DataFEE-App so that long-term user studies become possible.

In this thesis, the DataFEE-App is extended by designing and implementing a simulation based recommendation and point system that enables context aware ranking of thermal comfort actions according to their relative energy-efficiency. Thermal comfort is treated as a baseline condition, while energy-efficiency is used as an optimization criterion. In addition, gamification elements including points, badges, and leaderboards are integrated to support user motivation.

The simulation is validated using established accuracy metrics and guideline values, demonstrating sufficient absolute temperature prediction accuracy for application within the DataFEE-App. A user test is conducted to evaluate the effects of the introduced gamification elements. Results indicate that the app supports users in managing thermal comfort and that gamification increases initial motivation. However, the findings also show that, in its current state, the system does not yet provide sufficient motivation to sustain long-term use over extended periods.

Overall, this thesis represents a substantial step toward enabling long-term field studies with the DataFEE-App by providing a credible simulation-based foundation for gamification, while also identifying key challenges that must be addressed in future work.

Überblick

Bürogebäude machen einen erheblichen Anteil am Energieverbrauch aus, wobei Heizungs-, Lüftungs- und Klimaanlagen einen wesentlichen Beitrag leisten. Obwohl das Nutzerverhalten eine wichtige Rolle für einen energieeffizienten Betrieb spielt, fehlt es den Nutzenden häufig an Know-how, wie thermischer Komfort effizient erreicht werden kann. Um dieser Herausforderung zu begegnen, wird die DataFEE-App als Entscheidungsunterstützungssystem entwickelt, das durch intrinsische Motivation mittels Gamification energiebewusstes Verhalten fördern soll.

Vor dieser Arbeit existierte die DataFEE-App hauptsächlich als konzeptioneller Prototyp, der statische Empfehlungen und feste Punktzuweisungen bereitstellte, welche unabhängig von den Umgebungsbedingungen waren. Infolgedessen fehlte der App eine belastbare Grundlage für einen fairen Vergleich von Nutzeraktionen, und sie war nicht für langfristige Feldstudien geeignet. Ziel dieser Arbeit ist es, die DataFEE-App so zu erweitern, dass langfristige Nutzerstudien möglich werden.

In dieser Arbeit wird die DataFEE-App durch die Konzeption und Implementierung eines simulationsbasierten Empfehlungs- und Punktesystems erweitert, das eine kontextabhängige Bewertung von Maßnahmen zur Beeinflussung des thermischen Komforts entsprechend ihrer relativen Energieeffizienz ermöglicht. Der thermische Komfort wird dabei als Grundbedingung betrachtet, während die Energieeffizienz als Optimierungskriterium dient. Zusätzlich werden Gamification Elemente wie Punkte, Badges und Leaderboards integriert, um die Motivation der Nutzenden zu unterstützen.

Die Simulation wird anhand etablierter Genauigkeitsmetriken und Richtwerte validiert und zeigt eine ausreichende absolute Genauigkeit der Temperaturvorhersage für den Einsatz innerhalb der DataFEE-App. Zur Bewertung der Auswirkungen der eingeführten Gamification-Elemente wird ein Nutzertest durchgeführt. Die Ergebnisse zeigen, dass die App die Nutzenden beim Management des thermischen Komforts unterstützt und dass Gamification die anfängliche Motivation erhöht. Gleichzeitig verdeutlichen die Ergebnisse jedoch, dass das System in seinem aktuellen Zustand noch keine ausreichende Motivation bietet, um eine langfristige Nutzung über längere Zeiträume hinweg aufrechtzuerhalten.

Insgesamt stellt diese Arbeit einen wesentlichen Schritt zur Ermöglichung langfristiger Feldstudien mit der DataFEE-App dar, indem sie eine belastbare simulationsbasierte Grundlage für Gamification schafft und zugleich zentrale Herausforderungen identifiziert, die in zukünftigen Arbeiten adressiert werden müssen.

Acknowledgments

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Nomenclature

Symbol	Meaning	Unit
α	angle between wind direction and inward normal of window surface	$^\circ$
$\dot{m}_{\mathrm{HVAC}}$	mass flow rate of air supplied by the HVAC system	kg/s
$\dot{Q}_{\mathrm{Gains}}$	internal heat gains	W
$\dot{V}_{\mathrm{air}}$	volumetric airflow rate through the open window	m^3/s
$\dot{V}_{\mathrm{HVAC}}$	volumetric airflow rate through HVAC	m^3/s
$\dot{V}_{\mathrm{in}}$	volumetric airflow rate of incoming air	m^3/s
$\dot{V}_{\mathrm{out}}$	volumetric airflow rate of outgoing air	m^3/s
η	fan efficiency	–
ϕ	solar azimuth angle	$^\circ$
$\rho_{a,\mathrm{ref}}$	reference air density	$\mathrm{kg/m}^3$
ρ_{air}	density of the passing air	$\mathrm{kg/m}^3$
ρ_{in}	indoor air density	$\mathrm{kg/m}^3$
ρ_{out}	outdoor air density	$\mathrm{kg/m}^3$
s_{dis}	distance from origin to the Sun	AU
τ_{HVAC}	time constant for HVAC calculations	s
θ	solar zenith angle	$^\circ$
$\vec{dA}$	differential area vector normal to the window surface	m^2
x	x component of $\vec{dA}$	m^2
y	y component of $\vec{dA}$	m^2
z	z component of $\vec{dA}$	m^2
$\vec{e}_{\mathrm{Sun}}$	unit vector pointing from window origin toward the Sun	–
$\vec{I}_{\mathrm{Sun}}$	direct normal irradiance vector	$\mathrm{W/m}^2$
$A_{\mathrm{w;blind;tot}}$	total window area covered by blinds	m^2
$A_{\mathrm{w;close;tot}}$	total closed window area	m^2
$A_{\mathrm{w;open;tot}}$	total window opening area	m^2

Symbol	Meaning	Unit
A_{W}	window surface	m^2
A_{Window}	open window area	m^2
C_p	specific heat capacity of air	J/(kg·°C)
C_{st}	thermal buoyancy coefficient	(m/s)/(m·°C)
C_{wnd}	wind coefficient for wind-driven ventilation	s/m
$c_{InnerWall}$	thermal capacity of inner wall	J/°C
c_{Room}	thermal capacity of room	J/°C
COP	coefficient of performance	–
d_t	time step size	s
E_C	HVAC cooling energy consumption	J
E_F	energy consumed by fan	J
E_H	HVAC heating energy consumption	J
f_{win}	unobstructed, sun-exposed fraction of the window	–
$h_{\mathrm{w;fa}}$	free operable height of window	m
$h_{\mathrm{w;path}}$	height of window measured from floor level	m
$h_{\mathrm{w;st}}$	effective height for thermal buoyancy in window ventilation	m
$I_{\mathrm{Sun,eff}}$	effective irradiance entering the room	$\mathrm{W/m}^2$
I_{Sun}	direct normal irradiance (scalar)	$\mathrm{W/m}^2$
I_{Solar}	solar radiation intensity	$\mathrm{W/m}^2$
K_p	controller gain	–
N	number of people in room	-
o_{Room}	room orientation	°
p_{atm}	atmospheric pressure	Pa
P_{tot}	total pressure generated by the fan	Pa
$q_{\mathrm{V,arg,in}}$	volumetric airflow rate entering the room	m^3/s
$q_{\mathrm{V,arg,out}}$	volumetric airflow rate exiting the room	m^3/s
Q_{user}	heat emitted by user	J
$Q_{\mathrm{Ventilation}}$	total heat transferred by ventilation	J
Q_{Window}	total heat transferred through windows	J
R	thermal resistance	°C/W
R_{CCA}	thermal resistance of Thermally Activated Building Systems	°C/W
$R_{\mathrm{InnerWall}}$	thermal resistance of inner wall	°C/W
$R_{\mathrm{OuterWall}}$	thermal resistance of outer wall	°C/W
$R_{\mathrm{sp,air}}$	specific gas constant for air	J/(kg·°C)
R_{window}	thermal resistance of closed window	°C/W
$SHGC$	solar heat gain coefficient	–
SHR	sensible heat ratio	–

Symbol	Meaning	Unit
T_{CCA}	thermally activated building system temperature	°C
T_{HVAC}	temperature of the air delivered by the HVAC system	°C
$T_{\text{InnerWall}}$	inner wall temperature	°C
T_{Mixed}	mixed air temperature	°C
$T_{\text{NeighbouringRoom}}$	neighbouring room temperature	°C
T_{Out}	outdoor air temperature	°C
T_{Room}	indoor room temperature	°C
$T_{\text{Set,HVAC}}$	setpoint temperature of the air delivered by the HVAC system	°C
$T_{\text{Set,Room}}$	indoor room setpoint temperature	°C
u	wind speed	m/s
u_{dir}	direction vector of wind speed	-
u_{eff}	effective wind speed entering the room	m/s

Chapter 1

Introduction

"Der Mensch ist nur da ganz Mensch, wo er spielt."

—Friedrich von Schiller

Building energy demand is high.

Energy-efficiency has become a central pillar of global climate and energy policy. Buildings are responsible for approximately one-third of global final energy consumption, with non-residential buildings contributing about 8.76% of this total energy use [1]. While there are several strategies to improve building energy-efficiency, including constructing new energy-optimized structures or modernizing existing structures, these approaches often involve high costs and are not always feasible.

DataFEE-App motivates energy-efficient behavior through gamification.

A significant factor influencing energy consumption in non-residential buildings is human behavior. Studies have shown that behavioral changes related to Heating, Ventilation and Air Conditioning (HVAC) usage and window operation can reduce energy consumption by up to 30%, as demonstrated by Yan et al. [2018]. However, employees in non-residential environments are typically indifferent to the energy-implications of their actions. Conserva et al. [2017] argue that this is largely because occupants are neither aware of the impact of their behavior on en-

[1] www.iea.org/energy-system/buildings#tracking

ergy consumption nor financially responsible for energy-costs. Even when individuals are motivated to act more efficiently, they often lack the knowledge required to make energy-efficient decisions. The indoor temperature depends on multiple interrelated factors, including HVAC operation, window opening, room orientation, wind speed, and solar radiation. Consequently, identifying energy-efficient actions that also maintain thermal comfort can be a complex task.
To effectively reduce energy consumption through behavioral change, it is therefore necessary not only to motivate occupants to act more energy-efficiently but also to guide them in making the right decisions. In pursuit of this goal, the DataFEE-App is being developed at the E.ON Energy Research Center (E.ON ERC) at RWTH Aachen University. This web-app employs gamification techniques to encourage users, in the E.ON ERC main building, to save energy.

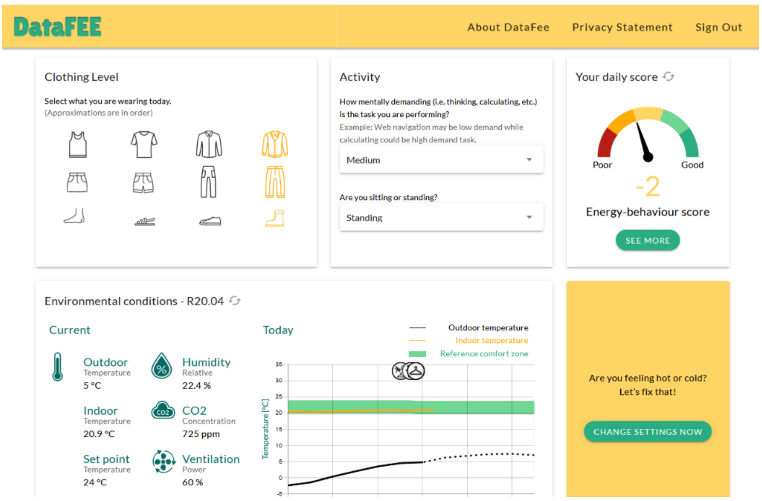


Figure 1.1: DataFEE-App Dashboard

Overview of the user interface in the current version of the DataFEE-App.

Figure 1.1 shows the dashboard of the DataFEE-App. In the top-left section, users can enter comfort-related information, including their activity and clothing level. The clothing input is structured into three rows representing the upper body, lower body, and footwear. Each row contains four selectable items arranged from left to right, ranging from the coldest to the warmest clothing option. The items are illustrated with icons, making the interface more intuitive and reducing cognitive load by minimizing the need

for reading.
Another input field concerns the user's activities. This includes specifying how mentally demanding the current task is. The user can choose between "Low," "Medium," and "High" from a drop-down menu. Below this, the user can also select their posture, such as sitting, sitting quietly, standing, or walking, using another drop-down menu.
The interface also includes real-time data on the environmental conditions are displayed to the user. The information includes outdoor and indoor temperatures, relative humidity, carbon dioxide (CO_2) concentration in the room, and the HVAC set-point and ventilation speed.
In addition, the outdoor temperature is shown on a graph. A solid line represents the previously recorded outdoor temperature, and this line continues as a dotted line to indicate the predicted temperature for the rest of the day. The indoor room temperature is displayed as a continuous yellow line that shows the recorded temperature throughout the day. No dotted line is provided for the indoor temperature, meaning no prediction is shown. The reference comfort zone is also highlighted in green, representing the temperature range in which the user is expected to feel comfortable.
The top-right section shows the user's energy behavior score. This is where the gamification aspect of the DataFEE-App first becomes visible. The app encourages users to save energy by motivating them to keep this score as high as possible. By clicking the "SEE MORE" button, the user can open the leaderboard depicted in Figure 1.2. There, the user can compare their energy behavior score with that of other users in the same building.
To obtain points, the user is required to click the button in the lower-right corner labeled "CHANGE SETTINGS NOW." This opens the pop-up window shown in Figure 1.3, where the user is asked how they currently feel and how they would like to adjust their thermal comfort. The pop-up then changes to the window shown in Figure 1.4, where the DataFEE-App presents recommended actions to achieve thermal comfort. Each option is assigned a point value based on its energy-efficiency. As a result, users who choose more energy-efficient ways of adjusting the indoor climate earn more points and achieve a higher ranking on the leaderboard.

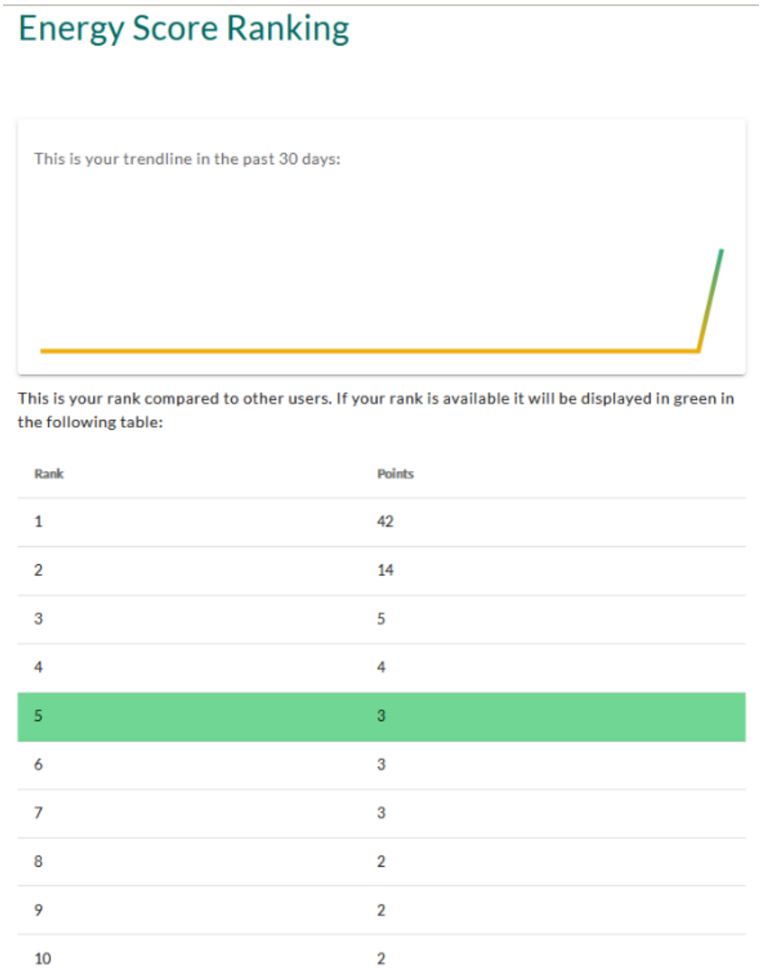


Figure 1.2: DataFEE-App Leaderboard

The E.ON ERC Main Building as the Basis for the DataFEE-App's Operation.

The DataFEE-App is designed for use in the main building of the E.ON ERC in Aachen, Germany. The strongly insulated walls and windows of the building reduce the energy needed for heating and cooling. Its thermal system is based on geothermal energy. A heat pump exchanges heat with an underground field of 40 boreholes, each 100 meters deep. Warmth or cooling is distributed through the concrete floors and ceilings.
If people in offices want additional heating or cooling, they can use the façade ventilation units, which provide warm air in winter and cool air in summer. Each workspace has a thermostat that controls its unit. The user can additionally adjust the fan speed, giving finer control over the airflow

Figure 1.3: DataFEE-App Thermal Comfort Input Window

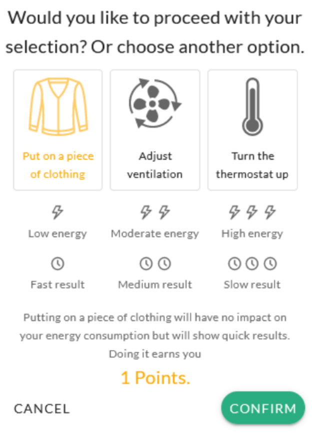


Figure 1.4: DataFEE-App Thermal Comfort Options

and comfort level. Fresh air for the offices is provided by a dedicated ventilation system.

As shown in Figure 1.5, this building has a cubic shape, with office spaces located along the northwest, southwest, southeast, and northeast façades, including several corner offices. It has four floors in total. The ground floor contains the foyer, nearby administrative areas, and several seminar and meeting rooms. The main entrance is on this level and faces the southwest side of the building. Below, the basement houses workshops, laboratories, and technical rooms. The first and second floors contain the primary workspaces as well as several smaller CIP pools. The DataFEE-App is intended for use in these office areas.

The office spaces are arranged along the outer edges of the cube. At the center of the building is a spacious shared area that connects the vertical voids and staircases. This central space supports activities such as reading, studying, relaxing, and social interaction.

All in all, the E.ON ERC main building was designed from the very beginning with energy-efficiency as a central goal. This approach made it possible to construct a genuinely sustainable building that remains future-proof in technological and functional terms, as well as environmentally and economically.

The DataFEE-App, described above, builds on this foundation by further supporting the building's energy-efficient operation without requiring users to sacrifice their thermal comfort.

Figure 1.5: E.ON ERC Main Building

DataFEE-App limited by static thermal-comfort suggestions.

However, the current version of the DataFEE-App still has limitations. The comfort-improvement options presented to users are static. They do not adapt to real-time environmental conditions such as weather data. To fully achieve the app's objectives, it is necessary to further develop it so that the comfort options are dynamic, weather-responsive, and evaluated in terms of their true energy-efficiency. This enhancement would ensure that the point system accurately reflects energy-saving behavior and provides meaningful motivation.
Due to these limitations, long-term user testing is currently not possible with the app. Therefore, the primary aim of this thesis is to enable long-term testing by further developing and implementing the DataFEE-App. This is achieved through the introduction of a dynamic point system that responds to changing environmental conditions. Beyond improving the accuracy and relevance of user feedback, this dynamic system allows the integration of additional gamification elements beyond points and leaderboards, thereby supporting sustained user engagement over extended testing periods.

1.1 Outline

To demonstrate how this thesis aims to achieve the goal of enabling long-term testing of the DataFEE-App, a clear logical structure is required. This structure is outlined in the following section.
This thesis addresses the problem of excessive energy consumption in office buildings and explores how energy usage can be reduced through optimized HVAC operation without sacrificing thermal comfort.
To achieve this goal, the DataFEE-App is extended with two complementary mechanisms. These extensions constitute the sole functional changes to the app and form the basis for the subsequent evaluation. First, to enable long-term usage, the app incorporates gamification elements as a supporting mechanism for intrinsically motivated user interaction. Second, to provide meaningful and energy-aware recommendations for achieving thermal comfort, a simulation-based approach is required to estimate energy consumption and indoor thermal conditions.
Accordingly the work focuses on two interconnected topics, as illustrated in Figure 1.6. The first topic concerns the development of a simulation-based tool that is integrated into the DataFEE-App to identify energy-efficient options for achieving thermal comfort. The second topic addresses the integration of gamification elements intended to intrinsically motivate users to engage with the app over longer periods.
Chapter 2 provides the theoretical background required to understand the methodology introduced later in the thesis. For the simulation component, the thermal simulation approach developed by Nienaber et al. [2020] is introduced, which serves as the basis for further extensions in the methodology chapter. For the gamification component, the reader is familiarized with the HEXAD model, and relevant gamification elements are discussed in relation to intrinsic motivation.
Chapter 3 presents the methodology of this thesis. The simulation model is extended to account for room orientation, enabling room-specific thermal comfort predictions and fair energy-aware ranking of user actions. In addition, the integration of gamification elements selected in the

previous chapter is described. This chapter also provides an overview of the backend and frontend architecture of the DataFEE-App and summarizes the system components modified or added within the scope of this thesis.
Chapter 4 presents the evaluation results. The accuracy of the simulation is assessed using the metrics Root Mean Square Error, Mean Absolute Error, and squared Pearson correlation coefficient, which are compared against established guideline values to determine their acceptability. The user experience of the extended DataFEE-App, incorporating gamification elements and a simulation-based recommendation tool, was evaluated through a user test in which participants interacted with the app and subsequently completed a questionnaire.
Finally, Chapter 5 brings together the results of the simulation accuracy and the findings on long-term usability. Based on this synthesis, conclusions are drawn and recommendations for future work are provided.

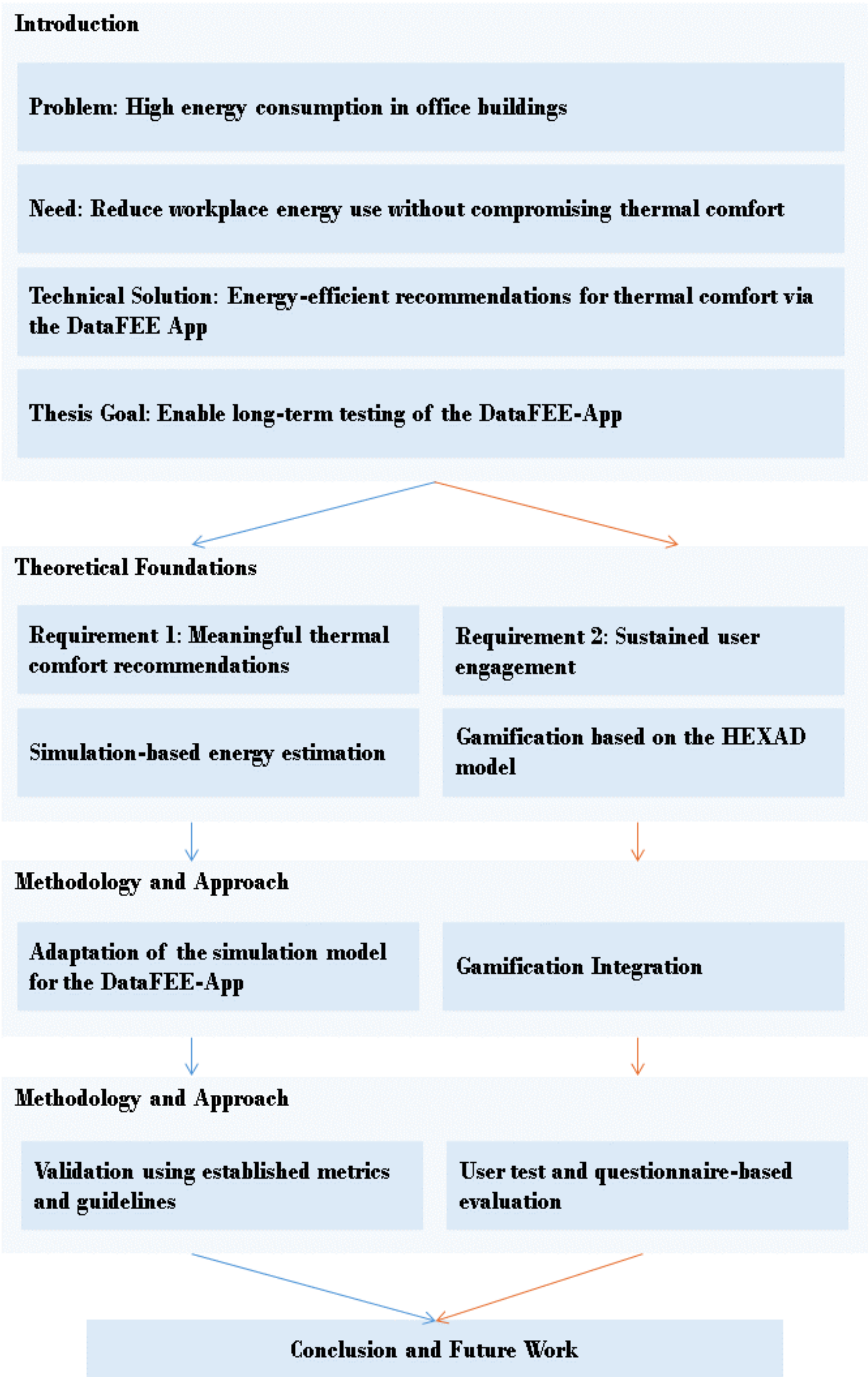


Figure 1.6: Conceptual Structure of this Thesis

Chapter 2

Theoretical Foundations

To enable long-term testing, this thesis focuses on the further development and implementation of the DataFEE-App. In doing so, two key aspects are addressed. The first concerns the gamification component, which aims to introduce additional game elements to ensure sustained user engagement and long-term use of the app. The second focuses on identifying the most energy-efficient options for achieving thermal comfort. This requires the development of an algorithm capable of evaluating and ranking these options based on their energy efficiency. Accordingly, this thesis will examine both aspects in detail in the following sections.

2.1 Related Work on Influencing and Identifying Energy Efficiency

The concept of applications that aim to reduce energy consumption by influencing human behavior has been explored in several previous studies. Similarly, various algorithms have been proposed in the literature to determine optimal user actions for energy efficiency. This chapter reviews these existing approaches and identifies the remaining gaps that need to be addressed.

2.1.1 Approaches to Studying and Encouraging Energy-Efficient User Behavior in Office Climate Control

Multiple LLEC apps combine visualization, feedback, and gamification for energy reduction.

According to Ubachukwu et al. [2025], the Living Lab Energy Campus (LLEC) at Forschungszentrum Jülich is also developing applications aimed at reducing energy consumption by influencing human behavior in office environments. The overall system consists of several interconnected tools: the Energy Dashboard, JuControl, JuPower, and Juracle. Together, these applications provide energy visualization, behavioral feedback, gamification, and user performance evaluation.

The Energy Dashboard serves as a visualization tool that provides users with feedback on the heating, cooling, and electrical demand of the campus. It displays both historical and real-time data, helping occupants understand the overall energy requirements of the building infrastructure.

JuControl is a web application that delivers room-level, real-time, and historical data on indoor conditions such as CO_2 concentration, relative humidity, and the state of windows and doors. Users can specify their preferred comfort range and office occupancy hours. Based on this information, JuControl proposes optimization strategies to maintain thermal comfort during working hours. The application also incorporates a gamification component, in which user behavior related to ventilation habits and indoor temperature setpoints is analyzed and scored according to predefined behavioral patterns.

The Juracle module evaluates user behavior by comparing it against that of an ideal occupant. This comparison is based on an optimal setpoint temperature and ideal ventilation duration, calculated for different conditions. For instance, continuous or "tilt" ventilation during the heating season is discouraged, as it is generally considered energy-inefficient in Germany. Deviations from the ideal behavior result in penalties within the gamified evaluation system.

A notable characteristic of this approach is that it defines optimal setpoint temperatures and ventilation durations for longer, predefined periods. However, these values may vary considerably depending on changing external conditions. In contrast, the DataFEE-App focuses on assessing user comfort and providing feedback in real time. Instead of enforcing general behavioral rules (e.g., avoiding tilted windows in summer), the DataFEE-App dynamically calculates the most energy-efficient options to achieve thermal comfort under current environmental conditions. This allows for adaptive, moment-to-moment guidance rather than static behavioral recommendations.

The Annex 66 project of the International Energy Agency's Energy in Buildings and Communities (IEA-EBC) programme [1] focuses on accurately modeling and quantifying the impact of human behavior on building energy use, both for energy prediction and simulation purposes. Its successor, Annex 79 [2], expands upon this work by integrating additional methods such as big data analytics and machine learning to further improve prediction accuracy.

Annex 66/79 improve modeling of occupant behavior for accurate energy simulations.

Although Annex 66 and Annex 79 offer valuable insights into understanding and simulating occupant behavior, especially in relation to HVAC operation and window-opening habits, their focus remains primarily on behavior prediction and estimation. However, they do not focus on actively improving user behavior or on strategies for effectively communicating energy-efficient actions to occupants.

2.1.2 Approaches to Achieving Thermal Comfort with Minimal Energy Use

To achieve thermal comfort through optimal operation of windows and HVAC systems, several control strategies have been proposed. The majority of these methods are based on the work of Wang and Greenberg [2015], where outdoor temperature and the HVAC setpoint temperature are used as the main parameters to determine whether window opening is recommended. As a general rule of thumb, this approach has proven to be effective and straightforward for improving indoor comfort while maintaining reasonable energy efficiency.

Common comfort strategies rely on outdoor and setpoint temperatures for window guidance.

However, when applying this algorithm to multiple rooms

Fair recommendation system needs to consider room orientation, occupancy, and internal heat gains.

1 `https://www.annex66.org/`
2 `https://annex79.iea-ebc.org/`

within the same building, several limitations emerge. In such cases, users across different office spaces are presented with the same control options, even though the room orientation, occupancy, and internal heat gains can vary significantly. For instance, south-facing offices may experience much higher solar gains than north-facing ones, and rooms with more occupants or electronic devices will naturally have higher internal heat loads. Providing identical comfort options across all offices therefore reduces both the accuracy and fairness of the system. To ensure fair and reliable recommendations, as many relevant environmental and contextual factors as possible should be considered in the decision-making process.

Advanced methods consider more weather conditions but still produce uniform recommendation.

Other control strategies, such as those proposed by Liu et al. [2021], additionally incorporate parameters like relative humidity into the window-opening logic. However, this factor is generally less critical for ventilation control in climates, where humidity levels are typically moderate, such as in Germany. Tognon et al. [2023] further suggest adapting ventilation strategies according to the season, distinguishing between heating, cooling, and transitional periods.
The core limitation of these approaches remains the same: they tend to produce uniform control outputs for all offices within a building, without accounting for local differences such as room orientation, occupancy density, or equipment load.

Dynamic recommendations possible by using simulation.

To overcome these limitations, the simulation model developed by Nienaber et al. [2020] can be employed. This model uses a set of differential equations to calculate indoor temperature for a time horizon of approximately 4–5 hours. Unlike simpler models, it incorporates internal heat gains, solar gains, concrete core activation, and wall heat transfer, in addition to outdoor temperature and HVAC operation. However, it does not explicitly account for heat exchange due to window operation, which can be integrated as an additional term in the model equations. The calculated indoor room temperature can be used to check whether the room configuration would be able to achieve the desired thermal comfort level.
Furthermore, this simulation framework can also be ex-

tended to estimate the energy consumption associated with different operational choices, such as opening windows versus using the HVAC system. The HVAC energy consumption can be calculated following the method described by Noubissie Tientcheu et al. [2019], while additional calculations would be required to account for transient energy use when switching HVAC systems on or off.

2.2 Foundations of Gamification

Gamification fosters intrinsic motivation for lasting energy-saving behavior.

As previously discussed, occupants of non-residential buildings often do not feel responsible for saving energy and therefore lack motivation to adopt energy-efficient behaviors. Several approaches can be used to encourage behavioral change. Monetary incentives, for example, may initially increase motivation. However, their effectiveness tends to decline over time due to the overjustification effect, where external rewards reduce intrinsic motivation once the incentives are removed, as suggested by Deci [1971].
To ensure long-term engagement and sustainable behavioral change, fostering intrinsic motivation is therefore more effective. One promising approach for achieving this is the use of gamification, supported by the findings of Wang et al. [2025]. Gamification is commonly defined as "the use of game design elements in non-game contexts" according to Deterding and Khaled [2011]. By incorporating elements such as points, feedback, and competition, gamification seeks to make routine or non-engaging tasks more enjoyable and rewarding, thereby encouraging users to consistently participate in energy-saving behaviors.

2.2.1 Player Typologies in Gamification: The HEXAD Model

Personalization via player types improves long-term engagement in gamified systems.

To enable long-term testing, the application must be adaptable to a wide range of individual users. Achieving this requires a deeper understanding of the user characteristics that influence behavior within a gamification system. Although users could be classified based on demographic

variables such as gender, age, or cultural background, or even combinations of these factors; Tomé Klock et al. [2020] suggests that personalization is often more effective when it is based on player typologies. These typologies segment users according to their psychographic traits, motivations, and behavioral patterns.
Several player-type models have been proposed in the literature, including Bartle's Player Types [1996], the BrainHex archetypes [2014], and the HEXAD model. Among these, the HEXAD model by Marczewski [2023] has become the most widely used framework in gamification systems aimed at influencing behavior, as it focuses explicitly on motivational drivers rather than gameplay mechanics.
The HEXAD model distinguishes six player types, each characterized by distinct motivations and preferences. Table 2.1 summarizes these underlying motivations for each player type and the corresponding game elements suggested by Tondello et al. [2016].

Tailoring game elements to player types strengthens engagement and long-term use.

By understanding these motivational profiles, gamification systems such as the DataFEE-App can be personalized by incorporating specific game elements that appeal to each player type. This ensures that every user can engage with aspects of the system that align with what they find most enjoyable and motivating, whether it is social interaction, autonomy, mastery, or purpose. Such a tailored design encourages sustained use of the application, as users remain engaged through elements that resonate with their intrinsic motivations. Indeed, as noted by Kotsopoulos et al. [2018], a gamified application promoting energy-saving behavior in the workplace can become part of users' daily habits if it includes at least progression, levels, and points as motivational elements.

Badges, leaderboards, and points target motivations of all player types.

For Philanthropists, one of the recommended elements is collection. This is integrated into the DataFee-App through a system of badges. Socializers, are motivated by social comparison, which is implemented through leaderboards. Free Spirits, benefit from Easter Eggs, which also appear as part of the badge system. Achievers, are driven by clear progression, so the app includes levels represented through experience points. Players, are generally motivated by

Player Type	Motivated by	Suggested Game Elements
Socializers	• relatedness • social interaction	• guilds or teams • social networks • social comparison • social competition • social discovery
Free Spirits	• autonomy • self-expression	• exploratory tasks • nonlinear gameplay • Easter eggs • unlockable content • creativity tools • customization
Achievers	• mastery • personal development	• challenges • certificates • learning new skills • quests • levels/progression • epic challenges ("boss battles")
Philanthropists	• purpose • meaning	• collection and trading • gifting • knowledge sharing • administrative roles
Disruptors	• change • innovation	• innovation platforms • voting mechanisms • development tools • anonymity • anarchic gameplay
Players	• extrinsic rewards (points, prizes)	• points • rewards/prizes • leaderboards • badges / achievements • virtual economy • lotteries/games of chance

Table 2.1: HEXAD Player Types and corresponding Game Elements

external rewards, meaning all previously mentioned elements are suitable for them as well.
The Disruptor, type is more challenging, since game elements for this group often involve chaos or interference, which does not fit the app's objectives. However, anonymity can serve as a motivating factor. The leaderboards are already planned to be anonymous due to data protection requirements, and this also helps address the Disruptor profile.
In summary, the integration of experience points, badges, and leaderboards ensures that each Hexad user type is addressed by at least one motivational game element.

2.2.2 Gamification Challenges in the Context of Green IS

The use of technology to support sustainable development has been explored in various projects and is commonly referred to as Green Information Systems (Green IS). The DataFee-App can also be classified within this category. However, implementing Green IS solutions can be challenging, and many things can go wrong if they are not carefully designed and managed. To ensure success, it is essential to understand potential pitfalls and address them proactively.

Addressing challenges identified through expert reviews.

Kirchner-Krath et al. [2024] have identified several challenges that may arise in Green IS projects, along with strategies to avoid them. In total, 55 challenges were outlined in this work. Through expert evaluation, 26 of these were recognized as the most significant. This selection process involved eight experts, each choosing their most critical challenges from the list. Any challenge selected by at least three experts was deemed particularly relevant.
Some of these key challenges have already been addressed in the current version of the app. For instance, one major challenge concerns negative attitudes toward smartphone use, which is mitigated by the fact that the DataFee-App is a web-based application. Other challenges, such as the lack of role models or social pressure, extend beyond the scope of this master's thesis. By discarding the previously men-

tioned challenges, the 26 key challenges can be reduced into the following 11 challenges:

- C1: Perception as part of work
- C2: Lack of personal need
- C3: Organizational rules that impede adoption
- C4: Forgotten in everyday work
- C5: Perception as unmotivating
- C6: Effort too high
- C7: Bugs in functionality
- C8: Unfulfillability of tasks
- C9: Conflict with work tasks
- C10: Lack of long-term motivation
- C11: Decrease in novelty

Gamification planned to resolve several key challenges.

Regarding C1, one could argue that the current state of the app already addresses this challenge, since adjusting the room temperature to achieve thermal comfort is usually performed by users either way. However doing this process via the app, makes users provide information about their current thermal comfort and indicate how it should be adjusted before performing any action. Even though this process is brief, it still introduces extra steps that may be perceived as additional work, particularly in a workplace environment. The same reasoning applies to C3, C6, C8, and C9.
Challenges C2, C4, C5, C10, and C11 are planned to be addressed through gamification. The next chapter will focus on these challenges by introducing experience points, badges, and leaderboards.

2.3 Climate Control Optimization Strategy

To implement a gamified system that promotes energy-efficient behavior by ranking various thermal comfort strategies based on their energy consumption, a reliable method for estimating the energy use of each option is required. This section outlines the approach used to calculate the energy consumption of these different strategies.

2.3.1 Predictive Estimation of Energy Usage

Energy demand for thermal comfort is estimated via simulation to compare alternative control strategies.

Assessing the energy demand associated with thermal control requires estimating how much energy is consumed under different operating conditions. In this work, the focus lies on comparing alternative strategies for achieving thermal comfort, including hypothetical variations in HVAC usage and window operation. To enable such comparisons, energy consumption must be estimated in a way that is comparable across different users and rooms.

One way to achieve this is through fully dynamic, physics-based building simulations, for example using Modelica-based libraries such as AixLib[3] in combination with tools like Dymola[4], which allow a detailed representation of building services, control strategies, and thermal mass. When combined with thermal zone models, for instance through co-simulation with EnergyPlus[5] or Spawn of EnergyPlus[6], these approaches can represent interactions between rooms, the building envelope, HVAC systems, and user behavior. Such methods are well suited for detailed system analysis.

However, these holistic simulation approaches also involve significant challenges. The parametrization and calibration of large multi-zone models are complex, especially for real buildings with incomplete or uncertain data. In addition,

3 https://github.com/RWTH-EBC/AixLib

4 https://www.3ds.com/de/products/catia/dymola

5 https://energyplus.net/

6 https://www.energy.gov/eere/buildings/articles/spawn-energyplus-spawn

such simulations can be computationally expensive and sensitive to modeling assumptions. For the intended application, simulation results must be available quickly and reliably, as users are expected to receive ranked options for achieving thermal comfort based on estimated energy consumption in near real time.

As an alternative, a simplified simulation model has been proposed in the literature by Nienaber et al. [2020]. This approach is based on a reduced thermal room model that predicts the temporal evolution of the room air temperature as well as the temperature of the air supplied by the HVAC system. The model focuses on dominant heat flows and user-influenced parameters, while neglecting detailed system dynamics. As a result, it offers increased robustness and low computational effort, at the cost of reduced physical detail.

Building on this modeling approach, energy consumption is not obtained directly from a detailed system model, but is instead derived from simulated room temperatures and HVAC supply air temperatures. This enables an estimation of energy demand that remains closely linked to user actions, such as setpoint changes, HVAC operation, or window opening, while keeping the simulation structure simple. The resulting energy metric is therefore well suited for comparative analyses, where relative differences in energy demand are of primary interest.

In the context of this work, the objective is not to determine the absolute energy balance of a building with maximum accuracy, but rather to enable a fair comparison of energy demand associated with different user behaviors under comparable boundary conditions. For this purpose, energy usage is estimated based on a simplified room air temperature simulation following Nienaber et al. [2020], from which HVAC energy demand is derived.

Energy demand related to thermal control arises mainly during HVAC operation. However, this does not imply that window opening is energy-neutral. While opening a window often leads to temporary HVAC deactivation, subsequent system reactivation may result in higher energy demand than continuous operation. The following subsections describe how energy demand is estimated for HVAC operation and for window-related effects within the chosen simulation framework.

2.3.1.1 Assessing HVAC Energy Consumption via Heat Flow

HVAC energy consumption fundamentals.

An HVAC system typically operates by extracting air from the room and mixing it with outdoor air, creating what is known as mixed air. This mixed air is then directed to the inlet, where it is conditioned, either heated or cooled, depending on the setpoint temperature. Once conditioned, the air is distributed back into the room using a fan, helping to maintain the desired level of thermal comfort. When the HVAC is operating energy will be consumed by controlling the temperature of the inlet and by operating the fan of the inlet. The consumed energy can be calculated as done by Noubissie Tientcheu et al. [2019].

$$E_H = \frac{\dot{m}_{\text{HVAC}} C_p (T_{\text{HVAC}} - T_{\text{Room}}) + E_F}{COP_{\text{heating}}} \tag{2.1}$$

$$E_C = \frac{\dot{m}_{\text{HVAC}} C_p (T_{\text{HVAC}} - T_{\text{Room}}) + E_F}{COP_{\text{cooling}} \cdot SHR} \tag{2.2}$$

Two separate formulas are used to calculate the energy consumption of the HVAC system. One formula applies to heating and the other to cooling. Both rely on the same fundamental principle.

In each case, the numerator represents the total energy demand of the HVAC system. This comprises two components: the energy consumed due to heat exchanged between the HVAC system and the room, and the energy consumed by the fan, denoted by E_F.

The energy consumption due to heat exchanged between the HVAC system and the room is expressed as:

$$\dot{m}_{HVAC} C_p (T_{HVAC} - T_{Room})$$

where:

- $\dot{m}_{HVAC}$ is the mass flow rate of air supplied by the HVAC system,
- C_p is the specific heat capacity of air,

- T_{HVAC} is the temperature of the air delivered by the HVAC system,
- T_{Room} is the indoor room temperature.

The energy consumed by the fan E_F can be calculated as:

$$E_F = \frac{\dot{V}_{\text{HVAC}} \cdot P_{tot}}{\eta}$$

where:

- $\dot{V}_{\text{HVAC}}$ is the volumetric airflow rate,
- P_{tot} is the total pressure generated by the fan,
- η is the efficiency of the fan.

The total energy demand of the HVAC system does not directly correspond to the electrical energy consumed. For both heating and cooling, this relationship is governed by the Coefficient of Performance (COP), which indicates how much electrical energy is required to deliver a given amount of thermal energy.

COP links thermal demand to electrical use.

In cooling mode, the Sensible Heat Ratio (SHR) is also considered. SHR represents the fraction of total cooling capacity used to remove heat, that does not involve moisture removal. In regions with low humidity, such as Aachen, Germany, latent heat loads are minimal. Therefore, it is reasonable to assume $SHR \approx 1$, simplifying the cooling energy calculation.
Furthermore, it is well established in thermodynamics that cooling processes generally result in greater energy losses than heating. This is reflected in the relationship:

$$COP_{\text{heating}} = COP_{\text{cooling}} + 1$$

This implies that, for the same amount of thermal energy transferred, more electrical energy is required for cooling than for heating. In other words, cooling is less energy-efficient than heating.

2.3.2 Indoor Room Temperature Simulation

Accurate energy estimation is essential for dynamic recommendations to achieve thermal comfort.

The heating load of the HVAC system provides a sufficiently accurate basis for estimating energy consumption. This load is directly proportional to the temperature difference between the HVAC supply air T_{HVAC} and the indoor room temperature T_{Room}. Accurately determining this temperature difference at all times requires a simulation model capable of dynamically estimating both values. Although this adds complexity to the system, it is a necessary step. Precise energy comparisons between different thermal comfort strategies are essential for achieving the objectives of this thesis.
Without accurate energy estimates, the gamification aspect of the application could only promote general energy awareness rather than guiding users to consistently select the most energy-efficient option for achieving thermal comfort in real time.
Despite the added complexity, the solution remains applicable across different office buildings, since the simulation can be implemented on a standard computer using any general-purpose programming language. The following section introduces the core concepts behind the simulation model used in the DataFEE-App.

Thermal simulation model predicts indoor temperature using heat-flow dynamics.

Nienaber et al. [2020] have developed a simulation model capable of predicting both indoor temperature and T_{HVAC} within a room. The model is based on solving a system of differential equations and is inspired by the principle of capacitor charging from electrical engineering. In this analogy, the room is modeled as a thermal capacitor capable of storing heat energy. Accordingly, the room is assigned a thermal capacity c_{Room} (in J/°C), representing the amount of energy required to change the room's temperature by one degree Celsius.
The rate of change in indoor temperature over time $\frac{dT_{\text{Room}}}{dt}$ multiplied by this thermal capacity, yields the net heat flow into the room. This net heat flow can also be expressed as the sum of all heat gains and losses in the system, thereby providing the necessary inputs to solve the differential equation descriging the indoor room temperature.
In this paper, the model accounts for heat gains from

the HVAC system, concrete core activation, neighboring rooms, outdoor temperature through the building envelope, and solar radiation.

$$
\begin{aligned}
c_{\text{Room}} \cdot \tfrac{dT_{\text{Room}}}{dt} = C_p \cdot \dot{m}_{\text{HVAC}} \cdot (T_{\text{HVAC}} - T_{\text{Room}}) \\
+1/R_{\text{CCA}}(T_{\text{CCA}} - T_{\text{Room}}) \\
+1/R_{\text{InnerWall}} \cdot (T_{\text{InnerWall}} - T_{\text{Room}}) \\
+1/R_{\text{OuterWall}} \cdot (T_{\text{Out}} - T_{\text{Room}}) \\
+I_{\text{Solar}} \cdot A_{\text{Window}} \cdot f_{\text{win}} + \dot{Q}_{\text{Gains}}
\end{aligned}
\tag{2.3}
$$

The principle used to calculate heat flow remains consistent across all sources. Heat flow is proportional to the temperature difference between the heat source and the sink. As established in basic thermodynamics, heat naturally flows from the hotter to the colder region. This means that the room can act either as a heat source or a heat sink, depending on the current temperature dynamics. By convention, positive values of heat flow indicate that heat is entering the room, while negative values indicate that heat is leaving the room.

By convention heat entering the room is positive and heat exiting is negative.

The heat flow from the HVAC system is calculated as described in subsection 2.3.1.1.
The heat flow originating from external sources, such as the outdoor environment, surrounding walls, and adjacent rooms, is calculated using the same fundamental principle. Whether the room acts as a heat source or sink is determined by the temperature gradient. The resulting heat flow is then scaled by a constant R, which represents the thermal resistance between the source and the sink, respectively. This resistance governs how much heat is transferred per time step and is expressed in units of °C·s/J. It can be interpreted as a linear factor that quantifies the ease or difficulty with which heat flows between two regions.

Heat flow from HVAC and surroundings modeled via temperature differences and resistance.

Solar heat gains are calculated differently from other forms of heat exchange, as they do not depend on a temperature gradient. Since solar radiation can only add energy to the system, it consistently acts as a heat source, and the direction of heat flow is always into the room. The heat flow from solar gains is determined by multiplying the solar ra-

Solar radiation adds heat independently of temperature differences.

diation intensity, I_{Solar} (measured in $\text{J/m}^2\cdot\text{s}$), by the effective area through which solar energy enters the room. This effective area is calculated as the product of the total open window area A_{Window} and the fraction of the window that is unobstructed and exposed to sunlight f_{win}.

Inner wall uses differential equation to model heat storage and transfer.

To model the temperature dynamics of the inner wall, Nienaber et al. [2020] employed an additional differential equation. This equation is based on the same fundamental principle as the one used for the indoor room temperature. The inner wall is assigned a thermal capacity $c_{\text{InnerWall}}$, which defines how much thermal energy it can store per degree Celsius. By multiplying this capacity with the time derivative of the wall temperature $\frac{dT_{\text{InnerWall}}}{dt}$, one can quantify the heat stored or released by the wall over time.
The inner wall exchanges heat with two potential sources or sinks: the room being simulated and its adjacent neighboring rooms. The direction and magnitude of heat flow are determined by the temperature differences between the inner wall and each of these spaces. This difference is divided by the thermal resistance of the wall $R_{\text{InnerWall}}$, multiplied by a factor of two.

$$\begin{aligned} c_{\text{InnerWall}} \cdot \frac{dT_{\text{InnerWall}}}{dt} = 1/R_{\text{InnerWall}} \cdot \tfrac{1}{2} \cdot (T_{\text{InnerWall}} - T_{\text{Room}}) \\ +1/R_{\text{InnerWall}} \cdot \tfrac{1}{2} \cdot (T_{\text{InnerWall}} - T_{\text{NeighbouringRoom}}) \end{aligned} \tag{2.4}$$

Modeling HVAC supply air temperature using an additional differential equation

The supply air temperature T_{HVAC} must also be simulated. Accurate prediction of T_{HVAC} is essential not only for modeling indoor room temperature but also for estimating the energy consumed by the HVAC system. To achieve this, Nienaber et al. [2020] incorporated an additional differential equation specifically designed to simulate the evolution of T_{HVAC}.

$$\frac{dT_{\text{HVAC}}}{dt} = \frac{T_{\text{Set,HVAC}} - T_{\text{HVAC}}}{\tau_{\text{HVAC}}} \tag{2.5}$$

This equation models T_{HVAC} as approaching the setpoint temperature of the air supplied by the HVAC system to the room $T_{\text{Set,HVAC}}$. The approach is assumed to be linear, with

the rate of change in T_{HVAC} per simulation time step governed by the time constant τ_{HVAC}.
$T_{\text{Set,HVAC}}$ is determined by an internal HVAC controller, which is modeled as a proportional controller. The controller gain is denoted by K_p. The purpose of this control strategy is to adjust $T_{\text{Set,HVAC}}$ such that the desired room temperature $T_{\text{Room,Set}}$ is achieved. It should be noted that the HVAC system operates within defined temperature limits. It cannot cool below $16°C$ or heat above $33°C$.

$$T_{\text{Set,HVAC}} = 16°C + \frac{\tanh(K_p \cdot (T_{\text{Set,Room}} - T_{\text{Room}})) + 1}{2} \cdot (33°C - 16°C) \tag{2.6}$$

Chapter 3

Methodology and Approach

In this chapter, the process of integrating the elements discussed in the previous chapter is examined in detail. Since the focus of this work lies both in the concept of gamification and the room temperature simulation, each topic will be addressed separately in the following sections. Furthermore, an overview is given of the original structure of the DataFEE-App and the adjustments made to implement the methods discussed in this chapter.

3.1 Integration of Gamification Elements

In the previous chapter, the Hexad user types were introduced, along with the selection of suitable gamification elements intended to address the motivations of each user type. The chosen elements were experience points, badges, and leaderboards. In this section, the implementation of these elements in the DataFee-App is described in detail, while also considering the challenges outlined in subsection 2.2.2.

3.1.1 Experience Points (XP)

The introduction of "Experience Points" is intended primarily to motivate users to save energy and to continue using the DataFEE-App over the long term. However, this must be achieved without requiring users to sacrifice their thermal comfort. To ensure this, the point-earning algorithm must take these factors into account and always prioritize user comfort above all else.

3.1.1.1 Algorithm for Determining Experience Points

Gaining experience points does not come in cost of thermal comfort.

The algorithm, illustrated in Fig 3.1, begins with the user's input. The user specifies a desired thermal comfort range by indicating whether they would prefer the room to become warmer, cooler, or remain at the current temperature in the near future. Based on this input, the application calculates a target temperature range that should be reached within a maximum of 30 minutes.
To achieve thermal comfort, several actions are available, such as opening the windows, tilting the windows, or adjusting the HVAC settings. The simulation model, which is explained in more detail in the next section, evaluates all possible options by determining whether they can reach the target comfort range within 30 minutes and whether the resulting comfort level can be maintained for at least 30 minutes. This second condition is especially relevant for window-based strategies, since an optimal solution might involve opening and closing windows in intervals of only one to five minutes.

Simulation ranks comfort actions by their energy efficiency and assigns points accordingly.

The simulation estimates the energy consumption of each option until lunchtime (12:00) when used in the morning or until the end of the workday (17:30) when used in the afternoon. From all feasible options, the three most energy-efficient ones are selected, provided that at least three exist. The most energy-efficient option is awarded three points, the second most efficient receives two points, and the third receives one point. If only two options are available, the more efficient one yields three points and the less efficient one yields one point. If only one option leads to thermal comfort, typically an HVAC adjustment, this option also grants three points. The idea behind this system is that thermal comfort remains the highest priority, and therefore earning three points must always be possible.

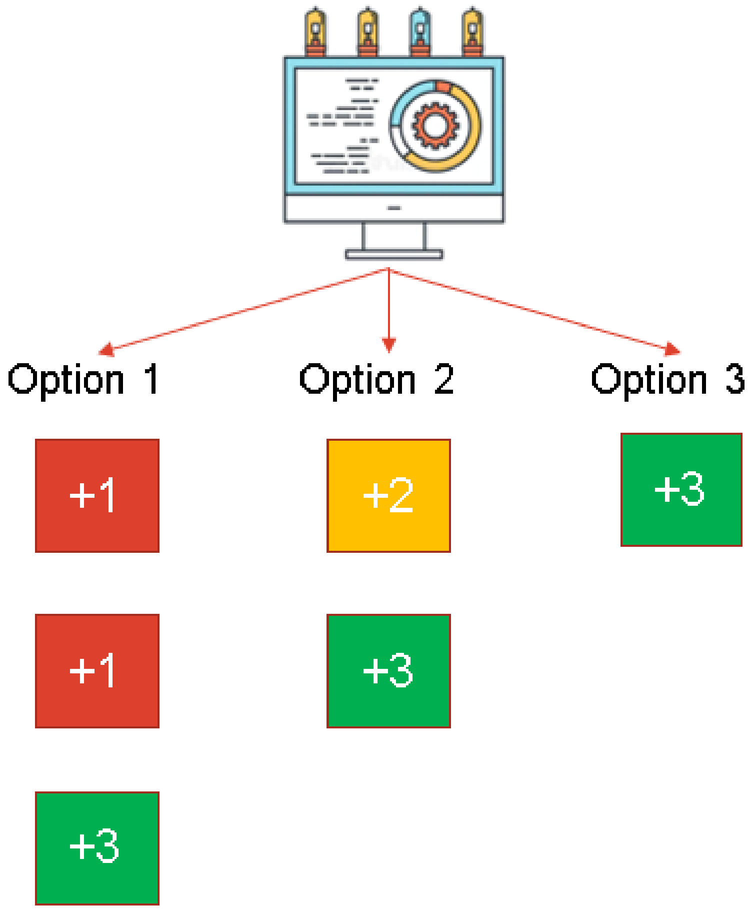


Figure 3.1: Point Earning Algorithm Overview

3.1.1.2 Additional Point-Earning Mechanisms

Minimizing required input at the cost of points.

Obtaining points is strongly tied to the simulation process. As discussed in the previous chapter, providing the necessary information to achieve thermal comfort can be time-consuming. Even if the process takes only around 30 seconds, it may still create additional stress in a work environment. This relates directly to several challenges: C1 (Perception of work), C6 (Effort too high), C8 (Unfulfillability

of tasks), and C9 (Conflict with work tasks).
The input regarding the desired comfort level cannot be avoided, since it is essential for identifying viable options to achieve thermal comfort. However, there are several additional inputs that provide useful information to the simulation but are not strictly required. These include information about the user's clothing, the physical intensity of the current activity, the user's posture, and the number of people present in the room.
The simulation can function without these inputs, although its accuracy decreases. This creates an opportunity to reward more motivated users with so called "Info Points". Providing this optional information contributes an additional two points to the daily score. Users who are less motivated or who perceive the additional input effort as too high can still use the app without limitations, but they receive fewer points.

3.1.2 Badges

Badges enhance motivation and address key challenges.

The following challenges (C2: Lack of internal need, C4: Forgotten in everyday work, C5: Perception as unmotivating, and C10: Lack of long-term motivation) are addressed through the implementation of badges. According to Park and Kim [2019], badges are an effective tool for providing feedback on user progress and for sustaining motivation over time.
In addition, the use of badges supports different player types. Philanthropists can engage with collection elements, free spirits benefit from hidden "Easter-Egg" badges and players who are intrinsically motivated receive continuous acknowledgment of their efforts.

These various badge types will be discussed in the following subsections.

3.1.2.1 Info Badges

Info Badges reward optional inputs with playful achievements.

The process of earning "Info Points" has already been de-

scribed. These points are obtained by providing information that supports the simulation. It is evident that earning such points is relatively easy and largely optional. The purpose of this badge type is to encourage new players to collect easily attainable points and to reward player types who respond well to frequent, low-effort rewards. Accumulating more of these points increases the number of badges within the category of "Info Badges".
According to Marczewski [2023], badge design is more effective when badges are given playful names. For this reason, the badges in this category will follow a playful naming style. The table below lists the available "Info Badges" and the information point thresholds required to obtain them.

Name	**Info Points**
First Input	2
Data Whisperer	20
Spreadsheet Intern	200
Data Scientist	600
Spreadsheet Board Member	1000
Chief Entry Officer	1400
Lord of Input	2000

Table 3.2: Info Badge Table

In the DataFEE-App, the "Info Badges" are displayed visually within the user's profile section. They can be accessed through the profile tab, where users find an overview of all badges they have earned as well as those still available to unlock. Each badge is represented with its name and a visual icon, allowing users to easily track their progress and identify which "Info Badges" they have already achieved. This central placement within the profile helps ensure that the badges remain visible, reinforcing user motivation and offering a clear sense of advancement throughout the simulation.

Profile tab shows earned Info Badges for user motivation.

All "Info Badges" in the DataFEE-App, are presented in Figures 3.3-3.9. These badge icons were designed using artificial intelligence. Any icon or playful image presented from here on forward has been created using artificial intelligence [1], since designing badges and playful images go beyond the scope of this thesis.

Figure 3.3: Info Badge: First Input

Figure 3.4: Info Badge: Data Whisperer

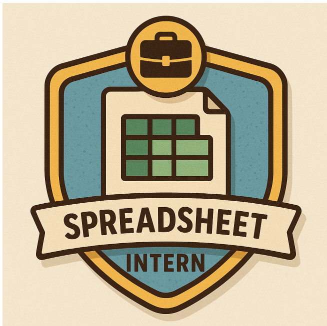


Figure 3.5: Info Badge: Spreadsheet Intern

Figure 3.6: Info Badge: Data Scientist

Figure 3.7: Info Badge: Spreadsheet Board Member

Figure 3.8: Info Badge: Chief Entry Officer

[1] `https://chatgpt.com/`

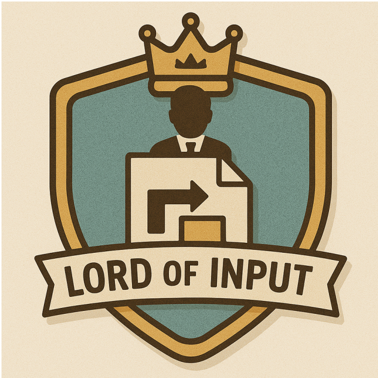


Figure 3.9: Info Badge: Lord of Input

3.1.2.2 Optimal Badges

"Optimal Badges" are not as easily obtained as "Info Badges". Although both badge types are awarded when users reach a specific threshold of points, they differ in the type of points they rely on. "Info Badges" are earned through the collection of "Info Points", while "Optimal Badges" are based on "Optimal Points". These "Optimal Points" were not introduced in the earlier points section because they operate in the background. They track how often a user chooses the most energy-efficient method to achieve thermal comfort. The more frequently users make such optimal decisions, the more "Optimal Points" they accumulate, and the more "Optimal Badges" they can earn.

Optimal Badges reward consistent energy-efficient decisions, enhancing intrinsic motivation.

This badge type carries significant meaning and was designed with the philanthropist player type in mind. In addition, it directly addresses challenge C2: Lack of internal need, as it rewards intrinsically valuable, environmentally responsible behavior. Table 3.10 lists all "Optimal Badge" names along with the required number of "Optimal Points" for each.

In the DataFEE-App, "Optimal Badges" are shown in the profile tab, where they form their own category within the overall badge overview. Unlike the more straightforward "Info Badges", these badges highlight how often users have selected energy-efficient actions during the simulation. Their placement in the profile allows users to quickly

Optimal Badges highlight users' efficient decisions and visualize progress in the profile tab.

Name	Optimal Points
You chose wisely	1
Watts up Doc?	10
Energy-Efficience Apprentice	100
Climatization Mage	300
Spellcaster of Energy	500
Thermostat Wizzard	700
The Oracle	1000

Table 3.10: Optimal Badge Table

recognize the progress of their optimal decisions without needing to monitor these actions directly. Each badge is presented with its icon, giving users a clear sense of how their behavior contributes to earning higher-level badges over time.
From Figures 3.11 to 3.17, all Optimal Badges are shown.

Figure 3.11: Optimal Badge: You chose wisely

Figure 3.12: Optimal Badge: Watts Up Doc?

Figure 3.13: Optimal Badge: Energy-Efficience Apprentice

Figure 3.14: Optimal Badge: Climatization Mage

Figure 3.15: Optimal Badge: Spellcaster of Energy

Figure 3.16: Optimal Badge: Thermostat Wizard

Figure 3.17: Optimal Badge: The Orcacle

3.1.2.3 Easter Eggs

Playful "Easter-Egg" badges sustain curiosity and motivate "Free Spirit" user type.

In addition to "Info Badges" and "Optimal Badges", the DataFEE-App includes a set of badges that function as "Easter Eggs". Unlike the other badge types, these badges are not designed to provide feedback on performance. Their primary purpose is to engage the “Free Spirit” player type and encourage long-term use of the app. They also help address Challenge C11: Decrease in novelty, since the possibility of discovering something unexpected creates a sense of ongoing curiosity and surprise.
To enhance engagement, these badges rely heavily on playfulness. For instance, the first "Optimal Badge", titled “You chose wisely”, is awarded for selecting the most energy-efficient method to achieve thermal comfort. In contrast, if the user chooses the least efficient option, they receive a humorous "Easter Egg" called “You chose poorly”, which playfully mirrors the previous badge. This easter egg is only awarded once, as the app aims to promote energy-efficient behaviour rather than reward repeated inefficient choices. Another example is an easter egg that appears when the user enters the well-known Konami Code on the DataFEE-App dashboard, giving curious users a reason to explore the interface more deeply.
Table 3.18 lists all available "Easter Eggs" and the conditions required to obtain them. As with the other badge categories, these badges have been given playful names and can be viewed in the profile tab along with the rest of the user’s badges.
Figures 3.19-3.25 show all "Easter Eggs" that can be unlocked.

Name	Requirement
You chose poorly	Pick the least energy-efficient method once.
True Gamer	Enter the Konami Code in the dashboard.
Curious User	Read the "About DataFEE-App" information.
Over Achiever	Find alternatives that preserve the current thermal comfort.
Kelvin Clein	Select "Shirt" as the current clothing item.
Uprigth Proffesional	Select "Standing" as your current posture.
Easter Egg Hunter	Unlock all easter eggs

Table 3.18: Easter Egg Unlock Requirements

Figure 3.19: Easter Egg: You chose Poorly

Figure 3.20: Easter Egg: True Gamer

Figure 3.21: Easter Egg: Curious User

Figure 3.22: Easter Egg: Over Achiever

Figure 3.23: Easter Egg: Kelvin Clein

Figure 3.24: Easter Egg: Upright Proffessional

Figure 3.25: Easter Egg: Easter Egg Hunter

3.1.3 Leaderboards: Design and Implementation

Multiple leaderboards encourage a wider range of active participants.

The implementation of leaderboards in the DataFEE-App introduces a competitive form of motivation designed especially for the socializer, achiever, and disruptor player types. As with the other game elements, this feature also appeals to the player type, who respond well to extrinsic motivation. In addition, leaderboards help address Challenge C4: Forgotten in everyday work by providing continuous competition, and Challenge C10: Lack of long-term motivation by encouraging ongoing engagement.
According to Park and Kim [2022], the accumulation of points can be difficult to implement fairly. Newer players may lose motivation if they compare themselves to users

who have been active for much longer. However, it is still important to acknowledge long-term commitment by reflecting a user's total accumulated points. To resolve this dilemma, several types of leaderboards were implemented, as suggested by Park and Kim [2021].

To reward overall progress without discouraging new users, the DataFEE-App includes a ranking system. A user's rank and total accumulated points are displayed only within their own profile tab. This ensures that long-term users still receive recognition for sustained engagement while preventing newer users from feeling discouraged, since these values are not publicly visible. The ranking system functions similarly to badges. As users gain more total points, their rank increases. The table below lists all ranks and the required point thresholds.

Private ranking rewards long-term progress without discouraging new users.

Furthermore, each rank is associated with a corresponding icon, shown in Figures 3.27 through 3.33. The icons follow a narrative pattern. An ice bear gradually gains more glacier area as energy savings increase, eventually allowing him to invite friends. He begins on a small glacier and ultimately reaches a glacier utopia surrounded by many companions. This storytelling approach follows the technique introduced by Marczewski [2023], which uses narrative elements in gamified applications to enhance user engagement.

Rank	Required Total Points
1	1
2	10
3	30
4	50
5	100
6	300
7	1000

Table 3.26: Ranking System

Figure 3.27: Rank 1: Polar Bear on a small glacier

Figure 3.28: Rank 2: Polar Bear on a bigger glacier

Figure 3.29: Rank 3: Polar Bear invites Penguin

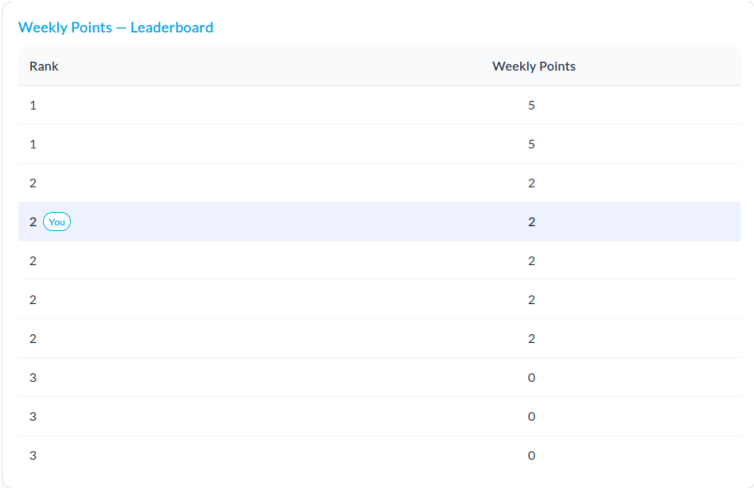
Figure 3.30: Rank 4: Seels join the friend group

Figure 3.31: Rank 5: Friend group built igloos

Figure 3.32: Rank 6: Polar Bear built a society

Figure 3.33: Rank 7: Polar Bear and friends build a glacier utopia

One of the leaderboard types included in the app is the "Weekly Leaderboard". This format gives new players an equal chance to compete because the points are reset every week. To avoid discouraging players who may appear lower in the ranking, the leaderboard is shown in a relative format. Each user sees only ten positions, with their own position centered in the display. Only ranks and points are shown, as anonymity is crucial. This prevents users from feeling pressured or fearing different treatment from colleagues based on their energy-saving performance.



Weekly Points — Leaderboard

Rank	Weekly Points
1	5
1	5
2	2
2 You	2
2	2
2	2
2	2
3	0
3	0
3	0

Figure 3.34: Weekly Leaderboard

"Info Points Leaderboard" motivates low-effort, continuous participation.

Additional leaderboard types were included to allow players to focus on the format they find most motivating. This broadens the appeal of the system and helps address the needs of different player types.
For players who prefer easy to earn points, an "Info Points Leaderboard" was implemented. Since "Info Points" are obtained through simple contributions to the simulation, this leaderboard gives users an accessible and low-effort way to stay competitive. At the same time, it also supports long-term engagement by motivating users to regularly provide additional information, which in turn helps the app determine more precise energy-efficient recommendations for achieving thermal comfort.

Ranking users by "Optimal Points" encourages long-term energy-efficient behavior.

Another leaderboard is based on the "Optimal Points" described in earlier sections. The app continuously tracks how often users choose the most energy-efficient recommendation. An anonymous leaderboard ranks users according to their accumulated "Optimal Points", reflecting their long-term commitment to energy-efficient behaviour. This leaderboard is intended to support motivate long-term energy-efficient behaviour.

3.1.4 Method for Evaluating User Experience in the DataFEE-App with Integrated Gamification

To validate the proposed gamification methods, a user test is required. The goal is to assess how well the gamification elements are received, whether they enhance user motivation, and whether they contribute positively to the overall user experience. These insights are essential for supporting long-term usability and keeping users engaged with the app.

At the moment, the app requires further development to integrate sensor data, which is necessary for the simulation to obtain the initial values needed to solve the differential equations. Furthermore, the app was originally intended to allow users to adjust the room's thermostat within the building, but this functionality has not yet been implemented. A user test is still intended as part of this master's thesis. However, because a conventional user test is not feasible due to the lack of sensor integration, alternative evaluation methods must be considered.

DataFEE-App simulates sensor inputs to mimic full functionality and permit early Wizard-of-Oz evaluations.

In the work of Nielsen [1993], the "Wizard of Oz" method was introduced as an effective alternative to conventional user testing. This approach is particularly useful when key system functionalities are not yet implemented, allowing early prototypes to be evaluated by simulating system behavior through a human operator. In this method, users are led to believe that the system is operating autonomously, as it would in its fully implemented form. In reality, a human, referred to as the "wizard", performs the actions that the system is expected to carry out, thereby simulating functionalities that have not yet been implemented.

Other early systems design practices such as field studies, thinking-aloud protocols, and rapid prototyping were also mentioned by Nielsen [1993]. However, Bernsen et al. [1993] argues that the advantage of the "Wizard of Oz" method over these approaches is that, if the user test is successful, it provides a clear indication of whether the system can be implemented in a manner that closely matches the created illusion.

In the case of the DataFEE-App it is not feasible for a person to manually input the data required from the sensors.

To apply the "Wizard of Oz" method, a small adjustment is made. Instead of having a human "wizard" configure the sensor data, this information is generated by the simulation developed in this thesis. The app assumes that the room temperature throughout the day follows the values generated by the simulation.
The simulation operates by solving differential equations, which requires assumptions about the initial room temperature at the start of app usage. For the user test, the initial room temperature is set to 20 $°C$. This value is based on recommended conditions for office environments in Germany, where indoor temperatures should range between 20 $°C$ and 22 $°C$ [2]. Since the user tests were conducted from December 3rd to December 5th in 2025, during winter, it is reasonable to assume that the starting room temperature is 20 $°C$. Additionally, the thermostat setpoint is assumed to be 20 $°C$, and the HVAC system is modeled with an initial fan speed of 50%.
As long as no errors occur during operation and the initial temperature assumption is accurate, this creates a convincing illusion that the app is functioning with real room-temperature sensor data.

Seven-point Likert questionnaire assessing whether Green IS gamification challenges were effectively addressed.

Bernsen et al. [1993] recommend analyzing the results of a Wizard of Oz test using a questionnaire that participants complete after finishing the test.
When designing a questionnaire, several different scaling methods can be used. Examples include graphic rating scales, itemized rating scales, comparative rating scales, semantic differentials, and Likert scales. Among these, the Likert scale is the most commonly used in research according to Baumeister et al. [2007]. A Likert scale measures respondents' attitudes or perceptions by asking them to indicate their level of agreement with a set of statements. There are multiple versions of the Likert scale, distinguished by the number of response options they provide. Taherdoost [2019] analyzed how the number of agreement options influences the reliability and validity of questionnaire results, as well as which formats users prefer. The study concluded that a seven-point rating scale is recommended when the goal is to avoid pushing respondents to-

[2] https://www.vbg.de/cms/arbeitsschutz/arbeit-gestalten/buero/raumklima-buero

ward either a positive or a negative side.
Hence for the questionnaire used in this user test, a seven-point Likert scale will be adopted. To allow for meaningful analysis of the collected data, and to evaluate how well the app was received as well as how the gamification elements were perceived, targeted questions will be included. These questions address the challenges associated with using gamification in the context of Green IS, as discussed in subsection 2.2.2. The questionnaire is presented in table 3.3 with an overview of the specific challenges each question is intended to examine. Formulating questionnaire items either positively or negatively can lead to acquiescence bias, which may result in unreliable data. To reduce this bias, Taherdoost [2008] proposed wording half of the items positively and the other half negatively. Accordingly, out of the 23 items, 12 were phrased positively and 11 were phrased negatively.
To improve the readability of the questionnaire and to reduce respondent fatigue, the items were formulated in accordance with the guidelines provided by the ZUMA Institute in Mannheim[3].
At the E.ON ERC, the primary working language is German. However, given the size of the institute and the number of international employees, it is reasonable to assume that many workers may not be native German speakers. To avoid potential language barriers, the questionnaire was provided in English. Creating separate questionnaires in different languages could introduce bias and lead to inconsistent or unreliable results, as noted by Toribio et al. [1999]. Therefore, all items were formulated in English.
In addition the questionnaire asked for the room orientation of each participant in order to determine whether certain room orientations may not have been represented accurately in the simulation. Participants were additionally asked whether they had used the DataFEE-App in a previous user test, which makes it possible to identify potential onboarding issues when interpreting the results. As noted earlier, the test took place from 03.12.2025 to 05.12.2025, and each user selected the date that suited them best. This information was included in the questionnaire to identify possi-

[3] `https://www.gesis.org/fileadmin/admin/Dateikatalog/pdf/howto/howto_question_wording_formulierung_fragebogen_fragen.pdf`

ble biases related to specific test dates. These questions are listed in Table 3.2.
Finally, two questions were added to capture the participants' overall impression of the system, as recommended by Bernsen et al. [1993] and presented in Table 3.4.

Index	Question
U1	What was the orientation of your room (NW, SW, NE, or SE) during the user test?
U2	Have you used the DataFEE app in a previous user test?
U3	On which date did you participate in the user test?

Table 3.2: User Test Questionnaire: Participant-Related Questions

Index	Item
C1: Perception as Part of Work	
Q1-1	The app integrates naturally into my work routine.
Q1-2	Using the app feels like work rather than a helpful utility.
C2: Lack of Personal Need	
Q2-1	The app helps me stay thermally comfortable during my workday.
Q2-2	The app makes it harder for me to manage my thermal comfort.
C3: Organizational rules that impede adoption	
Q3-1	I am able to use the app when I need it during working hours.
C4: Forgotten in Everyday Work	
Q4-1	The badge system helped me stay aware of the app during the day.
Q4-2	The leaderboards did little to keep me aware of the app during the day.
C5: Perception as Unmotivating	
Q5-1	The gamification elements increase my motivation to use the app.

Index	Item
Q5-2	The app gives me little sense of contributing to energy savings.
C6: Effort Too High	
Q6-1	Using the app to manage my thermal comfort feels stressful.
Q6-2	Making the dashboard input fields optional reduces the effort of using the app.
Q6-3	The number of different badge types in the app feels overwhelming to me.
Q6-4	I find it difficult to keep track of the different leaderboards in the app.
C7: Bugs in functionality	
Q7-1	The app worked reliably during the test.
C8: Unfulfillability of tasks	
Q8-1	I am able to use the app's recommendations to achieve thermal comfort.
Q8-2	It feels unrealistic for me to earn the maximum number of points per day (5 points).
C9: Conflict with Work Tasks	
Q9-1	Using the app to adjust thermal comfort interferes with my daily work.
Q9-2	Navigating the app distracts me from my work.
C10: Lack of long-term motivation	
Q10-1	I expect to use the app regularly over the next year.
Q10-2	The leaderboards encourage me to keep using the app over the next year.
C11: Decrease in novelty	
Q11-1	I believe the app will offer too little variety over the next year.
Q11-2	The Easter eggs make the app feel less repetitive.

Table 3.3: User Test Questionnaire: Seven-Item Likert Scale

Index	Question
O1	What did you like most about the app?
O2	What made the app difficult or annoying to use?

Table 3.4: User Test Questionnaire: Overall Impression of Participants

3.2 Implementation of the Indoor Simulation

Extending Nienaber's model with HVAC parameterization and additional heat-flow factors.

Simulation of the room temperature and the supply air temperature from the HVAC system was conducted using the same principles described by Nienaber et al. [2020] in the previous chapter. However, for the DataFEE-App, this system is not yet complete. The parametrization of the HVAC system is not specified, and heat flows introduced by opening windows are not considered. In addition, solar heat gains are modeled without accounting for the orientation of the office space. Although heat gains from occupants and electronic devices are mentioned in the original paper, no explicit method for their calculation is provided. Unless otherwise stated, meteorological input data used in the extended model are obtained via the Open-Meteo API[4].
In this section, the work of Nienaber et al. [2020] is extended to address these limitations.

3.2.1 HVAC System Parameters and Boundary Conditions

Parametrization of HVAC inlet temperature, Thermally Activated Building Systems, and heating and cooling limits.

In order to parametrize the HVAC component of the simulation model, the development of T_{HVAC} must first be approximated for periods when the HVAC system is turned off. It is known that, under these conditions, the inlet temperature approximates a mixed temperature between the return air and the outdoor air. According to Sugarman [2020], the mixed air temperature consists of approximately 20% outdoor air and 80% return air. Assuming that

[4] https://open-meteo.com/

the return air temperature is equal to the indoor air temperature, the mixed air temperature can be estimated as follows:

$$T_{\text{Mixed}} = 0.2 \cdot T_{\text{Out}} + 0.8 \cdot T_{\text{Room}} \tag{3.1}$$

When the HVAC system is switched off, the temperature of the air that would be available to supply the room, denoted as T_{HVAC}, is no longer actively controlled but becomes closely influenced by the temperature of the mixed air T_{Mixed}. This is because, in the absence of active conditioning, the air present in the ducts or mixing chamber tends to approximate the mixed air temperature. To capture how T_{HVAC} evolves toward T_{Mixed} over time, Formula 2.6 is modified such that T_{HVAC} is driven toward T_{Mixed} using the same time constant as the underlying simulation model. The modified formula is shown below.

$$T_{\text{Set,HVAC}} = 16^\circ C + \frac{\tanh(K_p \cdot (T_{\text{Mixed}} - T_{\text{Room}})) + 1}{2} \cdot (33^\circ C - 16^\circ C) \tag{3.2}$$

For the Thermally Activated Building Systems (T_{CCA}), the following estimation was used for the simulation:

$$T_{\text{CCA}} = -0.35 \cdot T_{\text{Out}} + 28^\circ C \tag{3.3}$$

In addition, HVAC systems have limited cooling and heating capacity. For the rooms in the E.ON ERC main building, this constraint was modeled based on the fan-speed setting. At 50% fan speed, the heating/cooling power was limited to

$$-150W < C_P \cdot \dot{m}_{\text{HVAC}} \cdot (T_{\text{HVAC}} - T_{\text{Room}}) < 1,000W.$$

At 100% fan speed, the corresponding limit was

$$-300W < C_P \cdot \dot{m}_{\text{HVAC}} \cdot (T_{\text{HVAC}} - T_{\text{Room}}) < 1,500W.$$

For simplicity, intermediate fan-speed values were not considered. Only the discrete settings of 0%, 50%, and 100% were used.

3.2.2 Modeling Heat Gains from Ventilation and Window Interaction

Modeling ventilation heat gain through open windows.

To model ventilation-related heat gains, it is necessary to account for the heat entering the room when the windows are open. The calculation is based on the method outlined by Rietchel and Fitzner [2008], with $\dot{V}$air representing the volumetric airflow rate through the open window and ρ_{air} indicating the density of the passing air. Additionally, the specific heat capacity of air, C_p, is assumed to be constant at 1005 $J/(kg \cdot ^\circ C)$, which allows for the calculation of sensible heat transfer based on temperature differences in degrees Celsius.

$$\frac{dQ_{\text{Ventilation}}}{dt} = \dot{V}_{\text{air}} \cdot \rho_{\text{air}} \cdot C_p(T_{\text{Out}} - T_{\text{Room}}) \tag{3.4}$$

Airflow direction and density determined by temperature differences.

The direction of airflow through the window is driven by basic thermodynamic principles, namely that warmer air flows toward cooler air. Accordingly, the air density used in the calculation depends on whether the inside or outside is warmer. If the outdoor temperature T_{Out} is lower than the room temperature T_{Room}, the indoor air density is used. Otherwise, the outdoor air density is considered.

The air density ρ_{air} is calculated using the ideal gas law:

$$\rho_{\text{air}} = \frac{p_{\text{atm}}}{R_{\text{sp,air}} \cdot T} \tag{3.5}$$

where:

- p_{atm} is the atmospheric pressure,
- $R_{\text{sp,air}}$ is the specific gas constant for air, assumed to be 287.058 $J/(kgK)$,
- T is the absolute temperature in Kelvin, derived from the chosen air temperature (either T_{Out} or T_{Room}) by converting from Celsius.

Note: In this work, temperatures are generally handled in degrees Celsius for consistency and simplicity. However, for the calculation of air density using the ideal gas law, the temperature must be converted to absolute temperature in Kelvin, as required by the physical principles underlying the equation.

The volumetric airflow rate through an open window is calculated using the method described in DIN [2017], which accounts for several influencing factors. This approach quantifies the airflow entering $q_{\text{V;arg;in}}$ and exiting $q_{\text{V;arg;out}}$ the room by considering both the temperature and density differences between indoor and outdoor air.

Window airflow modeled to compute ventilation-related heat transfer.

$$\dot{V}_{\text{in}} = \frac{\rho_{\text{a;ref}}}{\rho_{a;Out}} \cdot \frac{A\text{w;open;tot}}{2} \cdot \max(C_{\text{wnd}} \cdot u^2; C_{\text{st}} \cdot h_{\text{w,st}} abs(T_{\text{Out}} - T_{\text{Room}}))^{0.5} \tag{3.6}$$

$$\dot{V}_{\text{out}} = \frac{\rho_{\text{a;ref}}}{\rho_{a;Room}} \cdot \frac{A\text{w;open;tot}}{2} \cdot \max(C_{\text{wnd}} \cdot u^2; C_{\text{st}} \cdot h_{\text{w,st}} abs(T_{\text{Out}} - T_{\text{Room}}))^{0.5} \tag{3.7}$$

As shown in both formula, the reference air density at sea level, at 293 K, and under dry conditions $\rho_{\text{a,ref}}$ is divided by the indoor or outdoor air density. Additionally, the wind speed u is taken into account.
Further adjustments were made to the wind speed to obtain more precise results by considering only the portion of the wind that actually enters the room. This can be achieved using basic trigonometry. If α is the angle between the wind direction and the normal perpendicular inward pointing into the room of the window surface, the effective wind

Wind influence reduced to inward-facing component using trigonometry.

component entering the room u_{eff} can be calculated as follows, where u represents the full wind speed and o_{Room} denotes the room orientation in degrees:

$$u_{\text{eff}} = \begin{cases} u \cdot \cos(\alpha), & \text{if } -90^\circ < \alpha < 90^\circ \\ 0, & \text{else} \end{cases} \tag{3.8}$$

$$\alpha = |u_{\text{dir}} - ((o_{\text{Room}} + 180^\circ) \bmod 360^\circ)| \tag{3.9}$$

Ventilation parameters include opening area, wind coefficient, and buoyancy height.

In window ventilation calculations, the total window opening area Aw;open;tot is obtained by summing the free opening areas of all individual windows in the room. The wind coefficient C_{wnd}, accounting for wind-driven ventilation, can be assumed to be 0.001 (s/m), while the thermal buoyancy coefficient C_{st} is typically taken as 0.0035 $(m/s)/(m \cdot^\circ C)$. Both coefficients are defined by the same norm from which the underlying formula is derived.
The parameter $h_{\text{w,st}}$ denotes effective height for thermal lift for window ventilation. In order to calculate this, one can use the formula below, where $h_{\text{w;path;i}}$ is the height of the window i measured from the bottom, $h_{\text{w;fa}}$ is the height of the window i and N_{w} is the number of windows in the room.
The parameter $h_{\text{w,st}}$ represents the effective height for thermal buoyancy in window ventilation. It can be calculated using the formula below, where $h_{\text{w;path;i}}$ is the height of window i measured from the floor level, w;fa is the free operable height of window i, and N_w is the total number of windows in the room.

$$\begin{aligned} h_{\text{w;st}} = \max\nolimits_{i=1 \text{ till } N_{\text{w}}}(h_{\text{w;path}} + \tfrac{h_{\text{w;fa}}}{2}) \\ -\min\nolimits_{i=1 \text{ till } N_{\text{w}}}(h_{\text{w;path}} - \tfrac{h_{\text{w;fa}}}{2}) \end{aligned} \tag{3.10}$$

Since all windows in the E.ON main building have the same height and are positioned at the same elevation, the formula simplifies to:

$$h_{\text{w;st}} = h_{\text{w;fa}} \tag{3.11}$$

At this point, only the volumetric airflow needs to be inserted into Equation 3.4. As described above, the airflow is calculated as a single combined value that accounts for all windows collectively, rather than summing individual terms for each window. This simplification is valid because all other parameters in the equation are identical for each window.
Furthermore, as previously noted, two separate volume flow rates are calculated: one for the incoming airflow and one for the outgoing airflow. Since only a single net ventilation value is required in Equation 3.4, the appropriate heat flow direction is applied based on basic thermodynamic principles. Whether the volume flow rate is treated as inward or outward is determined by the temperature difference between the inside and outside air.

Ventilation direction chosen via thermodynamic temperature differences.

When the windows are closed, no natural ventilation occurs through them. However, to maintain good indoor air quality, mechanical ventilation is periodically activated in accordance with building regulations. This effect is significant and should not be neglected. Nonetheless, a detailed analysis of mechanical ventilation control is beyond the scope of this master's thesis. To account for it in a simplified way, the following assumption is made:
If the room temperature deviates from the setpoint by more than 3 $°C$, and the outdoor temperature is within 1 $°C$ of the setpoint, a constant airflow rate of 0.0167 m^3/s is assumed. This value has been estimated by following recommendations, listed in ashrae62.1-2022. This ventilation only takes place when the windows are closed, since no mechanical ventilation operates while the windows are open.

Simplified mechanical ventilation modeled when windows are closed.

When the windows are closed, heat transfer into the room is modeled similarly to heat transfer through a wall. Specifically, the heat entering is proportional to a constant R_{window}, which represents the thermal resistance between the closed window and the outdoor environment. This resistance is multiplied by the total area of the closed windows. Combined with the previous equation, the total heat entering the room through the windows at any given time is:

Heat flow through closed windows treated like wall conduction.

$$\frac{dQ_{\text{Window}}}{dt} = \frac{dQ_{\text{Ventilation}}}{dt} + \frac{A_{\text{w;close;tot}} \cdot (T_{\text{Out}} - T_{\text{Room}})}{R_{\text{window}}} \tag{3.12}$$

3.2.3 Modeling Internal Heat Gains from Occupants and Equipment

Heat gains from occupants and devices modeled using simplified assumptions.

Heat gains from occupants and their electronic devices represent one of the most significant factors in the simulation model. However, this aspect also requires several assumptions and simplifications to keep the model from becoming overly complex. It is therefore assumed that each occupant, aside from the user, generates the same amount of heat and that each person operates a fixed set of electronic devices at all times. Furthermore, all devices within a given category are assumed to emit the same amount of heat.
In an office environment, typical electronic devices include laptops, tower PCs, monitors, and smartphones. To estimate the heat emitted by these devices, it is necessary to make rough approximations of their average heat gains, both during active use and while in standby mode.

Standby device heat gains negligible and excluded from the model.

According to the Center for Sustainable Systems, University of Michigan [2024], an average desktop PC consumes approximately 1.9 W of electrical power in sleep mode, with laptops consuming a similar amount. Even assuming that all this electrical energy is converted into heat, the resulting heat gains are minimal. Therefore, heat emissions from devices in standby mode are considered negligible and are excluded from the simulation. Electronics are assumed to be in standby mode when occupants are not present in the room, primarily during lunch breaks.
The same reasoning applies to smartphones, which typically consume even less power and are assumed to remain in standby mode most of the time. As a result, heat gains from smartphones are not considered in the model.

Electronics' energy consumption approximated as total heat output.

To estimate the heat emitted by electronic devices, it is assumed that all electrical energy consumed is converted into heat. While this is not 100% accurate, it is a reasonable approximation. Since computers do not perform mechanical work, the consumed energy is not stored elsewhere, and nearly all components, such as CPUs, GPUs, and power supplies, ultimately release their energy as heat. This same assumption is also adopted by Ball [2012], further supporting its validity.

Idle Tower PC and laptop power used to estimate device heat gains.

To estimate the energy consumption of computers and laptops, data from Desroches et al. [2014] was used. In this study, 64 computers were analyzed, including 45 desktops, 11 laptops, and 8 unspecified systems. During active or active-idle states, the average energy consumption of desktop computers was reported as 66.1 $W \pm 7.6\ W$. Laptops, by comparison, were estimated to consume an average of 32.0 W, with a range of +7.0 W and $-5.2\ W$. These findings are further supported by data from the Center for Sustainable Systems, University of Michigan [2024], which reported idle power usage of 66 W for desktop PCs and approximately 33 W for laptops.
Hence, in the simulation model, electronic devices are assumed to be in idle mode, an assumption that, as previously discussed, is reasonable. For desktop computers, heat gains from monitors must also be considered and can be estimated at approximately 13 W according to the same source.

Estimating heat gains from individuals in the office space.

The sensible heat emitted by an individual engaged in typical office work can be approximated as 100 W, as reported in Bansal et al. [1994]. This value is therefore used as the assumed heat gain for each office occupant other than the user.
The user may optionally specify additional details such as posture and activity level, which are selected from drop-down menus. Based on data from the Engineering Toolbox[5], the heat gain associated with the chosen posture and activity intensity is calculated and listed below. The user's total heat gain is taken as the sum of the heat contributions from posture and activity level, as provided in the tables.
If the user does not provide these parameters, a default heat gain of 100 W is applied.

[5] https://www.engineeringtoolbox.com/metabolic-heat-persons-d_706.html

Posture	Heat Gain (W)
Sitting Quietly	90
Sitting	100
Standing	130
Walking	150

Table 3.35: Heat Gain by Posture

Activity Demand	Heat Gain (W)
Low	0
Medium	20
High	50

Table 3.36: Heat Gain by Activity Demand

Estimating occupant count using CO_2 concentrations if necessary.

The user may additionally enter the number of people present in the room in order to obtain more precise simulation results. If this information is not provided, a well-known equation can be used to estimate the number of occupants N. In this equation, V_{room} denotes the outdoor air volume flow into the room in m^3/s, CO_2room is the indoor CO_2 concentration in ppm, CO_2out is the outdoor CO_2 concentration in ppm, G_{person} is the CO_2 generation rate per person in m^3/s, and ϵ is a small tolerance term included to avoid negative values resulting from measurement noise. The value of CO_2room is obtained from the CO_2 sensors integrated into the system. For simplicity, V_{room} is assumed to be 150 m^3/s, CO_2out is set to 400 ppm, G_{person} to 20000 m^3/s, and ϵ to 50, all treated as constant values.

$$N = \text{round}(\frac{V_{room} \cdot \max(0, CO_2out - CO_2room)}{G_{person}}) \quad (3.13)$$

Typical office setup used to estimate total internal heat gains.

In the E.ON ERC main building working environment, it is common for each employee to use a laptop, and approximately half of them also use a desktop PC. Based on this typical setup, the total internal heat gains in an office space can be calculated as shown below, where N denotes the number of people in the room and Q_{user} represents the assumed heat gain for the user.

$$\frac{d\text{Gains}}{dt} = (N-1)\cdot 100 + Q_{user} + N\cdot 33 + \frac{N}{2}\cdot 79 \qquad (3.14)$$

3.2.4 Modeling Solar Radiation Heat Gains

The modeling of heat gains from solar radiation will also take into account the orientation of the office space. This not only improves the accuracy of the simulation model but also helps identify additional energy-saving opportunities. To calculate the solar heat gains entering the room, direct normal irradiance $\vec{I}_{\text{Sun}}$ is considered. This quantity represents sunlight that comes directly from the Sun. The position of the sun relative to the window determines how much direct sunlight enters the space and contributes to internal heat gains.

Solar heat gains modeled using sun position and room orientation.

The irradiance data can be obtained using the Python library pvlib [6]. To calculate the total irradiance entering the room, the following integral must be evaluated, where $^+$ denotes the positive part function:

$$I_{\text{Sun,eff}} = \iint_A (\vec{I}_{\text{Sun}} \cdot d\vec{A})^+ \qquad (3.15)$$

One will use Cartesian coordinates to solve this integral, following the convention (x, y, z). The origin $(0, 0, 0)$ is placed at the center of the window. The x-axis points from east to west, the y-axis from south to north, and the z-axis points outward into space. The differential area element $d\vec{A}$ is defined as a vector normal to the window surface.

Solar gain integral solved using window-centered Cartesian coordinates.

The direct normal irradiance, I_{Sun}, provided by the Python library pvlib, is a scalar quantity. This means we can express it as

$$\vec{I}_{\text{Sun}} = I_{\text{Sun}} \cdot \vec{e}_{\text{Sun}}$$

[6] https://pvlib-python.readthedocs.io/en/stable/

where I_{Sun} is the scalar irradiance value returned by pvlib, and $\vec{e}_{\text{Sun}}$ is a unit vector pointing from the origin toward the Sun.

pvlib supplies the solar zenith angle θ and azimuth angle ϕ. By convention:

- $\phi = 0°$ corresponds to due north, increasing clockwise when viewed from above. Thus, $\phi = 90°$ is east, $\phi = 180°$ is south, and $\phi = 270°$ is west
- The zenith angle θ is measured from the vertical axis. $\phi = 0°$ points straight up (zenith), and $\theta = 180°$ points straight down (nadir).

To construct the unit vector $\vec{e}_{\text{Sun}}$, we assume the distance from the origin to the Sun, s_{dis}, is constant and equal to 1 astronomical unit (AU). Using spherical to Cartesian conversion, the components of $\vec{e}_{\text{Sun}}$ in the window's coordinate system are:

$$\vec{e}_{\text{Sun}} = \begin{bmatrix} \sin(\theta)\sin(\phi) \\ \sin(\theta)\cos(\phi) \\ \cos(\theta) \end{bmatrix}$$

3.15 can now be written as

$$I_{\text{Sun,eff}} = I_{\text{Sun}} \iint_A (\vec{e}_{\text{Sun}} \cdot d\vec{A})^+$$

$$= I_{\text{Sun}} \int_x \int_y (\vec{e}_{\text{Sun}} \cdot (x, y, z))^+ dy dx.$$

Note that the dot product of the integral remains constant at each time step, where (x, y, z) are the fixed components of the differential area vector $d\vec{A}$. Therefore, it can be factored out of the integral, resulting in a constant term multiplied by the total area of the window.

$$= I_{\text{Sun}} \cdot (\vec{e}_{(\text{Sun}} \cdot (x, y, z)))^{+} \cdot A_{\text{Window}}$$

This model is not yet complete, as the amount of solar radiation entering the room depends on both the window opening and the position of the blinds. Similar to subsection 3.2.2, we separate the total window area into the relevant parts:

Solar heat gain adjusted for window opening and blinds.

- $A_{\text{w;open;tot}}$: total open area summed over all windows
- $A_{\text{w;open;tot}}$: total closed area summed over all windows
- $A_{\text{w;blind;tot}}$ total area covered by blinds across all windows

While combinations of open or closed windows with blinds in various positions are possible, we simplify the model by making the following assumptions:

- If the blinds are closed, the window is also closed.
- The inverse is not necessarily true: windows may be closed while the blinds remain open.

To account for how much radiation actually enters the room, we apply a solar heat gain coefficient $SHGC$, which ranges from 0 to 1:

- For fully open windows, the $SHGC$ is assumed to be 1.
- For closed windows with closed blinds, the $SHGC$ is assumed to be 0.
- For closed windows with open blinds, the $SHGC$ is assumed to be 0.35 [7].

[7] https://www.mannleecw.com/solar-heat-gain-coefficient-shgc/

Putting everything together, the heat gain from solar radiation is given by:

$$
\begin{aligned}
I_{\text{Sun,eff}} = I_{\text{Sun}} \cdot |\vec{e}_{(\text{Sun}} \cdot (x, y, z))| \cdot A_{\text{w;open;tot}} \\
+0.35 \cdot I_{\text{Sun}} \cdot |\vec{e}_{(\text{Sun}} \cdot (x, y, z))| \cdot (A_{\text{w;open;tot}} - A_{\text{w;blind;tot}})
\end{aligned}
\tag{3.16}
$$

3.2.5 Simulation Execution Guide

This subsection summarizes the extended simulation model presented in this section in a consolidated form, enabling direct application and reproducibility. Equations 3.17–3.23 represent the final set of governing equations that are solved numerically to obtain the room temperature T_{Room} and the temperature of the air delivered by the HVAC system T_{HVAC}.
The inner wall temperature $T_{\text{InnerWall}}$ is also computed as part of the model but is not used directly in subsequent evaluations. All parameters required for the simulation are summarized in Table 3.37. These include physical constants, building-specific constants, functional relationships, and assumed configuration values.
In this work, the resulting system of differential equations is solved using a fourth-order Runge–Kutta method. However, the choice of numerical integration method is not fundamental to the model formulation, and alternative standard integration schemes may be applied.

$$
\begin{aligned}
c_{\text{Room}} \cdot \frac{dT_{\text{Room}}}{dt} = C_p \cdot \dot{m}_{\text{HVAC}} \cdot (T_{\text{HVAC}} - T_{\text{Room}}) \\
+1/R_{\text{CCA}}(T_{\text{CCA}} - T_{\text{Room}}) \\
+1/R_{\text{InnerWall}} \cdot (T_{\text{InnerWall}} - T_{\text{Room}}) \\
+1/R_{\text{OuterWall}} \cdot (T_{\text{Out}} - T_{\text{Room}}) \\
+(N-1) \cdot 100 + Q_{user} + N \cdot 33 + \tfrac{N}{2} \cdot 79 \\
+I_{\text{Sun}} \cdot |\vec{e}_{(\text{Sun}} \cdot (x, y, z))| \cdot A_{\text{w;open;tot}} \\
+0.35 \cdot I_{\text{Sun}} \cdot |\vec{e}_{(\text{Sun}} \cdot (x, y, z))| \cdot (A_{\text{w;open;tot}} - A_{\text{w;blind;tot}}) \\
+\dot{V}_{\text{air}} \cdot \rho_{\text{air}} \cdot C_p(T_{\text{Out}} - T_{\text{Room}}) \\
+\frac{A_{\text{w;close;tot}} \cdot (T_{\text{Out}} - T_{\text{Room}})}{R_{\text{window}}}
\end{aligned}
\tag{3.17}
$$

$$\dot{V}_{\text{air}} = \begin{cases} \dot{V}_{\text{in}}, & \text{if} \quad T_{\text{Out}} \geq T_{\text{Room}} \\ \dot{V}_{\text{out}}, & \text{if} \quad T_{\text{Out}} < T_{\text{Room}} \\ & \text{if} \quad |T_{\text{Room}} - T_{\text{Set}}| < 3 \\ \dot{V}_{\text{HVAC}}, & \& \quad |T_{\text{Out}} - T_{\text{Set}}| < 1 \\ & \& \quad h_{\text{w,fa}} = 0 \end{cases} \tag{3.18}$$

$$\rho_{\text{air}} = \begin{cases} \rho_{\text{in}}, & \text{if} \quad T_{\text{Out}} \geq T_{\text{Room}} \\ \rho_{\text{out}}, & \text{else} \end{cases} \tag{3.19}$$

$$\begin{aligned} c_{\text{InnerWall}} \cdot \tfrac{dT_{\text{InnerWall}}}{dt} &= 1/R_{\text{InnerWall}} \cdot \tfrac{1}{2} \cdot (T_{\text{InnerWall}} - T_{\text{Room}}) \\ &+1/R_{\text{InnerWall}} \cdot \tfrac{1}{2} \cdot (T_{\text{InnerWall}} - T_{\text{NeighbouringRoom}}) \end{aligned} \tag{3.20}$$

$$\frac{dT_{\text{HVAC}}}{dt} = \frac{T_{\text{Set,HVAC}} - T_{\text{HVAC}}}{\tau_{\text{HVAC}}} \tag{3.21}$$

$$T_{\text{Set,HVAC}} = 16°C + \frac{\tanh(K_p \cdot (T_{\text{Set}} - T_{\text{Room}})) + 1}{2} \cdot (33°C - 16°C) \tag{3.22}$$

$$T_{\text{Set}} = \begin{cases} T_{\text{Set,Room}}, & \text{if} \quad T_{\text{HVAC is turned on}} \\ T_{\text{Mixed}}, & \text{if} \quad T_{\text{HVAC is turned off}} \end{cases} \tag{3.23}$$

Symbol	Value	Source / Notes
A_W	$4\,m^2$	bldg. const.
$A_{w;blind;tot}$	$A_W \cdot h_{blind}$	func.
$A_{W;open;tot}$	$A_W \cdot h_{w,fa}$	func.
$A_{W;close;tot}$	$A_W \cdot (1 - h_{w,fa})$	func.
$c_{InnerWall}$	$36{,}880{,}000\,J\,°C^{-1}$	bldg. const.
C_p	$1005\,J\,kg^{-1}\,°C^{-1}$	phys. const.
c_{Room}	$699{,}480\,J\,°C^{-1}$	bldg. const.
C_{st}	$0.0035\,m^2\,°C\,s^{-1}$	phys. const.
C_{wnd}	$0.001\,s\,m^{-1}$	phys. const.
dt	$100\,s$	fixed
$h_{w,fa}$	–	sensor
I_{Sun}	–	lib (pvlib)
N	see Eq. 3.13	user / func.
p_{atm}	–	API (Open-Meteo)
R_{CCA}	$0.01\,°C\,W^{-1}$	bldg. const.
$R_{InnerWall}$	$0.01\,°C\,W^{-1}$	bldg. const.
$R_{OuterWall}$	$0.75\,°C\,W^{-1}$	bldg. const.
$R_{sp,air}$	$287.05\,J\,kg^{-1}\,°C^{-1}$	phys. const.
R_{Window}	$\frac{0.33}{A_{window}}\,m^2\,°C\,W^{-1}$	bldg. const.
T_{CCA}	$-0.35 \cdot T_{Out} + 28\,°C$	func.
$T_{NeighbouringRoom}$	$20\,°C$	assumed
$T_{Set;Room}$	-	sensor
τ_{HVAC}	3	assumed (dimless)
u	–	API (Open-Meteo)
u_{dir}	–	API (Open-Meteo)
u_{eff}	see Eq. 3.8	func.
$\dot{V}_{in}$	see Eq. 3.6	func.
$\dot{V}_{out}$	see Eq. 3.7	func.
$\dot{V}_{HVAC}$	$0.0167\,m^3\,s^{-1}$	assumed
x	$-\cos(o_{Room})$	geom. const.
y	$-\sin(o_{Room})$	geom. const.
z	0	geom. const.
α	see Eq. 3.9	func.
$\dot{m}_{HVAC}$	$0.5\,kg\,s^{-1}$	bldg. const.
Q_{user}	see Tab. 3.35-3.36	func.
$\rho_{a;ref}$	$1.225\,kg\,m^{-3}$	phys. const.
$\rho_{a;Room}$	see Eq. 3.5	func.
$\rho_{a;Out}$	see Eq. 3.5	func.
$\vec{e}_{Sun}$	see Eq.	func.
θ	–	lib (pvlib)
ϕ	–	lib (pvlib)

Table 3.37: Parameterization of the Simulation Model

3.2.6 Evaluation Methodology of the Simulation Model

Validating room temperature simulation using recorded data.

Several user tests had already been carried out with the DataFEE-App. During these tests, room data from existing sensors in the E.ON ERC main building were recorded. These measurements were used to evaluate how well the simulation model presented in this thesis would have performed under the same conditions. In order to ensure a fair comparison, the same assumptions and the same Python libraries used in the DataFEE-App were applied here as well. This approach provides an accurate picture of how the simulation model would have behaved in the original test scenarios. For example, instead of using temperature data from sensors in neighboring rooms, these temperatures were assumed to be constant at 20 $°C$.
Whenever possible, sensor data were used as initial conditions for solving the differential equations, since these measurements are also available to the DataFEE-App itself. The window sensors were likewise used, as this information is accessible within the app. It would also have been useful to include the temperature of the air supplied by the HVAC system, but no sensor for this was available.

Validation based on rooms with varied building orientations.

The E.ON ERC main building contains several offices that were included in earlier user tests, providing multiple rooms with recorded measurements. However, analysing every room would make the evaluation difficult to follow, so the analysis was limited to four representative offices. Each office in the building faces one of four orientations: northeast, southeast, southwest, or northwest. In the set of rooms used in the previous user tests, all orientations except northeast were represented. Additionally, one monitored room was located at a building corner, giving it an overall eastern orientation. To assess how well the simulation handles room orientation, one room from each of the following orientations was selected for validation: northwest, southeast, southwest, and east.

Model tested for two periods within its five-hour reliability limit.

The model described in Nienaber et al. [2020] is stated to be reliable only for simulation periods of up to about five hours. The model used in this thesis is based on that work, and the same limitation applies. In the user tests, the app was typically used from the morning(08:00) until lunchtime (12:00) and again from lunchtime until the end of the workday (17:00). This interval can vary from person to person, but the essential requirement is that the app runs during the afternoon as well. In the worst case, this results in a simulation duration of four hours in the morning and five hours in the afternoon. For the analysis in this thesis, this worst case is assumed. The simulation is therefore run from 08:00 to 12:00 and from 12:00 to 17:00.

Chosen metrics to evaluate simulation.

For all rooms, the measured data from the period 04 April 2023 to 25 April 2023 are used. To evaluate the simulation accuracy, the following performance metrics were analyzed: Root Mean Square Error ($RMSE$), the squared Pearson correlation coefficient (R^2), Mean Absolute Error (MAE) and Mean Bias Error (MBE), defined in Eqs. 3.24-3.27, respectively. The first three metrics were selected because CIBSE and VDI-6020:2002 provide explicit benchmark values that define acceptable levels of model accuracy, as visualized by Table 3.38 and cited by Pachano and Fernández Bandera [2021]. $RMSE$ and MAE quantify the magnitude of the prediction error, with $RMSE$ penalizing larger deviations more strongly. The squared Pearson correlation coefficient (R^2) evaluates the strength of the linear relationship between simulated and measured values.
MBE was added to indicate whether the simulation tends to underestimate or overestimate the temperature of the interior room. However, the benchmark values refer to hourly values. The presented results of the simulation are validated in a 4 or 5 hour interval. As far as one has researched, there is no method on scaling these benchmark values to higher time frames. Nonetheless, they still provide a suitable reference for determining an appropriate value range.

Metric	**CIBSE**	**VDI-6020**
MAE (°C)	≤ 2.0	–
$RMSE$ (°C)	–	≤ 1.5
R^2 (%)	≥ 70	≥ 70

Table 3.38: Acceptable Hourly Error Limits

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(m_i - s_i)}{n}} \tag{3.24}$$

$$R^2 = \frac{\sum_{i=1}^{n}(m_i - \overline{m}) \cdot (s_i - \overline{s})}{\sqrt{\sum_{i=1}^{n}(m_i - \overline{m}) \cdot \sum_{i=1}^{n}(m_i - \overline{m})}} \tag{3.25}$$

$$MAE = \frac{\sum_{i=1}^{n} |m_i - s_i|}{n} \tag{3.26}$$

$$MBE = \frac{\sum_{i=1}^{n} m_i - s_i}{n} \tag{3.27}$$

3.3 DataFEE-App Overview and Implemented Modifications

To explain how the simulation and gamification elements were integrated into the DataFEE-App, this section outlines the essential structural components of the web application. It begins with Docker, which orchestrates the different containers as independent processes, running in the backend. The backend manages data storage, handles load balancing, and provides the API interfaces. Afterward, it introduces the frontend, which presents the application's functionality to the user. Finally, it summarizes the specific modifications applied to these components in the context of this work.

3.3.1 DataFEE-App: Backend

Docker manages separate containers and coordinates their operation.

The web application uses Docker[8] to run and manage the backend. This enables the system to run through a set of coordinated containers, each functioning independently.

8 `https://www.docker.com/`

Docker is lightweight and portable, which allows the application to be deployed on different servers while maintaining identical behavior across environments. It achieves this through images that define how each container should be built and executed. Containers are created from these images, and Docker manages and coordinates them during runtime.
The containers that run and support the DataFEE-App are the following: an Nginx container, an API host, an InfluxDB container and a Data-Writer container. Figure 3.39 provides an overview of how the containers interact and function together within the system architecture.

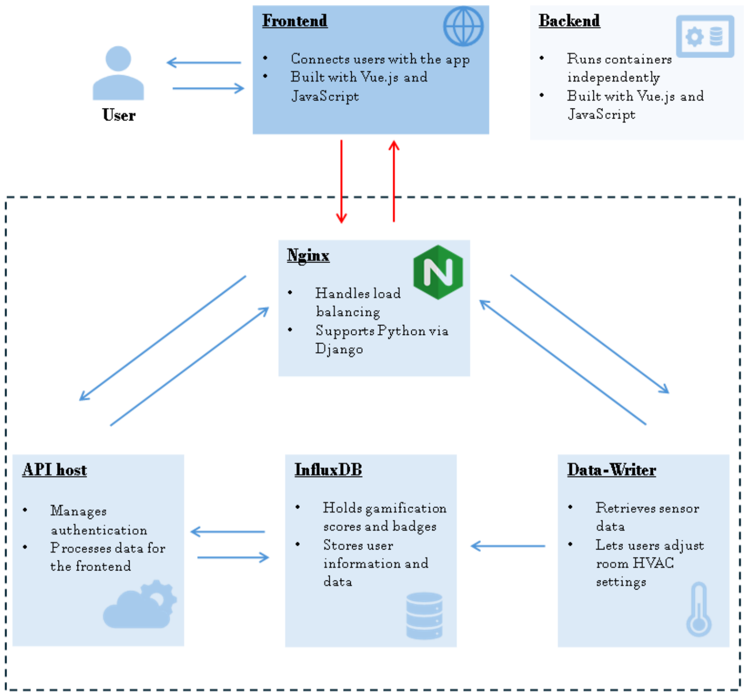


Figure 3.39: DataFEE-App Structure

The Nginx container enables load balancing and supports the execution of Python through the Django interface.

The Nginx container iangolo/uwsgi-nginx[9] handles all incoming requests within the DataFEE-App. This means that every request originating from either the backend or the frontend is processed through the functionality provided by this container. Because several users may access the DataFEE-App simultaneously, the server, which in this case is the virtual machine running the application, can receive

[9] `https://hub.docker.com/r/tiangolo/uwsgi-nginx/`

a high number of requests in a short period of time. The Nginx container coordinates these requests to prevent overload and to ensure stable operation. In addition, large numbers of requests can slow the application even when they are properly managed. To reduce this overhead and accelerate repeated queries, Nginx also caches frequently requested data so that it can be served more quickly.
This container also enables the web application to operate using Python through the Django framework. The backend logic can be implemented in Python, and Django allows the server to return JSON responses, which makes it possible to use the application as an API interface.

The API host container provides the execution environment for the backend logic of the DataFEE-App. It runs the Django application and handles all server-side operations that process incoming requests and generate the corresponding responses. One of these operations is the user authentication process. The container manages user registration and login, and it stores the corresponding username and password entries in the InfluxDB database, which is discussed afterwards. When a user attempts to sign in, the request is processed within this container.
When the web application requests environmental data, such as indoor temperature, outdoor temperature, or relative humidity, this container supplies the required information. It does not, however, retrieve raw sensor data. That task is performed in a separate container. The API host container receives the processed sensor data and returns it to the frontend in JSON format.
This container is also responsible for the gamification logic. All points earned by a user are written to the InfluxDB database through this backend. The energy behavior score displayed in the dashboard queries this container, which fetches the relevant information from the database. The same applies to the leaderboard. The leaderboard data is requested through this container, which collects and organizes all necessary values from the InfluxDB database before returning the structured results to the frontend.

The API host container manages authentication and processes the data that is presented in the frontend.

The InfluxDB[10] container is responsible for managing the data used in the application. The system relies on an early

The InfluxDB container stores user related information together with the gamification data of the DataFEE-App.

[10] https://www.influxdata.com/

version of InfluxDB. Each entry stored in the database is accompanied by a timestamp. In addition to the timestamp, every entry contains at least one field that consists of a key and a value. The key indicates the type of information being stored, for example a point entry, while the value represents the corresponding numerical value.
This version of InfluxDB is queried directly through the InfluxQL query language. Within the database, all account information is stored, including usernames, passwords, office room numbers, and the points written by the API host container.

The Data-Writer container retrieves sensor data and enables users to adjust HVAC related settings in the room.

The Data-Writer container also operates on Django, similar to the API host container. It is responsible for retrieving environmental data such as indoor temperature, outdoor temperature, relative humidity, and carbon dioxide concentration in the room. It also provides HVAC related information, including set point temperature and fan speed. All building related data requests are handled through the Aedifion platform. This connection also allows the HVAC parameters to be controlled through the application.
As described in Chapter 1, all users within a room can provide comfort related inputs, such as their perceived thermal comfort and their preferred adjustments. These inputs are processed to calculate a thermal comfort value for the room.

3.3.2 DataFEE-App: Frontend

The frontend is built with Vue.js, which provides reactive updates and a structured, component-based architecture.

The frontend comprises all user-facing elements displayed in the browser and is implemented using Vue.js[11]. Its reactive data model ensures that values shown in the interface update automatically whenever backend data changes. This is essential for presenting dynamic environmental information such as indoor and outdoor temperature, relative humidity, and similar metrics. The same applies to the DataFEE-App's gamification features, where elements like the energy behavior score and the leaderboard must update in real time.
Vue.js also enables a modular structure by allowing each UI

[11] `https://vuejs.org/`

component to be developed in its own .vue file. For example, the dashboard, depicted in Figure 1.1, is composed of multiple components, including the clothing and activity input fields, the energy behavior score, the environmental data display, the temperature graph, and the button used to restore thermal comfort in the office space. Figure 3.40 illustrates this modular layout by showing how the individual components are positioned within the dashboard.

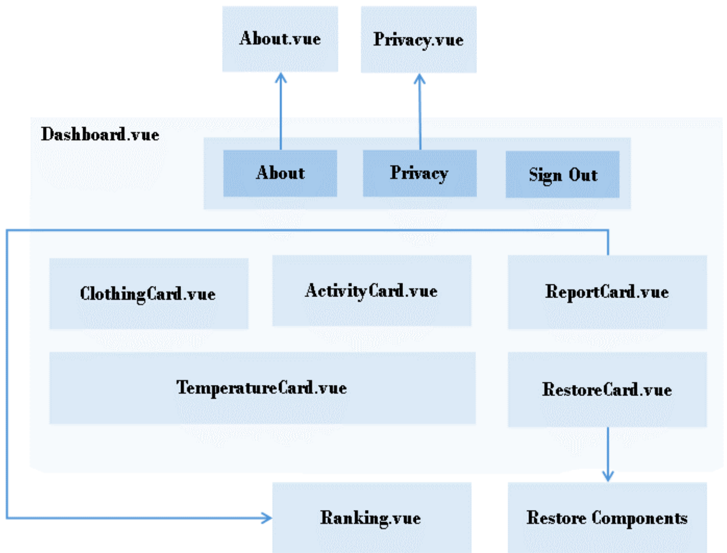


Figure 3.40: DataFEE-App Frontend Components

Figure 3.40 also illustrates how Vue.js enables navigation between components through button interactions. The buttons in the app bar at the top of the dashboard demonstrate this behavior. Selecting the "About DataFEE" button redirects the user to the About section of the DataFEE-App, which provides a brief overview of the application along with a notice explaining that certain personal data is collected for operation. Details on the collected data are presented in the Privacy component, which becomes visible when the "Privacy Statement" button is pressed. This button is adjacent to the "About DataFEE" button
A similar redirection occurs when selecting the "SEE MORE" button within the ReportCard component, which leads the user to the leaderboard view shown in Figure 1.2. In contrast, clicking the "CHANGE SETTINGS NOW" but-

The DataFEE-App's component structure supports clear organization and smooth interaction.

ton in the RestoreCard component does not redirect to a different page. Instead, it triggers a pop-up window, shown in Figure 1.3, which prompts the user to report their thermal comfort. Figure 1.4 then shows the available options to restore comfort.

3.3.3 DataFEE-App: Implemented Changes

To apply the methodology described in Sections 3.1 and 3.2, additional development of the DataFEE-App was necessary. This required modifications to both the frontend and the backend. The simulation features primarily demanded new backend functionality, while the gamification features additionally relied on extending and adapting existing backend components.
For clarity, the following subsections outline the adjustments made to the backend and frontend separately, allowing the changes to be presented in a structured and comprehensible manner.

3.3.3.1 Implemented Changes in the Backend

Replacing how the outdoor temperature is fetched

For the backend of the DataFEE-App, all modifications were made within the API host container shown in Figure 3.39. The remaining containers required no direct changes. Nonetheless, some updates in the API host container affected other containers due to their interdependencies. This applies in particular to the simulation method described in Section 3.2, which was implemented within the API host container.
In this implementation, the outdoor temperature is obtained directly from the Open-Meteo API[12] rather than being retrieved through the Data-Writer container. This adjustment was made because, at the time of development, sensor reading and writing in the Data-Writer container were not functioning as intended due to infrastructure changes in the E.ON ERC main building. Additionally,

[12] `https://open-meteo.com/`

fetching the outdoor temperature directly reduces computational overhead. To maintain consistency, this modified retrieval method is displayed in the outdoor temperature values shown on the DataFEE-App dashboard.

Integrating indoor simulation into the DataFEE-App and adjusting the thermal comfort reference zone due to non-functioning sensor data.

The indoor temperature simulation was integrated into the DataFEE-App at the API host level. This implementation was carried out together with the retrieval of outdoor temperature data, as this information is required to simulate indoor temperature throughout the day. The simulated indoor temperature is returned to the frontend in JSON format, where it can be displayed in the browser.

The same simulation model is also used to iterate through all available options in order to determine whether thermal comfort can be achieved. For each option, the system evaluates if the user feels thermally comfortable by running the indoor temperature simulation. This was originally done by using the Heat Balance Model defined in DIN EN ISO 7730. Here a reference thermal comfort zone is calculated and displayed as a green zone in the dashboard of the DataFEE-App , as depicted in Figure 1.1. However, this model requires additional sensor data, such as indoor air temperature and relative humidity. As described earlier, the current sensor data retrieval mechanism requires further modification before it can operate reliably. Therefore, the Heat Balance Model was temporarily replaced to ensure continued functionality of the DataFEE-App.

Based on findings reported by Battistel et al. [2023], indicating that most people can perceive a temperature change of approximately 1 $°C$, a simplified method to determine thermal comfort was adopted. One which does not depend on additional sensor data. Instead of using the Heat Balance Model, the system now checks whether a requested adjustment would result in a noticeable temperature change according to the simulation.

If the user requests the environment to be slightly warmer or slightly cooler, the simulation verifies whether the indoor temperature would increase or decrease by at least 1 $°C$. This change may be interpreted as ±0.5 $°C$, provided that it is sustained for at least 30 minutes, as described in subsection 3.1.1.1. If the user requests the environment to be warmer or cooler, the same process is applied using a threshold of 2 $°C$.

All feasible options are then compared based on their energy efficiency. The resulting set of recommended options is returned to the backend in JSON format.

Integration of Backend Logic for Gamification Elements in the DataFEE-App.

Several modifications were also required in the backend to support the gamification features. These changes were implemented within the API host container and primarily involved storing user points, managing badge logic and persistence, and organizing leaderboard data.
The energy behavior score depicted in the dashboard was revised so that negative scores are no longer possible. The lower bound was set to 0 points, while the upper bound was limited to 5 points. In addition, new point categories were introduced. These include the "Info Points" described in subsection 3.1.1.2 and the "Optimal Points" described in subsection 3.1.2.2. As with the previously implemented scoring system, all points are stored in the InfluxDB.
Furthermore, these points are used to calculate user rankings, which are displayed in the leaderboards described in subsection 3.1.3 and presented in the frontend.
The InfluxDB also stores all badges accumulated by each user. When the frontend detects that a badge may be earned, it first communicates with the backend to verify whether the badge has already been obtained before awarding it.

3.3.3.2 Implemented Changes in the Frontend

As described in the implemented changes in the backend, the Data-Writer container caused issues because the fetching and control of sensor data no longer function correctly due to changes in the underlying infrastructure. As this rendered the DataFEE-App inoperable, modifications were required in the frontend to prevent the affected data from being fetched.
This applies, for example, to the recorded indoor temperature displayed in the dashboard, which was temporarily removed for the purposes of this thesis. In addition, the environmental data shown in the dashboard was replaced with placeholder values.
As a result, the application no longer relies on live sensor

data but instead operates using temporally stored application states. This includes user interactions such as opening or closing windows and adjusting HVAC settings. All such actions are recorded when initiated by the user. However, there is no sensor-based verification of these states.
Despite the temporary removal of sensor-based feedback, an indoor room temperature simulation was integrated into the frontend, as illustrated in Figure 3.41.

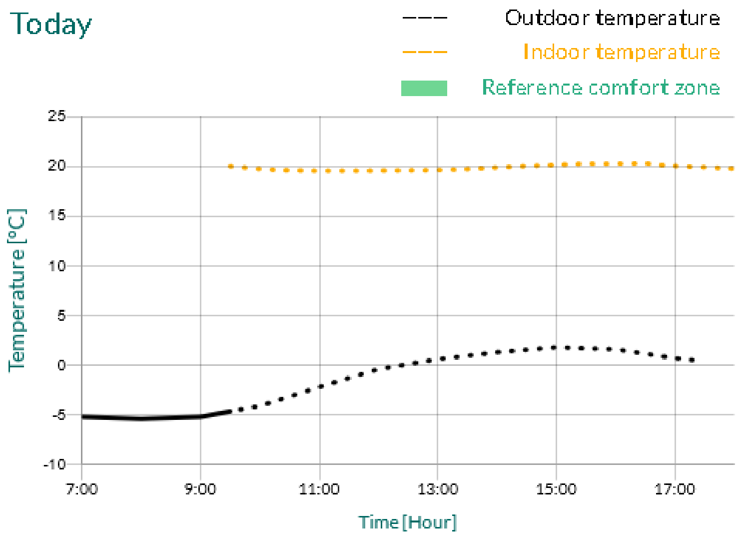


Figure 3.41: Room Temperature Simulation

Figure 3.40 provides an overview of the frontend structure of the DataFEE-App. To integrate the gamification aspects discussed in section 3.1, the overall structure is retained while specific components are modified and new components are introduced.
As discussed earlier, the number of people in a room has a significant impact on indoor temperature. For this reason, users are able to provide this information to improve the accuracy of the simulation. Consequently, the ActivityCard component has been modified from Figure 3.42 to Figure 3.43, where an additional input field for the number of people in the room has been added.
The Ranking component has also been updated. The previous leaderboard, shown in Figure 1.2, has been replaced by three new leaderboards: a weekly leaderboard depicted in Figure 3.34 and leaderboards for "Info Points" and "Optimal Points" as described in subsection 3.1.3.

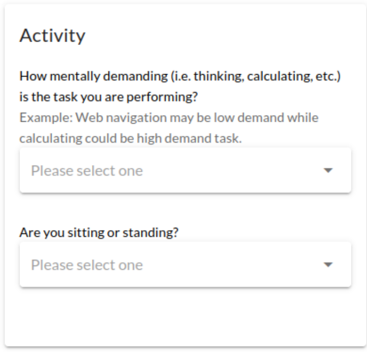


Figure 3.42: ActivityCard Component Before Modification

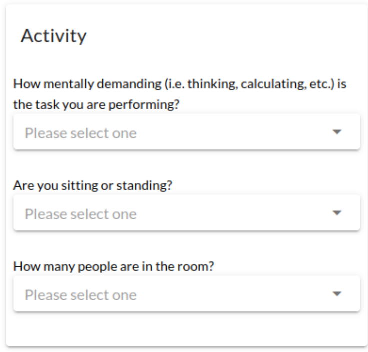


Figure 3.43: ActivityCard Component After Modification

Additionally, a new frontend component labeled "Profile" has been introduced, as shown in Figure 3.44. This component can be accessed via the app bar at the top of the application. Its primary purpose is to provide users with feedback on their progress while using the app. All badges described in subsection 3.1.2 and the rankings discussed in subsection 3.1.3 are displayed here.

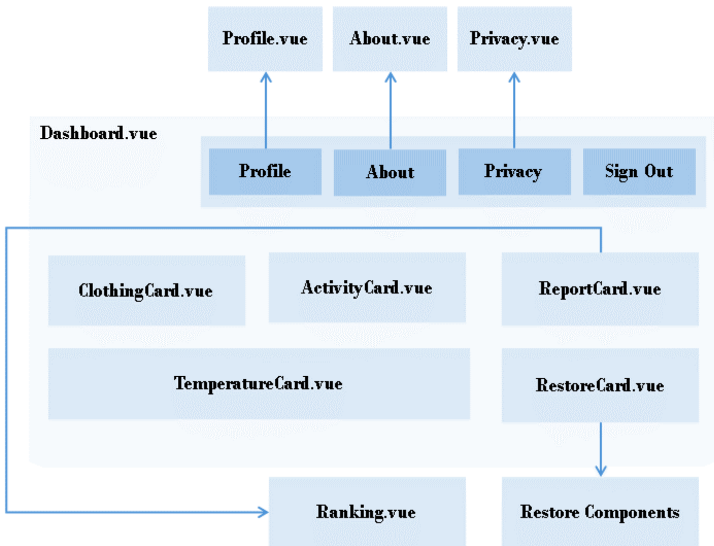


Figure 3.44: DataFEE-App additional Frontend Components

Chapter 4

Results and Discussion

To validate the results presented in this thesis, two separate evaluations are carried out. First, the simulation itself is validated. Measured room temperatures from previous user tests conducted by the E.ON Institute for the DataFEE-App are used and compared with the simulated room temperatures obtained using the methodology described in this thesis.

Separate evaluation for simulation and gamification.

The second step is to validate the app itself, focusing on the user experience. This involves performing user tests to determine whether the implemented features achieved the intended effects. After completing the test, the participants fill out a questionnaire that provides feedback.

4.1 Evaluation of the Simulation Method

In this section, the simulation model implemented in the DataFEE-App is validated using measured room temperature data from previous user tests. Simulated room temperatures are compared with measured values using the Root Mean Square Error ($RMSE$), the squared Pearson correlation coefficient (R^2), Mean Absolute Error (MAE) and Mean Bias Error (MBE).

The simulation uses recorded sensor data as input and applies the same assumptions and numerical implementation

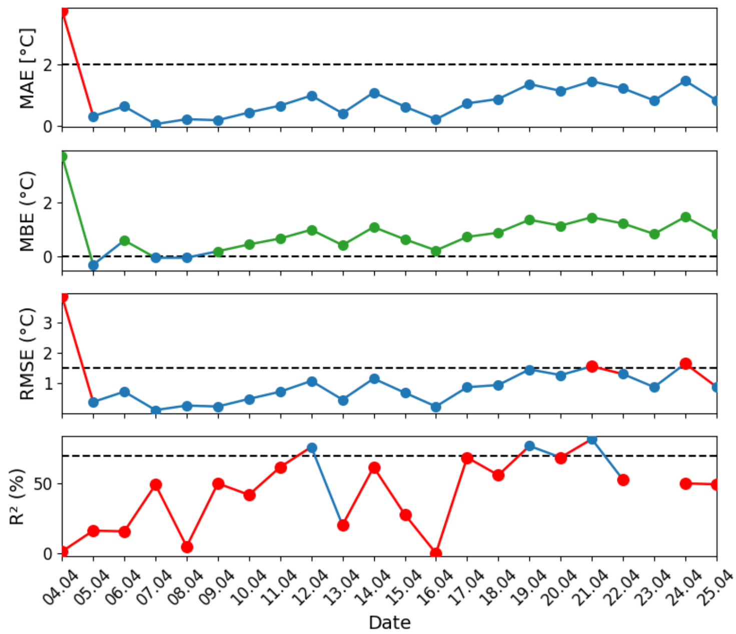
as described in subsection 3.2.6. In particular, neighboring rooms are assumed to have a constant temperature of 20 $°C$. The validation is based on measurement data collected between 04 April 2023 and 25 April 2023.
To account for different building orientations, four representative rooms were selected, facing northwest, southwest, southeast, and east. Each room is evaluated separately for two simulation periods: a morning period from 08:00 to 12:00 and an afternoon period from 12:00 to 17:00. This choice reflects both typical app usage and the stated reliability limit of approximately five hours for the underlying model.
The data have a temporal resolution of 15 minutes. The evaluation metrics $RMSE$, MAE, and R^2 are computed for each room and time period as defined in Equations 3.24–3.27.

4.1.1 Representation of Data

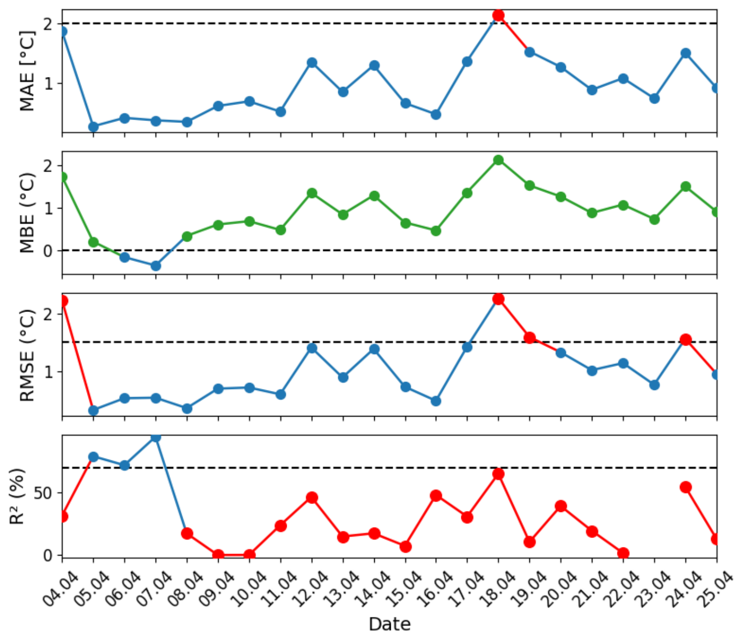
Simulation accuracy is shown in separate figures, each corresponding to a room orientation.

The following figures present the validation results for the investigated room orientations and corresponding time windows. For each orientation, two plots are shown, representing the morning (08:00–12:00) and afternoon (12:00–17:00) periods. Figure 4.1 corresponds to the northwest oriented room, Figure 4.2 to the southwest oriented room, Figure 4.3 to the southeast oriented room, and Figure 4.4 to the east oriented room. Together, these figures provide a comparative overview of simulation performance across orientations and time windows.
In all figures, dashed reference lines indicate the recommended threshold values for the applied evaluation metrics. For MAE and $RMSE$, the dashed lines represent the maximum acceptable error limits, above which the simulation accuracy is considered insufficient. Data points corresponding to simulations that meet these accuracy criteria are marked in blue, while simulations exceeding the error thresholds are highlighted in red. For the mean bias error, a dashed line at zero is included to indicate whether the simulation tends to underestimate or overestimate the room temperature. Positive MBE values, indicating underestimation, are shown in green, whereas negative values, indi-

cating overestimation, are shown in blue. For the squared Pearson correlation coefficient (R^2), the dashed line denotes the minimum recommended threshold that should be achieved to indicate adequate agreement between simulated and measured temperature dynamics. Simulations achieving this threshold are marked in blue, while those falling below it are indicated in red.

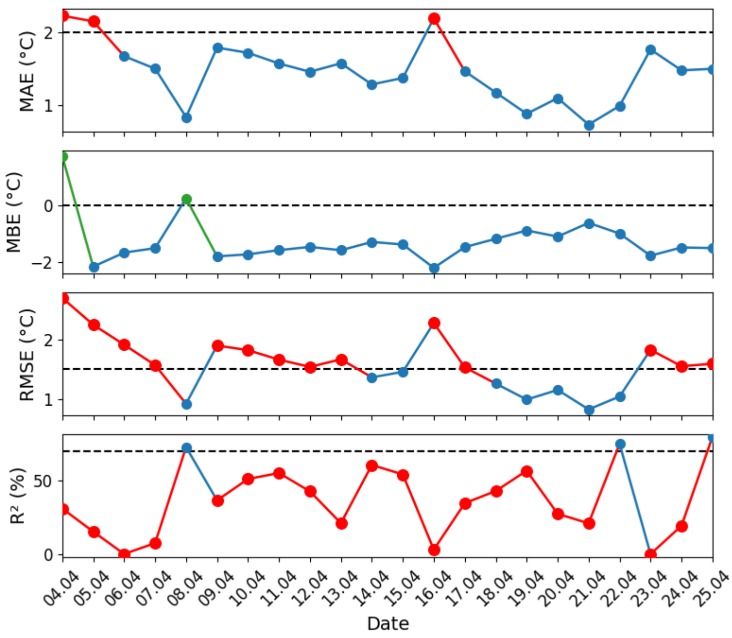


(a) Morning Time Window (04.04.2023–25.04.2023, 08:00–12:00)

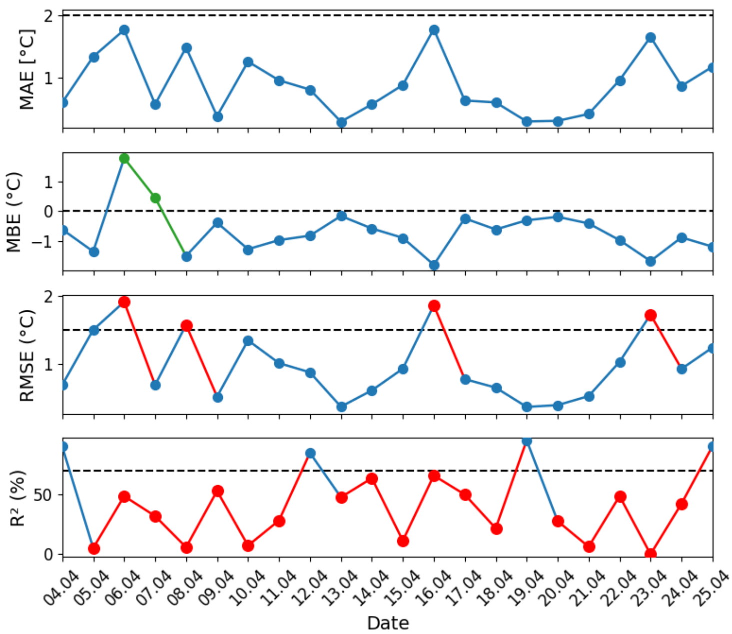


(b) Afternoon Time Window (04.04.2023–25.04.2023, 12:00–17:00)

Figure 4.1: Results for Room 136 (Northwest Orientation, 306 °)

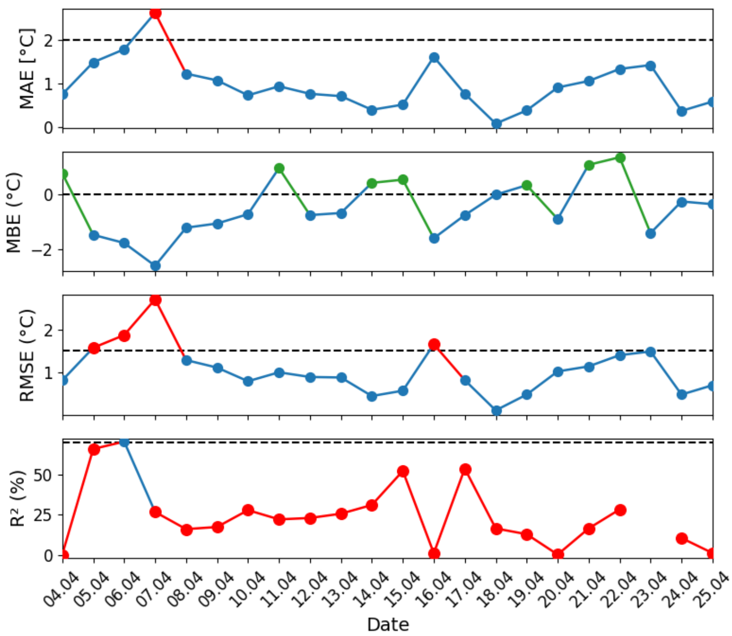


(a) Morning Time Window (04.04.2023–25.04.2023, 08:00–12:00)

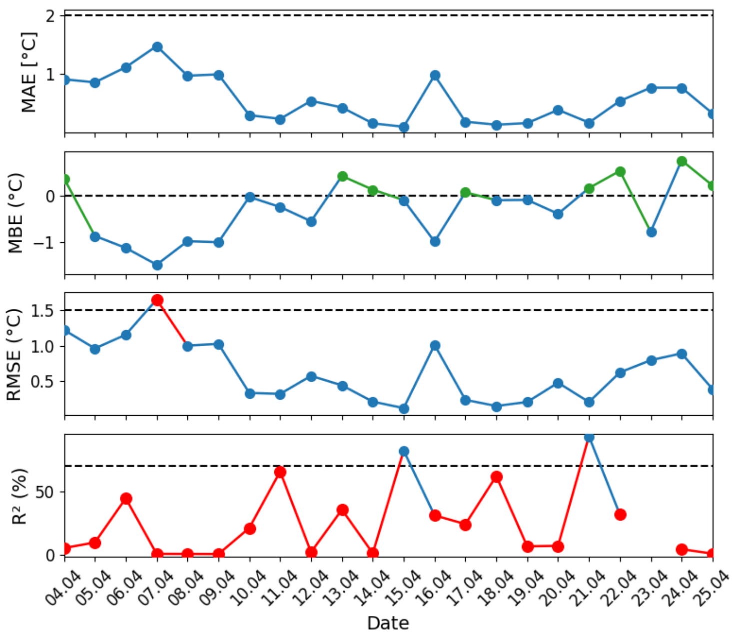


(b) Afternoon Time Window (04.04.2023–25.04.2023, 12:00–17:00)

Figure 4.2: Results for Room 146 (Southwest Orientation, 216 °)

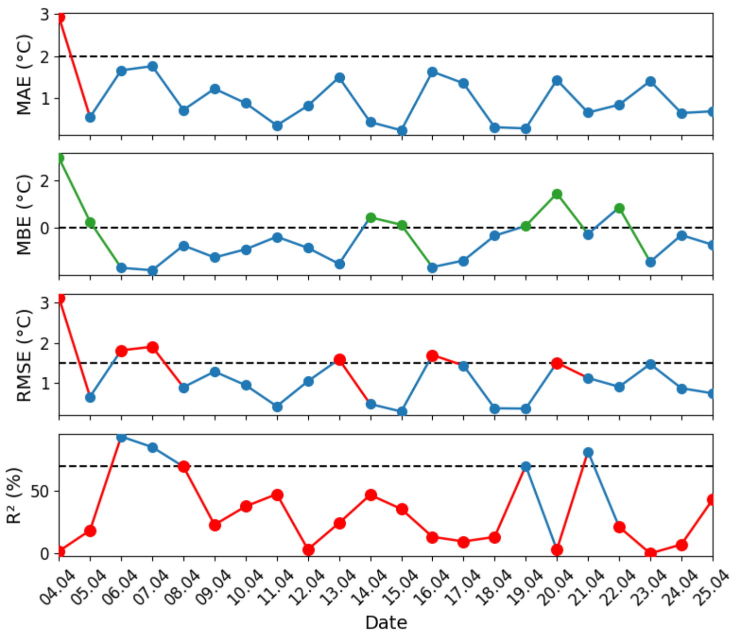


(a) Morning Time Window (04.04.2023–25.04.2023, 08:00–12:00)

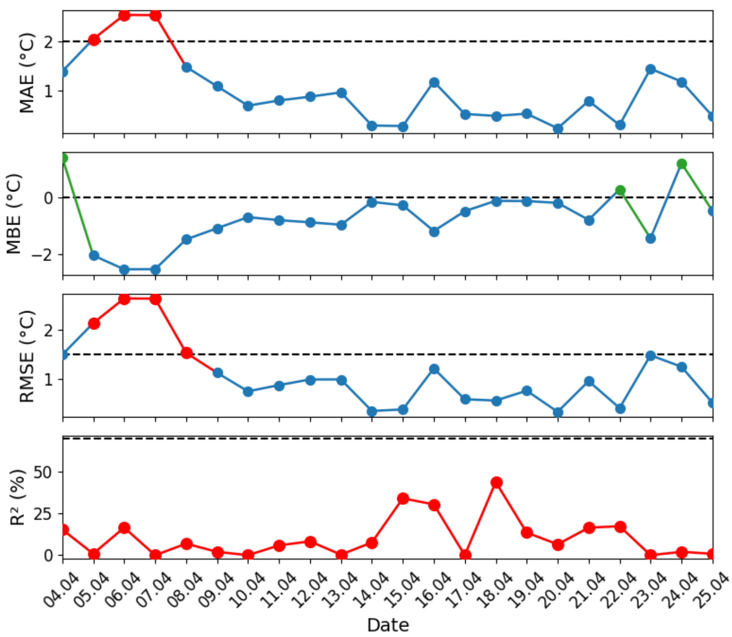


(b) Afternoon Time Window (04.04.2023–25.04.2023, 12:00–17:00)

Figure 4.3: Results for Room 121 (Southeast Orientation, 126 °)



(a) Morning Time Window (04.04.2023–25.04.2023, 08:00–12:00)



(b) Afternoon Time Window (04.04.2023–25.04.2023, 12:00–17:00)

Figure 4.4: Results for Room 125 (East Orientation, 81°)

MAE and RMSE generally remain within acceptable ranges, with a few outliers.

For all investigated room orientations, MAE and $RMSE$ values generally lie within the recommended threshold range for reliable indoor temperature simulation according to VDI-6020:2002 and CIBSE. Each orientation nevertheless includes isolated days on which these thresholds are exceeded.

A pronounced outlier is observed for the northwest oriented room on 04.04.2023 during the morning time window, where the MAE reaches $3.7°C$ and the RMSE increases to $3.88\ °C$, exceeding the recommended thresholds by more than a factor of two. Comparable levels of inaccuracy occur on 06.04.2023 during the morning period for the southeast oriented room and on 04.04.2023 during the morning period for the east-oriented room.

A more common deviation is the exceedance of the $RMSE$ threshold alone. Depending on orientation and time window, this typically occurs on three to five days per evaluation period out of the 22 analyzed days. An exception is the southwest oriented room during the morning time window, where approximately half of the evaluated days exceed the $RMSE$ threshold. Across most rooms, threshold exceedances occur more frequently in the morning than in the afternoon, indicating slightly reduced model accuracy during the earlier hours.

In contrast, exceedances of the MAE threshold are considerably less frequent. Across all rooms and time windows, only 10 out of 176 simulations exceed the MAE limit, indicating that even when simulation performance degrades, the average temperature error generally remains below 2 °C. The fact that $RMSE$ values remain below 1.5 °C in most cases further indicates that larger temperature errors occur infrequently and do not dominate overall simulation performance.

Comparison of MAE and RMSE across room orientations and time windows.

Although no room orientation consistently outperforms the others across all metrics, clear differences in the frequency and severity of deviations can be observed. The southwest oriented room exhibits the highest number of $RMSE$ exceedances during the morning time window. However, the corresponding MAE values largely remain within acceptable limits, with only three minor exceedances. During the afternoon period, the number of $RMSE$ exceedances for this room is reduced to four, making its performance com-

parable to that of the other orientations.
The east and northwest oriented rooms show fewer $RMSE$ exceedances overall but include isolated outliers with substantially larger errors, particularly during the morning period on 04.04. In contrast, the southeast oriented room exhibits the lowest number of outliers. For this room, the $RMSE$ threshold is exceeded four times in the morning time window and only once during the afternoon, with a maximum value of 1.65 $°C$. MAE exceeds the threshold only once for this orientation.
Across all orientations, a common pattern emerges in which the majority of MAE and $RMSE$ outliers occur during the morning time window. This indicates generally higher absolute accuracy during the afternoon period, a trend that is particularly pronounced for the southwest-oriented room, where the number of $RMSE$ exceedances is reduced by approximately one third in the afternoon.

MBE values indicate no clear bias toward over- or underestimation of room temperature.

With respect to systematic bias, no consistent pattern across all orientations can be identified. The northwest oriented room exhibits predominantly positive MBE values in both time windows, indicating a tendency toward underestimation of room temperature. In contrast, the southwest oriented room shows predominantly negative MBE values, indicating a tendency toward overestimation. For the southeast-oriented room, MBE values are more evenly distributed around zero, suggesting no persistent bias toward either over- or underestimation. Similarly, the east-oriented room does not exhibit a consistent bias overall. However, during the afternoon period, MBE values tend to be more negative, indicating a temporary tendency toward overestimation during this time window.
These observations indicate that systematic bias is more strongly related to room orientation than to the time window considered.

R^2 values remain consistently below the acceptable dynamics threshold.

Regarding the squared Pearson correlation coefficient, the majority of evaluated days remain below the recommended threshold of 70%, with only occasional exceedances. Typically, the threshold is reached on three to five days per time window, depending on room orientation. An exception is the southeast oriented room, where the threshold is reached once during the morning period and twice during the after-

noon.
No clear pattern emerges indicating consistently better dynamic performance for either the morning or afternoon time window across all orientations. For the northwest and southeast oriented rooms, the number of days exceeding the R^2 threshold is similar for both time windows. A similar pattern is observed for the southwest oriented room. However, when exceedances occur in the afternoon, R^2 values are closer to 100%, whereas morning exceedances tend to be closer to the 70% threshold. Also, the simulation on 19.04 (afternoon) for the southwest oriented room represents the best-performing case across all metrics, with MAE and $RMSE$ close to 0 °C and R^2 approaching 100%, as shown in Figure 4.5.

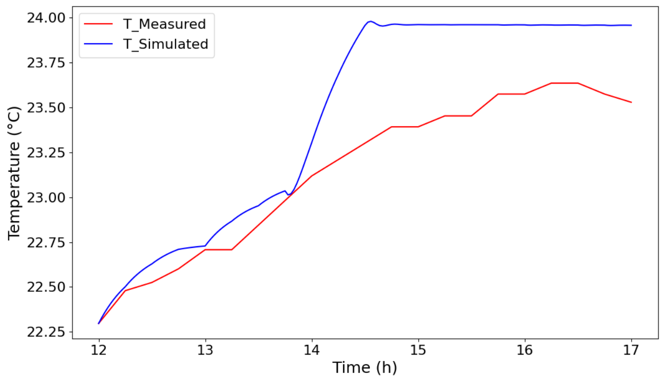


Figure 4.5: Simulated vs. Measured Temperatures, Southwest Orientation, Afternoon (19.04)

In contrast, for the east oriented room, the morning time window outperforms the afternoon period with respect to dynamic accuracy. Here, the R^2 threshold is exceeded five times in the morning, while afternoon values remain consistently below 50%. Overall, however, R^2 values fluctuate substantially and remain below the recommended threshold in most cases, indicating that temporal temperature dynamics are reproduced only to a limited extent. This variability is further illustrated by individual cases with contrasting metric behavior. For the northwest oriented room on 16.04 during the morning period, the simulation exhibits an R^2 value close to 0, while absolute error metrics indicate high accuracy, with MAE = 0.22 °C and $RMSE$ = 0.23 °C,

as can be seen in Figure 4.6. Conversely, on 18.04 during the afternoon period, the simulation achieves an R^2 value of approximately 65%, while absolute errors are substantially larger, with MAE = 2.14 °C and $RMSE$ = 2.26 °C, as can be seen in Figure 4.7.
It should be noted that R^2 could not be calculated for some cases, such as 23.04 for the northwest and southeast oriented rooms, as the measured room temperature remained constant throughout the day, rendering the metric undefined.

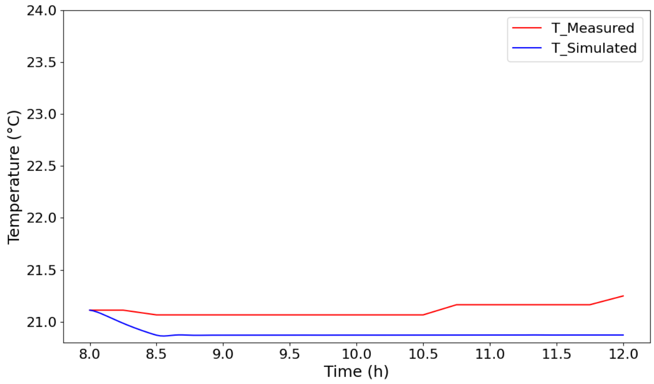


Figure 4.6: Simulated vs. Measured Temperatures, Northwest Orientation, Morning (16.04)

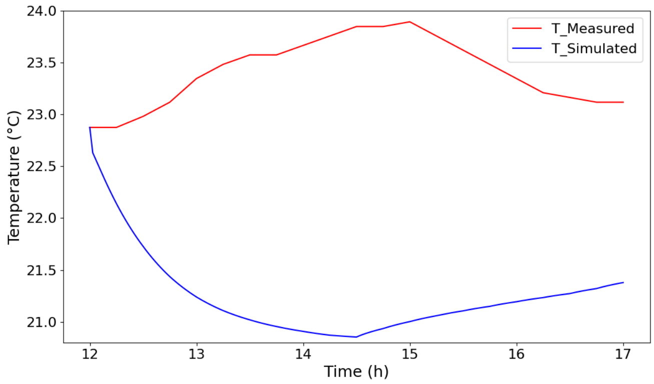


Figure 4.7: Simulated vs. Measured Temperatures, Northwest Orientation, Afternoon (18.04)

The presented validation results demonstrate that the simulation achieves reliable absolute temperature accuracy across all investigated room orientations, while exhibiting limitations in reproducing short-term temperature dynamics. In the following discussion chapter, the underlying causes of these deviations are examined in more detail, and their implications for model applicability and potential improvements are critically assessed.

4.1.2 Discussion

In this subsection, possible causes of the observed deviations between simulated and measured room temperatures are discussed, and implications for model improvement and applicability are outlined.

Good MAE and RMSE, but low R^2 indicates HVAC modeling limitations.

According to the threshold values defined by CIBSE and VDI-6020:2002 the simulation generally achieved acceptable performance in terms of MAE and $RMSE$. Although individual outliers were observed, the majority of values remained within the recommended limits, indicating that the model is suitable for estimating absolute indoor room temperatures.

Depending on the room configuration, the simulation exhibited tendencies toward both overestimation and underestimation of room temperature. Even within the same room, this bias was not consistent over time. A major contributor to this behavior is the estimation of internal heat gains. Assumptions regarding occupant numbers and equipment usage directly influence the simulated temperature level. For example, the assumption that all occupants use a laptop and that half additionally operate a desktop computer does not necessarily reflect actual office usage. Nevertheless, as MAE and $RMSE$ largely remain within recommended limits, these simplifications are considered acceptable for the present application. Internal heat gain assumptions primarily affect absolute temperature levels and are therefore expected to have a stronger influence on MAE and $RMSE$ than on R^2.

A more significant limitation is the simplified representation of HVAC operation. Time constants were used to describe the convergence of mixed air temperature toward indoor temperature, and the rate of change of supply air temperature was assumed to be constant. While these simplifications did not substantially affect MAE and $RMSE$, they had a pronounced impact on the coefficient of determination. For none of the analyzed rooms did R^2 consistently reach the recommended threshold of 70%, indicating that short-term temperature dynamics are not adequately reproduced. Since HVAC operation is the dominant driver of indoor temperature variation and the component with the strongest simplifications, it is likely the primary cause of the limited dynamic accuracy.

This distinction explains why simulations can perform well in terms of MAE and $RMSE$ while exhibiting low R^2 values. Minor temporal shifts between simulated and measured temperature profiles, such as delayed cooling phases or missed short-term fluctuations, can significantly reduce R^2 while only marginally affecting absolute error metrics. In contrast, high R^2 values alone do not guarantee acceptable simulation performance if MAE and $RMSE$ exceed recommended thresholds.

A further limitation of the squared Pearson correlation coefficient arises from its insensitivity to the physical plausibility of temperature trajectories. While R^2 captures the strength of a linear relationship, it does not distinguish between positively and negatively correlated dynamics. As a result, cases in which simulated and measured temperatures exhibit opposing trends, such as decreasing simulated values coinciding with increasing measured values, may still yield high R^2 values. This effect can be observed in Figures 4.6 and 4.7 where strong correlation is achieved despite substantial deviations in absolute temperature levels.

Additional sources of uncertainty include unmonitored door opening events and the simplified treatment of neighboring room temperatures. Open doors can introduce unmodeled heat exchange, potentially affecting MAE, $RMSE$, and, if irregular, also R^2. The temperature of neighboring rooms was assumed to be constant at 20 $°C$. While this assumption may influence R^2 to some extent, its effect on MAE and $RMSE$ was limited. Modeling dynamic neighboring room temperatures would significantly increase model complexity and require additional assumptions, while likely providing only marginal accuracy improvements.

The simulation method is sufficient for the DataFEE-App despite limitations in temperature dynamics.

Overall, the simulation approach provides reliable absolute temperature estimates but shows limitations in reproducing short-term dynamics. For applications such as the DataFEE-App, where it is essential to estimate temperature ranges and general heating or cooling trends rather than exact temporal behavior, the model performance is considered sufficient. The primary purpose of the simulation is to ensure that the DataFEE-App provides appropriate and reliable recommendations for achieving thermal comfort, a requirement that is met by the observed level of absolute temperature accuracy.

In summary, this evaluation demonstrates that simplified room temperature simulations can achieve acceptable accuracy in terms of absolute error metrics while maintaining low computational complexity. The main limitation lies in the reproduction of short-term temperature dynamics, which is primarily caused by simplified HVAC modeling. Secondary sources of uncertainty, such as internal heat gain assumptions, door opening events, and neighboring-room temperatures, have a comparatively smaller impact on overall accuracy. Within the defined scope and application context, these limitations are acceptable, and the simulation fulfills its intended purpose. Future improvements should therefore prioritize a more detailed representation of HVAC dynamics, as this offers the greatest potential for improving model performance without substantially increasing user input or computational overhead.

It should be noted that the evaluation is based on a limited number of rooms, orientations, and measurement days, which may restrict the generalizability of the results. In addition, no direct measurements of HVAC supply air conditions were available, requiring assumptions regarding supply air temperature and mixing behavior, which may contribute to the observed limitations in dynamic accuracy.

Results are influenced by data scope, HVAC assumptions, and aggregation.

Furthermore, the applied evaluation metrics were computed over aggregated four to five hour time windows, whereas the recommended threshold values are defined on an hourly basis. This temporal aggregation may smooth short-term deviations and should therefore be considered when interpreting the absolute error magnitudes.

4.2 Evaluation of User Experience in the DataFEE-App with Integrated Gamification

This section presents the validation of the DataFEE-App through a user test combining quantitative questionnaire data and qualitative user feedback. The evaluation focuses on user perception of system usefulness, reliability, and motivational impact, with particular attention to the gamification elements.

Validation is based on a post-test questionnaire consisting of Likert-scale items (Q1-1 to Q11-2) and open-ended questions. The Likert-scale items are grouped into conceptual categories (C1–C11), which correspond to the Green IS challenges introduced in subsection 2.2.2. Each category addresses a specific aspect of app usage, such as perceived usefulness, organizational compatibility, effort of use, reliability, motivation, and novelty. For most categories, two items are used: one positively framed item, where agreement indicates a positive evaluation, and one negatively framed item, where disagreement indicates a positive evaluation. Results are therefore analyzed separately for positively and negatively framed items to avoid ambiguity.
An overview of the individual Likert-scale items and their meanings is given below.

- C1: Perception as part of work
  - Q1-1: App is naturally integrated into the workflow
  - Q1-2: App feels more like additional work than support
- C2: Lack of personal need
  - Q2-1: App helps the user stay thermally comfortable
  - Q2-2: App makes managing thermal comfort more difficult
- C3: Organizational rules that impede adoption

  - Q3-1: Ability to use the app during working hours
- C4: Forgotten in everyday work
  - Q4-1: Badges help the user stay aware of the app
  - Q4-2: Leaderboards did not help the user stay aware of the app
- C5: Perception as unmotivating
  - Q5-1: Gamification elements increase motivation
  - Q5-2: App gives little sense of contributing to energy savings
- C6: Effort too high
  - Q6-1: Managing thermal comfort with the app feels stressful
  - Q6-2: Optional input fields reduce the effort of using the app
  - Q6-3: Number of different badge types feels overwhelming
  - Q6-4: Number of different leaderboard types feels overwhelming
- C7: Bugs in functionality
  - Q7-1: App worked reliably during the user test
- C8: Unfulfillability of tasks
  - Q8-1: User can use the app's recommendations to achieve thermal comfort
  - Q8-2: Maximum number of points (5 points) feels unrealistic to achieve
- C9: Conflict with work tasks
  - Q9-1: Using the app interferes with work tasks
  - Q9-2: Navigating the app distracts from work
- C10: Lack of long-term motivation
  - Q10-1: User expects to use the app regularly over the next year

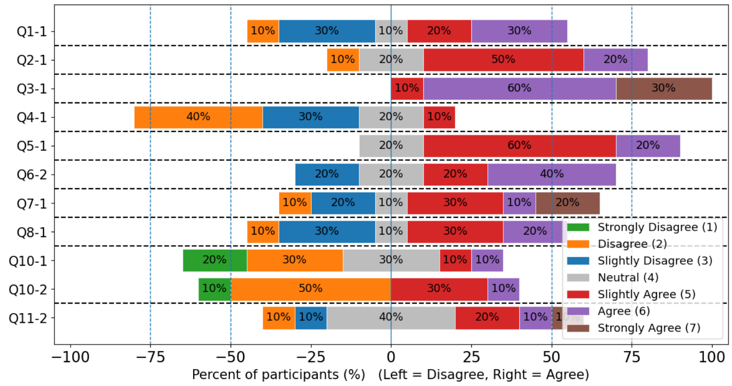
    - Q10-2: Leaderboards encourage continued use over the next year
- C11: Decrease in novelty
    - Q11-1: App offers too little variety over the next year
    - Q11-2: Easter Eggs make the app feel less repetitive

In addition to the overall response distributions, the questionnaire results are also examined with respect to room orientation, test date, and prior experience with the DataFEE-App. This analysis is used to explore whether user responses differ depending on these factors. The results are not intended to be statistically representative, but rather to identify general tendencies that may help interpret the evaluation results and support the discussion of strengths and limitations of the app.

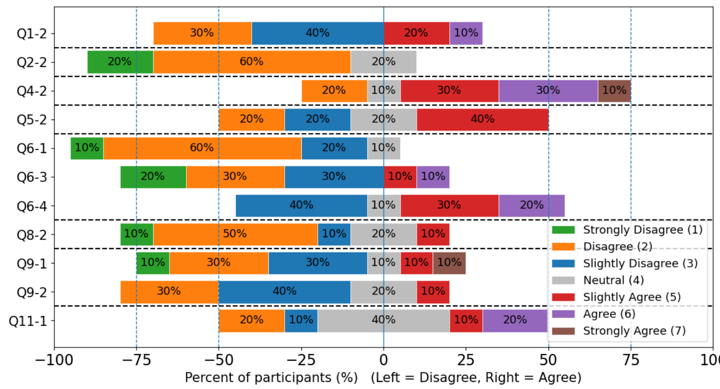
4.2.1 User Test Overview

Ten participants completed a questionnaire after the DataFEE-App user test.

The user test was conducted during the first week of December. Participants were free to choose their participation date, resulting in a total of ten users taking part between 03.12.2025 and 05.12.2025. The test was carried out in rooms with different orientations, including southeast, northwest, and southwest. Five participants had previously taken part in a user test of the DataFEE-App, while the remaining five were first-time users. This mixed background allows potential onboarding-related effects to be considered in later analyses, although responses are not separated by prior experience in this overview.
After completing the user test, all participants filled out the questionnaire listed in Tables 3.2-3.4. To reduce response bias, the questionnaire was designed with a balanced structure, consisting of both positively and negatively framed Likert-scale items. Approximately half of the items were phrased positively and half negatively. To ensure consistent interpretation, results are presented separately for positive and negative items, as agreement and disagreement represent opposite evaluations depending on item framing.



(a) Positively framed questionnaire items



(b) Negatively framed questionnaire items)

Figure 4.8: Overall response distributions for the questionnaire items

Agreement was observed for most categories in the positively framed items.

Figure 4.8a shows the distribution of responses for the positively framed questionnaire items. In the diverging Likert representation, the right side corresponds to agreement and the left side to disagreement, with neutral responses centered and contributing equally to both sides.
When neutral responses are distributed evenly, the majority of positively framed items show agreement levels between 50% and 75%. In particular, C2 (Lack of Personal Need), C3 (Organizational rules that impede adoption), and C5 (Perception as Unmotivating) display predominantly agreeing response patterns. Among these, C3 stands out as especially positively evaluated, with several participants select-

ing strong agreement, indicating that organizational constraints did not strongly limit app usage during working hours.
In contrast, lower agreement levels are observed in C10 (Lack of long-term motivation), suggesting more uncertainty regarding sustained use over an extended period. The most pronounced disagreement appears in Q4-1 (Forgotten in Everyday Work), where over 75% of responses fall on the disagreeing side. As this item relates to the badge system, this result indicates that badges did not substantially contribute to reminding users of the app's presence throughout the workday.
Neutral responses are present across several items but generally remain limited in proportion and do not dominate any category. As a result, most items show a clear tendency toward either agreement or disagreement.

Figure 4.8b presents the results for the negatively framed questionnaire items. For these items, disagreement represents a positive evaluation, as it indicates rejection of negative statements about the app.
Overall, users tended to disagree with most negatively framed statements. Strong disagreement appears in several categories, most notably C2 (Lack of Personal Need), C8 (Unfulfillability of tasks), and C9 (Conflict with Work Tasks). This suggests that users generally did not perceive the app as unnecessary, unrealistic in its task demands, or strongly conflicting with their daily work.
An exception within C9 is observed for item Q9-1, which concerns using the app to adjust thermal comfort. This item received a small number of agreeing responses, including one instance of strong agreement, indicating that for some users this aspect may interfere with work tasks. However, this result contrasts with the overall trend of disagreement within the category.
C6 (Effort Too High) shows generally favorable results, with multiple items receiving strong disagreement, suggesting that users did not perceive the app as overly demanding. However, the item related to difficulty tracking multiple leaderboards (Q6-4) received higher agreement than other items in the category, pointing to a more mixed perception of this specific feature.
More neutral response patterns are observed in C11 (De-

crease in novelty), indicating uncertainty regarding long-term variety and engagement. In contrast, C4 (Forgotten in Everyday Work) shows a strong tendency toward agreement among the negatively framed items, exceeding the 75% mark and including an instance of strong agreement. As the negatively framed item in this category relates to the leaderboards' ability to keep users aware of the app, this finding indicates that leaderboards were not perceived as an effective reminder during everyday work.

When considering responses at a broader category level, most categories lean toward positive user perception. Categories related to organizational constraints, personal need, and task feasibility show particularly favorable response distributions. In contrast, aspects related to long-term motivation, continued novelty, and awareness during everyday work exhibit more mixed or critical response patterns across multiple categories.

Items yielded overall positive evaluations.

These observed patterns provide a structured overview of the questionnaire results and serve as a foundation for further cross-sectional and comparative analyses in the following subchapters.

4.2.2 Qualitative Feedback from Open Questions

In addition to the Likert-scale questionnaire, participants provided open-ended feedback regarding their experience with the app. The responses were analyzed and grouped into recurring themes, which are summarized below.

Several participants highlighted positive aspects of the app's concept and interface. Users generally described the user interface as visually appealing and appreciated the dashboard layout, which was perceived as theoretically useful for monitoring indoor conditions. In particular, the overview of room temperature and the provision of feedback related to energy efficiency were mentioned as desirable features.

Response distributions for positively framed user remarks are summarized.

Participants also expressed interest in the possibility of controlling the thermal setpoint, noting that having direct influence over the thermal environment was appealing.

Additionally, gamification elements, including competition with colleagues, were viewed as motivating and socially engaging.
Several remarks emphasized that the app would be considered more interesting if measurement data were fully available and correctly displayed, and if users could clearly see the effects of their actions, such as changes in comfort or energy-related outcomes.

Response patterns for negatively framed user remarks are summarized.

Negative feedback primarily concerned issues related to system completeness, clarity, and functionality. Multiple users described the app as feeling incomplete, particularly due to missing or non-functional data. Some participants found parts of the user interface confusing, including interaction elements that were not clearly explained or behaved unexpectedly.
A recurring theme was the lack of integration with room temperature and thermostat controls, leading users to question why adjustments needed to be made both physically and through the app. This contributed to distrust in the app's recommendations.
A user commented on the onboarding process, noting that it felt fragmented and overly extensive, suggesting that a more concise introduction would be preferable. Another user mentioned that recommendations were sometimes impractical or insufficiently contextualized, such as suggestions to wear additional clothing without considering the user's current situation.
The presentation of data visualizations was also criticized. A participant reported difficulty understanding plotted information, particularly when values were missing or when visual elements such as dashed lines and reference zones were unclear or unexplained.
Finally, a user perceived the frequency of interaction prompts as overwhelming, especially when interpreted as requiring action at regular intervals. The fact that the application ran in a web browser rather than as a native app was also mentioned as a limitation, with users expressing a preference for a dedicated app-based solution.

4.2.3 Cross-Sectional Analysis of Questionnaire Results

Building on the overall questionnaire results, the following subsection examines whether user responses vary with respect to contextual and experiential factors that may influence the app's perceived performance. Responses are analyzed according to room orientation, date of participation, and prior experience with the DataFEE-App. These factors were selected to assess potential influences related to simulated environmental conditions, system stability over time, and onboarding or learning effects.

Room orientation minimally affected responses and reliability linked to engagement.

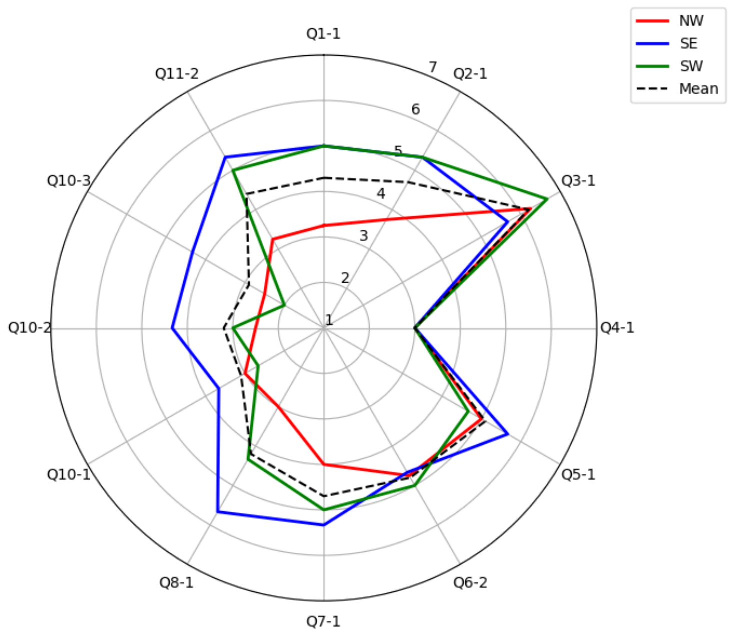
Of the ten participants, four were located in northwest-oriented offices, while three participants each worked in southeast- and southwest-oriented offices, resulting in a relatively balanced distribution across orientations. Figure 4.9 depicts the mean Likert-scale values for each questionnaire item, separated by room orientation (northwest, southeast, and southwest). The analysis aims to identify whether room orientation, which may have influenced the accuracy of the underlying simulation, is associated with differences in user responses.

Item Q7-1, which addresses whether the app worked reliably during the user test, provides an initial reference point. Users in southeast oriented rooms reported the highest mean values (between slightly agree and agree), followed by users in southwest-oriented rooms, who on average selected slightly agree. In contrast, users in northwest-oriented rooms reported a mean value corresponding to neutral. While this does not imply that the simulation model was more accurate for specific orientations, it provides an indication of perceived system reliability across different room contexts.

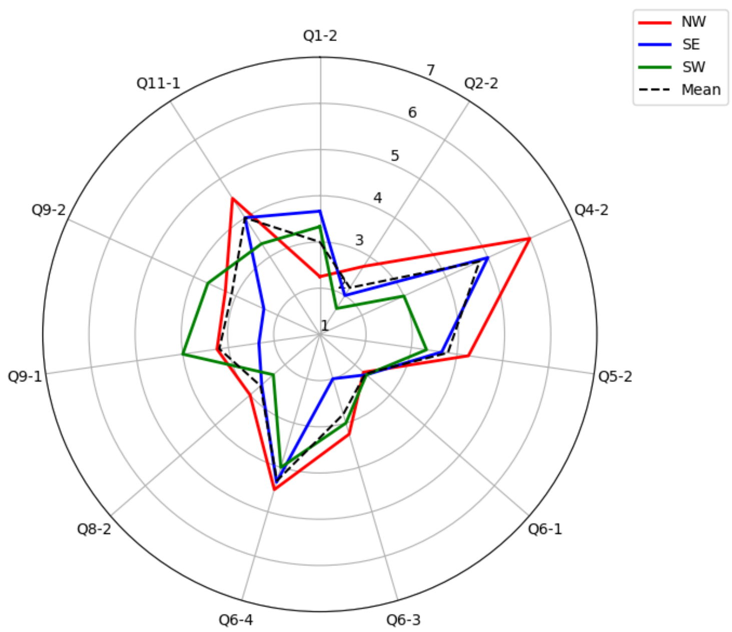
For several positively framed items, similar response tendencies can be observed across room orientations, particularly in categories related to overall system perception and long-term engagement. However, this pattern is not consistent across all categories. For C1 (Perception as Part of Work) and C11 (Decrease in Novelty), differences observed in the positively framed items are partially offset by the corresponding negatively framed items, resulting in a more balanced overall evaluation.

No comparable orientation-dependent tendency is visible in C3 (Organizational Rules that Impede Adoption), suggesting that organizational constraints were perceived independently of room orientation. Similarly, items related to gamification elements, including the items in category C4 (Forgotten in Everyday Work) and Q5-1 (Motivation through Gamification), do not exhibit a clear alignment with the perceived reliability of the app across orientations. This indicates that evaluations of gamification features were less influenced by perceived system performance.

In contrast, Q5-2, which addresses whether the app contributes to a sense of supporting energy efficiency, shows a tendency more closely aligned with perceived system reliability. Categories C6 (Effort Too High) and C9 (Conflict with Work Tasks) do not display consistent orientation-dependent patterns. C10 (Lack of Long-Term Motivation), however, shows a tendency similar to Q7-1 across room orientations, suggesting that perceptions of long-term engagement may be influenced by how reliably the system was experienced. Category C11 (Decrease in Novelty) shows a mixed pattern. While item Q11-1, which addresses the perceived variety of the app in general, follows a tendency similar to Q7-1, item Q11-2, which focuses specifically on Easter Eggs deviates from this pattern.



(a) Positively framed questionnaire items



(b) Negatively framed questionnaire items

Figure 4.9: Questionnaire response distributions separated by room orientation

Test date showed minor variation but no consistent technical bias.

To further investigate whether technical issues or malfunctions may have influenced the user study, the results were additionally analyzed according to the date on which the test was conducted. Out of the ten participants, four completed the study on 03.12, two on 04.12, and four on 05.12. Due to the small and unevenly distributed sample, particularly on 04.12, results from this date are considered less informative and are interpreted with caution. These results are depicted in Figure 4.10.

As an initial indicator for potential technical instability, item Q7-1 was examined, which assesses the perceived functionality and absence of bugs in the application. The mean value for participants on 03.12 lies between neutral (4) and slightly agree (5), while the mean for 05.12 is slightly above slightly agree (5). The difference between these two dates is smaller than the differences previously observed between room orientations. Notably, the mean value for Q7-1 on 03.12 aligns closely with the overall mean across all participants.

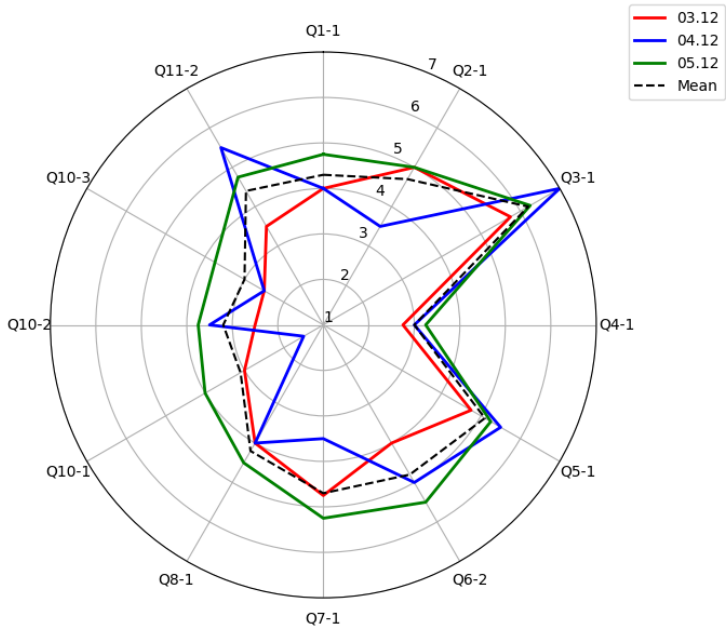
A similar alignment with the total mean was observed for most positively framed items on 03.12. In contrast, this tendency was less consistent for negatively framed items. For example, item Q1-2, which assesses whether the app feels more like work than a helpful utility, and item Q2-2, which addresses whether the app complicates thermal comfort management, showed slightly higher agreement than the overall average on 03.12.

For Category C4 (Forgotten in Everyday Work), both positively and negatively framed items exhibited consistent results across all test dates, including 05.12, which also closely approached the overall mean. A comparable pattern was observed for Category C3 (Organizational Rules that Impede Adoption) as well as items Q4-1 and Q4-2, which relate to the influence of badges and leaderboards on not forgetting the app during the workday.

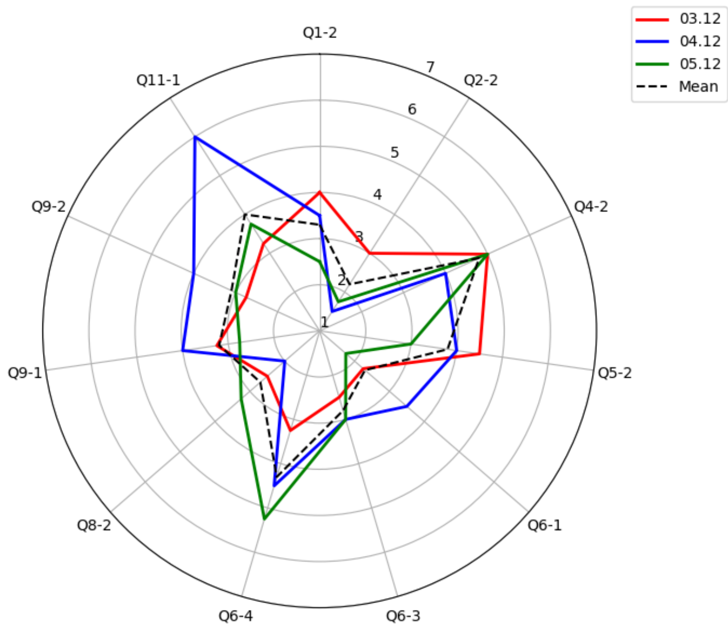
While participants on 05.12 reported slightly higher agreement in item Q5-2, indicating a stronger perceived contribution to energy savings, this observation follows the general tendency that lower perceived technical reliability in Q7-1 is accompanied by lower scores in early categories related to personal usefulness and perceived effort. However, this tendency was not observed for Category C6 (Effort of Use), Category C9 (Conflict with Work Tasks), or Category

C11 (Decrease in Novelty), which showed no systematic variation across test dates.

Overall, while minor variations between test dates can be observed, no consistent or substantial temporal bias attributable to technical issues was identified. Given the small sample size and uneven distribution of participants across dates, these findings are interpreted as indicative rather than conclusive.



(a) Positively framed questionnaire items

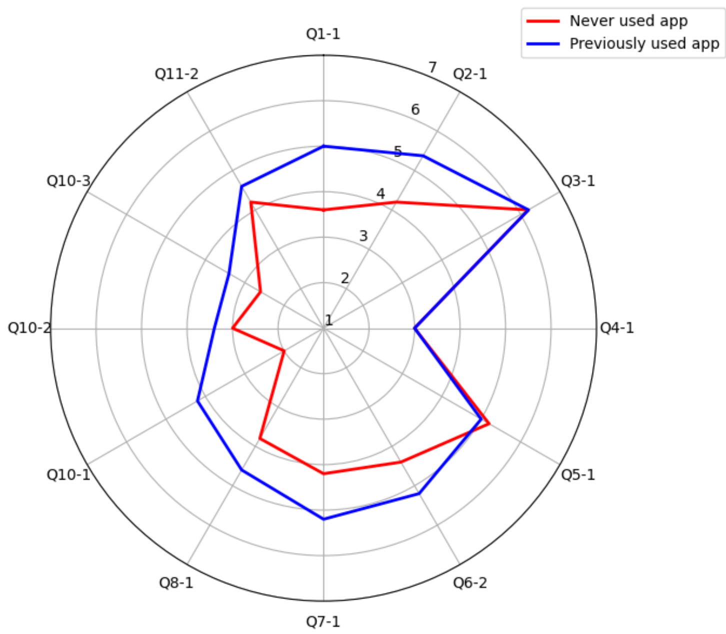


(b) Negatively framed questionnaire items)

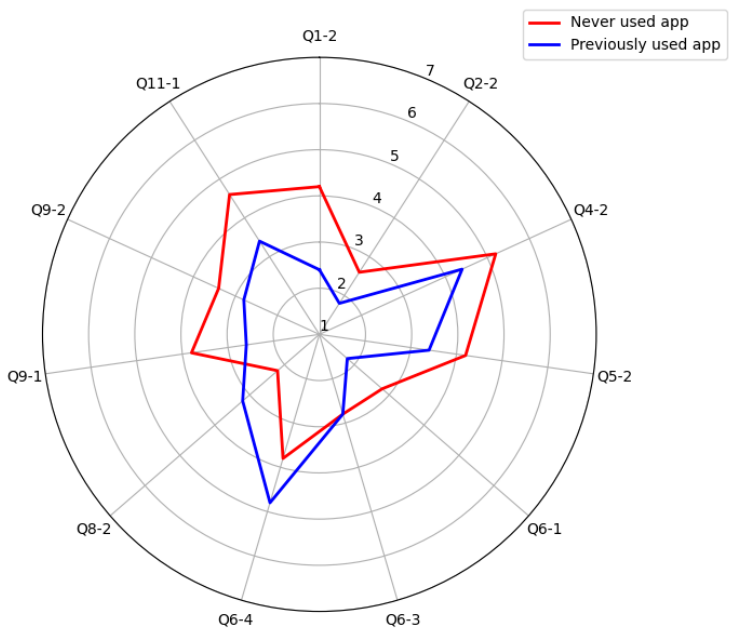
Figure 4.10: Questionnaire response distributions grouped by the date of the DataFEE-App user test

Prior app experience yielded more favorable responses than first-time use.

Finally, the analysis focuses on differences between users who had previously participated in a DataFEE-App user test and those who had not. Of the ten participants, five had prior experience with the app, while five were first-time users, resulting in an even distribution between the two groups.
Figure 4.11 illustrates the mean Likert-scale values separated by prior experience with the DataFEE-App. Subfigure 4.11a presents the positively framed items, while subfigure 4.11b shows the negatively framed items.
Across both subfigures, users with prior experience generally report more favorable responses than first-time users. For positively framed items, this is reflected in higher mean agreement values, while for negatively framed items, it is reflected in lower mean agreement values (i.e., stronger disagreement). This tendency is observable across multiple categories and appears more pronounced than differences observed when separating responses by room orientation.
Consistent with the orientation-based analysis, item Q3-1 (ability to use the app when needed during working hours) shows nearly identical mean values across both user groups, indicating that organizational constraints were perceived similarly by experienced and first-time users.
However, this tendency toward more favorable responses among experienced users is not uniform across all items. For Q4-1 (Forgotten in Everyday Work – badge system), prior experience does not appear to influence responses, whereas a difference is observed for the corresponding leaderboard-related item (Q4-2). A similar absence of this tendency is observed for items Q6-3 and Q6-4, which address whether the number of badges and leaderboards is perceived as overwhelming, as well as for Q8-2, which concerns the perceived realism of achieving the maximum number of daily points. These items either show comparable mean values across both groups or deviate from the general pattern.



(a) Positively framed questionnaire items



(b) Negatively framed questionnaire items)

Figure 4.11: Questionnaire response distributions separated by prior experience with the DataFEE-App

4.2.4 Discussion

This subsection discusses the findings of the evaluation in relation to the contributions of this thesis and their implications for the long-term applicability of the DataFEE-App. The discussion focuses on the introduction of a dynamic, simulation-based recommendation and point system and on the added gamification elements intended to support user motivation and engagement. The results are interpreted with respect to system completeness and user perception, while explicitly acknowledging the limitations of the conducted user study.

Users valued comfort benefits but perceived energy savings remained abstract.

The evaluation results indicate that users experienced the DataFEE-App as helpful in managing thermal comfort throughout the day. Participants reported that the app supported them in maintaining thermal comfort and in handling temperature-related adjustments more easily, even though the system was not fully complete at the time of the study. This finding is particularly relevant, as thermal comfort is directly perceptible and therefore immediately meaningful to users.
In contrast, user responses regarding perceived energy savings are predominantly neutral. This outcome can be interpreted as a consequence of the established recommendation logic. Since all suggested actions are designed to achieve thermal comfort, users experience similar comfort outcomes regardless of which option they select. Differences between options are reflected primarily in abstract energy-efficiency rankings rather than in perceptible comfort changes.
As a result, users benefit from improved comfort management but do not necessarily feel that they are actively saving energy. Energy-efficiency is optimized at the system level but remains largely abstract from a user perspective, which helps explain why comfort-related evaluations are positive while energy-saving awareness and motivation remain limited.

Gamification motivated users but reliability and familiarity drove stronger perceptions.

Cross-analyses of the questionnaire data indicate that evaluations of gamification elements do not show systematic dependencies on room orientation, date of participation,

or the specific test session. This suggests that motivation-related responses are largely independent of short-term contextual or environmental factors.
In contrast, prior experience with the app and perceived system reliability show consistent associations with more favorable evaluations across multiple categories. Users who perceived the app as working reliably, as well as those with prior exposure, tended to evaluate other aspects of the system more positively. This indicates that trust in system functionality and familiarity act as moderating factors for user perception, including motivation-related items.
The perceived incompleteness of the app during the user test therefore represents a critical limitation. While comfort-related outcomes were still perceived positively, missing sensor data and partially simulated feedback reduced users' confidence in the system as a whole and likely weakened trust in point allocation and rankings.

Gamification motivated initially but reliability issues limited trust and engagement.

At an aggregate level, the evaluation confirms that gamification elements are perceived as motivating. A dedicated questionnaire item assessing whether gamification increases motivation to use the app received overall positive agreement. This indicates that the integration of gamified mechanics contributes positively to users' initial willingness to engage with the DataFEE-App.
Furthermore, most gamification elements were not perceived as requiring excessive effort. With the exception of leaderboard-related aspects, users generally did not experience the gamification elements as burdensome or distracting. This suggests that the amount of gamification integrated into the app was largely appropriate and did not interfere with the app's primary function of supporting thermal comfort.
However, when individual gamification elements are examined separately, their effects on sustained engagement appear limited.

Badges and leaderboards did not remind users of the app daily.

In the category addressing whether the app is forgotten during everyday work, the results are unambiguous. Both badges and leaderboards fail to support habitual use. No clear positive tendencies are observed, and differences between elements are minimal.
This finding aligns with qualitative remarks in which users

stated that they would not use the app regularly in its current state. Habit formation appears to require not only motivational incentives but also a perception of system completeness, reliability, and relevance within everyday work processes.

A more differentiated picture emerges when considering long-term motivation. While neither badges nor leaderboards achieve clearly positive evaluations, leaderboards show more potential than badges in this regard. Badge-related items are predominantly evaluated negatively, followed by neutral responses, indicating that badges are often perceived as unhelpful rather than merely ineffective.
Leaderboard-related items, in contrast, exhibit fewer neutral responses and a wider distribution of ratings. This reduced neutrality suggests stronger user opinions and greater differentiation in how leaderboards are perceived. Some users appear to respond positively to competitive elements, while others react negatively, indicating selective appeal rather than uniform effectiveness.

Leaderboards showed selective long-term appeal while badges were largely ineffective.

Three types of badges were implemented: "Info Badges", which were obtained by providing optional user input to improve simulation accuracy; "Optimal Badges", which rewarded the selection of the most energy-efficient recommendation; and "Easter Eggs", which were unlocked through exploratory interaction with the app.
"Info" and "Optimal" badges follow a repetitive acquisition pattern, as the same badge is awarded after performing a given action a predefined number of times. This repetitiveness likely contributed to their predominantly negative or neutral evaluations with respect to long-term motivation. While these badges provide feedback and transparency, they appear to lack sufficient variety to sustain engagement over time.
Easter Eggs, in contrast, were less repetitive and were generally received more positively. Although responses regarding a decrease in novelty remain largely neutral, Easter Eggs appear to contribute more effectively to perceived variety and playfulness. Importantly, the number of badges was not perceived as overwhelming, suggesting that the quantity of badge elements was appropriate, but that their design requires greater diversity rather than reduction.

Badges motivated only when non repetitive as with Easter eggs.

Incomplete sensing reduced trust fairness perceptions and long-term motivation overall.

The limited effectiveness of gamification elements must be interpreted in the context of system completeness. Due to missing sensor data and partial Wizard-of-Oz implementation, users perceived the app as incomplete. In particular, the absence of expected data such as CO_2 concentration and relative humidity reduced system credibility and led to confusion regarding control actions. These limitations likely influenced perceptions of fairness and meaningfulness, particularly for competitive elements such as leaderboards, which depend on trust in the underlying system logic.
Importantly, these limitations appear to have affected trust and long-term motivation more strongly than immediate comfort outcomes, which were still perceived positively.

Single day participation limited insights into competition and long-term motivation.

Participation in the user study was intentionally limited to a single day per user. This design decision was made to increase the number of participants and to avoid potential frustration caused by the incomplete state of the system. As a result, users had limited opportunity to experience longer-term dynamics such as sustained competition, ranking changes, or progression over time.
While this does not affect the interpretation of short-term perception, usability, and acceptance, it restricts the extent to which conclusions can be drawn regarding the emergence of competitive behavior or long-term motivational effects. The study was therefore not designed to capture fully developed competitive dynamics, but rather to assess initial responses to the introduced system logic and gamification elements.

Chapter 5

Conclusion and Future Work

In this thesis, the DataFEE-App was extended from a conceptual prototype toward a more mature system that supports simulation-based decision support and the integration of gamification elements. These extensions represent an important step toward enabling future long-term field studies. The primary objective was to make long-term user tests possible by extending the app with gamification elements and simulation-based decision support.

The DataFEE-App was extended with a simulation-based decision support to enable gamification integration and show initial motivational effects.

During the course of this work, it became evident that meaningful gamification requires a credible and context-aware foundation. To address this, a dynamic recommendation and point system based on room temperature simulation was designed and implemented within the scope of this thesis. The simulation predicts room temperature development over the course of the day and enables the ranking of alternative actions according to their relative energy efficiency while ensuring thermal comfort.

Validation results show that the implemented simulation achieves reliable absolute temperature accuracy, with mean absolute error and root mean square error values largely within the recommended limits according to VDI-6020:2002 and CIBSE guidelines. Although the reproduction of short-term temperature dynamics, reflected by the squared Pearson correlation coefficient, is less accurate, the simulation quality is sufficient to support relative comparisons be-

tween alternatives. This capability is essential for establishing fair, transparent, and energy-aware rankings, and therefore represents a prerequisite for the effective use of gamification elements.
By treating thermal comfort as a baseline condition and energy efficiency as an optimization criterion, the introduced approach establishes a feedforward mechanism that allows users to anticipate the effects of their actions. The evaluation indicates that users perceived the app as supportive in managing thermal comfort throughout the day, even in its incomplete state. Gamification elements were generally not perceived as distracting and contributed positively to initial motivation, although their effectiveness for long-term engagement remains limited.
Overall, this thesis demonstrates that the combination of simulation-based decision support and carefully integrated gamification constitutes a substantial step toward enabling long-term field studies with the DataFEE-App. At the same time, the results indicate that further development is required before this goal can be fully realized.

Future work should integrate sensors, support multi-user interaction, refine simulation fidelity, and systematically evaluate gamification effects.

In future research, and building on the results of this thesis, several extensions are required to enable long-term field studies with the DataFEE-App. A key next step is the full integration of environmental sensors to replace the Wizard-of-Oz approach used in the present study. In particular, reliable measurements of indoor air quality parameters such as CO_2 concentration and relative humidity would increase system transparency, reduce user confusion, and strengthen trust in the app's recommendations and point allocation.
In the current implementation, only a single user per office was asked to operate the DataFEE-App during the user test. While this approach was sufficient for initial evaluation, it does not reflect typical office environments in which thermal comfort is shared among multiple occupants. With full sensor integration, the underlying heat balance model could be used to establish a common reference comfort zone for all occupants in a room. This would enable simultaneous interaction by multiple users and allow the system to account for shared comfort dynamics. Future evaluations should therefore investigate multi-user scenarios in real office spaces to assess how collective interaction in-

fluences comfort perception, motivation, and energy-aware behavior.

From a simulation perspective, further improvements can be achieved by refining the representation of HVAC system operation. In the current implementation, several simplifying assumptions were necessary due to limited access to system-specific data. A more detailed modeling of HVAC behavior has the potential to improve the reproduction of short-term temperature dynamics and thereby increase the squared Pearson correlation coefficient. At the same time, such refinements would reduce the transferability of the simulation framework to other buildings. Future work should therefore balance simulation fidelity against general applicability, depending on the intended deployment context of the app.

In addition, the evaluation metrics applied in this thesis are based on established VDI-6020:2002 and CIBSE guidelines, which are primarily defined for hourly assessments. Since the DataFEE-App operates on shorter decision horizons of several hours, future work could investigate whether these evaluation criteria should be adapted to better reflect medium-term prediction performance. This consideration is particularly relevant for the interpretation of dynamic accuracy metrics, where the simulation showed limitations despite adequate absolute temperature accuracy.

With respect to user motivation, future studies should place stronger emphasis on the systematic investigation of gamification effects across different user types. Established questionnaires for identifying Hexad user types could be applied prior to evaluation, allowing motivational mechanisms to be analyzed in a more differentiated manner. This would enable clearer conclusions regarding which elements are effective for specific user groups.

Based on the findings of this thesis, future iterations of the DataFEE-App could also refine the design of individual gamification elements. The number of leaderboards may be reduced to limit perceived complexity, while badge systems could be redesigned to emphasize variety rather than repetition. In particular, exploratory elements such as "Easter Eggs" showed more favorable reception and may be expanded to reduce perceived repetitiveness and support long-term engagement.

In addition, the evaluation revealed that remembering to

use the app during everyday work represents a weak point. Future work may therefore investigate the integration of reminder mechanisms, such as context-aware notifications, to support continued engagement throughout the day. While such mechanisms could improve habit formation, they also introduce the risk of increased intrusiveness. Consequently, reminder and notification features should be designed cautiously to avoid overwhelming users or reducing acceptance of the app.
Overall, these extensions would contribute to improving system completeness, credibility, and motivational effectiveness. Together, they represent necessary steps toward realizing the goal of enabling long-term field studies of the DataFEE-App.

Bibliography

[1] Energy performance of buildings – Ventilation for buildings – Part 7: Calculation methods for the determination of air flow rates in buildings including infiltration (Modules M55). DIN EN16798-7, 2017. Brussels, Belgium.

[2] ashrae62.1-2022. ANSI/ASHRAE Standard 62.1-2022: Ventilation and Acceptable Indoor Air Quality. Standard, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta, United States, 2022.

[3] Philip Ball. Computer engineering: Feeling the heat. *Nature*, Vol. 492(174), December 2012. doi.org/10.1038/492174a.

[4] N.K. Bansal, G. Hauser, and G. Minke. *Passive Building Design : A Handbook of Natural Climatic Control*. Elsevier Science B.V, 1994.

[5] Richard Bartle. Hearts, clubs, diamonds, spades: Players who suit MUDs. In *Journal of MUD REsearch*, number 1, 1996.

[6] Laura Battistel, Andrea Vilardi, Massimiliano Zampini, and Riccardo Parin. An investigation on humans' sensitivity to environmental temperature . *Scientific Reports*, Vol. 13(21353), December 2023. doi.org/10.1038/s41598-023-47880-5.

[7] Roy F. Baumeister, Kathleen D. Vohs, and David C. Funder. Psychology as the Science of Self-Reports and Finger Movements: Whatever Happened to Actual Behavior? *Perspectives on Psychological Science*, Vol. 2(4), December 2007. doi.org/10.1111/j.1745-6916.2007.00051.

[8] Niels Ole Bernsen, Hans Dybkjær, and Laila Dybkjær. Wizard of Oz Prototyping: When and How? 1993.

[9] Center for Sustainable Systems, University of Michigan. Information Technology Factsheet. Pub. No. CSS09-07, 2024. https://css.umich.edu/publications/factsheets/information-technology-factsheet.

[10] CIBSE. The Chartered Institution of Building Services Engineers, Requirements to be met by calculation methods for the simulation of thermal-energy

efficiency of buildings and building installation. Standard, The Chartered Institution of Building Services Engineers, London, United Kingdom, 2020.

[11] Andrea Conserva, Gema Millán, Juan Aranda Usón, Alfonso Alcalde, María Herrando, and Ignacio Zabalza. Selection and assessment of a set of 250 energy efficiency measures integrated in a serious game to promote citizens' behaviour change towards energy efficiency in buildings. In *further adjust citation*, MobileHCI '23 Companion, New York, NY, USA, October 2017. Association for Computing Machinery. `doi.org/10.1145/3565066.3608695`.

[12] Edward L. Deci. Effects of externally mediated rewards on intrinsic motivation. *Journal of Personality and Social Psychology*, Vol. 18(1), April 1971. `doi.org/10.1037/h0030644`.

[13] Louis-Benoit Desroches, Heidi Fuchs, Jeffery B Greenblatt, Stacy Pratt, Henry Willem, Erin Claybaugh, Bereket Beraki, Mythri Nagaraju, Sarah K. Price, and Scott J. Young. Computer usage and national energy consumption: Results from a field-metering study. Technical report, Lawrence Berkeley National Laboratory, 2014. URL `https://example.com/report-url`.

[14] Sebastian Deterding and Rilla Khaled. Gamification: Toward a Definition. In *Conference: CHI 2011 Gamification Workshop Proceedings*, 2011.

[15] DIN EN ISO 7730. Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria . Standard, International Organization for Standardization, Geneva, Switzerland, 2005.

[16] Jeanine Kirchner-Krath, Benedikt Morschheuser, Nevena Sicevic, Nannan Xi, F.O. arald von Korflesch, and Juho J. Hamari. Challenges in the adoption of sustainability information systems: A study on green IS in organizations. *International Journal of Information Management*, Vol. 77, August 2024.

[17] Dimosthenis Kotsopoulos, Cleopatra Bardaki, Stavros Lounis, and Katerina Pramatari. Employee Profiles and Preferences towards IoT-enabled Gamification for Energy Conservation. *International Journal of Serious Games*, Vol. 5(2), June 2018.

[18] Weihao Liu, H. Burak Gunay, and Mohamed M. Ouf. Modeling window and thermostat use behavior to inform sequences of operation in mixed-mode ventilation buildings. *Science and Technology for the Built Environment*, Vol. 27(1), January 2021. `doi.org/10.1080/23744731.2021.1936629`.

[19] Andrzej Marczewski. *The Gamification Design Handbook: Even Ninja Monkeys Like to Play*. Gamified UK, 2023.

[20] Lennart E. Nacke, Chris Bateman, and Regan L. Mandryk. BrainHex: A neurobiological gamer typology survey. *Entertainment Computing*, Vol. 5(1), January 2014.

[21] Jakob Nielsen. *Usability Engineering*. Morgan Kaufmann, 1993.

[22] Felix Nienaber, Alexander Kümpel, Kai Rewitz, and Dirk Müller. Implementation of a User Feedback System and its Impact on User Satisfaction and Energy Demand. In *Proceedings of the 25th International Conference on Mobile Human-Computer Interaction*, MobileHCI '23 Companion, New York, NY, USA, September 2020. Association for Computing Machinery. `doi.org/10.1145/3565066.3608695`.

[23] Simplice Igor Noubissie Tientcheu, Shyama P. Chowdhury, and Thomas O. Olwal. Intelligent Energy Management Strategy for Automated Office Buildings. *Energies*, Vol. 12(22), November 2019. `doi.org/10.3390/en12224326`.

[24] José Eduardo Pachano and Carlos Fernández Bandera. Multi-step building energy model calibration process based on measured data. *Energy and Buildings*, Vol. 252(1), December 2021. `doi.org/10.1016/j.enbuild.2021.111380`.

[25] Sungjin Park and Sangkyun Kim. A Badge Design Framework for a Gamified Learning Environment: Cases Analysis and Literature Review for Badge Design. *JMIR SERIOUS GAMES*, Vol. 7(2), April 2019. `doi.org/10.2196/14342`.

[26] Sungjin Park and Sangkyun Kim. Leaderboard Design Principles to Enhance Learning and Motivation in a Gamified Educational Environment: Development Study. *JMIR SERIOUS GAMES*, Vol. 9(2), April 2021. `doi.org/10.2196/14746`.

[27] Sungjin Park and Sangkyun Kim. Points and the Delivery of Gameful Experiences in a Gamified Environment: Framework Development and Case Analysis. *JMIR SERIOUS GAMES*, Vol. 10(3), September 2022. `doi.org/10.2196/35907`.

[28] H. Rietchel and Klaus Fitzner. *A Pattern Approach to Interaction Design*. Springer Berlin, Heidelberg, 2008.

[29] Samuel C. Sugarman. *HVAC Fundamentals 3rd Edition*. River Publishers, 2020.

[30] Hamed Taherdoost. Testing the Stability of an Acquiescence Style Factor Behind Two Interrelated Substantive Variables in a Panel Design. *Sociological Methods Research*, Vol. 36(4), May 2008. `doi.org/10.1177/0049124107313901`.

[31] Hamed Taherdoost. What Is the Best Response Scale for Survey and Questionnaire Design; Review of Different Lengths of Rating Scale / Attitude Scale / Likert Scale. *International Journal of Academic Research in Management*, Vol. 8(1), March 2019.

[32] Giacomo Tognon, Marco Marigo, Michele De Carli, and Angelo Zarrella. Mechanical, natural and hybrid ventilation systems in different building types: Energy and indoor air quality analysis. *Journal of Building Engineering*, Vol. 76 (None), October 2023. `doi.org/10.1016/j.jobe.2023.107060`.

[33] Ana Carolina Tomé Klock, Isabela Gasparini, Marcelo Soares Pimenta, and Juho Hamari. Tailored gamification: A review of literature. *International Journal of Human-Computer Studies*, Vol. 144(None), December 2020.

[34] Gustavo F. Tondello, Rina R. Wehbe, Lisa Diamond, Marc Busch, Andrzej Marczewski, and Lennart E. Nacke. The Gamification User Types Hexad Scale. In *CHI PLAY '16: Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play*, pages 229 – 243, New York, NY, USA, October 2016. Association for Computing Machinery.

[35] Jenny Ann Toribio, Simon John More, and Basito S. Cotiw-an. Problems translating a questionnaire in a cross-cultural setting. *Preventive Veterinary Medicine*, Vol. 41(2-3), July 1999. `doi.org/10.1016/S0167-5877(99)00041-0`.

[36] Eziama Ubachukwu, Jana Pick, Lea Riebesel, Paul Lieberenz, Philipp Althaus, André Xhonneux, and Dirk Müller. User engagement for thermal energy-efficient behavior in office buildings using dashboards and gamification. *Applied Thermal Engineering*, Vol. 266, May 2025.

[37] VDI-6020:2002. VDI-Fachbereich Technische Gebäudeausrüstung, Requirements to be met by calculation methods for the simulation of thermal-energy efficiency of buildings and building installations. Standard, Verlag des Vereins Deutscher Ingenieure, Düsseldorf, Germany, 2000.

[38] Liping Wang and Steve Greenberg. Window operation and impacts on building energy consumption. *Energy and Buildings*, Vol. 92(None), April 2015. `doi.org/10.1016/j.enbuild.2015.01.060`.

[39] Tianchi Wang, Zhang Xin, Xingyu Ma, Suqi Wang, Divine Senanu Ametefe, Dah John, and Tumani Darboe. Gamification as a catalyst for energy efficiency in buildings: Behavioural design, engagement dynamics, and implementation pathways. *Results in Engineering*, Vol. 27, September 2025.

[40] Zhang Yan, Xuemei Bai, Franklin P. Mills, and John C.V. Pezzey. Rethinking the role of occupant behavior in building energy performance: A review. *Energy and Buildings*, Vol. 172, August 2018. `doi.org/10.1016/j.enbuild.2018.05.017`.

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