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Abstract

Thermal comfort, measured through satisfaction with the thermal environment, has significant effect on the occupants' physiological and psychological well-being, productivity, and health. Due to the variability in occupant activities, clothing, health, and other human factors, the subjective measure of thermal satisfaction of individual occupants reveals conflicts in temperature preferences and control decisions. In most commercial spaces, temperature control systems operate on predefined temperature setpoints or rule-based control strategies. These strategies regulate thermal zones that typically serve many occupants and thus cannot consider the individual occupant. As a result, temperature control systems in use today fail to deliver transparent or comprehensive decisions, resulting in high dissatisfaction rates among occupants. Recent research suggests that personalized comfort models operating in micro-zones can provide high thermal satisfaction levels for individuals, albeit with rare application in commercial buildings.

This dissertation introduces TREATI (Tool for Rationale management with Event-based Arbitration of Thermal comfort In shared spaces). This rationale human-in-the-loop temperature decision-making tool is critical for achieving high levels of occupant comfort in shared spaces with dynamic occupancy. The TREATI framework targets thermal conflict resolution using decision management techniques while considering both individual and group thermal satisfaction, fairness, effort, and energy efficiency outcomes. TREATI was validated using an object-event simulation to test non-trivial configurations of human and environmental factors. The decisions were compared against two traditional baseline controls and revealed that TREATI produces higher occupant satisfaction, greater fairness, and lower energy demand than these baselines.

Zusammenfassung

Zufriedenheit mit der thermischen Umgebung hat erhebliche Auswirkungen auf das physiologische und psychologische Wohlbefinden, die Produktivität und die Gesundheit von Menschen. Aufgrund ihrer subjektiven Natur kann die thermische Zufriedenheit von einzelnen Menschen zu Konflikten bei Entscheidungen über die Temperaturregelung führen. In den meisten gewerblich genutzten Räumen arbeiten Temperaturregelungssysteme mit vordefinierten Temperatursollwerten oder regelbasierten Regelungsstrategien, um thermische Zonen zu regulieren, die viele Nutzer versorgen, und können daher den einzelnen Nutzer nicht berücksichtigen. Infolgedessen liefern die heutigen Temperaturregelungssysteme keine transparenten oder umfassenden Entscheidungen, was zu einer hohen Unzufriedenheit unter den Nutzern führt. Neuere Forschungsergebnisse legen nahe, dass personalisierte Komfortmodelle, die in Mikrozonen arbeiten, hohe thermische Zufriedenheitsraten für Einzelpersonen liefern, die in kommerziellen Gebäuden nur selten Anwendung finden.

Diese Dissertation stellt TREATI vor, ein Werkzeug für rationale Human-in-the-Loop-Temperaturentscheidungen in gemeinsam genutzten Räumen mit dynamischer Belegung. Das TREATI-Framework wurde entwickelt, um thermische Konflikte mit Hilfe von Techniken aus dem Entscheidungsmanagement zu lösen und dabei sowohl individuelle als auch gruppenspezifische thermische Zufriedenheit, Fairness, Aufwand und Energieeffizienz zu berücksichtigen. TREATI wurde mit Hilfe einer Objekt-Ereignis-Simulation validiert, bei der nicht-triviale Konfigurationen von menschlichen und Umweltfaktoren getestet wurden. Die Entscheidungen wurden mit zwei traditionellen Basissteuerungsstrategien verglichen. Die empirische Validierung hat gezeigt, dass TREATI eine höhere Zufriedenheit der Bewohner, größere Fairness und einen geringeren Energiebedarf als diese Basisstrategien erzeugt.

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Contents

Conventions

This dissertation uses American English, except for literal quotations. Inline citations are accentuated using “double quotes”, whereby changes that direct citations are marked [within brackets].

Text in *italic* font and text in ‘single quotation marks’ emphasize key terms. Essential aspects are emphasized using **bold** font. Technical terms (e.g., Static control) are capitalized. Components of the framework (e.g., `Evaluator`, `IEQ`), as well as elements of models and figures, are written in upper camel case and `teletype` font.

Temperatures are given in degrees Celsus °C, except for literal quotations.

In model descriptions, 1-to-many multiplicities (`1..*`) may be described in singular, e.g., `Issue` instead of `Issue(s)`. If no multiplicity is explicitly stated, the default of `1` is assumed. Abstract classes, attributes, and methods are written in *italic* font.

To indicate important aspects, colored boxes present definitions, observations, and research goals:

Definition 0.1 – Short Title <<*description*>>

Observation 0.1 – <<*description*>>

Research Goal 0.1 – Short Title. <<*description*>>

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Chapter 1
Introduction

> A human must turn information into intelligence or knowledge. We've tended to forget that no computer will ever ask a new question.
>
> — Grace Hopper

In November 2021, the United Nations Environment Programme published guidelines to address sustainable cooling in response to warming in cities.[1] Due to the global rise in temperature and the 'heat island effect'[2], cooling demand and cooling energy costs continue to increase. These demands pose new challenges for building management systems to simultaneously accommodate energy efficiency, occupant satisfaction, and building constraints [Wan+18; Ene17].

In developed countries, humans spend 80-90 % of their time indoors [Kle+01]. It is well known that both outdoor and indoor environmental quality significantly influence

[1] United Nations Environment Programme. November 3, 2021. Beating the Heat: A Sustainable Cooling Handbook for Cities.

[2] Heat islands occur in urbanized areas where urban structures, such as buildings, absorb and re-emit the sun's heat in a larger capacity than natural landscapes. This leads to rising temperatures in buildings, which are compensated by overcooling the respective spaces. In turn, the resulting increase in energy use contributes to global warming, leading to a predicamental causal loop.

our health, productivity, and overall well-being [Fis02]. Many studies have emphasized the importance of improving indoor environmental quality (IEQ) in buildings [Kim+13; KDD12; Mit+07; AZLH06; Fis02]. There are several indicators for determining IEQ; the most commonly applied are: Acoustic quality, air quality, visual quality, and thermal comfort [FW11]. Humans are good sensors for indoor environmental quality [Par15]. However, some individuals can be more sensitive to specific indicators than others. For instance, some humans suffer from nasal congestion whenever their workplace's air temperature drops below a temperature threshold or drafts increase, while others do not experience any discomfort.
Some indicators are easier to measure through mechanical sensors, such as CO or CO_2, which are colorless, odorless, and thus not detectable by humans [Who, p. 10]. Other indicators depend on occupants' perceptions, such as thermal comfort [Par15]. A wide body of literature addresses the optimization of building responses to the quantitative indicators of air quality, thermal quality, visual quality, and also energy efficiency. Common approaches include building system automatic responses or introducing (some level of) occupant-centric control. For example, operable windows could be automated or user-controlled to improve ventilation and air flow. User-controlled task lighting allows occupants to establish their desired brightness for a specific task [Lof+09]. Acoustic quality is situation- and workplace-dependent and often difficult to control, e.g., construction site sounds near a building cannot be muted. In buildings where energy efficiency is monitored, many environmental controls have the additional goal of reducing plug load and saving energy sustainably [PLOP08].

The focus of this dissertation is on thermal comfort. Thermal comfort is a subjective condition influenced by factors such as air temperature, radiant temperature, relative humidity, and air flow conditions, as well as the occupant's activity, clothing [Ame20; Fan70], and other situational and contextual factors [Ene17; DB98]. As a result, thermal comfort is highly individual and requires frequent occupant feedback to maintain high occupant satisfaction levels. Several standards exist that are dedicated to delivering thermal comfort, evaluated by the percentage of satisfied occupants. The most recognized standards for thermal comfort are ASHRAE 55 in the USA [Ame20] and ISO 7730 in Europe [Int05]. These standards propose to maintain target air temperatures but also to include feedback scales, such as thermal sensation or thermal satisfaction, to provide an average of occupant perceptions. However, developed in controlled laboratory conditions, these standards may not be accurate for the variety of occupants and spatial changes in a building. In the field, occupant satisfaction is often assessed by measuring individual perceptions using thermal sensation and preference scales. These individual perceptions not only depend on the external climate and indoor environmental conditions, such as air quality, but on a multitude of human factors, including metabolism, clothing insulation, activity [Fan70], skin temperature [Cho10], or gender-based differences [Cha+18].

Interaction among occupants and available control options also influence thermal comfort. Often, buildings are controlled through a centralized building management system (BMS) and divided into large mechanical zones that have a single sensor and control point: a single thermostat controlling a damper. Such zones can contain from one to as many as 200 occupants [Par15], providing them with uniform thermal conditions, even though there may be significant differences in occupant density, occupant locations relative to windows, or air diffusers. Centralized BMS also apply temperature setpoints to anticipate a fully occupied environment. In summer, buildings are typically pre-cooled in the morning to prepare for occupant arrival and higher afternoon temperatures. These low-temperature setpoints in the mornings, and assumptions of business attire even in summer, lead to high levels of dissatisfied occupants [MG10]. Even in spaces where occupants have more control options to influence their thermal environment, conflicts among occupants about desired temperatures occur frequently. This phenomenon is commonly referred to as the 'battle of the thermostat'[3] or 'thermostat war'[4].

In the 1960s and '70s, Povl Ole Fanger introduced the Predicted Mean Vote (PMV) model, which uses environmental and human factors to estimate the average thermal sensation of a group of occupants [Fan70]. Thermal sensation is a measure of thermal comfort that describes how an occupant experiences the thermal environment. It is commonly measured using a 7-point feedback scale, as illustrated in Figure 2.8. The ASHRAE 55 standard uses the PMV model to establish the requirements for indoor thermal conditions, mandating that a minimum of 80% occupants should be satisfied [Ame20]. While the PMV model works well in static environments with large groups of occupants, it has drawbacks for spaces with dynamic occupancy and cannot address the comfort needs of individual occupants.

In recent years, multiple efforts have shifted the focus to personalized thermal comfort controls [ACM22; FRBL20; KSB18; ASR15]. Personalized controls aim to provide each occupant with personal control devices, i.e., task conditioning options, allowing them to adjust their thermal environment or have it automatically controlled based

[3]Veronique Greenwood. May 22, 2019. 'Battle of the Thermostat': Cold Rooms May Hurt Women's Productivity. *The New York Times*. `https://www.nytimes.com/2019/05/22/health/women-temperature-tests.html`

[4]Sandee LaMotte. November 13, 2019. Who's winning the thermostat wars in your home? *Cable News Network*. `https://edition.cnn.com/2019/11/13/health/thermostat-wars-wellness`

on their learned individual feedback and control behavior. These solutions are typically designed for well-equipped spaces with access to the required sensors and control options. However, even personalized solutions for centralized controls do not reflect conflicting demands when multiple occupants are involved. Behavioral adjustments require not only the acceptance of occupants for applying control options but also the system's knowledge of available control options to generate more accurate comfort temperature ranges. These challenges are addressed in TREATI (Tool for Rationale management with Event-based Arbitration of Thermal comfort In shared spaces).

1.1 The Battle of Control

Thermal comfort is a mutual goal for both occupants and facility management. However, the size of the mechanical zone, which is intended to deliver occupant comfort without task control options, and the differences in individual occupants' preferences make it difficult to achieve 80% occupant satisfaction with the thermal environment [DB98]. Facility managers often select 'safe' temperatures that achieve the least complaints, and high-ranking or senior office members often exploit their status to enforce their own thermal preferences – despite the fact that it is an intrinsic goal of employers to create a comfortable indoor environment to maintain productivity, health, and satisfaction levels for their employees. In many offices, controls are not physically accessible to occupants [Par15]. Even when accessible, the different preferences can lead to temperature control conflicts among occupants [Fra21; HAZA06]. Conflicts between occupants are often neglected, and energy efficiency implications can further confound the 'battle for control' of the thermostat: The design of building management systems leads to conflicts between optimizing energy demands and achieving high occupant comfort [PN18].

Due to the subjectivity of thermal comfort, achieving 80% or more occupant satisfaction regarding the thermal environment is challenging if personal control options are limited [KSA18; Luo+18; DB98]. Commercially-used approaches to estimate and regulate thermal comfort include the PMV model [Fan70], adaptive models [DB98], or applying temperature setpoints derived from standards, such as ASHRAE 55 [Ame20] or ISO 7730 [Int05]. However, such standards are configured for the average commercial building, not taking into account the specific characteristics that constitute individual buildings, such as the building envelope, location, mechanical zone size and location of the thermostat, or changing climate conditions [Cho10; Fan73].

Over the last decade, research focus on personalized comfort has grown to include each occupant's individual preferences, which can be managed through personal control systems [Luo+18; KSB18]. Francis and Quintana et al. [Fra+19] and Choi et al. [CY17] use data-driven models to target shared spaces with frequently changing occupancy, such as lecture halls or conference rooms. However, data-driven approaches require extensive data collection periods to generate models for each occupant that allow for personalized control [KSB18; Zha19]. Seasonal changes in climate and clothing require a re-training of these models. In addition, the collection of the required personalized comfort data may intrude on occupant privacy, primarily through the collection of bio-signals such as skin temperature [CY17], heart rate [CLL12], or the assessment of human emotions [Ko+20]. Shared preferences among occupants and resulting equal actions cannot be accommodated by personalized comfort models.

In summary, the main issues in thermal control are as follows:

Issue 1: Centralized thermal control does not take task control into account.

Issue 2: The control decision is often the responsibility of a single person; other occupants' preferences are ignored.

Issue 3: If the control system's focus is on the group, occupant feedback is averaged, which can increase dissatisfaction.

Issue 4: If the control system's focus is on the individual, the interaction within the group of occupants sharing a zone is not considered.

This dissertation contends that appropriate control actions must be determined by individual occupant preferences and feedback regarding the thermal environment, aggregated into a collective served by each zone. Using conflict management techniques, a continuous and well-established feedback approach is necessary to decide on appropriate control actions – regardless of the type of control.

1.2 Hypotheses

Existing efforts aimed at addressing thermal comfort conflicts often: fail to engage the occupants of the space; omit the individual occupant in the decision-making process; are not applicable in real-world scenarios; or only support one solution for all types of thermal conflicts.

This dissertation integrates rationale management and negotiation techniques into the thermal comfort decision-making process, keeping the individual occupant in the loop. The following hypotheses were investigated in this research:

> **Hypothesis 1 – Rationale Management Solves Thermal Conflicts**
> A computational rationale management approach that supports collective decision-making techniques will resolve thermal conflicts in shared spaces with higher levels of thermal satisfaction and higher levels of energy savings compared to conventional thermal control.

> **Hypothesis 2 – Rationale Management Ensures Occupant Involvement**
> Engaging the individual occupant in thermal control decision-making processes and continuously integrating the individual occupant's thermal preferences provides a higher level of thermal satisfaction through all seasons and spatial changes.

Chapter 3 verifies Hypothesis 1 through the design of a conceptual framework. Chapter 4 validates Hypothesis 1 using a simulation of several high-stress situations to address thermal comfort conflicts. Hypothesis 2 is verified through a literature review in Chapter 2 and validated by a simulation of a closed-loop scenario with different configurations of occupant behavior in Chapter 4.

1.3 Research Process

The main goal of this dissertation is to develop a human-in-the-loop thermal control decision-making framework for shared spaces, entitled TREATI (Tool for Rationale management with Event-based Arbitration of Thermal comfort In shared spaces). The development follows a formative mixed-methods research approach to verify and validate the TREATI framework. This process is based on the information systems research process by Nunamaker et al. [NJCP90] and Hevner et al.'s design science research framework [HMPR+04]. In addition, March and Smith have extended this process with the following artifacts [Win08; MS95]: *Construct*, i.e., a metamodel; *models*, such as process models and architectural models; and *methods*, including a simulation that validates the system. The overall research process followed in this dissertation is presented in Figure 1.1.

An ontological approach is used to extract concepts and terminology regarding the problem domain. With regard to the goals and hypotheses from the theoretical foundation, a conceptual framework is constructed that results in the TREATI metamodel. The conceptual framework and the metamodel are the basis for the system development activity. This is followed by observation and experimentation activities that validate TREATI through iterative simulations of the resolution of thermal conflicts.

Figure 1.2 shows the validation activity as a homomorphism. The main compo-

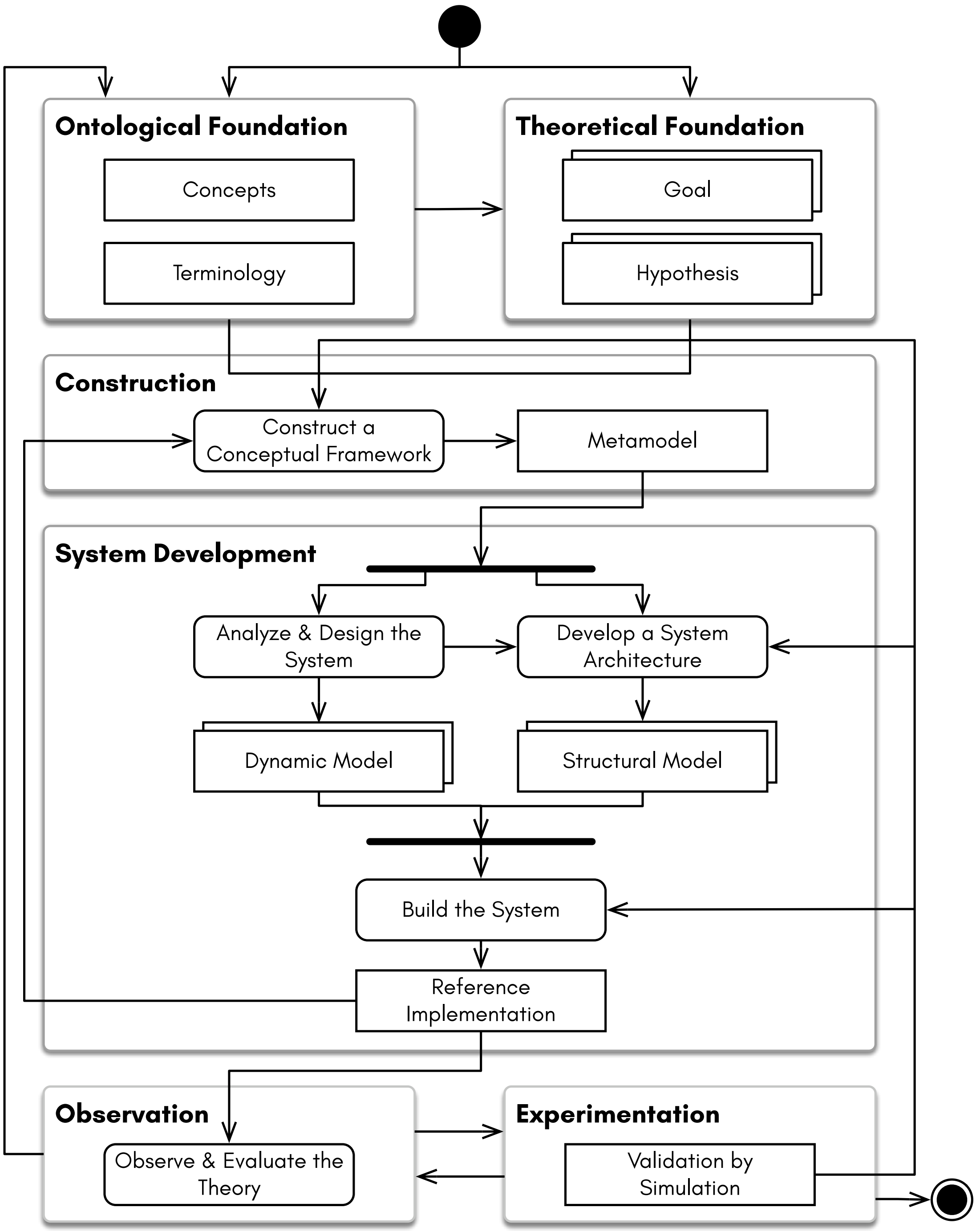


Figure 1.1: **Research Process** of the dissertation (based on [HMPR+04; MS95; NJCP90])

nents are the `Environment`, which represents the occupied thermal environment and is described in Chapter 2, the `TREATI` framework that is derived in Chapter 3, and the `Simulation Model` detailed in Chapter 4. `TREATI` is modeled based on an object-oriented approach, consisting of a `Metamodel` and `Dynamic` and `Structural` models. The `Simulation Model` models the dynamic behavior of the `Environment` derived

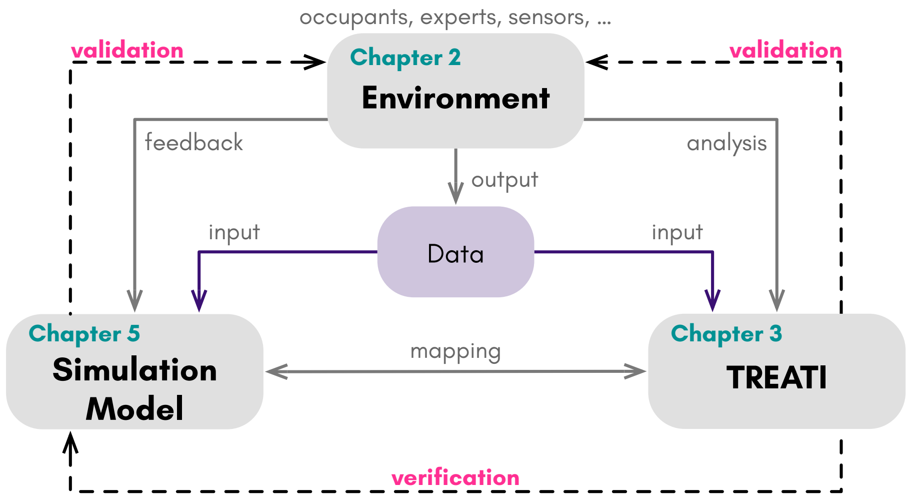


Figure 1.2: **Validation Model** – The `Simulation Model` uses the real-world environmental data to test scenarios and identify errors. These are then rectified in TREATI and are reconciled with the simulation model. The validation model is based on the work from Robert G. Sargent [Sar99] and Donald A. Norman and Stephen W. Draper [ND86]

from literature, anecdotal evidence, models, and real-world observations. It is synchronized with `TREATI` to verify the dynamic and structural models of the framework. It uses data from the `Environment` to identify mismatches between `TREATI` and the `Simulation Model`. These mismatches are then rectified in an incremental and iterative process leading to either a new version of the `Simulation Model` or of `TREATI`. The goal is to keep `TREATI` and the `Simulation Model` synchronized. Validating `TREATI` against an actual occupied `Environment` was not feasible in the scope of this dissertation, due to COVID-19 restrictions.

1.4 Research Scope

The design of the TREATI framework is situated at the junction of software architecture and building architecture. The addressed topics focus on the domains of rationale management on the software side and indoor environmental quality on the architecture side, with regard to thermal comfort conflicts specifically. The goal is to develop a tool to allow the semi-automatized decision-management of thermal comfort conflicts in shared spaces. The central objective is the combination of environmental and human feedback loops.

TREATI mainly focuses on thermal comfort and on aspects of indoor air quality, as both IEQ indicators are closely coupled. TREATI is designed to be extensible to other IEQ indicators, such as air quality, acoustic quality, and lighting quality. It focuses on decision management rather than on the concrete translation of decisions to building control tasks, which have to be tailored to each individual building management system. Control decisions are defined so that occupants can understand the rationale behind them. Occupant feedback regarding thermal comfort is an essential parameter for temperature control decision-making. TREATI is further designed to include personalized comfort models as additional control strategies, which could be tested in future work.

1.5 Outline of the Dissertation

The dissertation is organized as follows:

Chapter 2 establishes the relevant background, related work, and own research as the foundation of TREATI. Common methodologies of capturing and presenting knowledge, as well as decision management concepts, are discussed. This chapter explores IEQ fundamentals with a focus on the thermal comfort domain and formulates the research goals.

Chapter 3 models TREATI as an object-oriented framework to realize and verify the research goals. TREATI uses a metamodel so that additional conflicts and strategies can be added from other domains.

Chapter 4 describes the validation model based on the Goal Question Metric model. The validation of TREATI uses an object-event simulation. The simulation is based on synthetic occupants and environmental sensor data.

Chapter 5 describes the validation results, with respect to occupant satisfaction, energy efficiency, fairness, and effort as decision metrics, and discusses findings and threats to validity.

Chapter 6 summarizes the contributions and gives an outlook for future work and directions for further research.

Chapter 2

Foundations

> The more I read, the more I acquire, the more certain I am that I know nothing.
>
> Voltaire

This dissertation is situated at the intersection of software engineering practices and indoor environmental quality (IEQ) research. Numerous approaches exist that attempt to resolve inter-human conflicts regarding IEQ indicators using data science techniques [Qui21; Fra+19; KSB18; GK13b; Cho10] or complex rule-based models

[Peñ+16; TD05]. However, these approaches often lack a comprehensive understanding of the underlying human factors or only target one aspect, relying on the availability of device infrastructure and models of a 'perfect world'. This dissertation aims to bridge the gap between personalized and group-based models or rule-based systems.

This chapter establishes the relevant background, related work, and own research as the foundation of TREATI to create a common knowledge base. Section 2.1 captures common methodologies of knowledge. Section 2.2 presents decision management theory, common processes, and negotiation techniques. Section 2.3 explores IEQ indicators with the focus on thermal comfort research.

2.1 Knowledge Modeling

Philosophers use the following classification of knowledge [MB+93; Kan86]: metaphysics, epistemology, and ethics. Metaphysics is the description of the structure of knowledge and refers to the study of the truth and reality, whereas epistemology is concerned with the study of knowledge and justified belief. Ethics describe moral principles that shape an individual's behavior.

One branch of epistemology is the Platonic epistemology, which is a knowledge theory developed by the Greek philosopher Plato. In his work 'Theaetetus', Plato defines knowledge as perception and true judgment with an account of a subject [Cha21]. Plato establishes four levels of knowledge: imagining, belief, thinking, and perfect intelligence. On this basis, psychologists Joseph Luft and Harrington Ingham coined the term "unknown knowns"[1] in their model of awareness of interpersonal relationships, the so-called Johari window model [LI61]. This model categorizes interpersonal relationships into four quadrants. Figure 2.1 summarizes this knowledge classification in the knowledge matrix using two dimensions: the individual and the aspect in question [Col10; Kra02; LI61]. It further illustrates the relationship between these dimensions and the four knowledge types: *Known-knowns* describe aspects that an individual is knowingly aware of, i.e., explicit knowledge that relies on facts. *Known-unknowns* are aspects of which an individual anticipates and is aware of but does not possess,

[1] Donald Rumsfeld, the Secretary of State of the United States of America from 2001 to 2006, used this notion and gave the response "there are known knowns" at a Department of Defense news briefing when asked about an issue regarding a lack of evidence linking the Iraqi government to the supply of weapons to terrorist groups.[2] The matrix representation of knowledge types is also often referred to as the "Rumsfeld matrix" or "Rumsfeld effect" [Ham+12].

[2] Department of Defense press transcript, DoD News Briefing - Secretary Rumsfeld and Gen. Myers, February 12, 2002, `https://archive.ph/20180320091111/http://archive.defense.gov/Transcripts/Transcript.aspx?TranscriptID=2636`.

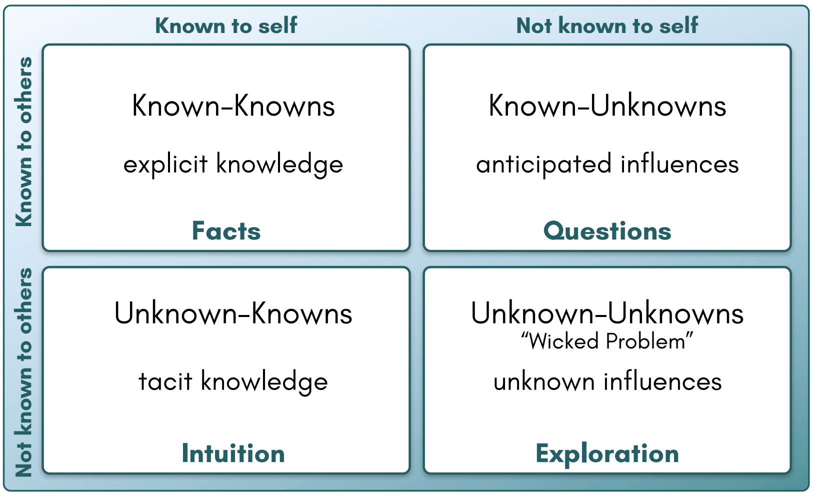


Figure 2.1: **Knowledge Type Classification** (adapted from [Col10; Kra02; LI61])

such as unanswered questions. *Unknown-knowns* are aspects that an individual is unknowingly aware of, this includes tacit knowledge. Tacit knowledge describes an individual's intangible understanding or ability that is deeply ingrained in the mind [PS09]. This type of knowledge often relies on intuition, for example, knowing how to walk without explicitly thinking about concrete steps. *Unknown-unknowns* are unknown influences or aspects of which the individual has no knowledge. When exploring a new aspect, unknown-unknowns can become known. When a complex issue has many unknown influences and is difficult or impossible to solve, it is often referred to as a *wicked problem*. In software engineering, wicked problems refer to complex issues in the design of systems that are difficult to define and have no definitive solution [DS90; Rit72]. Often, the system requirements are incomplete, conflicting, or frequently changing during the software engineering lifecycle.

Many problem-solving aim to maximize utility or rely on static decision rules, assuming complete knowledge of all relevant factors. However, in real-world problems, it is often impossible to identify or obtain knowledge of all these factors due to associated costs and limited resources, such as time and budget. This limitation poses a significant challenge for human decision-makers, as humans are not omniscient and cannot possess comprehensive knowledge of all factors, all possible alternatives, and all potential consequences. Consequently, humans tend to simplify and abstract the prevailing issue [Bec62; Sim66; Sim55].

Building on economic research, the political scientist Herbert A. Simon is credited with introducing the concepts of *bounded rationality* and *satisficing* to describe and balance these challenges [Sim79; Sim56; Sim55]: Simon argued that individuals operate within a framework of bounded rationality, where they make decisions by satisficing rather than optimizing, given the complexity of real-world problems. Bounded rationality verbalizes the limitations of human decision-makers due to cognitive constraints, incomplete information, and uncertainty regarding an issue. It builds upon the concept of satisficing as an attempt to counterbalance exhaustive searches for optimality: Rather than undergoing an exhaustive search to find the most optimal solution, the decision-maker selects the first satisfactory alternative that meets their requirements and aspirations [Sim79].

This introduces a dynamic approach to decision-making, as requirements are dynamically adapted to the issue and prevailing constraints.

2.1.1 Mental Modeling

Psychology defines *ontology* as the study of the nature of being or reality. Various fields and applications have incorporated the idea of describing reality or knowledge about reality using a representation or theoretical description that defines the characteristics, behavior, and patterns of an object or physical being. In 1921, philosopher Ludwig Wittgestein's *Tractatus Logico-Philosophicus* (TLP) postulated that a language could only correctly reflect reality if the sentences are logical and can be validated empirically [Wit21]. He presumed that philosophical problems originate from linguistic misunderstandings. The TLP targets the barrier of languages against thoughts; humans create models of facts, which represent images of reality.

Computer science defines ontology as a structure for representing knowledge as a set of concepts within a domain that uses a shared vocabulary to describe types, properties, and their inter-relationships [UG96].

A model is an abstract representation of knowledge regarding a specific subject. In 1943, Kenneth Craik established the term *mental model* to explain a thought process [Cra43]. A mental model is an internal "*... model of external reality and of [an organism's] own possible actions within its head, it is able to try out various alternatives, conclude which is the best of them, react to future situations before they arise, utilize the knowledge of past events in dealing with the present and future, and in every way to react in a much fuller, safer, and more competent manner to the emergencies which face it*" [Cra43].

Reality R and its model M consist of many interrelated components. The relationships can be formalized as a homomorphism, where i is the transformation that maps the reality to its model, and f_M is a relation [Goo13]: $f_M \circ i = i \circ f_R$.

In the field of human-computer interaction (HCI), the concept of mental models is widely recognized and used to explain and characterize a user's thoughts and ideas.

A mental model is a representation of an individual's impression of the surrounding world, either of specific elements or the individual's perception of certain actions or behavior [ND86]. Mental models rely on tacit knowledge that enables individuals to derive appropriate behavior for situations they have never encountered before.

A *conceptual model* is an abstract or high-level representation of a system [JH02]. Conceptual models are conveyed to the individual through the design and interface of the actual product, while a mental model is a portrayal that the individual develops of the interacting object. In HCI, Don Norman distinguishes between three conceptual models that represent the system's idea from different perspectives: the design model, user model, and system image [ND86]. The design model is a consistent, coherent conceptualization, whereas the user's model is the mental model that evolves as the user interacts with the system. The user's model expresses how they understand the system's operation. The system image reflects the impression that is portrayed by the created physical structure to the user. System designers strive for equivalence between the user's model and the design model [Nor02]. In reality, all communication and knowledge exchange between the designer and user occurs through the system image, often leading to a gap between the design model and the user's model [ND86]. Thus, system designers strive to minimize this gap to ensure that the system matches the correct conceptual model [Nor02].

2.1.2 Metamodeling

The Unified Modeling Language (UML) was developed by Grady Booch, Ivar Jacobson, and James Rumbaugh in 1995 [BJR+96; Boo95] and adopted by the Object Management Group (OMG) in 1997 as a standard [Obj97]. UML is a widely used framework for conceptualizing and describing models at different levels of abstraction.

Metamodeling describes the concept of generating a model to define another model. Metamodels provide a language to "describe the relevant aspects of a subject under consideration that are of interest for the future users of the created model" [Hof07]. In 2003, OMG introduced the Meta Object Facility (MOF) as a standard for model-driven engineering [Obj15]. MOF allows its users to acquire and structure knowledge and define the relations among objects. It provides a common language to describe a topic on different levels of abstraction. MOF is designed as a closed four-layered architecture, see Figure 2.2. Layer M3 defines the meta-metamodel, which provides the language to model metamodels on layer M2. M2 metamodels describe elements of the M1 layer, the object layer. For instance, UML is defined on the M2 layer, and M1 models are modeled using UML. The last layer, M0, describes real-world objects. For instance, since mental models (Section 2.1.1) describe perspectives from the real world, they are modeled in M0.

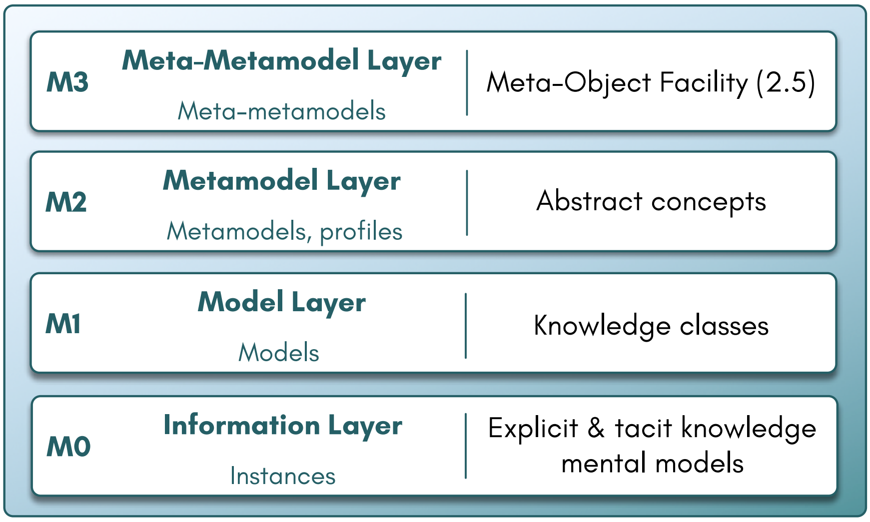


Figure 2.2: The **Meta Object Facility (MOF)** is a closed metamodeling architecture with four layers (adapted from [Obj15])

Several works have made efforts to describe aspects of ubiquitous computing using MOF: Jonas presents a metamodel for multimodal interactions to control buildings [Jon16]. On this basis, Scheuermann models a metamodel to describe cyber-physical systems [Sch17], and Avezum approaches urban sustainability in her smart sustainable city metamodel [Ave20]. These works remain between the M1 and M2 level and do not address conflict resolution between humans and their instrumented environment.

Research Goal 2.1 – Metamodel. Knowledge regarding the resolution of conflicts between humans and their instrumented environment needs to be extracted, abstracted, and modeled.

2.1.3 Rationale Modeling

Disputes and debates cause *issues*, which refer to disagreements on a particular subject[3]. In 1970, Kunz and Rittel introduced IBIS, an *Issue-Based Information System*, as an argumentative process to resolve issues within administrative groups, such as governments, agencies, or in politics [KR70]. Their approach defines *issues*, *positions*, and *arguments* as the core elements of the process, and illustrates the relationships among them in Figure 2.3.

In software engineering, the interaction among a variety of actors with different backgrounds necessitates decision-making concerning a wide range of issues during

[3]Cambridge Dictionary, `https://dictionary.cambridge.org/dictionary/english/issue`

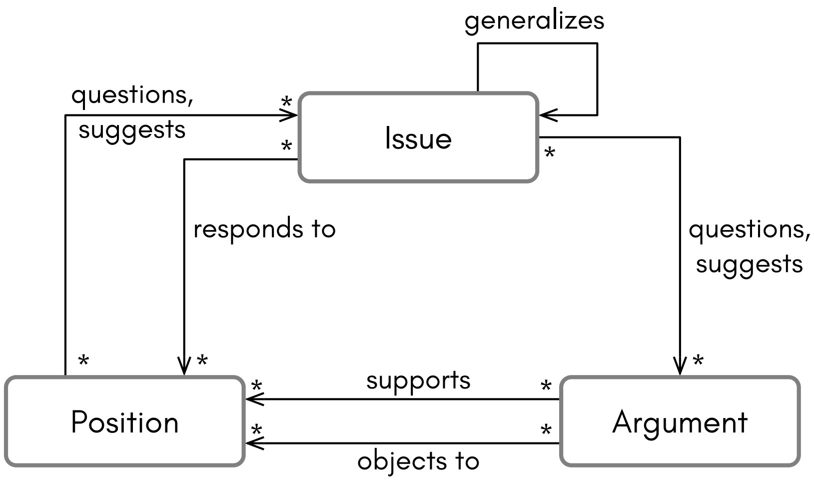


Figure 2.3: **IBIS** (adapted from [KR70]

the development process. Hence, decisions need to be formed following logical, structured methods. Many methods use *rationale* to justify a particular decision or action [DMMP00; CY91; Mos85]. Historically, research in the software engineering domain focused on design. Thus, the term *design rationale* was introduced as "an explanation of why an artifact is designed the way it is" [LL91]. Lee and Lai define the elements of rationale, which "can include not only the *reason* behind a design *decision* but also the *justification* for it, the other *alternatives* considered, the *tradeoffs* evaluated, and the *argumentation* that led to the decision" [LL91].

> **Definition 2.1 – Rationality** encompasses the gain of knowledge to attain a goal while considering available information and logical reasoning.

In 2000, Dutoit et al. revisited this definition and extended it to all activities during the software engineering lifecycle [DMMP00]. They define rationale as a means for communication and knowledge management among the different stakeholders. Using rationale in decision-making processes separates rationality from the emotions associated with the issue. This separation improves the fairness and traceability of decisions. Fairness ensures equitable decision-making processes by promoting inclusivity, transparency, and consistency [Lev80, pp. 29]. It allows for considering diverse perspectives, can offer equal opportunities for participation, helps mitigate biases, and ensures compliance with ethical standards [SF97; Lev80].

Based on IBIS [KR70], Brügge and Dutoit define five core rationale elements [BD10]:

- *Issue* to be resolved, posed as a question or design problem
- *Alternatives* are a set of possible solutions that aim to resolve the issue
- *Criteria* that are used to guide the decision

- *Argumentation* during all aspects of the decision-making process
- *Decision* that resolves the issue

Rationale management establishes consistent aspects that guide each issue resolution process. One central objective of this dissertation is to improve fairness in thermal conflict resolution by transitioning from emotional to rational decisions and implementing a consistent process. Rationale management serves as the basis of the decision-making framework introduced here. By incorporating rationale management, the decision-making process becomes transparent, and accountable, and allows for the integration of objective criteria and evidence-based reasoning. As a result, this improves the overall fairness and effectiveness of thermal conflict resolution.

> **Definition 2.2 –** Rationale is the justification behind decisions. It comprises the following **Rationale Elements**:
>
> - *Conflict* that describes the topic
> - *Issue* to be discussed
> - *Proposal*, or *Proposed Strategy*, that provides the means to resolve the issue
> - *Decision*, i.e., the chosen proposal that resolves the issue
> - *Position*, or *Context*, that reflects constraints or preferences of the conflict
> - *Arguments* (pros, cons) are used to guide the decision following a position
> - *Debate* that participants go through to reach a decision

Rationale Management is the process of extracting rationale elements and reaching a decision. It facilitates issue resolution by iteratively making decision elements explicit, enabling the reevaluation of decisions to address change in the future [DMMP00].

Brügge and Dutoit describe four levels of *rationale capture* [BD10]: (RC1) No explicit rationale capture, the rationale is only found in developer communication, (RC2) rationale reconstruction focuses on the system design, (RC3) rationale capture where the rationale is captured as a separate model, and (RC4) rationale integration with the rationale model being the central knowledge base.

In thermal comfort decision-making, facility managers typically adhere to their own rationale model, i.e., RC1, which could be approving occupants' requests or manually choosing the lowest energy cost. The deployment of traditional control models, such as the Predicted Mean Vote (PMV) model [Fan70], integrate their own rationale into the system model (RC2). Recent works have been situated between RC2 and RC3 [Qui21; Fra+19; KSB18]: Rationale information are collected and transformed into data-driven control models. However, these approaches use their rationale model as a 'side note' and not as the central aspect, and aspects, such as transparency and fairness during the decision-making process, are overlooked. This dissertation aims to address this limitation and focuses on leveraging rationale models as the primary basis for decision-making, targeting RC4.

2.2 Decision-Making

Decision-making research originates in the field of psychology. It aims to understand human behavior when prompted to make a decision and provides methodologies and tools to support decision-makers. In 1910, John Dewey described five steps to structure reflective thinking processes to understand rational thinking and problem solving [Dew10, pp. 72–78]: problem identification, problem analysis, solution criteria definition, rational elaboration of ideas, and idea verification and conclusion. Herbert A. Simon outlines them into three phases, establishing the theoretical foundation for decision-making processes [Sim60, p. 6]:

1. **Intelligence** – Identify the need for decisions
2. **Design** – Determine possible courses of action
3. **Choice** – Select a decision

Decision-making involves a cognitive reasoning process through which a decision-maker selects an option from a set of possible alternative options, guided by predetermined criteria or strategies [WWPP06; WLR04]. A decision represents the resulting artifact, describing the conclusion reached after resolving a question. It signifies the point in time when an entity commits to a particular course of action after evaluating and comparing multiple alternative options [KK91]. The alternative options do not have to be complete. In the literature, the term 'decision management' is often used interchangeably with 'decision-making' when referring to managerial decision-making processes [Lee90; Sim60, p. 1].

> **Definition 2.3 – Decision-Making** describes the process of proposing a solution to a conflict from multiple alternatives, considering the given situational context and arguments.

The terms *decision-making* and *decision management* are used interchangeably in the remainder of this dissertation.

2.2.1 Decision Theory

Decision theory is concerned with the study of choosing a course of action, given a set of alternatives. It involves descriptive decision theory, which focuses on the process of how individuals behave to reach decisions, and normative decision theory, which focuses on how individuals ought to behave and determine optimal decisions [Rap98]. Prescriptive decision-making describes methods to improve and modify decision-making. The following focuses on descriptive decision theory to understand and abstract the main elements of decision-making processes.

Descriptive Decision Theory

Early pioneers, such as Alan Turing, emphasized the significance of teaching machines in a manner similar to how one would educate a child, highlighting the idea of artificial intelligence as a learning process [Tur50]. Building upon this notion, the 'symbol processing hypothesis' sought to replicate the logical reasoning of human decision-making [NSS58]. This hypothesis postulates that the cognitive processes involved in thinking and problem-solving activities rely on rules or algorithms, manipulating symbolic representations, such as mental depictions of objects, concepts, or relationships, similar to how computers process symbolic information.

Allen Newell and J.C. Shaw proposed a theory that outlines the fundamental components of human problem-solving processes, emphasizing the cognitive processes involved [NSS58]. Their theory highlights the importance of problem representation, goal setting, and problem restructuring in human problem-solving: Problem representation involves creating mental models or representations of problems and the relevant context. Goal setting guides problem-solving efforts and allows individuals to define coherent goals. Problem restructuring involves reframing or reorganizing problems to facilitate effective solution strategies.

In 1959, Allan Newell, J.C. Shaw, and Herbert A. Simon introduced the General Problem Solver (GPS) program to simulate a human's thought process to solve simple mathematical problems [NSS59], such as the Towers of Hanoi. The GPS was built on a means-ends analysis as a problem-solving strategy, where subgoals are used to bridge the gap between the current state and the desired state. The GPS postulates that problem-solving involves a search space for possible solution strategies and that humans employ heuristics to navigate this space. It operates on symbolic logic and constructing general solution plans to reach a decision.

Herbert A. Simon further distinguishes between programmed and non-programmed decisions [Sim60, p. 5]. Programmed decisions arise from repetitive and routine issues, such as mathematical issues, and are addressed using established processes, as the prevailing circumstances adhere to a specific pattern. Non-programmed decisions have not yet occurred and require tailored solutions. Such solutions rely on problem-solving activities to determine an appropriate solution: Pre-programmed activities and preceding decisions need to be identified to "permit an adaptive response of the system to [such] a situation" [Sim60, p. 6].

> **Definition 2.4 – Problem Solving** involves setting a goal, determining the difference between the actual state and desired state, and applying tools to decrease this difference.

Simon deduces problem-solving techniques that depend on the nature of the issue [Sim60, pp. 7–8], as depicted in Figure 2.4. Traditional, human inference-based techniques for programmed decisions include habit and already established procedures and structures. Computational inference relies on logical approaches, such as operations research or data processing. Techniques for non-programmed decisions regarding human inference are based on rationality and common sense. Computational inference approaches use computer-based decision-making heuristics that are applied to either train decision-makers or develop computer programs.

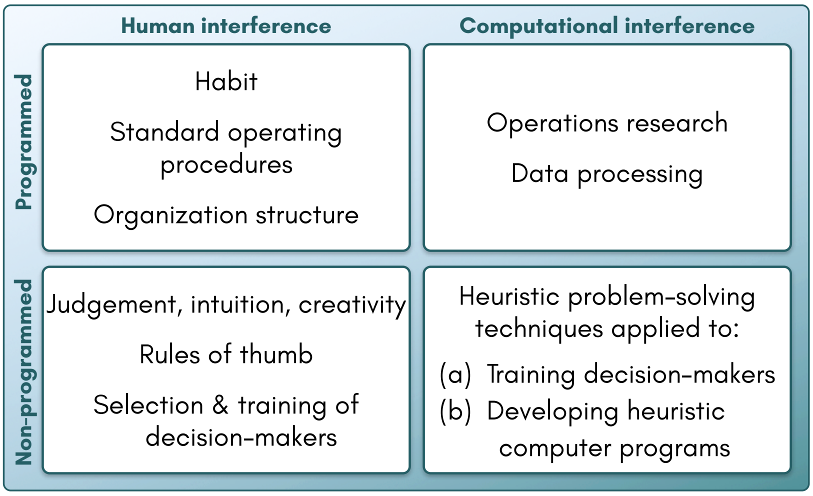


Figure 2.4: **Decision-making Tool Matrix** (adapted from [Sim60, p. 8])

Following Simon, Mintzberg et al. focus on non-programmed decisions and distinguish between the three phases *identification*, *development*, and *selection* [MRT76, pp. 252–259]. Each phase is further divided into routines and sub-routines to reach a decision. The first phase, identification, recognizes the need to make a decision and the diagnosis where issues are defined. In the development phase, most resources are used to identify and design potential solutions. The potential solutions are screened during the selection phase: Inappropriate solutions are eliminated and evaluated using judgment, bargaining, and analysis to select a course of action, i.e., reach the decision. The decision needs to be authorized and approved before it is carried out.

Naturalistic Decision-Making

Naturalistic decision-making “attempts to understand how humans actually make decisions in complex real-world settings” [KK91].

Several approaches attempt to understand and extract a pattern from the human thought process, such as the General Problem Solver [NSS59], Multi-Attribute Utility Analysis [VWF75], or Decision Analysis [How88]. The Multi-Attribute Utility Analysis (MAUT) relies on an analytical approach to generate a wide range of options and weighted evaluation criteria, which are then evaluated, and the option with the highest score is chosen [VWF75]. Decision Analysis (DA) is a systematic calculative approach to identify and assess the minimum and maximum outcomes of a decision [How88]. It promotes the use of quantitative methods and tools, such as decision trees or influence diagrams, to aid in decision-making. The General Problem Solver [NSS59] could not solve real-world problems, as the complexity of such problems leads to a combinatorial explosion since there are too many variables and objects to consider. Similarly, the MAUT or Decision Analysis approaches require extensive work to identify all relevant factors, especially under uncertainty, which cannot be properly represented due to the strict analytical methods used. Further, they have shortcomings when attempting to solve real-world problems under time constraints, as they generally take too long to reach a decision. Such decision-making approaches do not separate their methods by function or task but rather apply one method for all, similar to what was later defined as a *golden hammer*, an antipattern in software engineering [Koe98].

In 1989, the field of naturalistic decision-making (NDM) emerged with the aim of understanding how humans navigate decision-making processes when faced with complex real-world problems. Such problems encompass situations with continually and dynamically changing conditions, limited time, organizational constraints, high stakes, uncertainty, and unclear goals.

> **Definition 2.5 – Naturalistic decision-making** relies on cognitive processes, such as sense-making, situational awareness, and planning, to reach decisions. The underlying objective is identifying common elements of human decision-making processes to derive decision-making models.

Researchers examined real-world decision-makers, such as nuclear plant operators [Ras85], fire ground commanders [KCCC86], or highway engineers [HHGP87], regarding their decision-making approaches and to extract the methods that were applied per decision task. The findings indicate that humans rarely apply strict logical decision-making but rely on instincts and previously obtained knowledge, depending on the decision task. For instance, Hammond et al. found that highway engineers employ analytical skills for estimating traffic but rely on intuition when assessing the surface conditions of a road [HHGP87].

Klein analyzed the decision-making of fire ground commanders, who are primarily responsible for resource allocation during emergency situations, such as search-and-rescue missions [KCCC86]. Klein found that the commanders were not making choices based on extensive research and reviewing alternatives. Instead, they operated on an "acting and reacting basis of prior experience" to dynamically adapt to the situation [Kle89, p. 272]. They "were more interested in finding an action that was 'workable,' 'timely,' and 'cost effective' " [KK91]. Arising issues lead to adapting or rejecting an approach and searching for another "most typical reaction." Klein summarizes the findings in the recognition-primed decision (RPD) model [Kle89, pp. 273–276]: The RPD model describes how decision-makers use previous experience to recognize a course of action in unknown situations. They start with a situational assessment, determine an option, evaluate the option, i.e., mentally simulate potential outcomes, and then implement, modify, or reject it, as illustrated in Figure 2.5. Based on this initial model, Klein identifies three decision-making strategies [Kle89]: After identifying the need for a decision and the situational context, the decision-maker has to determine the 'typical' issue, i.e., extract decision elements from previous situations. This entails the definition of goals, determining the relevant context, and setting constraints and expectations for the issue, which need to be considered.

2.2.2 Decision-Making Processes

Decision-making processes encompass the necessary steps and elements required for reaching a decision. Researchers have derived decision-making processes tailored to specific domains based on the previously described approaches. These decision-making processes and models are often derived from human behavior.

Irena Bakanauskienė and Laura Baronienė differentiate between rational, incremental, and intuitive decision-making processes [BB17]. Rational decision-making processes, such as financial analysis, are based on logical reasoning, facts, and objectivity. Incremental decision-making processes are often deployed in political decision-making, with mixed subjective and objective positions, e.g., salary negotiation. Intuitive decision-making is based on creativity, common sense, heuristics, and experience, e.g., a chef creating a new dish. Similarly, Herbert A. Simon classifies decision-making processes as rational, non-rational, and irrational [Sim93]. Non-rational decision-making targets the limitations of rational decision-making and dispenses the optimiza-

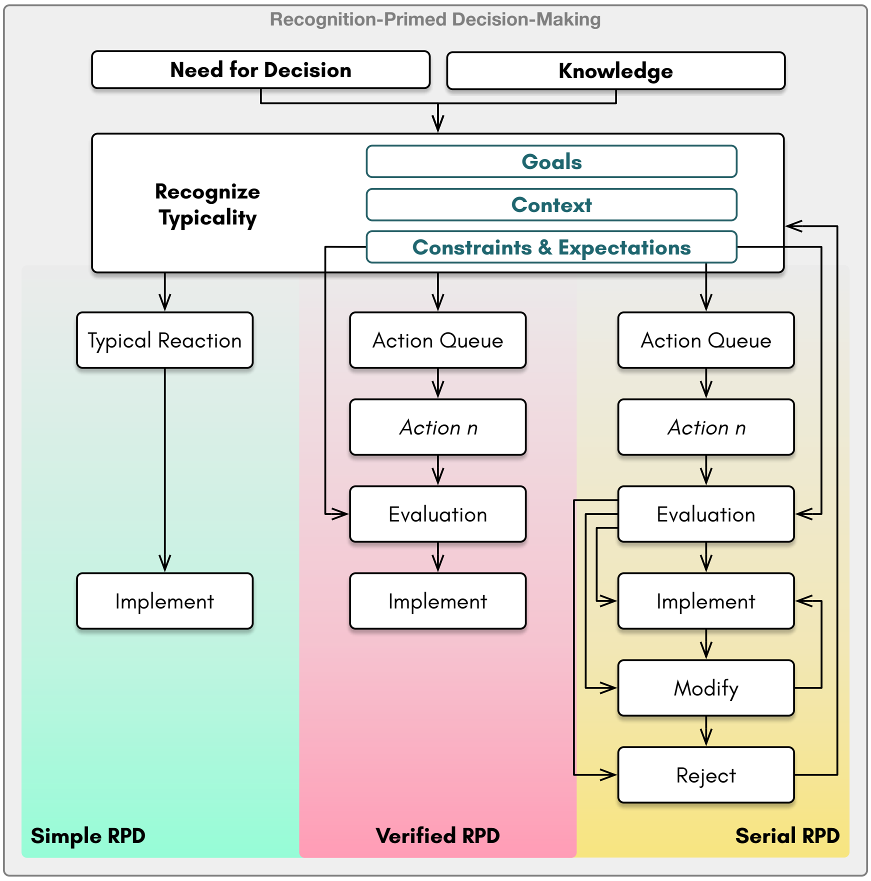


Figure 2.5: The **Recognition-Primed Decision-Making Model** identifies three decision-making strategies (adapted from Klein [Kle89])

tion ideal using bounded rationality, satisficing, and procedural rationality[4] [GG15]. Irrational decisions defy logic and are often made hastily and with misguided beliefs.

As a contrasting approach to rational decision-making, Michael D. Cohen, James G. March, and Johan P. Olsen proposed a *garbage can* model in organizational choice [CMO72]. The organization is seen as a "collection of choices looking for problems, issues and feelings looking for decision situations" and is characterized by uncertainty and changing or unclear participation, as each individual may have different intentions. Three disconnected streams – problems, solutions, and participants – are chaotically "dumped" into the garbage can and, under consideration of fixed parameters and context variables, merge into the choice opportunities stream in the "decision arena". Choice opportunities describe possible courses of action that the organization can take. Depending on the predefined time period, a decision is either made or no decision is

[4]Procedural rationality refers to "the outcome of appropriate deliberation", contrary to substantive rationality – the achievement of "given goals within the limits imposed by given conditions and constraints" [Sim76].

reached. The decision is seen as "an outcome or interpretation of several relatively independent streams within an organization" [CMO72].

Contrary to decision-making processes derived from human behavioral observations [Sim55; Kle89], Wang et al. derived a formal mathematical model of a decision-making process based on human cognition [WWPP06; WLR04], as illustrated in Figure 2.6.

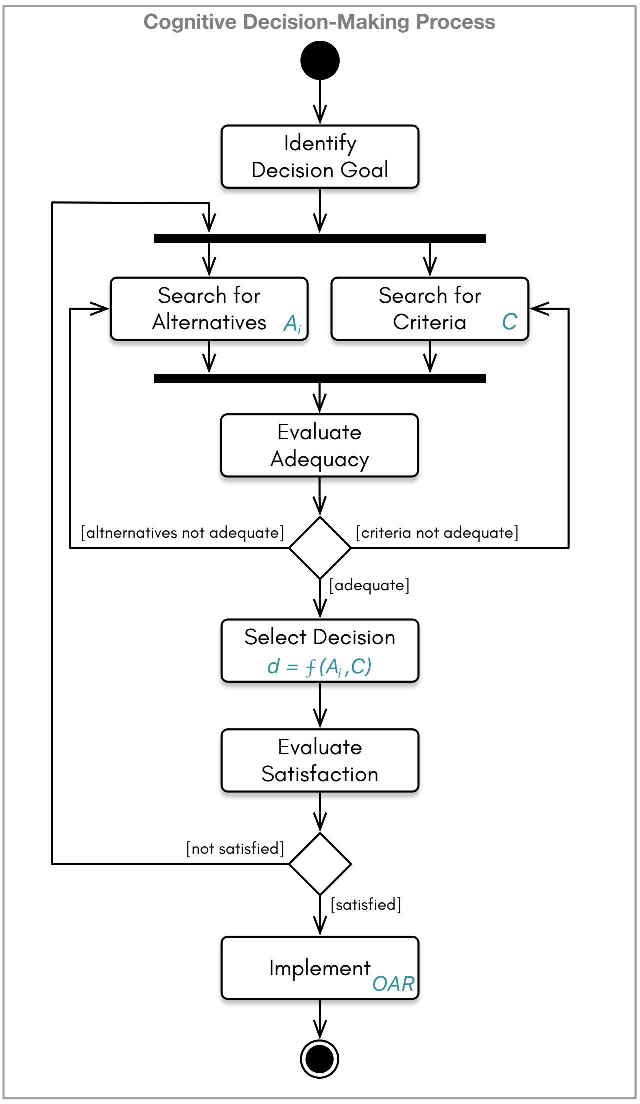


Figure 2.6: **Cognitive Decision-making Process** (adapted from [WLR04])

Wang et al.'s model is built upon their layered reference model of the human brain, divided into six layers and 37 cognitive processes [WWPP06]. They consider decision-making as a higher cognitive function at the highest layer. Using this reference model, Wang et al. further analyze and formalize the decision-making process into a mathematical model [WLR04]. They assume that the decision d is selected from the Cartesian product of a set of alternatives $A, with\ A_i \mid i \in I$ with a set of criteria C, where

C can consist of simple or complex criteria [WLR04]:

$$d = f : A_i \times C \rightarrow A_i, i \in I, A_i \subseteq U, A_i \neq \varnothing \tag{2.1}$$

Wang et al. further establish a taxonomy for strategies, i.e., the solution alternatives, classified into four categories [WLR04]: intuitive (arbitrary, preference, common sense), empirical (trial and error, experiment, experience, consultant, estimation), heuristic (principles, ethics, representative, availability, anchoring), and rational. Rational strategies are divided into static, i.e., objective functions, and dynamic strategies, such as interactive events or games. Their decision-making model is based on the assumption, that complex problems can be broken down into multiple iterations of the process, thus a composite of multiple solution strategies. Alternative solutions and criteria of the respective issue (object) are determined, quantified, and evaluated simultaneously. After selecting a decision, it is evaluated and either rejected, and a new search process is invoked, or implemented, i.e., the decision is stored in memory.

Saarelainen et al. investigated group decision-making processes in software evolution [Saa+07]. Based on Mintzberg [MRT76], they propose a rational decision-making process, which can be invoked by an individual or on a group basis. This sequential process assumes full knowledge and choosing the best alternative among a set of alternatives. After Carrel et al. [CJH97], Saarelainen et al. include an evaluation step for all alternatives to allow a rational choice of the best alternative. Their findings show that rational decision-making processes are applicable to organizations with defined team structures and roles.[Saa+07] Based on this research, Drury-Grogan and O'Dwyer analyze decision-making in agile teams and propose an adapted decision-making process to respond to change [DGO13]. They refactor a step in each of Mintzberg's three phases: In the problem identification phase, decision-makers analyze the situation (diagnosis) after the decision is identified. New solutions can be designed in solution development if no ready-made solution exists. To select the most optimal alternative, alternatives are first screened and then evaluated.[DGO13]

Bakanauskienė and Baronienė extend traditional (such as [Sim93; CMO72]) decision-making models with an additional step [BB17]: After identifying a decision alternative, additional decision evaluation criteria are identified. These criteria include compatibility with the environment, financial and resource criteria, as well as risks and advantages. This step is performed using *controlled intervention* – "the conditions for deciding whether to use the proposed (financial) resources to implement specific activities by [...] giving the institution control over the implementation and outcome of the decision" [BB17]. Subsequently, the additional criteria are assessed, the alternatives evaluated, and an appropriate alternative is chosen.

Fred C. Lunenburg analyzes two decision-making process models grounded in rationality [Lun10] – the rational model and the bounded rational model – by the example of school administrators. The rational models follows March [Mar94] and Schoenfeld [Sch10], and relies on the premise of making decisions that are completely rational, i.e., alternatives and outcomes are clearly defined and known. Following Herbert Simon's definition of bounded rationality [Sim79], Lunenburg introduces additional concepts into the rational decision-making process to simplify complex situations. These concepts include heuristics, satisficing [Sim93], the primacy and recency effect [BM80], bolstering the alternative [Bub13], intuition [MM02], incrementalizing [Lin89], and the garbage-can model [CMO72].

Oriana-Helena Negulescu defines the complex decisional process (CDP) to describe the different inputs and outputs that are taken into account in each decision-making phase [Neg14]. Inputs include environmental constraints, existing knowledge, and ethical principles. Before the decision implementation phase, the decision's impact is analyzed regarding its estimated consequences.

While research in the social sciences focuses on understanding how the human mind works and how humans form decisions, these aspects are often overlooked in other fields. Tang et al. disclose their results from a literature review on human aspects in rational decision-making processes in software architecture [TRPH17]. They focus on the requirements and design phase, comparing 33 publications regarding decision-making behavior and the tools and methodologies used ("decision-making practice"). Their findings include that only a few other works include human aspects with the majority concentrating on technology. In addition, they corroborate a symbiotic relationship between behavioral decision-making and the software practice, which could improve limitations, such as cognitive biases or knowledge management.

Observation 2.1 – Expanding upon the foundational works of [DGO13; WLR04; KK91; Sim60; MRT76], a rational decision-making process can be described by extracting and defining the following key phases:

1. *Issue Identification*: The need for a decision and its goals are defined. Based on the prevailing situation, relevant knowledge pertaining to the issue is gathered and prioritized.
2. *Solutioning*[5]: Possible courses of action are determined.
3. *Choice*: The courses of action are compared against each other. Based on this evaluation and pre-defined goals, the most fitting alternative is selected.
4. *Solution Evaluation*: The decision's impact on the issue is evaluated.

Figure 2.7 illustrates this process. Note that, based on the application domain, it remains up to the user or decision-maker to decide how to proceed and define acceptance or rejection criteria after reaching a decision.

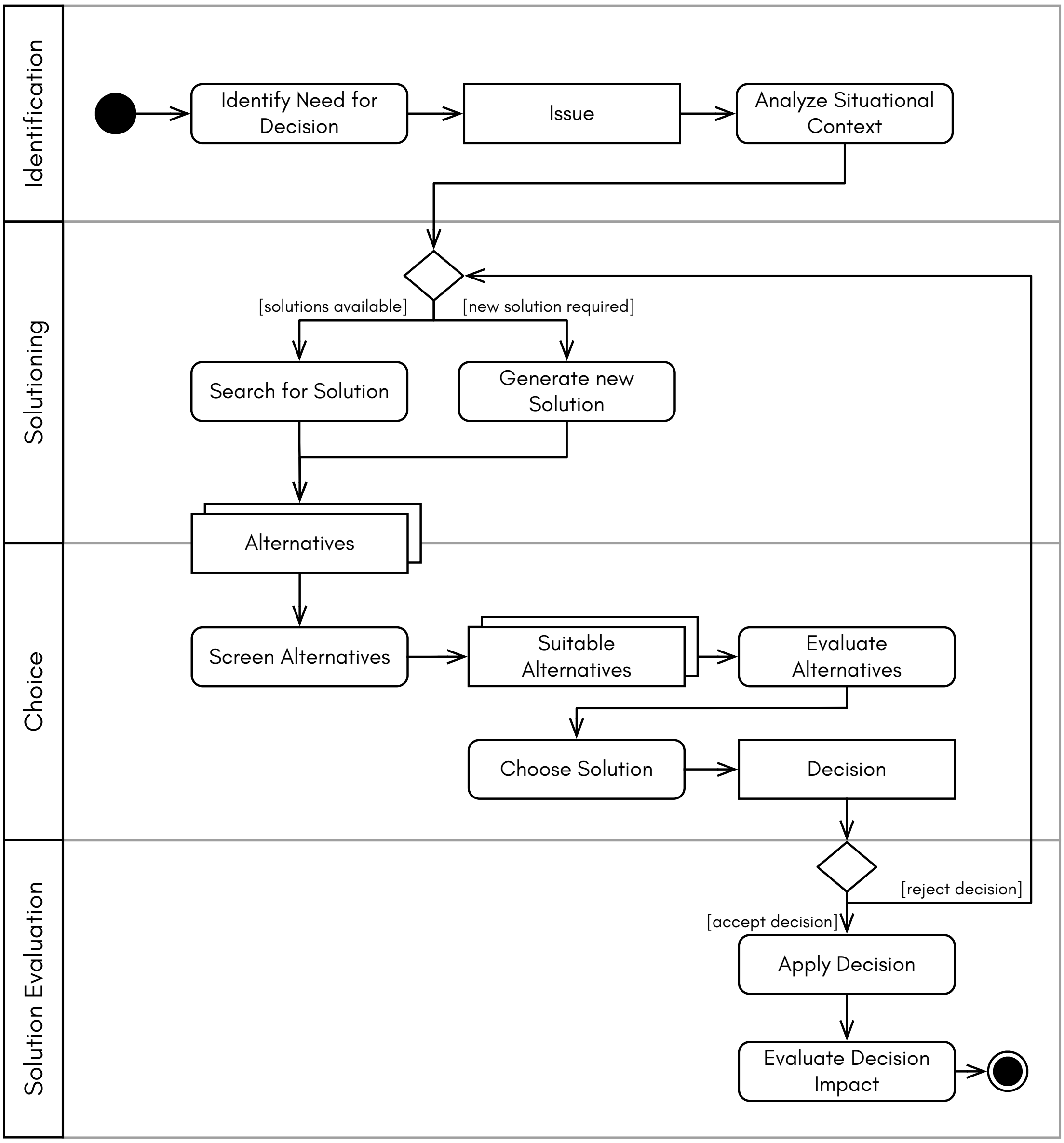


Figure 2.7: **Rational Decision-Making Process** (based on the works of [DGO13; WLR04; Kle89; MRT76; Sim56])

[5]In general problem solving, this phase is called the *solution design*. However, in human-computer interaction research, the term "design" has been overloaded and is often associated with the actual system's design. Thus, to avoid confusion, this dissertation uses the term *solutioning* to describe the process of finding and generating solutions to the given issue.

2.2.3 Conflicts & Negotiation

A *conflict* is a disagreement among at least two parties [Tho92; MS57]. Conflict management deals with the process and techniques to resolve a conflict. There are many works that address organizational conflict resolution, such as conflicts between employees, between employers and employees, or among business partners [DDW03; SP00; Ant98; MS57]. According to Jehn et al. , there are three main aspects of conflicts: task, relationship, and process conflicts [JGLS08]. Task conflicts are disagreements among members of a group about a task that needs to be performed. Relationship conflicts are disagreements among group members that concern personal opinions. Process conflicts deal with the process of how tasks are addressed and mainly concern organizational processes, such as delegation.

> **Observation 2.2** – Thermal comfort conflicts are composed of task, relationship, and process conflicts: the main task is temperature control, interpersonal relationships often dictate the course of action, and there needs to be a decision on how a new control action is conducted.

Negotiation is the process of reaching a mutually acceptable agreement between two or more parties to achieve a goal when a conflict has occurred [TWG10]. It is a decision-making process that occurs when no rules or procedures exist for resolving the issue [Lew+11]. This process is often irrational and caused by cognitive bias, i.e., errors in a person's judgment or beliefs [HNM15; NSS59].

Negotiation has been the subject of psychology research for many years and has undergone many phases, reflected by societal evolution. In the 1960s, research primarily focused on the individuality of negotiators and the situational characteristics [BCMV00; Mar94]. In the 1980s, researchers formalized negotiation models, influenced by behavioral decision theory [Sim55] and game theory, following Nash [Nas50]. In the 1990s and early 2000s, negotiation theory drew from social psychology and focused on negotiators' behavior, their incentives behind actions, situational circumstances, and cultural influences on negotiation behavior [Bre00; PC93].

The Negotiator's Power Struggle

A traditional negotiation involves at least two parties who each propose a solution to a problem. Each party follows their own agenda and defines a "no-deal option", the best alternative to a negotiated agreement (BATNA), which describes the last possible alternative from which the negotiator will accept an offer. The parties go back and forth, often involving several offers and counter-offers, until a mutual agreement is reached. This is also known as positional bargaining [FUP81].

> **Definition 2.6 – Negotiation** is a discourse among two or more parties with the aim of reaching a decision regarding an issue. Each party has static and dynamic constraints.

There are three negotiation styles [FUP81]: soft (cooperative), hard (competitive), and principled. In principled negotiation, the involved parties function as problem solvers rather than friends or adversaries.

> **Definition 2.7 – Principled Negotiation** separates people from the problem and aims at reaching a decision based on interests rather than positions [FUP81]. People, interests, options, and criteria form the basis.

Richard Luecke defines two main types of negotiation [Lue03, pp. 2–9]: *Distributive* negotiation represents a competition where each involved party aims to receive maximum benefit from a fixed value (win-lose). Each party only discloses selected information with the goal of increasing their own standing. In an *integrative* negotiation, all parties focus on cooperating to receive maximum benefits (win-win). All interests are integrated into an agreement, and the value must be divided. Simultaneously, each party tries to claim the most value. Negotiations often involve aspects of both types, depending on the power distribution. This is also known as the *negotiator's dilemma*, as the negotiator needs to decide which end of the continuum between competition and cooperation they situate themselves [FUP81].

Negotiation Elements

Roy J. Lewicki, David M. Saunders, and John W. Minton define six characteristics of a negotiation [Lew+11]: The negotiation involves at least **two parties**, there is a **conflict of interest** between at least two parties, the parties rely on **negotiation** to advance their position, the parties **strive for agreement** rather than a fight, the negotiation aims to reach a **compromise**, and **tangible** and **intangible** factors are involved. A tangible factor describes the terms of the agreement. Intangibles are defined as "underlying psychological motivations that may directly or indirectly influence the parties during a negotiation" [Lew+11]. It is crucial to manage intangible factors proactively during the negotiation process.

Four stages in negotiation can be identified, following a mixed-motive interaction approach [AB05]: Relational positioning, problem identification, generating solutions, and reaching an agreement. Relational positioning takes place on the interpersonal level and refers to determining relationships. Negotiation needs to produce a 'wise agreement', be efficient, and not damage relationships between parties [FUP81].

Observation 2.3 – A negotiation involves the following phases:

1. Preparation – Data collection
2. Opening – Conflict identification
3. Exploration – Investigating criteria
4. Generating solutions – Presenting offers, bargaining
5. Concluding – Reaching a mutual agreement

These phases relate to the previously established phases of decision-making in Section 2.2.1 by [MRT76; Sim60].

The Power Continuum

Negotiation takes place on intrapersonal, interpersonal, group, organizational, and virtual levels [TWG10]. The intrapersonal level concerns the individual's needs and emotions, often regarding power, gender, and affect [TWG10]. Structural power – an individual's ability in an organization to form decisions – is the ability to influence the other party's outcome [TWG10]. The BATNA is the negotiator's indicator of their relative power [FUP81]. Negotiators do not disclose their BATNA to other parties. During a negotiation, there is a zone of possible agreement.

Definition 2.8 – Zone of Possible Agreement This zone is the differential of the lowest and highest parties' BATNAs and represents the set of potential agreements in a negotiation.

Research has revealed a gender bias in negotiation [TWG10]. For instance, females less often initiate negotiations, and if they did were perceived as demanding and unfriendly (as perceived by their male negotiating partners) [SGBG07]. However, many factors drive behavior in a negotiation, e.g., motive and structural power. Thus, gender alone cannot be considered on an intrapersonal level.

Joseph Forgas defines affect as the impact of an individual's mood on cognitive processing [For95]. Emotions, motivation, and mood influence the negotiator's verbal expressions and their power. The interpersonal level refers to interaction with the other parties [TWG10], either through emotional reactions or relationships [MK02]. The group level analyzes how group dynamics influence negotiation processes regarding the individual's identity, e.g., relational vs. collective or their cultural identity [TWG10]. At the organizational level, the negotiator is embedded in a network or marketplace layer to analyze dyadic relationships to analyze the social structure.

During a virtual negotiation, the interaction among the parties takes place computer-mediated, e.g., through emails or applications [TWG10].

Observation 2.4 – Negotiation is an emotional decision-making process that is shaped by biases, interpersonal relations, and structural power.
Computer-mediated negotiation allows to deflect intrapersonal and interpersonal factors regarding emotions and relationships, aiming for a higher rationality.

2.3 Indoor Environmental Quality & Thermal Comfort

Building control systems aim at ensuring appropriate quality and sustainability of an inhabitable environment [Ene17]; after all, humans spend around 80 - 90 % of the day indoors [Kle+01]. The IEQ affects the psychological and physiological well-being of occupants, including their productivity and motivation [Cui+13], health [FR97], and general satisfaction [Hum05; Fan70]. A literature review by Frontczak and Wargocki [FW11] concluded that thermal comfort, air quality, acoustic quality, and visual quality represent the most important IEQ indicators. Energy efficiency is considered a crucial factor – many building control decisions are driven by their impact on the resulting energy use [Lud+16; Fis02]. Each IEQ indicator's intent is defined as follows:

Thermal Comfort conveys an occupant's subjective satisfaction with their thermal environment [Ame20]

Air Quality describes the types and concentrations of airborne contaminants [Wee+20]

Acoustic Quality refers to the surrounding sound situation on auditory events [Cow93]

Visual Quality compares the illuminance and glare levels to the required levels of the respective task [Fis02]

Energy Efficiency indicates the use of less energy to perform a task

Indicators are typically measured using sensors and occupant feedback. Some parameters are associated with more than one indicator; for instance, a draft from windows or diffusers (air quality) also influences the perception of temperature of an individual (thermal comfort), while air temperature and humidity (RH) have an effect on formaldehyde emission factors, which is in turn a measure for air quality [Wee+20].

Unhealthy conditions in buildings are referred to as Sick Building Syndrome (SBS) [Org82]. The SBS describes conditions where more than 30% of occupants experience symptoms, such as respiratory issues, headaches, fatigue, or irritated skin, which are "associated with a particular building by their temporal pattern of occurrence and clustering among inhabitants or colleagues" [RSC97]. Such symptoms are often associated with air quality alone [Sar+21], as symptoms caused by the other indicators are usually less visible, e.g., lightning affects eyesight, but symptoms of eyestrain usually develop gradually over time. Standards and guidelines exist to regulate and prevent such conditions. Well-known examples are the World Health Organization's (WHO) global guidelines [Org21] and the ASHRAE 62 standard [Ame19] for air quality and the ASHRAE 55 standard, which describes optimal thermal quality in buildings [Ame20]. They suggest thresholds, e.g., for carbon dioxide concentrations in the air [Ame19] or a minimum and maximum indoor air temperature depending on the season [Ame20]: 23.3 °C – 27.8 °C in the cooling season and 20.0 °C – 25.5 °C in the heating season.

Available actions to improve acoustic quality are usually limited to the use of the respective space and the occupants' behavior. Other factors that contribute to sound pollution, such as nearby construction sites or traffic, generally cannot be influenced. There are concrete thresholds for maintaining good air quality [Org21], which are often already regulated through the respective HVAC (heating, ventilation, and air conditioning) system. The visual quality depends on the available control options, e.g., ambient lighting and task lights at occupants' workstations, but also on the location and surrounding of a workstation, such as glare caused by a light source. Lighting control is often divided into controlling either the task or ambient environment [CLA12]. A deviation from conditions classified as 'good' caused by one of these three indicators generally affects humans in a similar way.

Thermal comfort is a subjective measure that relies heavily on occupant feedback. Studies have suggested that thermal comfort is deemed as the most important, but also challenging, IEQ indicator as it has a considerable influence on overall satisfaction in indoor environments [FW11]. Discrepancies among occupants and occupants and facility management occur often – even when adhering to temperature ranges defined in standards. Occupants can influence their own thermal comfort, for instance, through their daily clothing choices, diet, activity, and task actions, such as turning on a desk fan. These actions also depend on the respective space; many offices still require dress codes, perceived thermal comfort can vary across genders, and task fixtures are not always available or practical.

> **Definition 2.9 – Thermal Comfort** is "that condition of mind which expresses satisfaction with the thermal environment" [Ame20]. It has a significant effect on an occupant's physiological and psychological well-being, as it impacts their health, productivity, and overall well-being [Fis02]. Due to the subjectivity and non-deterministic nature of thermal comfort, control systems need to address differences among occupants, such as physiological and cultural factors [FW11].

Building management systems aim at achieving a thermal equilibrium.

> **Definition 2.10 –** A **thermal equilibrium** is defined as the balance between two forces in a space: the state of the system, described in terms of constraints, such as energy efficiency or IEQ thresholds, and occupant satisfaction. The ultimate goal is to achieve a constant state of equilibrium.

This research addresses thermal comfort in shared spaces in a commercial context. The following summarizes the background of thermal comfort and outlines the current state of research regarding control and decision-making approaches, followed by occupant involvement in thermal comfort applications.

2.3.1 Origins & Evolution of Thermal Comfort Applications

Control of the thermal environment is the main concern for maintaining and improving an occupant's thermal comfort. To identify the best control option, thermal environments are divided into task and ambient environments.

> **Definition 2.11 –** A **Task Environment** is a specific workspace that enables an occupant to complete a particular task or set of tasks under environmental conditions suitable for the task. An occupants can use task items, such as task lights and desk fans, to influence their individual task environment.
> The **Ambient Environment** describes the surrounding that encompasses all task environments in addition to unoccupied spaces, such as hallways. Building management systems control the ambient environment's conditions.

Thermal comfort is generally described as a psychological state where an individual is content with the thermal environment and does not desire any changes [Ame10; Fan70]. Human physiology and thermoregulation explain thermal comfort as the rate of nervous signals from the thermal receptors in the human skin to the hypothalamus; the lower the signals, the higher the comfort level [May93]. In bioenergetics, thermal comfort is defined as reaching thermal equilibrium, where the human body's amount of internal heat generation and external heat loss are in balance [But98; Fan70]. These definitions imply that there are both measurable and also non-deterministic aspects to each individual human's perception of the thermal environment.

> **Definition 2.12 – Thermal Comfort Conflicts** are disagreements about the prevailing thermal conditions between occupants and the environment (*internal*), inter-occupant disagreements based on thermal preferences (*social*), or a violation of building and control system constraints (*external*).

While one occupant's request for a temperature change may be easily resolvable, for instance, through decreasing the temperature or opening a window to increase air flow, other occupants sharing the same space are also affected by such changes. If their temperature preferences differ and a temperature change does not satisfy all occupants, the conflict is defined as a non-trivial conflict. For example, if one occupant prefers a temperature increase and one occupant prefers a temperature decrease, neither a temperature increase nor a decrease would satisfy both.

> **Definition 2.13 – Non-trivial Conflicts** , or *high-stress conflicts*, are conflicts where there is no easy solution that leads to 80% occupant satisfaction.

Povl Ole Fanger was one of the most influential researchers in the field of thermal comfort [AOP17]. During the 1960s and 1970s, he developed the Predicted Mean Vote (PMV) model, an energy balance model of the human body for assessing thermal comfort as a combination of environmental and human factors [Fan70; Fan67]. Its mathematical model is based on the heat transfer between the clothed human body and the environment, as understood by bioenergetics, physics, and human physiology. It estimates the mean comfort vote for a group of occupants on the standardized seven-point thermal sensation scale using four environmental factors (indoor air temperature, mean radiant temperature, air speed, and humidity (RH)) and two human physiological factors (metabolic rate and clothing insulation). The mathematical model is comprised of heat balance equations and an occupant's physiological responses to varying thermal conditions that were measured in a climate chamber with 1396 subjects, who were mainly male and college-aged students. The Predicted Percent Dissatisfied (PPD) is a function based on the PMV. It predicts the rate of occupants who are dissatisfied with the thermal conditions [Fan70; Fan67].

While the PMV-PPD model is the foundation for many subsequent works, its application and accuracy tested in field and laboratory studies have been questioned [Mai14; VH08; HN02]: The model expects steady-state conditions in thermal environments, which are impossible to meet in the real world. Cheung et al. analyzed the ASHRAE Global Thermal Comfort Database II to explore the PMV's accuracy [Che+19]. They found that an individual's thermal sensation is correctly predicted only in 34% of cases, derived from a sample size of 56 771 records.

Other efforts for estimating thermal comfort include the Pierce Two-Node Model (PTNM) [Gag71] and the adaptive model [DB98]. The PTNM was introduced in 1970 and has been continuously extended since. It models the human body as two nodes, the core and the shell (the skin), as a control system. Similar to the PMV, it applies heat balance equations to estimate the core body temperature and skin temperature to derive the occupant's thermal sensation and thermal comfort [Gag71]. The PNTM also assumes constant environmental conditions and was found to overestimate skin wetness (sweat) [AGB86].

In contrast to the static nature of the PMV, adaptive thermal comfort theory, also referred to as the adaptive theory, builds on the assumption that contextual factors determine an occupant's expectations and preferences towards the thermal environment [HNR07; DB98]. Humphreys et al. summarize the main principle of the adaptive theory: "*If a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort*" [HNR07]. The adaptive theory draws from field studies and relies on the premise of behavioral and physiological adjustments, i.e., adjustments occupants make to influence their own thermal comfort. Richard J. de Dear and Gail Schiller Brager sub-classify these into *personal* (e.g., removing a clothing item), *technological* (e.g., turning on a desk fan), and *cultural* responses (e.g., an afternoon nap) [DDB02]. The adjustments further encompass, e.g., acclimatization, habituation, behavioral adjustments, and general expectations [Yan+15].

> **Definition 2.14 – Behavioral Adjustments** or **Task Actions** are efforts that occupants make to influence their thermal comfort. They are classified into *personal* responses, *technological* control options, and *cultural* adaptions [DDB02].

Richard de Dear and Gail Brager introduced the Adaptive Model in 1998 [DB98]. It is a linear regression model that assumes a correlation between indoor and outdoor air temperature. The authors found that a neutral vote on the thermal sensation scale correlates most with the indoor operative temperature T_o; hence, given a as the model constant and b as the gradient, they define the mean thermal sensation $\overline{ts}$ as:

$$\overline{ts} = a + b * T_o \tag{2.2}$$

The Adaptive Model assumes that, by including behavioral adjustments in the overall comfort temperature estimation, the acceptable air temperature range per occupant can be extended, compared to the standardized ranges defined in ASHRAE 55 [DB98].

2.3.2 Control Approaches

The PMV, PTNM, and adaptive models are aggregate models that predict comfort levels of large populations but perform worse for smaller groups [Che+19; KSA18; Cha03]. In practice, the PMV is not designed to consider individual occupants. The human factors metabolism and clothing insulation are either estimated or set as fixed values for the entire population of occupants.

Dounis and Manolakis describe the main issues of thermal comfort control as a twofold problem, *"the interpretation of the comfort requirement, and [...] the making* *of a decision on which subsystem to use at a particular moment"* [DM01]. In the last decade, researchers have investigated methods to connect the two research fields of thermal comfort and building control to reach a more universally accepted comfort definition and improve occupant satisfaction and energy use at the same time. A particular focus has been on the use and extensions of the PMV, fuzzy logic controllers, artificial neural networks, and hybrid models, as detailed in a literature review by Diana Enescu [Ene17]. June Young Park and Zoltan Nagy observed that research until 2017 has focused more on energy savings than occupant satisfaction [PN18].

Research Goal 2.2 – Balancing Building and Human Requirements. Control approaches need to consider both building and human requirements. In particular, energy efficiency and thermal comfort need to be considered when forming control decisions to ensure sustainable and comfortable environments.

The following summarizes common control approaches, with an emphasis on the use of human factors. Rule-based control (RBC) systems rely on static pre-defined rules to form control actions. They are created based on human – usually the engineer's or facility manager's – intelligence. For instance, a common rule is that air conditioning is turned *ON* if the outdoor air temperature rises above 23 °C. RBCs rely on the accuracy of mechanical sensors. Sensors often emit faulty data, thus inducing unwanted actions which are intransparent from the occupant's view. This was established as part of a semi-informal interview conducted in [Hau20] with a facility management expert who is responsible for all BMS on the Carnegie Mellon University campus.

Fuzzy logic temperature controllers are real-time expert systems that use a set of 'fuzzy' rules to generate output from an input vector that consists of environmental or human factors. Fuzzy logic is an approximation of experienced rules compared to the if-the-else rules from traditional RBCs. Along with RBCs, they are one of the most frequently installed controllers in buildings. Fuzzy logic temperature controllers are mainly used to extend or replace classic PID controllers.[6] They imitate experienced human operators who can control a process without knowledge of its dynamics [KM77]. Fuzzy logic controllers update the parameters in each control cycle. However, fuzzy controllers have shortcomings if inputs are unknown. Dounis and Manolakis propose a fuzzy logic[7] control system to encompass control systems that expect a specific set of predefined conditions or can only operate with a single controller or a control subsystem. Their controller takes the outdoor climate, the PMV index, and occupant

[6]PID (proportional-integral-derivative) controllers are mechanical controllers that use a feedback control loop to control process variables. They are one of the most used controllers in buildings, along with rule-based controllers.

feedback as inputs to generate an system action vector that consists of heating and cooling setpoints and the window position [DM01].

Other approaches have extended existing models or RBCs by fuzzy logic control systems [Cia+15; TD05; CLGRS04; TH91]. Thompson and Dexter introduced a model-based predictive control system for controlling an air conditioning system using fuzzy logic [TD05]. Ciabattoni et al. base their model on the PMV and include weather conditions to improve the suitability of output actions [Cia+15]. These approaches found that including additional context indicators, such as weather conditions, and moving towards dynamic temperature setpoints rather than static setpoints, can improve overall occupant satisfaction.

> **Definition 2.15 – Context** indicators relevant for an individual's thermal comfort include, but are not limited to:
>
> - **Environmental Factors** – indoor air temperature, indoor humidity (RH), outdoor air temperature, outdoor humidity (RH), weather, location, season, solar gain, time of day
> - **Human Factors** – general preference towards temperature, conflict readiness, activity, bio-signals, clothing insulation, diet,

Karmann, Schiavon, and Edward Arens analyzed thermal satisfaction votes from 52980 occupants in 351 office buildings [KSA18]. In 43% of the buildings, occupants reported dissatisfaction, which could be attributed to existing HVAC control systems not allowing for personalized control. The authors found that only 2% of all observed buildings achieve more than 80% occupant satisfaction.

Occupants are not "passive recipients of their immediate environment, but constantly interacting with and adapting to it" [YYL14]. Recent research has shifted towards data-driven control models investigating the physiological differences between humans and their perception of thermal comfort. Human factors, such as heart rate variability [CLL12], skin temperature [CLL12], body shape [Fra+19], or differences between females and males [Cha+18; Kar12], are explored as potential determinants for occupants' estimated thermal comfort votes.

Yu and Dexter applied reinforcement learning (RL) to adjust a fuzzy controller to determine the optimal parameters for improving thermal comfort and energy efficiency simultaneously [YD10]. They validated their approach using a simulation and observed that thermal comfort outcomes were outperformed by the fuzzy controller during the learning phase, while energy costs decreased.

Chenlu Zhang presented the reinforcement learning control system called 'Bio-REAL' [Zha19]. This system deploys an agent per occupant that, in addition to environmental parameters, uses the occupant's wrist temperature to predict the occupant's thermal preference and issues a control action. If multiple occupants' preferences cause a conflict, a negotiator subsystem resolves it by comparing each agent's decision's expected reward (the utility an agent receives for performing a 'good' action) to select the highest one. The approach was tested and validated in a multistep process, including a simulation and field studies. Zhang found a 52% increase in comfort compared to the baseline (standard Static control schedule with a setpoint at 22 °C) in a tropic climate. The system's goal was to maximize thermal comfort; energy efficiency had a lower priority and therefore there was a slight increase in energy use compared to the baseline [Zha19].

> **Observation 2.5 –** A comfort control system needs to consider temperature change implications for each individual occupant as well as the group of occupants as a whole that shares a space.

2.3.3 Occupant Involvement

Even though the automation of building control systems has evolved to closed-loop control approaches that provide a higher level of comfort than traditional control systems, there is a need for occupants' control over their environment to influence their own thermal comfort [Par+19; DD04]. As discussed in the previous section, this is addressed using personal comfort models or approaches that rely on occupant feedback. Occupant feedback is crucial during the thermal control decision-making process as it determines the direction of temperature change but also gives an indication of the overall occupant satisfaction [SH19; DD04].

Studies have found that there is a need for transparent control actions [ZAZ15; Kar13; YN13]. Transparency refers to explaining the intent behind and impact of a decision. Transparency also improves predictability, i.e., the extent to which an occupant can estimate the effects of their own actions and thus may adjust their behavior themselves [JJS03]. If occupants understand and trust decisions, occupants may be more willing to accept the respective control system [Kar13].

> **Research Goal 2.3 – Occupant Involvement.** Occupants need to be involved throughout the thermal control decision-making process. They should be able to actively provide feedback to the control system regarding their perceived

thermal comfort. Control decisions should be designed in a way that their impact is comprehensible to occupants.

Feedback Scales

Three scales are commonly used to measure an occupant's thermal comfort: thermal sensation [Ame20], thermal preference [McI80], and thermal satisfaction [Ame20]. Thermal satisfaction expresses an occupant's contentment with the environment. It does not provide any direction, only whether an occupant is satisfied or not, and is therefore rarely used in comfort studies alone other than taking a momentary snapshot of the overall satisfaction level [HAZA06]. The thermal sensation scale is a 7-point scale used to calculate the PMV and the PTNM indices. It indicates how an occupant feels about the thermal setting. The thermal comfort community is divided about its usage in comfort studies, as the phrasing might lead to misunderstandings between researchers and participants. An occupant may feel *'warm'* but would prefer no change; many studies interpret a rating of *'warm'* as *I want it cooler*, leading to a temperature decrease [FLB21]. *'Slightly warm'* and *'slightly cool'* are often treated as neutral as a result of a lack of information on required changes [DDB02]. The 3-point thermal preference scale indicates what change in temperature an occupant would prefer. It is not sensitive enough to indicate a clear direction for temperature changes; a '*warmer*' vote could either mean a slight adjustment by 1 °C or a bigger adjustment by 3 °C . It is, however, often used in comfort studies since it provides a better direction of change than thermal sensation.

Research Goal 2.4 – Thermal Comfort Scales. A comfort system needs to address the common scales of thermal sensation and thermal preference [Ame20; McI80; Fan70]. Thermal satisfaction is seen as an approximate measure of overall comfort. The thermal desirability scale introduced by von Frankenberg et al. provides for a finer-grained sense of control than the thermal preference scale [FLB21] and is therefore also explored. The scales and their encodings are illustrated in Figure 2.8.

To date, there has been no comprehensive study of each scale and its uses in different contexts to give clear indications or a standardization of their temperature setpoint identification. Some studies interpret the encoding of a step on the thermal sensation scale as the respective temperature change value, e.g., 'warm (+2)' would translate to a temperature decrease of 2 °C [BTGA13]. Others limit the one-step change to 0.83 °C (1.5 °F) based on the thermal preference scale [Jaz+14]. Varick L. Erickson and Alberto E. Cerpa derive an offset temperature based on the PMV and occupant votes to identify a temperature setpoint [EC12]. Other studies focus on predicting the

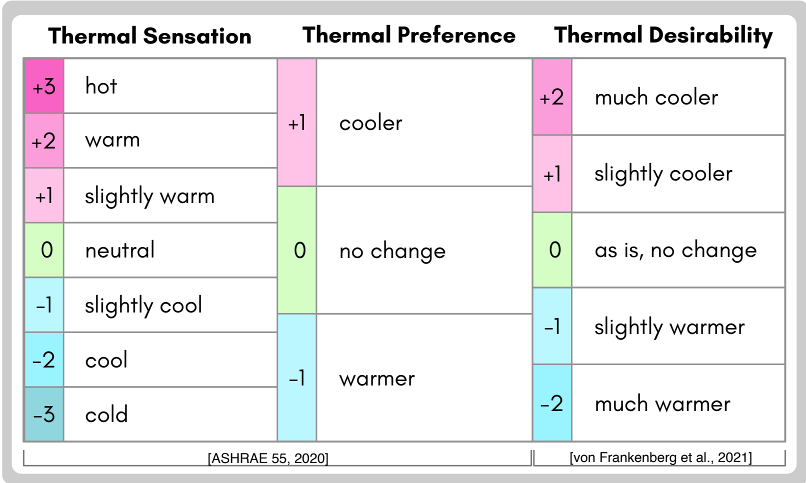


Figure 2.8: **Thermal Comfort Feedback Scales** (adapted from [FLB21; Ame20])

occupant's thermal sensation but do not include a translation to temperature setpoints [CY17; Sim+16]. In a study that investigates outdoor thermal perception patterns, Kántor, Kovács, and Takács determined temperature ranges for each step on the thermal sensation scale in different climates [KKT16]. Griffiths introduced a method to estimate a mean temperature for groups which assumes a constant rate of vote change per unit of temperature change [Gri90]. It calculates the comfort temperature T_{ct} is the sum of the operative temperature T_{op} and the thermal sensation vote's difference to the comfortable vote (neutral) v_{ts} divided by the constant α [Gri90]:

$$T_{ct} = T_{op} + \frac{v_{ts_{neutral}} - v_{ts}}{\alpha} \tag{2.3}$$

The lack of standardization or guidelines for mapping occupant votes to temperature changes is also referred to as the *temperature amplitude problem*.

Personalized Control

In recent years, control has shifted from centralized to personalized control by introducing comfort models that use machine learning techniques to learn an individual's comfort preferences [ACM22; FRBL20; KSB18; ASR15; LYW14; SS13]. Personal comfort models are trained on active feedback, predominantly through votes, and passive feedback, such as biosignals or behavior, from occupants.

Peter Xiang Gao and Srinivasan Keshav added a linear regression model to the PMV index [GK13b]. Their extension combines the respective occupant's sensitivity for each factor used in the PMV model and the occupant's thermal preference vote. This model outputs a temperature setpoint for each occupant based on sensor data. In a follow-up paper, the authors extend and compare their system to predictive control, which uses a k-nearest-neighbor algorithm to predict occupancy and a learning-based predictive control model to predict indoor air temperature [GK13a]. The model results in one occupant's predicted setpoint temperature. The predictive control system reached greater comfort levels and used less energy than the reactive system.

Ghahramani, Tang, and Becerik-Gerber introduced an online learning approach for modeling personalized thermal comfort using a Bayesian Optimal Classifier and Adaptive Stochastic Modeling [GTBG15]. Their approach was 14.08% more accurate than the traditional PMV-PPD model.

Kim et al. found that using personalized models in combination with a personal control system (a heated chair) lead to higher accuracy when estimating the occupant's comfort and to higher levels of comfort compared to the PMV as a baseline [KSB18]. This result is in line with the adaptive approach's idea of behavioral adjustments – there is a need for task action items to improve an individual occupant's comfort in relation to zone air temperature.

The commercially available product "Comfy" by Building Robotics Inc. (owned by Siemens) is a platform that visualizes several building metrics to occupants and allows them to book rooms and control lighting and air temperature. Comfy relies on personal comfort – if a temperature change request is received, warm or cold air is blown into the occupant's (nearest) zone for between 10 minutes and an hour. It uses machine learning to learn the occupant's control behavior to adjust the temperature automatically over time.[8] Comfy also targets temperature disagreements: If two occupants or more share a zone and others would be impacted negatively by a temperature action, there is a grace period, and the respective occupant is given the choice of either addressing the issue verbally or finding another space with more comfortable thermal conditions.[9]

100% occupant satisfaction can be achieved through the implementation of personal comfort models and optimal control conditions. However, they require extensive data collection and training periods and are often not applicable in a real-world setting. Many studies only investigate a very limited setting regarding location, season, and participant demographics or cannot minimize human bias. The premise of personal comfort models is the availability of smart personal control options for each occupant, which in reality, are often limited. They assume consistent occupancy and cannot accommodate location changes. In addition, model-induced actions are often not

[8] Comfy. *How It Works – Temperature.* `https:\www.comfyapp.com/how-it-works/#temperature`.

[9] Comfy. *What Happens When Two People Disagree About the Temperature?* 11/29/2016. `https://comfyapp.com/what-happens-when-two-people-disagree-about-the-temperature/`.

transparent from the point of view of occupants and can even be distracting. Personal comfort models are "designed to predict thermal comfort for a single person; hence, they are not necessarily directly applicable to other occupants" [KSB18].

> **Observation 2.6 Comparableness of Different Approaches –** Data-driven approaches compare their model's outcome to baselines (most often the PMV or similar models) to assess their accuracy in terms of energy efficiency or occupant satisfaction.

Context Indicators

All of the above-mentioned approaches use context factors in addition to air temperature and occupant votes.

> **Definition 2.16 – (Thermal Comfort) Context** describes circumstantial factors that contribute significantly to an occupant's thermal comfort.

Several works reviewed the most important and most used context factors to fit models that estimate thermal comfort aspects [Fen+22; Ene17]. Diana Enescu compared the input factors used in 23 works that predict the PMV index [Ene17]. Indoor air temperature was included in all 23 studies, followed by mean radiant temperature (19/23), mean relative humidity (18/23), air velocity (13/23), clothing insulation (12/23), and metabolic rate (10/23). Gender, water vapor pressure, occupancy, age, solar radiation, outdoor air temperature, and wet bulb temperature were only included in a few of the reviewed studies [Ene17]. Francis and Quintana et al. use body shape (shoulder circumference, height, and weight) to infer an occupant's general thermal comfort preferences [Fra+19]. The authors tested different configurations of environmental factors (zone temperature, outdoor temperature, and outdoor relative humidity) and human factors (gender, shoulder circumference, height, weight, skin temperature, clothing insulation, activity, and galvanic skin response (GSR)) to identify the most accurate feature set for seven personal comfort models, including random forest, kNN, and decision tree classifiers, and the PMV index. The thermal comfort vote was based on a custom 5-point scale. They found higher accuracies for the feature sets that contained all features (except for activity and GSR) and for environmental factors and just body shape information: The differences for the kNN and random forest classifiers resulted in an improvement by 6–7%, all other models provided similar results [Fra+19].

In their literature review, Feng et al. divide comfort model input factors into environmental and human factors, which are categorized into anthropometric, physiological, and behavioral factors [Fen+22]. Figure 2.9 shows an overview of common environmental and human factors applied in comfort models and control approaches that are based on Feng et al. 's categorization [Fen+22] and the mentioned parameters in the previous paragraphs, including gender [Kim+13], heart rate [CLL12], skin wetness [GFB+86], emotion [Ko+20], and body shape [Fra+19].

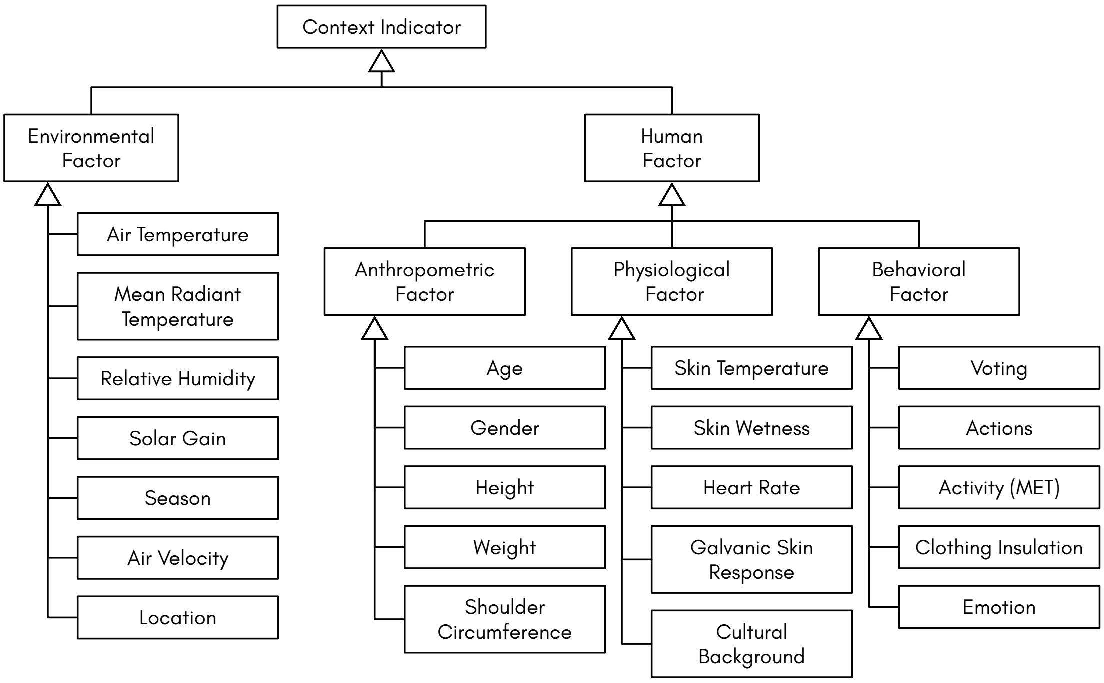


Figure 2.9: **Common Context Factors** relevant for an occupant's thermal comfort, adapted from [Fen+22] (UML Class Diagram)

Based on these observations, a thermal conflict's context is an important aspect to determine suitable actions.

> **Research Goal 2.5 – Context Identification.** As the outcome of decision-making processes depends on the available knowledge, it is necessary to analyze the prevailing situation, i.e., the conflict, and determine the relevant context indicators. Context indicators include environmental and human factors.

Decision Metrics

ASHRAE 55 describes seasonal temperature ranges and the optimum occupant satisfaction of $\geq 80\%$ as constraints for temperature control decisions [Ame20].

Ethical and fair decision-making is a key aspect of decision management [Luf97]. Depending on the prevailing conflict, not all occupants' preferences can be met when choosing a decision. For instance, if two occupants prefer a warmer air temperature while ten occupants prefer a cooler air temperature, the thermal control system would achieve a higher occupant satisfaction of over 80% when lowering the air temperature than when averaging across all votes (20-60%) or increasing the air temperature (16%). Due to human anatomic and genetic factors, these preferences can lead to reoccurring conflicts, which would be treated similarly each time. This could lead to some occupants' preferences to not be considered over a longer period, increasing occupant dissatisfaction over time.

Research Goal 2.6 – Metrics of Success. The expected outcome of each solution strategy must be comparable based on the following metrics:

Occupant Satisfaction describes the anticipated overall occupant satisfaction

Energy Efficiency describes the expected increase or decrease in energy when applying a solution strategy

Situational Applicability describes whether the solution strategy is applicable to the circumstances in which the conflict has occurred

Fairness describes whether any occupants' preferences are unintentionally disregarded in the decision

The metrics need to be prioritizable and adjustable to accommodate changes in the environment and adjust the overall goals:

Research Goal 2.7 – Metric Prioritization. Decision metrics need to be prioritizable to ensure the desired outcome, with respect to the system's goals.

Chapter 3

TREATI Framework

> Using a thermostat as a proxy for thermal comfort is like calling baking soda a cake.
>
> Robert Bean, ASHRAE Fellow[1]

This chapter describes the TREATI framework to the problem described in Section 1.1: TREATI (Tool for Rationale management with Event-based Arbitration of Thermal comfort In shared spaces) addresses the resolution of thermal comfort conflicts in shared spaces using rationale management techniques.

[1] Mentioned in: Julie Wernau. June 2, 2022. Brrr! Air-Conditioned Offices Give Chilly Reception to Returning Workers. *The Wall Street Journal*.

The chapter is organized as follows: Section 3.1 presents the TREATI metamodel. The metamodel has two objectives: first, to conceptualize knowledge of 'unknown unknowns' (Luft and Ingham [LI61]). Unknown unknowns emerge through the constant evolution of software systems, in particular with regard to designing new building management systems [HN18; Aug07], and because humans identify new interaction methods [VKT11; CYD06]. For instance, non-trivial conflicts – random, split, and majority voting conflicts (Definition 2.13) – can be addressed with the metamodel when designing an interactive temperature control system. These conflict types are unknown in current temperature control systems – they are not defined and thus cannot be addressed. TREATI addresses such unknown conflict types and indirectly transforms them into 'known unknowns' by integrating and addressing them using specific resolution methods. This dissertation hypothesizes that the concrete method to a conflict type does not need to be exactly defined, as they may consist of a set of various methods, depending on the prevailing context. To summarize, the first goal of the metamodel is to conceptualize known unknowns (conflicts) and unknown knowns (decision-making strategies), eventually transforming unknown unknowns into explicit knowledge regarding the decision (see Figure 2.1).

Indoor environmental quality (IEQ) research aims at considering all indicators when addressing conflicts [LWPA21; FBB11; FW11]. While this dissertation focuses on thermal comfort, consequences on other IEQ indicators need to be considered to ensure acceptable decisions. The second objective of the metamodel is, therefore, to make TREATI extensible with respect to decision-making in other IEQ domains, in particular for acoustic quality, visual quality, and air quality.

Section 3.2 describes the dynamic architecture of TREATI. Traditional decision-making in building control only considers environmental factors and generalizes human factors, e.g., through the PMV or fixed satisfaction levels. These approaches lack consideration of the dynamic nature of perceived air temperature and thus consist of a single feedback loop. TREATI extends this mechanism with an occupant feedback loop: TREATI is modeled as a nested non-linear control system consisting of two feedback loops (see Figure 3.3): an environmental control loop and an occupant feedback loop that incorporates both active and passive occupant feedback, allowing for a more comprehensive understanding of occupant comfort.

Section 3.3 derives TREATI's main concepts and organizes them into packages. The environment and building management package are modeled in Section 3.3.2. Section 3.3.3 describes the occupant package, which centers around occupants and their relationship with thermal comfort. Issues are identified using events, hence, the event package and issue identification process are explained in Section 3.3.4. Section 3.3.5 identifies context indicators that are relevant for resolving thermal conflicts as part of the context package. The rationale decision-making package is elaborated in Section 3.3.6. Finally, Section 3.3.7 provides an overview of TREATI's object model.

3.1 Metamodel

The TREATI metamodel is structured into two parts: the core *metamodel* and the *IEQ extension*. The TREATI metamodel is based on the IBIS model introduced by Kunz and Rittel [KR70] and the decision documentation model by Hesse and Paech [HP13], which is based on rational decision-making and the naturalistic decision-making model by Klein [KK91]. Section 3.1.1 describes the relevant decision-management metaclasses on the M2 level. Section 3.1.2 contains a detailed description of the metamodel extension with respect to the IEQ domain.

3.1.1 TREATI Metamodel

The TREATI metamodel for rational decision-making is modeled as a UML class diagram in Figure 3.1. It abstracts core concepts from decision-making (see Section 2.2) and rationale management (see Section 2.1.3). The key abstractions of *rationale* (Definition 2.2) are the `Issue`, `Strategy`, and `Argument`, based on IBIS [KR70].

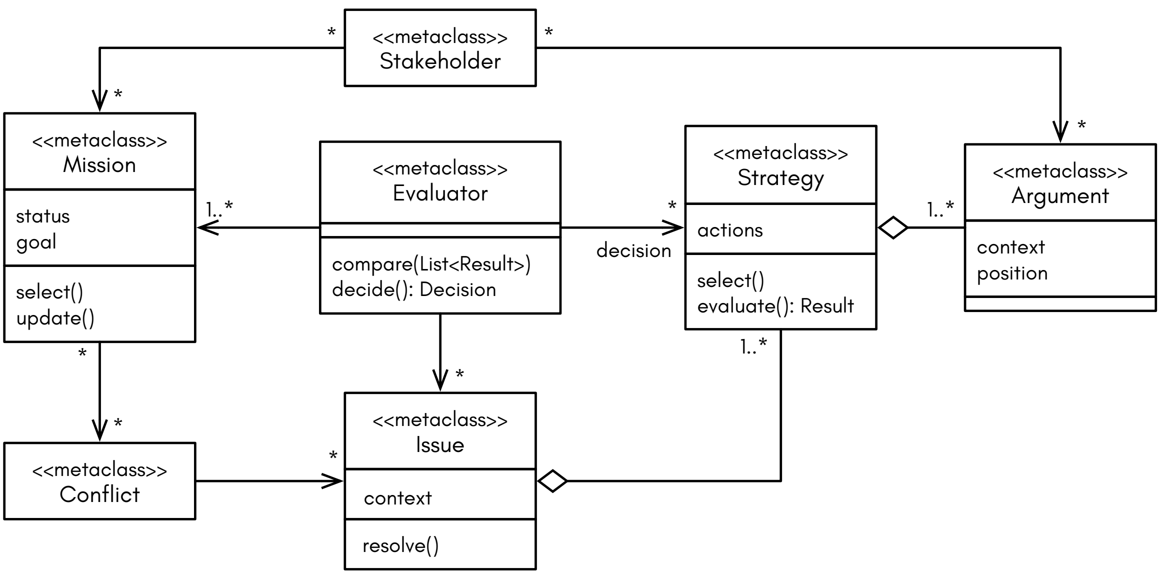


Figure 3.1: The **Rationale Decision-Making Metamodel** (MOF level M2, see Section 2.1.2) applies concepts from rationale management to address decision-making conflicts (UML Class Diagram)

Conflict resolution techniques follow `Strategies`[2] to evaluate `Conflicts`. A `Conflict` defines the type and the domain of a disagreement. A `Strategy` includes coherent actions that can be used to resolve an `Issue`. An `Issue` is a specific problem in a given context, i.e., circumstantial factors that contribute to the disagreement. Hesse and Paech model an `Issue` as a *question* [HP13]. In the metamodel, questions are not explicitly modeled – an `Issue` can however be expressed as a question. Question, context, argument, and solution are *decision components*, which represent *abstract knowledge* [HP13]. In TREATI, the relevant *position*s and *context* that establish a `Strategy` are collectively summarized in the `Argument` metaclass. The context is assumed to provide the necessary information needed to make a well-informed decision after Klein's naturalistic decision-making model [KK91]. Positions contain directed information from the problem environment. In IBIS, Kunz and Rittel describe a *discourse* that develops, where arguments and potential solutions are established [KR70]. This discourse occurs between participants, experts, documentation, systems, and other `Stakeholder`s. Each involved `Stakeholder` follows their own goals and holds a position to reach an acceptable resolution of the `Issue`.

While issue-based information systems support external decision makers that are not explicitly modeled [HP13; KR70], the metamodel includes an `Evaluator` metaclass as *discourse moderator*. The `Evaluator` is an entity, such as a person or a subsystem, that decides how an `Issue` is resolved.

The metamodel is further extended by a `Mission`, as an abstraction of Kunze and Rittel's *topic* [KR70], to reflect the overall domain's *goals* and their respective *status*. `Stakeholder` or the `Evaluator` can select and update the `Mission`'s goals. Each `Strategy` is evaluated by its `Argument`s The `Evaluator` compares these results and selects the one that best matches the `Mission` as the `Decision`.

3.1.2 IEQ Extension

Figure 3.2 presents the *IEQ Extension* of the TREATI metamodel, which targets conflicts in the domain of indoor environmental quality (IEQ).

Constraints are internal policies and an important part of decision management [HP13] as they define the boundaries of the applied strategies. The metamodel allows to extend the `Mission` with `Constraint`s and the most common `IEQ` indicators (see Section 2.3): `AcousticQuality`, `VisualQuality`, `AirQuality`, and `ThermalComfort` [FW11]. `EnergyEfficiency` is modeled as subclass of `IEQ` to reflect the overall environmental impact. For each `IEQ` indicator, various `Constraint`s exist based on

[2]Rationale management theory uses the term *'Proposal'* [KR70]. Since the focus is on addressing conflicts, the metamodel uses the term `Strategy` to emphasize the intentionality of the proposal, i.e., the planned course of action.

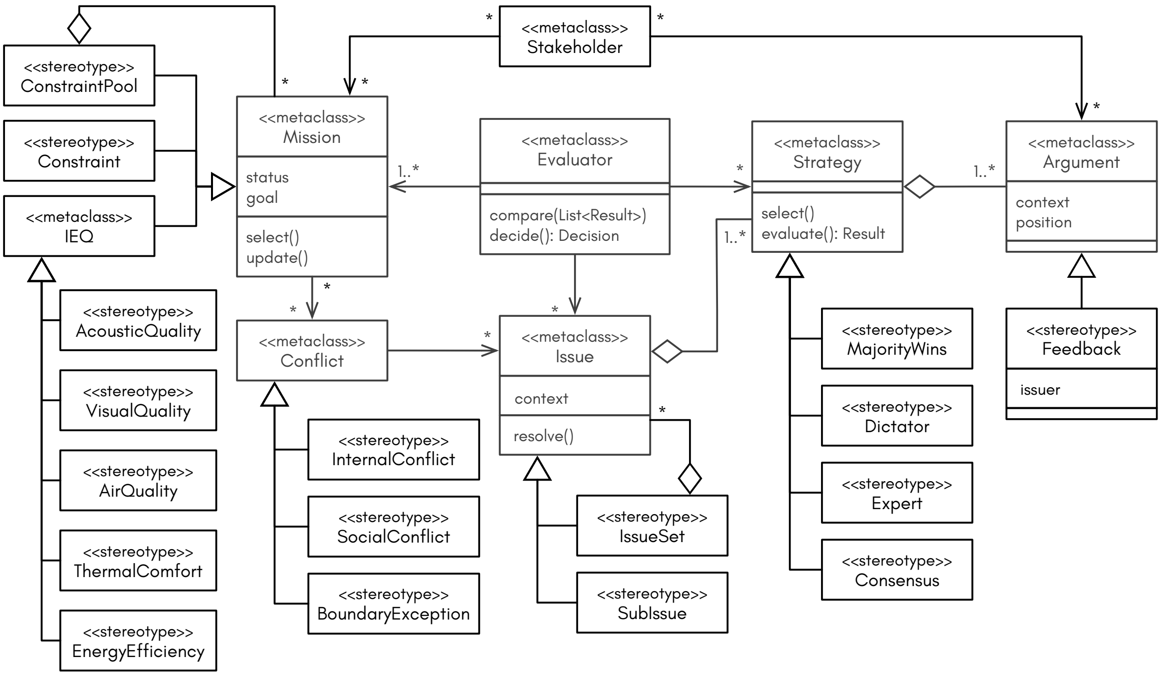


Figure 3.2: **IEQ Extension** of the TREATI metamodel (UML Class Diagram)

the respective application domain. A `Constraint` refers to a limitation or restriction on the decision-making process. Constraints can be physical, financial, operational, or regulatory. They impose boundaries or conditions that must be considered when making decisions or taking actions related to IEQ regulation, building maintenance, and improvements. Constraints influence the available control choices and options, thereby affecting the overall effectiveness and efficiency of the building management control system. A `ConstraintPool` aggregates `Constraints` and `IEQ` indicators.

Different domains use different categorizations of conflicts, whereby each type of conflict requires a different approach to resolving it [Jeh97; Sim55]. Three stereotypes extend the metaclass `Conflict`: `InternalConflicts` describe the discrepancy between an occupant's preference and the respective environmental state, `SocialConflicts` deal with differences among occupant preferences, and `BoundaryExeptions` describe the non-compliance with constraints.

Based on Jehn et al. 's four conflict dimensions (emotions, norms, resolution efficacy, and importance) [JGLS08; Jeh97] and Bruegge and Dutoit's exemplary strategies used in conflict resolution [BD10], the metamodel includes four main types of `Strategies`: `MajorityWins` (importance), `Dictator` (emotions), `Expert` (norms), and `Consensus` (resolution efficacy). Conflicts, where the majority (>50%) of occupants request a temperature change, are considered as important. In these cases, the overall occupant satisfaction is below 50%, i.e., a change supporting the majority group is required, i.e., the `MajorityWins`. Temperature decisions are often made by senior or higher-ranking office members on an emotional level; they exploit their rank to force their preferences on other office members (`Dictator`). `Expert` strategies are well-formed decisions with rational reasonings, usually based on norms and standards. In `Consensus` strategies, all participants enter a discourse and negotiate an acceptable decision.

Conflicts concerning IEQ stem from multiple factors affecting one or multiple IEQ indicators [TBAZ10; HP07]. For instance, solar radiation has an impact on visual quality and on thermal comfort. Modeling such problems as a single issue could lead to additional conflicts. Therefore, connected issues are defined as an `IssueSet` that contains multiple `SubIssue`s. Considering factors of the problem as a separate `SubIssue` within the larger context of an `IssueSet` allows for a more comprehensive and holistic analysis of conflicts.

Feedback is an essential component when assessing IEQ [HH07; DD04]. Actions related to the feedback `issuer` need to be re-assessed after a decision has been applied. To involve participants, such as occupants or facility managers, in the discourse, `Feedback` is defined as a specific `Argument`.

3.2 Non-linear Feedback in TREATI

The research goals (Section 2.3) state that the resolution of a thermal conflict requires the consideration of environmental and human factors and a distinction between the task and ambient environment to reach a decision.

Environmental conditions in buildings are commonly regulated by control systems. In control theory, the main objective is to command a system to reach a desired output, based on a set of inputs, while optimizing a predefined level of stability [DFT13, pp. 1–3]. Control systems often follow feedback loops[3], which aim to bring the system from a current state to a desired state, deciding on a control strategy and actions.

Traditional thermal controllers are based on conventional on/off proportional-integral-derivative controllers that operate on temperature setpoints. Thermal controllers based on the Predicted Mean Vote (PMV) model use six environmental and human input factors – air temperature, mean radiant temperature, air velocity, relative humidity, clothing insulation, and metabolic rate – to determine an averaged thermal sensation, based on which they derive a temperature setpoint [Fan70]. Others produce setpoints that target energy efficiency but ignore occupant satisfaction [PN18].

[3] Feedback loops are defined as a set of instructions given to a system with no final step, i.e., a feedback loop requires at least one input and produces at least one output. The output is then used as input in the subsequent feedback cycle.

These multiple-input single-output (MISO) systems produce a temperature setpoint as single-output, which is forwarded to the controller. Research efforts have extended such control systems in the last decade by including additional factors. For instance, Liang et al. extended the PMV controller to include energy savings [LD05]. Zang et al. have integrated a camera to capture and learn activity and clothing insulation of occupants in a thermal comfort control loop [ZXT19].

Thermal control systems that require occupant interaction are called *closed-loop MISO systems* with two types of input categories [Fen+22]:

Human factors , which include anthropometric, physiological, and behavioral factors (see Section 2.3.3)

Environmental factors , i.e., outdoor and indoor conditions that have an influence on occupant thermal comfort

These closed-loop MISO systems can evolve into *antipatterns* (cf. Andrew Koenig [Koe98]): The described environmental control processes have a linear nature, while thermal conflicts are non-deterministic and cannot be solved using static solutions. Occupant involvement – and in particular feedback – is essential in thermal control systems (see Research Goal 2.3). TREATI uses occupant feedback as a backchannel aspect to apply a causal non-linear feedback loop in addition to the environmental control loop: The decision output also functions as input and is fed back into the system for re-adjustment in the next cycle. Thus, TREATI is designed as a multiple-inputs and multiple-outputs (MIMO) system with two feedback loops: the *Environmental Control Loop* and the *Occupant Feedback Loop*. Figure 3.3 illustrates both feedback loops on a high level. The `Environmental Influence` and the `Controlled Influence` from the `Operation` (the building control system) determine the current thermal state. In the control action loop, the `Decision` issues control `Actions` to the `Operation` component. In the occupant feedback loop, occupant feedback regarding the current thermal state is analyzed and defines the `Desired State`. The `Desired State` is compared to the `Current State`, and the `Decision` issues a `Rationale` explanation regarding the control `Actions` for re-evaluation to the `Occupant`.

Formally defining the most important aspects of the MIMO system includes establishing the issue C as the difference between the desired state $\tilde{x}$ to the current state of the system x:

$$C_{\tilde{x}}^{x} = \tilde{x} - x, \text{ with } C \neq \varnothing \tag{3.1}$$

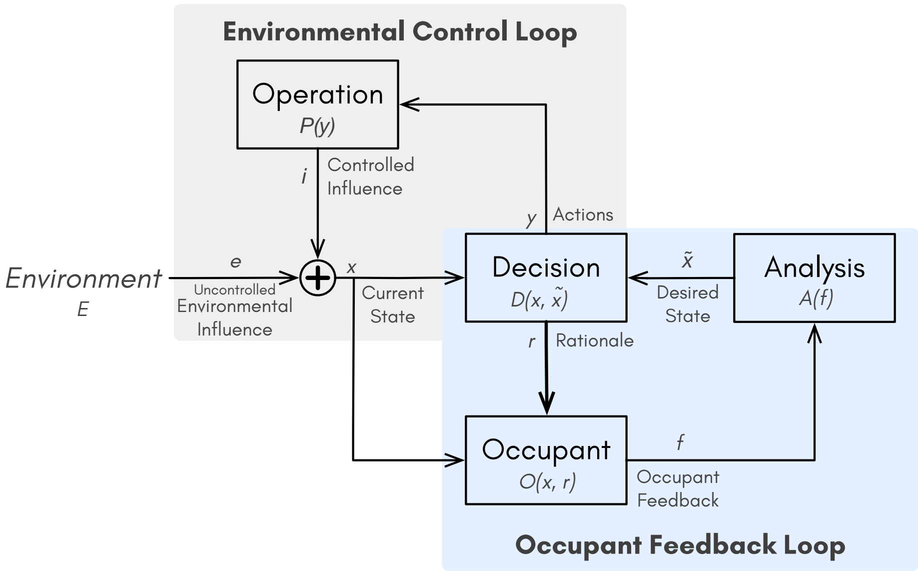


Figure 3.3: **Causal Non-linear MIMO Control System** with two feedback loops (Block Diagram)

The decision D is modeled as a control variable, not merely an output that is defined at the startup time of the system. Inputs in D are the current state of the system x and the desired state $\tilde{x}$, which is the output of the analysis A. The current state of the system is an accumulation of the uncontrolled environmental influence e, e.g., the outdoor weather, and the controlled influence i, e.g., a change in the indoor room temperature. y are the tasks to control the BMS and given to occupants O to adjust their task environment, depicted as operation P. P determines the controlled influence, e.g., in the form of a concrete task set that influences the indoor conditions. r is the rationale given to occupants O to allow them to understand the control decision D. Occupants give feedback f, based on x and r. The output of D is defined as the vector of the estimated influence on P as $\hat{P}$, based on the difference of the desired $\tilde{x}$ and current state x, and the rationale r:

$$D(x, \tilde{x}) = \begin{bmatrix} y(x, \tilde{x}) \\ r(x, \tilde{x}) \end{bmatrix} = \begin{bmatrix} (\tilde{x} - x) \times \hat{P}^{-1} \\ r \end{bmatrix} \tag{3.2}$$

3.3 Structural Model

The previous section describes TREATI on a high-level to formalize the relevant variables and system states (see Figure 3.3). This structure is now transformed into an object model to represent the individual objects manipulated by the system, and their properties and relationships.

First, the main concepts are derived in form of a package diagram in Section 3.3.1. Each subsystem is then described in detail, with a focus on the feedback loops and their dynamic aspects. The overall architecture is presented in Section 3.3.7.

3.3.1 Object Model

The abstractions from Figure 3.3 are mapped to the following six packages: `Environment`, `Building Management`, `Occupant`, `Event`, `Context`, and `Rationale`, as illustrated in Figure 3.4.

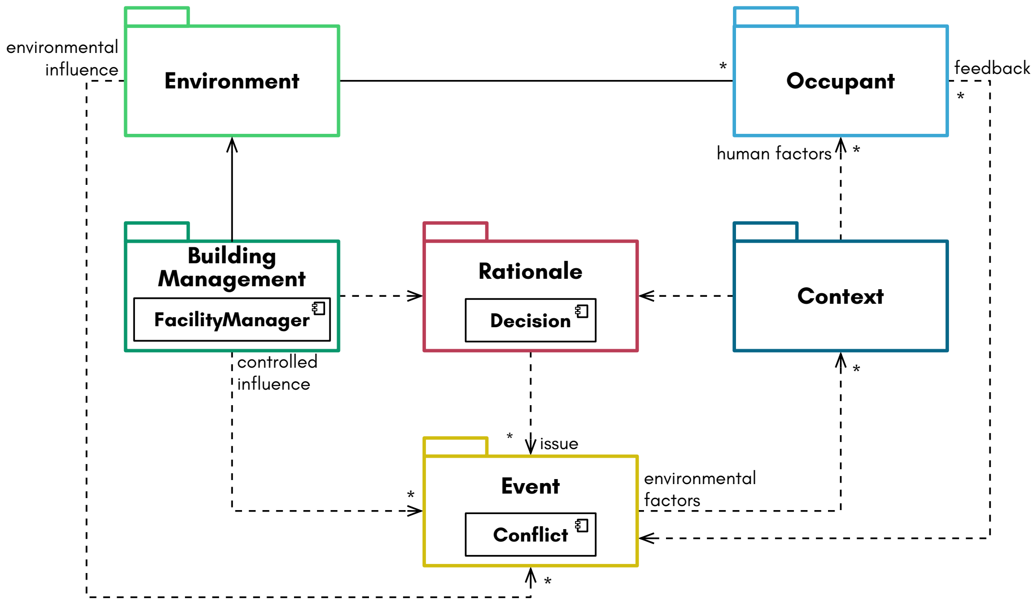


Figure 3.4: **High-level View of TREATI** organized into six packages (UML Package Diagram)

The `Occupant` package models the end-user, i.e., humans occupying the `Environment`. The uncontrolled and controlled influences determine the current state of the control system. The `Event` package identifies the difference between the current to the desired state in the form of an issue, i.e., the `Conflict`. The *Analysis* from Figure 3.3, which describes the process of evaluating occupant feedback and the current state to form the desired state, is distributed across the `Event` and `Rationale` packages.

The Decision is part of the Rationale package, which identifies the difference between the states as a Conflict and passes it on to the Decision component for its resolution. Human factors and environmental factors are summarized as the Context, which is used by the Rationale package to determine potential actions and a decision regarding an issue. The Context identifies additional factors necessary for resolving issues, such as a history of events, or environmental and human factors from the Occupants. The *Operation* from Figure 3.3 is mapped to the Building Management Package in TREATI, the main abstraction is called the Facility Manager.

3.3.2 Environment-in-the-Loop & Temperature Control

The Environment package and parts of the Building Management package from Figure 3.4 are described below. They encompass objects based on the definitions and observations defined in Section 2.3.1.

Building management systems (BMS) have a hierarchical architecture and often operate on three levels: the field level, automation level, and management level [MHH09, pp. 41–43]. Control loops on the field level define how the thermal environment is controlled through physical devices, such as sensors, dampers, valves, and a controller. The automation level addresses communication between individual systems through interfaces for monitoring, controlling, and regulating building services, such as HVAC, electricity, or plumbing [MHH09, p. 7]. The third level presents the central management of the system, often through web-based applications [MHH09, p. 201]. Facility managers determine when signals are sent to a control loop. For example, the predefined rule $\{if\ (T_{air} < 19\,°C)\ then\ raise\ T_{air}\ until\ T_{air} > 19\,°C\}$ would send a signal to the controller to raise the air temperature if the air temperature drops below 19 °C. Figure 3.5 abstracts and combines these three levels.

The TREATI framework focuses on environments, such as instrumented buildings, that are equipped with Sensors and Actuators:

Sensors detect events in their immediate environment

Actuators are devices, such as desk fans or task heaters, that enable occupants to influence their personal thermal comfort

Zones are areas that are controlled by a single thermostat and can comprise multiple floors [Par15]. Therefore, instead of a detailed breakdown of individual buildings to represent a Space, TREATI defines a Space as a composition of multiple Zones shared by at least two Occupants, regardless of the building's concrete layout. The thermal environment is divided into TaskZone and AmbientZone, see Definition 2.11. Since TaskZones affect the environmental quality of the respective AmbientZone, TREATI

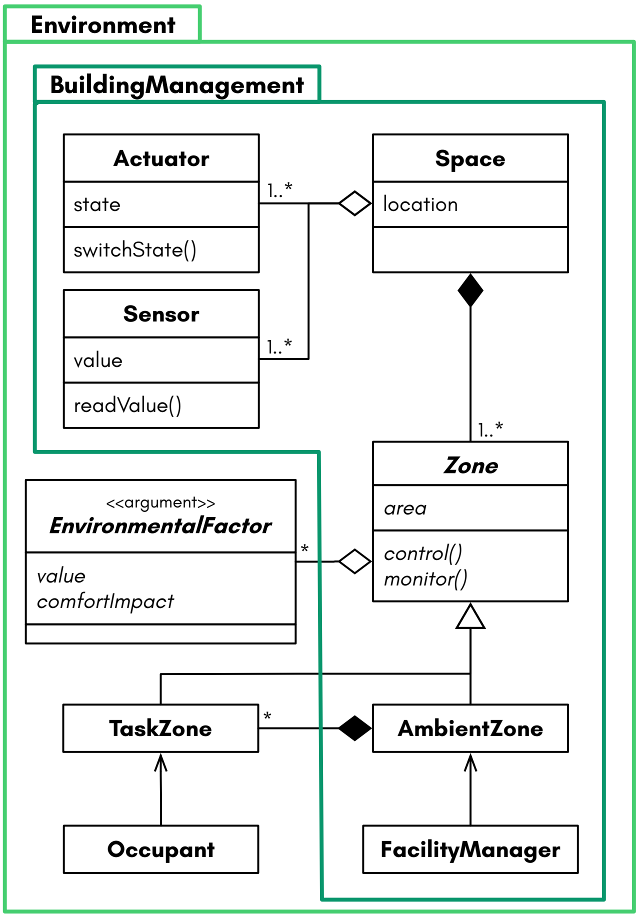


Figure 3.5: **Environment Package** (UML Class Diagram)

encompasses `TaskZones` as part of an `AmbientZone`. For instance, if an occupant uses a task heater, the heat exchange also has an impact on the ambience and can increase indoor air temperature over time. The `AmbientZone` is monitored and controlled by the building management system and supervised by `FacilityManagers`. `Occupants` are situated in a designated `TaskZone` where they can monitor sensor values and control actuators. A `Zone` consists of `EnvironmentalFactors` (derived from Figure 2.9) that have an influence on occupant thermal comfort, denoted `comfortImpact`. `EnvironmentalFactors` are used as arguments during the decision-making process.

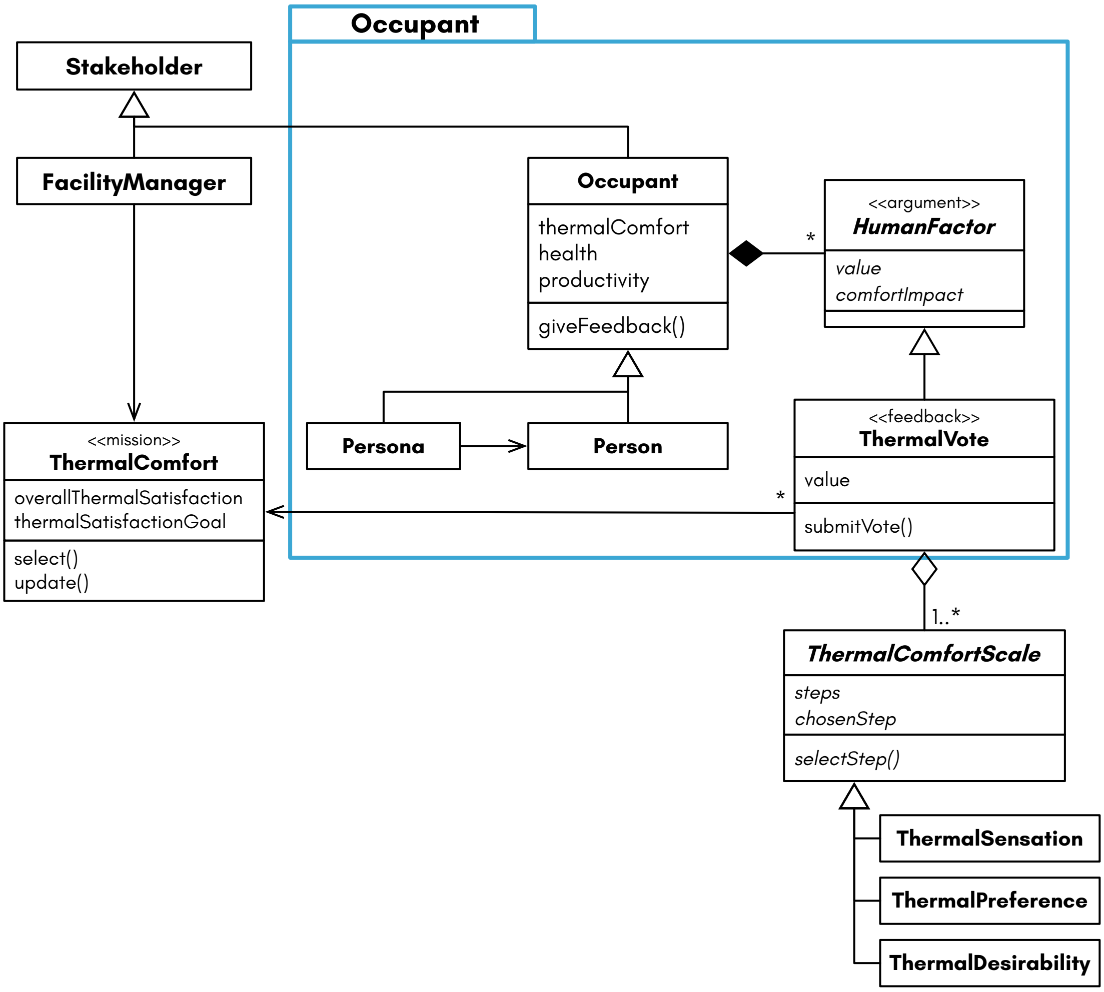


Figure 3.6: **Occupant Package** (UML Class Diagram)

3.3.3 Bringing the Occupant Back into the Loop

Two types of `Stakeholders` interact with TREATI, namely `FacilityManager` and `Occupant`. The `FacilityManager` is part of the building management package (Section 3.3.2) and determines the constraint thresholds and priorities of a mission and controls the ambient zone. Figure 3.6 shows the interaction between the facility manager and the occupants to achieve thermal comfort.

`Occupants` determine the occurrence of conflicts due to differing temperature perceptions. Occupant behavior, considered a `HumanFactor`, is important for understanding and maintaining an occupant's `ThermalComfort` [NR17; CBM10]. Thus, `HumanFactors` are included as parameters in thermal control decision-making. These include, for instance, the general preferences towards temperature, gender [CK19], or biosignals, such as skin temperature [CLL12]. The taxonomy including common human factors derived from literature is illustrated in Figure 2.9.

`ThermalComfort` is associated with many `ThermalVotes` submitted by `Occupants`.

The FacilityManager selects the thermalSatisfactionGoal. The overallThermalSatisfaction is updated by the ThermalVotes. Occupants submit ThermalVotes as a feedback regarding their thermal satisfaction. A ThermalVote consists of either ThermalSensation, ThermalPreference, or ThermalDesirability and the chosenStep on the respective scale.

If a Person cannot be determined, the Person is substituted by a Persona.[4] In the occupant model (cf. [Iyi21; Iyi20]), a Persona is an abstract representation or proxy of a real Person, embodying behaviors and motivations relevant to the resolution of thermal conflicts. Personas portray sensitive human factors, such as health issues, or behaviors relevant to thermal conflicts, which may compromise the person's privacy.

3.3.4 Event and Issue Identification

Traditional building management systems (BMS), such as Johnson Controls[5], and frameworks (e.g., OSIsoft[6]) rely on pre-defined static sensor thresholds in order to detect deviations from the expected values. Using rule-based approaches allows facility management to customize the control strategy with respect to the building envelope, such as orientation, window management, and wall insulation. However, this prevents any dynamic changes at runtime that are crucial to respond to occupant feedback [LFHO17]. A rule-based approach to occupant feedback limits the interaction and resolution possibilities while also increasing the rules' complexity [PSCC19]. The definition of a rule set per situational context change would be required, which quickly becomes complex and error-prone. In addition, thresholds and values used to identify an issue are often not valid and justifiable [PSCC19; LDH16].[7] For instance, the rule *if* $T_{in} > 24\,°C$*, cool until* $T_{in} \leq 24\,°C$, with an slight indoor air temperature increase $T_{in} = 24.1\,°C$ may lead to confusion and dissatisfaction among occupants: While humans cannot perceive a $0.1\,°C$ change, the HVAC system would turn the air conditioning on, resulting in an energy increase.

Sensors measure the state of a physical phenomenon at predefined intervals. Most BMS use sensors that transmit their measurements periodically to detect and react

[4]Personas are used in the field of human-computer-interaction in user modeling and denote a "*[...] fictitious user representation created in order to embody behaviors and motivations that a group of real users might express, representing them during the project development process*" [JF05].

[5]https://www.johnsoncontrols.com/building-automation-and-controls/hvac-controls/thermostats/networked-thermostat-controllers

[6]https://www.osisoft.com/industries/facilities-and-infrastructure

[7]This compares to defining explicit values regarding health risks: A person is considered at risk of heart attack with increased blood pressure: if the systolic pressure is higher than 180 or if the diastolic pressure exceeds 120 [GH+86, pp. 108–111]. A person with a diastolic pressure of 119 would, according to the textbook definition, not be considered at risk, even though they have a comparable risk to a person with a value of 121. Hence, other factors need to be considered, such as general fitness, diet, and preexisting conditions, when assessing a person's risk of heart attacks.

to changes. This often causes a communication overhead since all measurements are passed on to the same processing component and need to be analyzed [DL11; Zha+14].

The issue identification in TREATI is event-driven, which leads to less communication overhead and ensures that events will only be evaluated when a predefined threshold is exceeded, or the current status is surpassed [HJC08]. Figure 3.7 shows TREATI's event model. An `Event` is the occurrence of a message that conveys new or

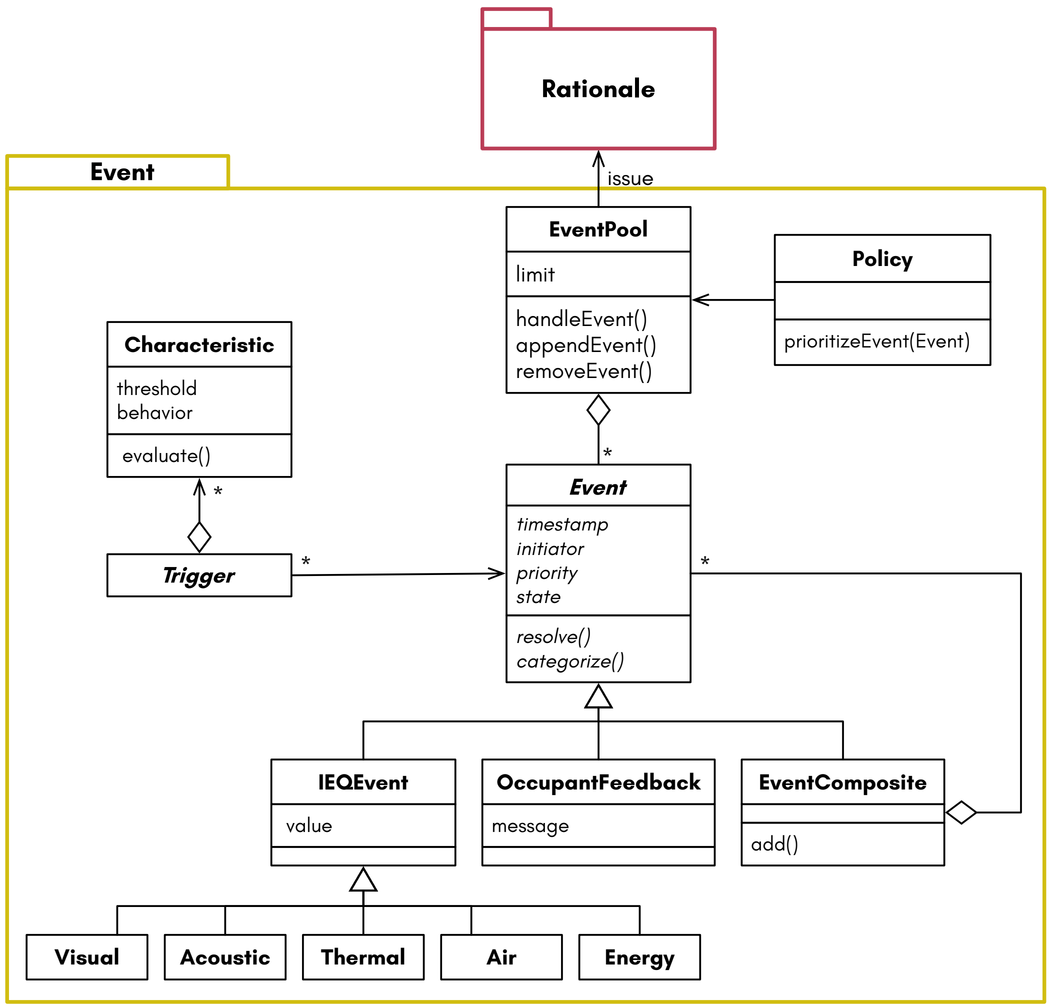


Figure 3.7: **Event Package** (UML Class Diagram)

changed measurements on a particular subject [LF98]. It describes an asynchronous change in the environment that is invoked by a `Trigger`, such as a rise in indoor temperature or an increase in solar radiation. `Trigger` have `Characteristics`, which describe `thresholds` or `behavior`. For instance, an increase in air temperature is measured and triggered by an air temperature sensor. TREATI distinguishes between two event types: `IEQEvents` and `OccupantFeedback`. `IEQEvents` are environmental events and mainly rely on sensor readings. Research has shown that occupants can be good sensors for IEQ performance [Par15], thus, `OccupantFeedback` is treated as an observed value, hence, an `Event`. `OccupantFeedback` can be active, such as occupant votes, or passive; an occupant opening a window also causes an `Event`.

An `EventComposite` is a set of multiple events that changes dynamically. For instance, an `EventComposite` could contain a `Thermal` event for air temperature changes and an `OccupantFeedback` event for occupant votes. The `EventComposite` is appended to the `EventPool`, e.g., whenever an occupant provides feedback. The `EventPool` provides handling of `Events` and forwards issues to the `Rationale` package. The `EventPool` has a `limit`, such as a time frame in which events are evaluated or the minimum and the maximum number of events to be evaluated. Once an `Event` is relevant, it is `appended` to the `EventPool`. Relevant `Events` include the `IEQEventsThermal`, `Air`, and `Energy`, or `OccupantFeedback`. Irrelevant events include `Acoustic` and `Visual` events, as they do not affect thermal comfort. The `Policy` evaluates the `EventPool` regarding `Trigger Characteristics` and determines whether it results in an issue.

Figure 3.8 describes the transformation of an event into an issue. The `Event` enters the `EventEvaluation` state where the `Policy prioritizes` the `Event` based on the `Mission`'s goal. Any `Event` that affects the thermal equilibrium (see Definition 2.10) is an issue and requires an evaluation. For instance, a '*no change*' occupant vote or an increase in the air temperature by 0.1 $°C$ within 30 minutes do not imbalance the equilibrium. Two occupant votes for '*cooler*' or an air temperature increase by 0.6 $°C$ within 30 minutes are identified as issues. This `IssueEvaluation` requires the determination of the context. Once an issue has been identified, the context is

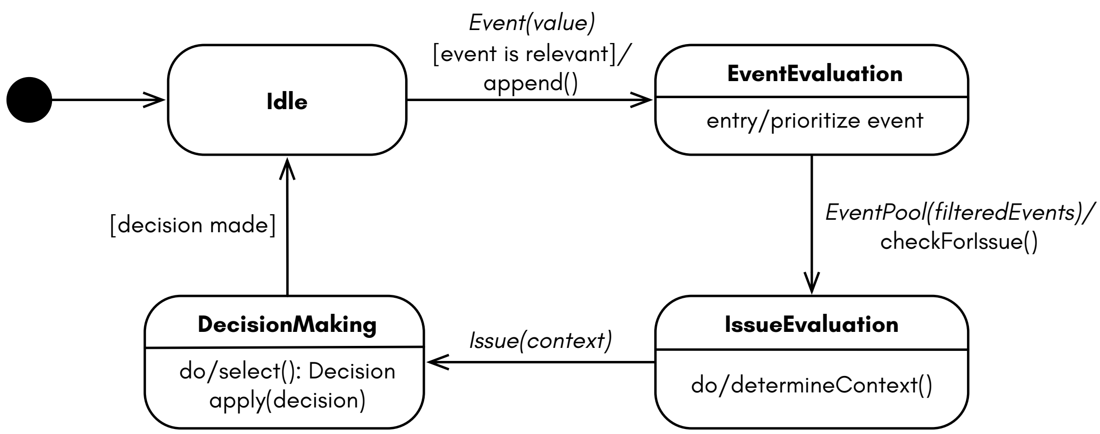


Figure 3.8: **TREATI's State Model** shows how events are transformed into issues (UML State Diagram)

determined, and the `DecisionMaking` state is entered. If an issue has been identified, it is forwarded to the `Rationale` package.

3.3.5 Context Management

An occupant may feel warm due to solar gain through a window, while another may feel cold due to an incoming draft from a tilted window. Such circumstantial information are defined as the issue's *context*. Existing systems consider environmental and human factors as context factors [LMK18; KSB18; Fra+19; Yan+15; DDB02; Fan70].

Figure 3.9 presents the context package. The `ContextManager` determines the `Context`, which is composed of `ContextIndicators`. `EnvironmentalFactors`, `HumanFactors`, thresholds and constraints (i.e., the `Mission`), and `Arguments` have an `impact` on the `Issue`, and are defined as `ContextIndicators`. `EnvironmentalFactors` and `HumanFactors` have a history which may be relevant to the `Issue`, such as an air temperature curve (`EnvironmentalFactor`) or occupant load (`HumanFactor`).

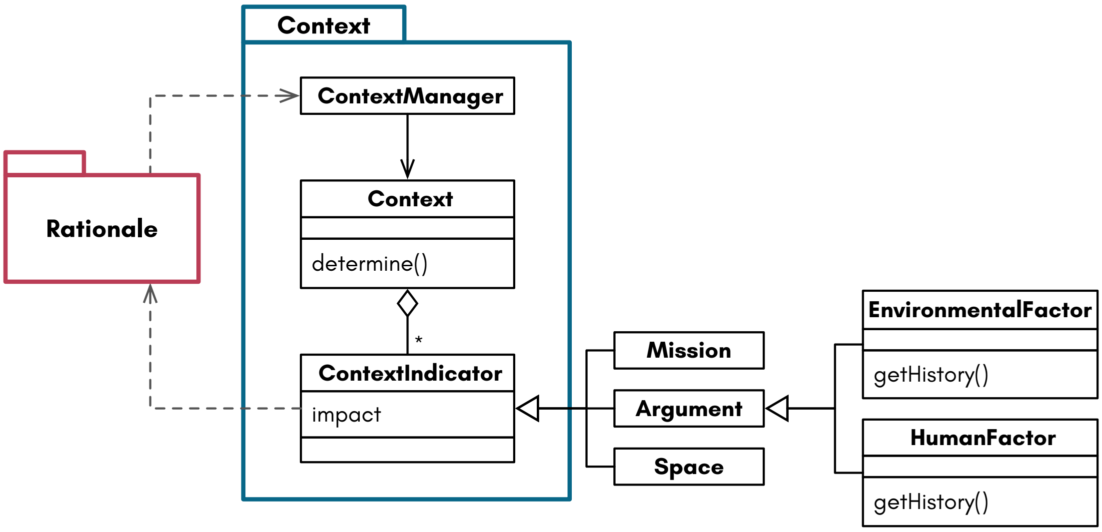


Figure 3.9: **Context Model** (UML Class Diagram)

3.3.6 Rationale Decision-Making

The rationale package describes TREATI's decision-making process and its components. Rationale management is an effective way of capturing decisions and proposed alternatives during the increments and iterations of processes [SH94]. TREATI's decision-making process draws from Figure 2.7 and Observation 2.1, based on work by [DGO13; MRT76; Kle89; Sim56].

Figure 3.10 presents an overview of the phases of TREATI's decision-making process adapted from [Fra21]. The process starts with the `Categorization` phase. After an `Event` is registered, it is categorized and filtered (detailed in Section 3.3.4).

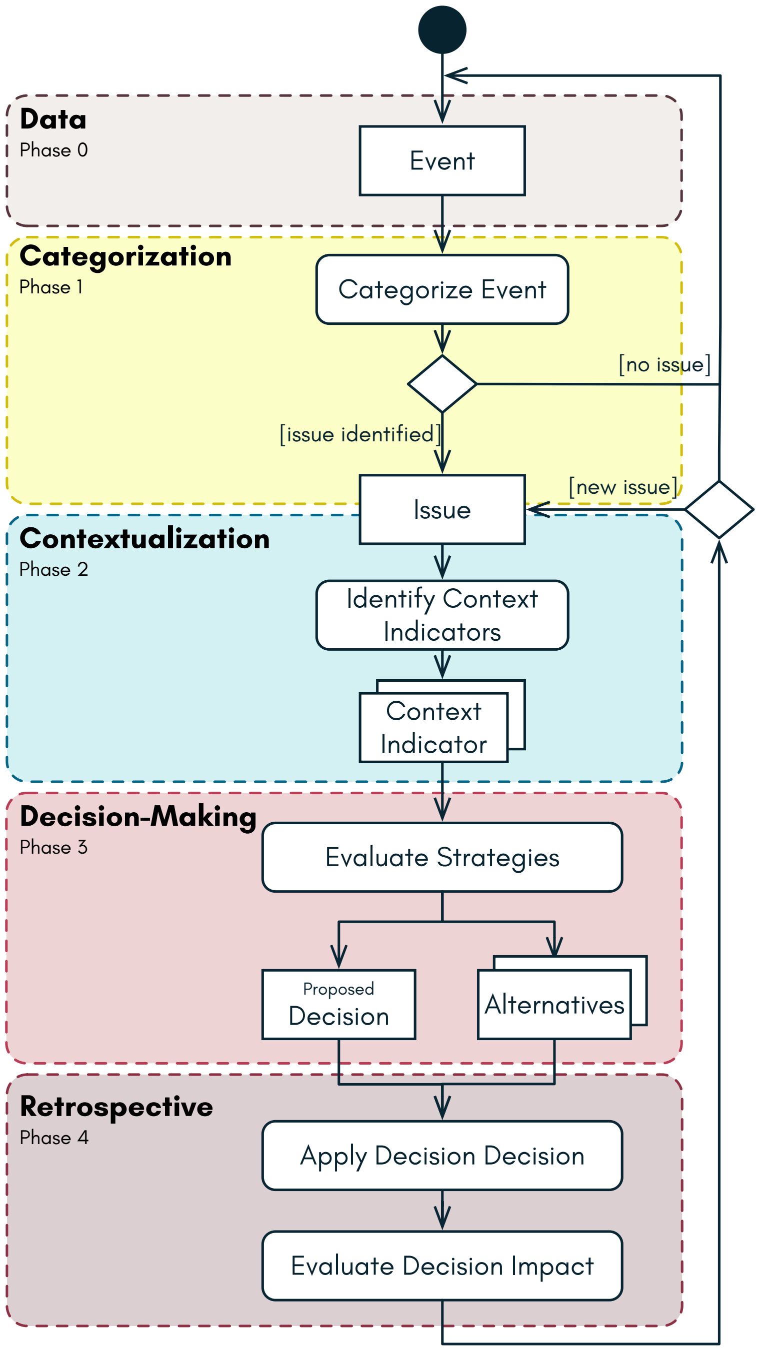


Figure 3.10: **TREATI's Decision-Making Process** (adapted from [Fra21], UML Activity Diagram)

If there is a need for a decision, i.e., an `Issue` was identified, the `Contextualization` phase establishes the relevant `Context Indicators`. The `Decision-Making` phase evaluates or generates new strategies and selects a `Decision`. In the `Retrospective` phase, the decision is applied, and the impact on the environment and occupants is evaluated. If the `Retrospective` results in another `Issue`, the process enters the `Contextualization` phase again; otherwise, it waits for a new `Event`.

Figure 3.11 models the decision-making concepts as classes and associations. The naming of the stereotypes is based on the TREATI metamodel (Figure 3.2).

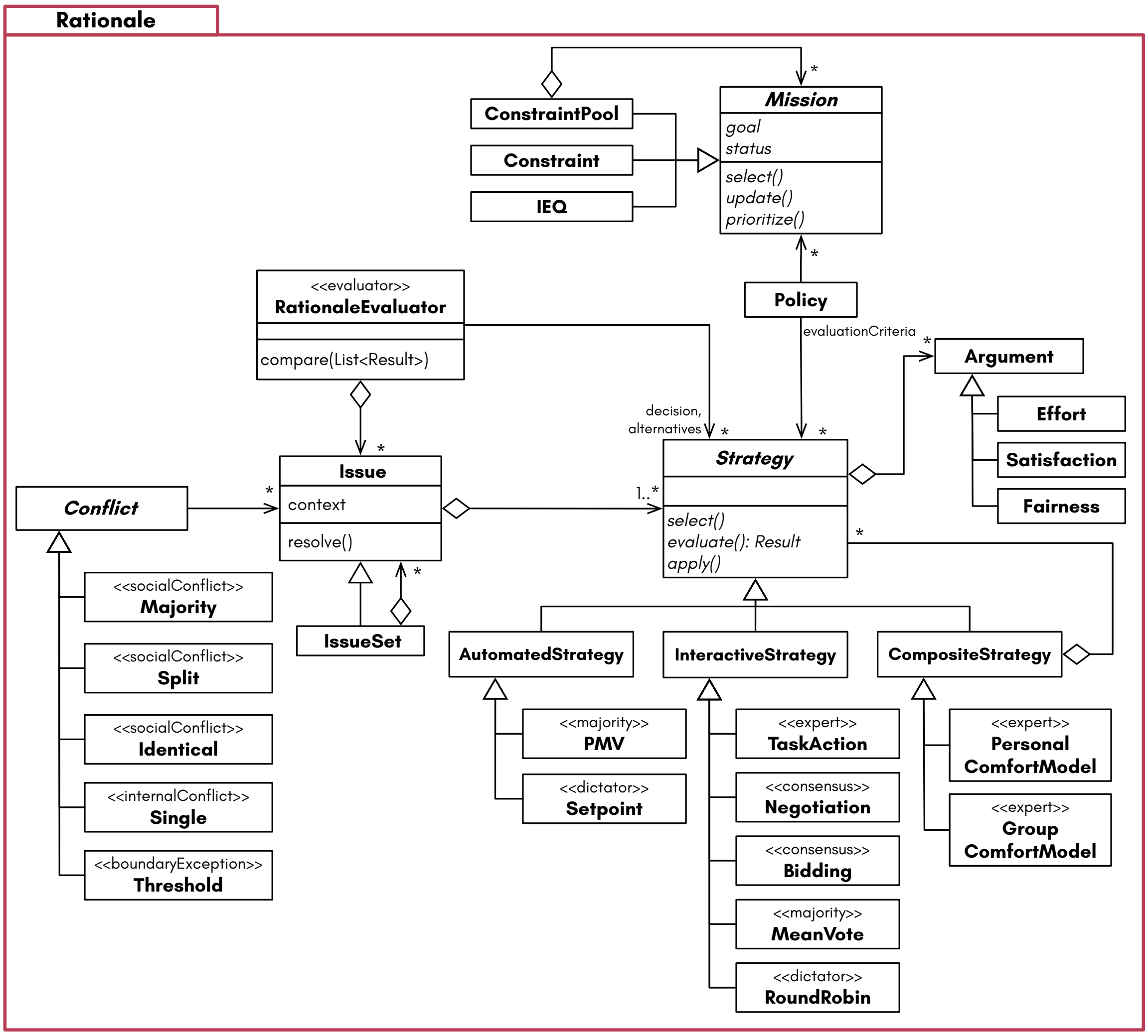


Figure 3.11: **Rationale Model** (UML Class Diagram)

An `Issue` represents an event or a question, such as *"What is the optimal temperature for Room 313?"*. `Issues` may occur in conjunction with other `Issues`, constituting an `IssueSet`. `Issues` in an `IssueSet` might conflict with each other. TREATI deals with five types of conflicts that were derived from de Dreu and Weingart [DDW03], Simons and Peterson [SP00], and Jehn [Jeh97]: `Majority` conflicts, where the overall majority's preference regarding the `Issue` is in contrast to the minority's preferences; `Split` conflicts describe at least two equal-sized cohorts with differing preferences each; `Identical`, where all occupants have the same preference but conflict with the environment's energy efficiency goal; `Single`, where a single occupant requests a change; and `Threshold`, which describes a breach of the minimum or maximum threshold values of a `Mission`.

The `Rationale Evaluator` compares the `Strategies` based on their `Arguments` and the `Missions`' implications, which are analyzed by the `Policy`. The `Policy` determines how an `Issue` needs to be resolved and `prioritizes` the `Missions`. For example, a `Policy` goal can either be the selection of the most sustainable decision or the selection of the decision that provides the highest occupant satisfaction.

There are three types of `Strategies`: `AutomatedStrategies`, `InteractiveStrategies`, and `CompositeStrategies`. An `AutomatedStrategy` contains pre-defined algorithms that do not require occupant interaction, such as the `PMV` (Predicted Mean Vote) model introduced by Fanger [Fan70] and the `Setpoint` strategy, which relies on standards, such as ASHRAE 55 [Ame20].

The `InteractiveStrategy` relies on occupant interaction and feedback. There are five subclasses of `InteractiveStrategies`: The `TaskAction` strategy suggests a behavioral adjustment to a single occupant. `Negotiation` and `Bidding` are consensus strategies: Occupants negotiate the temperature setpoint by suggesting future control proposals to opposite negotiators until consensus is reached or the negotiation ends. The `Bidding` strategy consists of at least two rounds. In the first round, occupant votes are submitted. In the second round, acceptable alternatives are proposed, and occupants bid on their preferred alternative. The alternative with the most votes is selected. The `MeanVote` strategy averages across all occupants' votes or general preferences. The `RoundRobin` strategy allows each occupant, in turn, to control the thermostat based on their preferences or by setting a specific temperature setpoint.

TREATI allows the definition of `CompositeStrategies`, which are sets of multiple strategies. For example, a `CompositeStrategy` consists of an `AutomatedStrategy` to control the `AmbientZone` and a `TaskAction` to resolve an occupant's issue. Other examples for a `CompositeStrategy` are `PersonalComfortModels` and `GroupComfortModels`. A `PersonalComfortModel` estimates the behavior or satisfaction of a single occupant and provides task actions or direct control of the task environment. A `GroupComfortModel` estimates the behavior or satisfaction of a group of occupants and provides a temperature setpoint for the ambient zone or a set of task actions.

3.3.7 Top-Level Design

Figure 3.12 provides an overview of TREATI's object model which is partitioned into six packages introduced in the previous sections.

The `Environment` package contains the `Space` which is instrumented with `Sensor`s and `Actuator`s. A `Space` consist of many `Zones`, which are either `TaskZone`s or `AmbientZone`s. `Occupant`s occupy a `TaskZone`, which has a direct impact on the `Occupant`'s thermal comfort, health, and productivity. The `AmbientZone` is monitored and controlled by the `FacilityManager`.

`Actuator`s, `Sensor`s, and `Occupant vote`s trigger `Event`s, which are appended to an `EventPool`. The `Policy` determines how the `EventPool` is handled. The `Policy` further `prioritize`s `Mission`s, and identifies the `evaluationCriteria` for the `Strategies`. `Events` from the `EventPool` are identified as `Issue`s (see Figure 3.8) and resolved by the `RationalEvaluator`. The `ContextManager` determines the context by means of `Event`s, `Actuator`s, `Sensor`s, `EnvironmentalFactor`s, and `humanFactors`. The `RationaleEvaluator` compares the `Strategies`' results based on the `context` and selects a `decision`. The `FacilityManager` applies the `decision` to the respective `Zone`. The `Occupant` can review the `decision`.

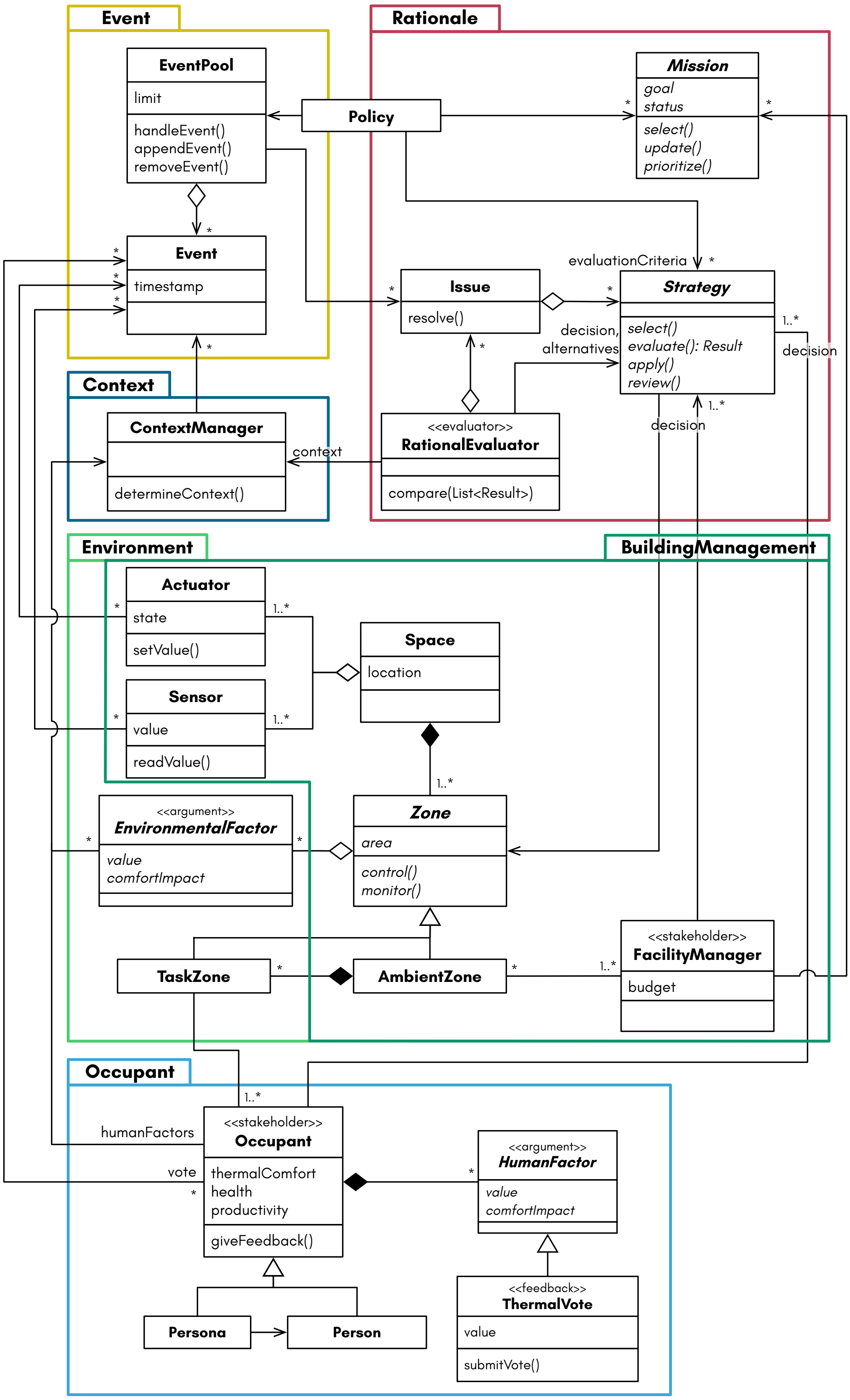


Figure 3.12: The detailed **TREATI Object Model** consists of six packages and the associations between them (UML Class Diagram)

Chapter 4
Validation

> It doesn't matter what temperature the room is, it's always room temperature.
>
> Steven Wright

This chapter validates the TREATI framework regarding hypotheses H1 and H2. Section 4.1 describes the validation methodology based on Basili and Weiss' Goal Question Metric (GQM) Model [BW84]. TREATI's conflict resolution process is validated using a human-in-the-loop (HITL) simulation with personas[1]. Section 4.2 defines and formalizes the simulation model.

The simulation results, findings, and threats to validity are discussed in Chapter 5.

[1] In human-computer interaction, personas traditionally describe fictitious persons as stand-ins for real persons [Coo99]. In this validation, personas are used as proxies for real occupants.

4.1 Goal-Question-Metric Model

The validation uses the Goal-Question-Metric (GQM) model by Victor Basili and David Weiss [BW84] to measure and test hypotheses H1 and H2. The GQM model systematically transforms the research hypotheses into goals, defines a set of questions per goal, and uses metrics to address each question, as explained in Table 4.1.

Goal	Question	Metric
Validation goals are derived from hypotheses H1 and H2	Validation questions are deduced to target specific aspects of each goal	Validation metrics provide measurable observations to the questions

Table 4.1: **Basili & Weiss' Goal Question Metric Model** [BW84]

The two main goals that guide this validation (VG) are:

VG1 Evaluate the impact of TREATI on the resolution of thermal comfort conflicts (→ H1)

VG2 Evaluate the effect of occupant involvement in TREATI's decisions (→ H2)

The validation model presented in Table 4.2 is comprised of these validation goals, with validation questions, validation metrics, and methods.

Validation questions 1, 2, and 3 address the overall efficiency of TREATI compared to the *Predicted Mean Vote* model by Fanger [Fan70] and *Static* control, which ignores occupant feedback. The influence of different context parameters on the decision is also explored. Validation questions 4 and 5 target occupant involvement through voting behavior and task actions. Overall, addressing validation questions 1 through 5, TREATI is evaluated using *Occupant Satisfaction*, *Energy Efficiency*, *Fairness*, and *Task Actions* as the key validation metrics by means of automatic object-event simulation. The validation metrics are defined in Section 4.2.5. Validation question 6 assumes consistent occupant voting using a manual object-event simulation to determine whether a closed-loop approach (as described in Section 3.2) can ultimately achieve 80% occupant satisfaction, the target set by the ASHRAE 55 standard [Ame20], as described in Section 5.1.5.

<table>
<tr><th>Validation Goal</th><th>Validation Question</th><th>Metrics</th><th>Method</th></tr>
<tr><td rowspan="3">VG1 Evaluate the impact of TREATI on the resolution of thermal comfort conflicts</td><td>VQ1 How does the evaluation and selection of multiple strategies compare to traditional control methods?</td><td rowspan="5">Occupant Satisfaction
Energy Efficiency
Fairness
Task Actions</td><td rowspan="5">Automatic Object Event Simulation</td></tr>
<tr><td>VQ2 Does the resolution of non-trivial conflicts using TREATI lead to better results, compared to traditional control methods?</td></tr>
<tr><td>VQ3 How do different parameters influence the results?</td></tr>
<tr><td rowspan="3">VG2 Evaluate the effect of occupant involvement in TREATI</td><td>VQ4 How does occupant involvement in the form of comfort votes, in combination with human factors in the decision-making process, affect TREATI's outcomes?</td></tr>
<tr><td>VQ5 How do strategies that include occupant involvement influence decision outcomes, compared to non-composite actions?</td></tr>
<tr><td>VQ6 Does consistent occupant voting in combination with the decision-making process over time lead to $\geq 80\%$ occupant satisfaction?</td><td>Occupant Satisfaction</td><td>Manual Object Event Simulation</td></tr>
</table>

Table 4.2: **Validation Model**

4.2 Conflict Resolution Experiment

Iterative computer simulations are used to validate and verify TREATI. Simulations imitate real-world operations over time [BCINN05], and they allow the definition and testing of multiple scenarios[2]: Environmental conditions and human behavior are controlled precisely without the risk of bias, inconsistencies, or ethical concerns. Design errors and limitations are disclosable without exposing a human to a stressful environment, thus risking an impact on their health or productivity. In addition, human bias towards the system and each other during the feedback process – such as power struggles between high- and low-ranking office members – is avoided. The simulation is modeled as time-independent to reduce additional influential factors such as time zones or shift work.

[2]A *scenario* in the context of simulations refers to a specific configuration during one period of observation [BCINN05].

4.2.1 Simulation Methodology

To determine TREATI's impact and occupant involvement, the validation goals (see Table 4.2) are evaluated using an equation-based object-event simulation that models and generates data. No suitable available historic dataset covering the required parameters, thermal conflicts, or dynamic changes exists to the best of this author's knowledge. There are a few open-source thermal comfort databases, such as the global ASHRAE thermal comfort database [Lič+18], data from short-term group comfort experiments [Fra+19], and data from personal comfort experiments, such as LATEST [FRBL20] and SPOT* [RK16]. These neither provide the data needed for this validation nor represent thermal conflicts or the resolution thereof. The data generation tool (based on [Mah21]) and a reference implementation of TREATI's conflict resolution process (adapted from [For21; Had21]) were developed to form a simulation model, for generating environmental and human factors and to simulate decisions.

The simulation model consists of the *existing conditions model*, described in Section 4.2.3, and the *conflict resolution model*, which is outlined in Section 4.2.4. The existing conditions model comprises the environmental and human factor parameters and variables as input for the conflict resolution model. Parameters describe constants in a scenario, e.g., outdoor air temperature. A variable in the simulation represents the state of an object that is subject to change during a scenario, such as occupant feedback or indoor air temperature. The conflict resolution model describes TREATI's actions and metrics of success in Section 4.2.5. The simulation model is validated and verified to ensure the overall findings' validity. Table 4.3 gives an overview of the applied methods. The simulation model's validation and verification results are presented in Section 4.2.7.

4.2.2 Simulation Design

The overall simulation process is illustrated in Figure 4.1; its parameters are derived from the environment package (see Section 3.3.2) and occupant package (see Section 3.3.3). The conflict resolution model is in alignment with the processes and elements discussed and derived in Section 2.2.1. It describes the outputs, i.e., solution strategies consisting of the range of control actions: task actions (clothing, task conditioning systems, and beverages) and temperature setpoints. The solution strategies are evaluated, and a decision is determined by means of pre-defined metrics. The control choices are then re-evaluated, and the loop repeats. Each iteration of this process is equivalent to one simulation run, with the specified existing condition model's parameters forming the run's configuration.

<table>
<tr><th colspan="2">Method</th><th>Description</th><th>Test</th></tr>
<tr><td rowspan="5">Validation</td><td>Data Relationship Correctness</td><td>Ensure common relationships among environmental and human parameters that exist in the real world</td><td>Based on related work & existing data; design and output supervised by domain expert</td></tr>
<tr><td>Event Validity</td><td>Compare events from existing data with the simulation output</td><td>Comparison to PMV example data from ASHRAE 55 [Ame20]</td></tr>
<tr><td>Face Validity</td><td>Ensure reasonable logic and behavior of simulation model</td><td rowspan="3">Test scenarios, compare output to expected output</td></tr>
<tr><td>Internal Validity</td><td>Analyze the amount of stochastic variability</td></tr>
<tr><td>Predictive Validation</td><td>Compare the predicted output of the system against the actual output</td></tr>
<tr><td rowspan="2">Verification</td><td>Sensitivity Analysis</td><td>Determine & verify the effect of changes to the system's behavior</td><td rowspan="2">Test scenarios with input parameters from Table 4.4</td></tr>
<tr><td>Extreme Condition Test</td><td>Test the robustness of the system with unusual input parameters</td></tr>
</table>

Table 4.3: **Simulation Model Validation and Verification** (the overall approach follows Sargent's validation procedure [Sar99])

The simulation requires multiple runs with different configurations to address the validation questions and identify the process's shortcomings. Five simulation parameters are variable: Outdoor air temperature, indoor air temperature, task action choices, persona types, and group voting behavior. Each of the five parameters has different configurations that are permutated and amount to a total of 320 scenarios.

Parameter Configuration

An occupant's thermal comfort depends on a variety of environmental and human factors [DD04; NH02]. Given the controls available in building management systems, the most important factor to determine thermal comfort is air temperature. Thus, indoor air temperature and outdoor air temperature were selected as simulation parameters. Task action choices, persona types, and voting behavior were selected as human parameters in the simulation, as presented in Table 4.4.

Five configurations for the indoor air temperature are tested, drawing from the lower bound (19 °C) and the upper bound (27 °C) of ASHRAE 55 [Ame20], in 2 °C steps. For the outdoor temperature, four temperatures in the range between 1 °C to 31 °C were chosen to mimic different seasons. In addition to clothing choices from 0.5 *clo* up to 1.2 *clo* [Ame20], task action items include a desk fan, task heater, and

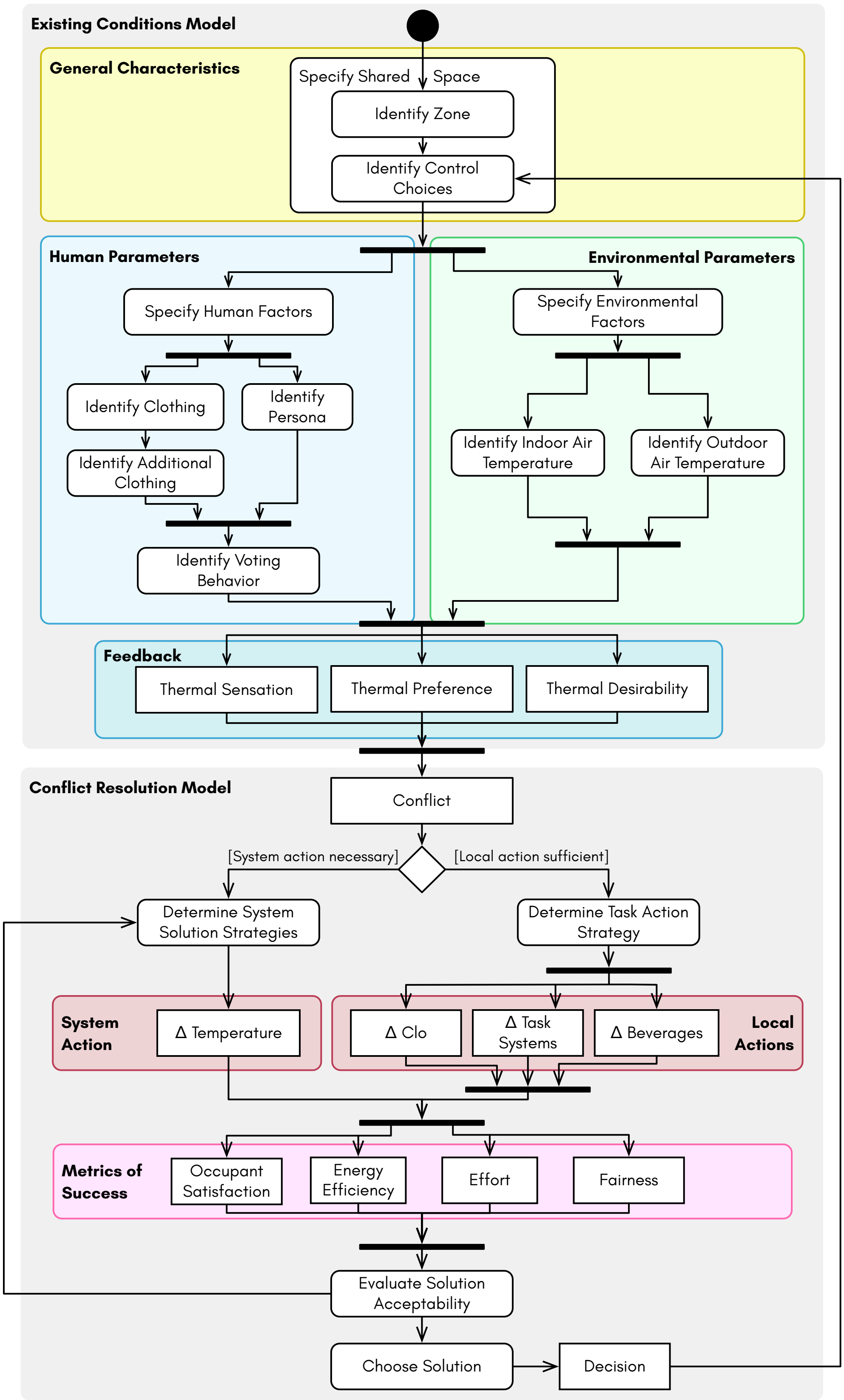


Figure 4.1: **TREATI's Simulation Process** (UML Activity Diagram)

Outdoor Air Temperature	Indoor Air Temperature	Task Action Choices	Persona Types	Voting Behavior
1 °C 11 °C 21 °C 31 °C	19 °C 21 °C 23 °C 25 °C 27 °C	No Actions All Actions: Clothing Vest, Sweater, Suit Jacket Beverages Hot, Cold Task Conditioning Task Heater, Desk Fan	Cooler Neutral Warmer Combination	Randomized Split
			Cohort Split	Majority

$(4 * 5 * 2 * 4 * 2) + (4 * 2 * 2 * 1 * 1) = 320 + 40 = 360$ *permutations*

Table 4.4: **Existing Conditions Input Parameters**

hot and cold beverages. Existing research has shown that, especially in mixed-gender offices, broad ranges of preferred temperatures exist [CK19; KML15]. To mimic this behavior and investigate its effect on TREATI, four persona types are represented as typically preferring *cooler*, *neutral*, or *warmer* temperatures, or a randomized mixed combination. The personas are named according to their types hereafter and represent attributes relevant to the resolution of thermal conflicts, such as conflict handling type or voting frequency. All other environmental conditions, such as radiant temperature or air speed, are assumed to remain constant throughout all simulation runs, as described in Section 4.2.3. The validation of TREATI is performed for a shared office space with multiple occupants. The number of occupants sharing a thermostat can vary, with an average of 12 occupants per thermostat in the U.S. [Par15, p. 103]. Hence, the simulation models 12 occupants.

Voting Design

Three group voting behaviors are examined to test different conflict scenarios: *Random* voting behavior leads to a random distribution and a randomly generated number of votes to mimic and investigate realistic occupant voting behavior. *Split* voting behavior describes conflicts with two equal-sized cohorts where each prefers a different temperature. *Majority* voting behavior describes conflicts from contradicting votes from two cohorts with a majority and minority vote distribution. The scenarios are described in Table 4.5. For simplicity and comparability reasons, the majority is comprised of 75% of the occupants, the minority of 25%. Two cases are of particular interest: (1) The majority is satisfied but the minority prefers a different temperature, and (2) the majority prefers a different temperature and the minority is satisfied. The conflicts are evaluated in Section 5.1.

Split and majority voting behavior conflicts involve all 12 occupants to eliminate potential implications through low participation. For instance, a conflict between

	Scenario	Voting Implications		
		Cohort 1	**Cohort 2**	**Abstentions**
1	Randomized	Random number of occupants and random vote distribution		
2	Split	50% Too warm	50% Too cold	No abstentions
3	Majority vs Minority	75% Satisfied	25% Too warm	
		75% Satisfied	25% Too cold	
		75% Too warm	25% Satisfied	
		75% Too cold	25% Satisfied	

Table 4.5: **Group Voting Behavior Scenarios**

three occupants with nine abstentions may lead to different results than a conflict involving 10 occupants, as the amplitude can be larger. The direction of votes on the thermal comfort scales is randomized to test different variations. The effects of occupant participation are discussed in Section 5.2.

4.2.3 Existing Conditions Model

To evaluate TREATI, the decisions are compared against two baselines to determine the significance of its impact. The chosen baselines are the PMV (Predicted Mean Vote) model [Fan70] and the Static strategy. PMV is a widely used temperature control model that includes diversity in environmental factors (air temperature, radiant temperature, air velocity, and relative humidity) as well as generalized human factors (metabolic rate and clothing insulation).

Often, occupants are frustrated because their feedback is ignored and does not initiate the desired temperature changes. This is reflected by the Static strategy, which attempts to maintain a single chosen indoor temperature setpoint. The environmental parameters required for the PMV form the basis input parameters of the simulation.

General Characteristics

The simulation assumes a generic multi-office building's zone, i.e., an office, with a single-person office and a larger shared area, see Figure 4.2. The same shared space is used for all scenarios.

While the measurements and the space's characteristics have only limited use for generating the model's output, they demonstrate the underlying understanding of the space: The German workplace regulation defines the minimum area for single-person offices as $8m^2$ ($86sqft$) [Bun20]. Each additional workstation in the same room must be at least $6m^2$ ($64.6sqft$). For large shared spaces, the area must be at least $12m^2$ ($129sqft$). With 12 occupants in the shared space and one single-person office, the

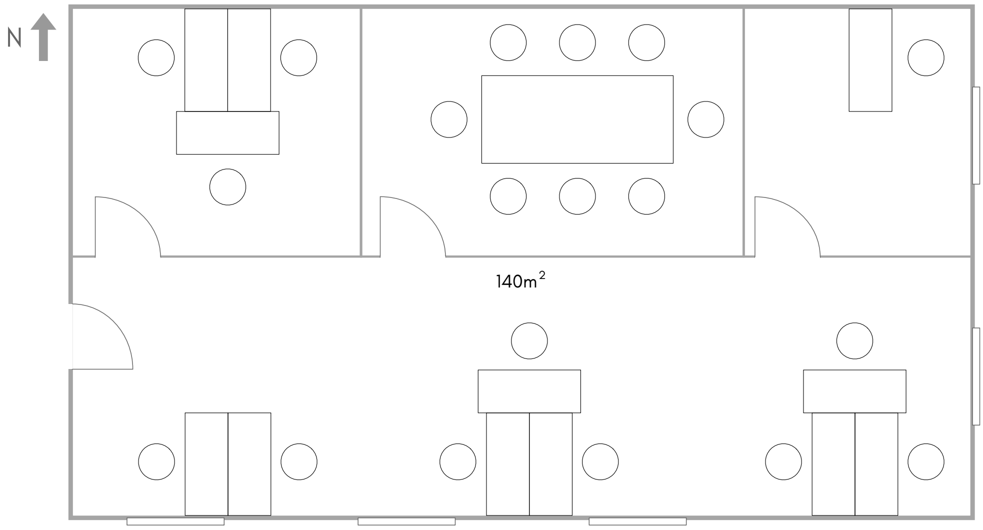


Figure 4.2: **Room Model of the Shared Office used in the Simulation**

modeled office's area is $140m^2$ ($1507sqft$). The average height requirement of an office room is $3m$ ($9.84ft$). The building envelope, including doors, windows, and walls, as well as geographical factors such as building elevation or vegetation are not factored into the simulation. The model assumes optimal insulation, with the HVAC system performing at peak efficiency, i.e., low expendable energy losses.

Other temperature control conditions are assumed to remain constant, such as mean radiant temperature, air speed, air humidity, and occupancy, see Table 4.6.

Factor	**Value**
Environmental Factors	
Mean Radiant Temperature (MRT)	Identical to Indoor Air Temperature
Solar Heat Gain Coefficient (SHGC)	0
Air Speed	$0.1m/s$
Indoor Air Humidity (RH)	$30\% - 60\%$
Outdoor Air Humidity (RH)	$30\% - 60\%$
Human Factors	
Occupancy	No changes during each run
Activity	1 [MET] (typing/sedentary)
Health	No issues

Table 4.6: **Thermal Control Condition Assumptions**

Environmental Input Parameters

A study by Rijal et al. has investigated the use of building controls and compared the effects of indoor and outdoor air temperature on control decisions [Rij+08]. Their study presented a behavioral model with adaptive algorithms to manage building controls. The model is based on the premise that indoor air temperature is the main causation for a change in occupant comfort. Similarly, Morgan and de Dear have explored the relation between weather, clothing, and indoor thermal comfort [MD03]. Their study hypothesizes that outdoor conditions influence clothing choices for indoor environments. Based on these findings, the environmental model is comprised of controlled indoor air temperature and outdoor air temperature.

In the simulation, the controlled indoor air temperature T_{in} is assumed to remain spatially constant $i \in \mathbb{R}$ within the occupied thermal zone:

$$T_{in} = i \tag{4.1}$$

There can be high variability regarding building orientation, building materials, season, location, and other geographical factors that would impact mean radiant temperatures on the façade and other surfaces. In a well-designed building, these factors are assumed to remain constant and are not considered in the simulation model.

The outdoor air temperature T_{out} is also modeled as a constant $z \in \mathbb{R}$ to eliminate geographical characteristics and unwanted dependencies during the conflict resolution processes of all scenarios:

$$T_{out} = z \tag{4.2}$$

Human Input Parameters

The most important human input parameter is feedback in the form of thermal comfort votes. A vote can be measured as thermal sensation on a 7-point scale [Ame20], thermal preference on a 3-point scale, and desirability on a 5-point scale [FLB21]. As mentioned in the simulation design, the simulation model distinguishes between three different voting types (see Section 4.2.2):

Random. The number of occupants and type of votes are semi-randomly generated based on additional human factors for each individual occupant.

Split. The occupants are divided into equal-sized cohorts. Both cohorts' votes are semi-randomly generated, based on one randomly chosen occupant's attributes from each cohort.

Majority. The occupants are divided into cohorts with a 75%–25% distribution to ensure that there is a majority and a minority cohort. Both cohorts' votes are generated randomly, but the model ensures that they are opposite votes.

Split and majority voting behavior conflicts are designed with 100% occupant participation to ensure comparability among all simulation runs. Both voting behavior scenarios are described in more detail below.

The simulation uses **personas** as stand-ins for real human occupants (see Section 3.3.3).[3] Each persona holds a set of attributes:

General preferred thermal setting (or temperature) defines the occupant's general preference for thermal conditions

Voting frequency describes how often an occupant generally submits a vote

Conflict tendency represents the occupant's conflict-handling style

The styles that are considered in this simulation are avoiding, dominating, and compromising [RB79].[4] The other three conflict handling styles describe the occupant's tendency to initiate a thermal conflict report, which determines whether an occupant submits a vote in a simulation run. Personas are chosen randomly during both random and split voting scenarios (see below) to mimic real office situations. For majority votes, the majority and minority cohorts are assigned opposing personas.

Three **feedback** points are collected on each individual occupant in the zone: Thermal sensation, thermal preference, and thermal desirability, see Figure 4.3. Thermal sensation describes how an occupant experiences temperature, thermal preference indicates Thermal sensation and thermal preference [Ame20] are the dominant scales to estimate occupant comfort in buildings. In the thermal comfort community, there is an ongoing discussion as to which feedback scale should be used in temperature control systems and when. Many comfort studies apply either thermal sensation, thermal preference, or a combination of both standardized scales or custom scales, such as [FLB21; Fra+19; JMBG13]. The main reason behind this is the lack of a standardized mapping, which often leads to misunderstandings between researchers and occupants. The sole use of thermal sensation as an indicator for thermal comfort, in particular, has been criticized, as it does not give a clear indication if a change is really being requested. For instance, studies often interpret a *slightly warm* thermal

[3] In the following, the terms persona and occupant are used interchangeably.

[4] The integrating and obliging conflict handling styles are not considered as they refer to interpersonal conflict resolution, which is not addressed in this experiment.

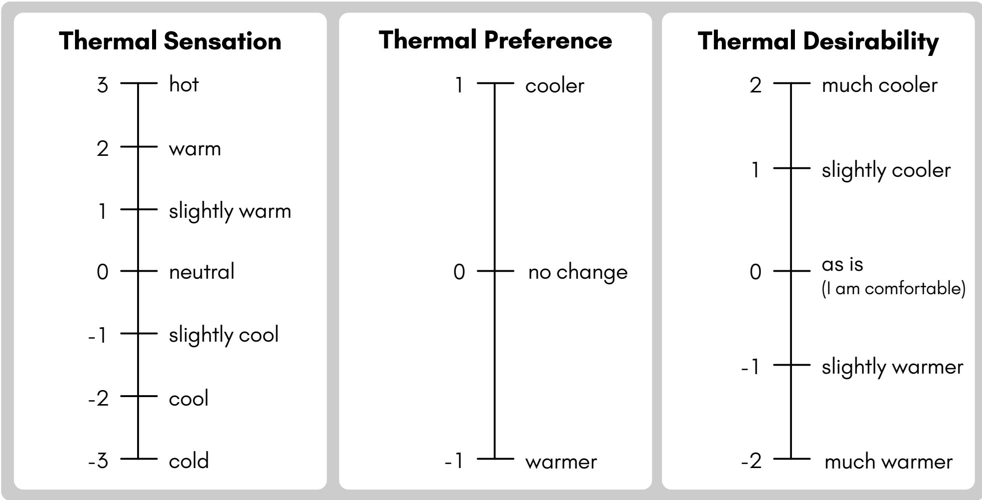


Figure 4.3: **Thermal Comfort Feedback Scales** (adapted from [FLB21; Ame19])

sensation vote (4 on a 7-point scale) as the request for a temperature decrease [HH07; DB98], while the occupant may actually feel comfortable and hence would not prefer a temperature change. Thermal preference indicates whether an action to increase or decrease the temperature is actually being requested [Ame20], but it does not address the magnitude of the change, which is also referred to as the 'temperature amplitude problem'. Due to these drawbacks of standardized scales, the simulation model includes the thermal desirability scale, providing for a more fine-grained indication for control [FLB21].

Modeling three scales[5] – rather than a single or a combined scale – validates the system's applicability across different types of feedback and further allows TREATI to investigate behavior regarding different control ranges.

Indoor air temperature remains the main control for ensuring occupant thermal comfort [DB98]. The occupant's general preference regarding the thermal environment, such as a preference for a cooler indoor temperature, also influences an occupant's comfort. It follows that the difference between the occupant's estimated comfort temperature $ct_o \in \mathbb{R}$ and the prevailing air temperature reflects the occupant's vote direction on all three scales (thermal sensation, preference, and desirability):

$$\Delta(ct_o, T_{in}) = ct_o - T_{in} \tag{4.3}$$

Occupants can generally feel comfortable within a temperature range – rather than at one specific setpoint [NR17; LMH10], depending on activity, clothing, and other envi-

[5] While it is unrealistic to assume that three-scale voting leads to long-term continuous occupant feedback, the simulation model and reference implementation's intent is to showcase the different types of feedback that can be included and their effects on TREATI. The model and reference implementation are adaptable to only operate on a single scale or a combination of multiple scales.

ronmental and social factors. However, individual occupant's general preferences need to remain within an overall air temperature range of $[min(T_{op}),\ max(T_{in})] = [19,\ 27]$, as recommended by the ASHRAE 55 standard to ensure group comfort [Ame20]. The simulation model distinguishes between the three general preferred thermal settings $\xi \in \{$*'cooler', 'neutral', 'warmer'*$\}$. With 23 °C as the baseline temperature derived from other proposed air temperature ranges [Cui+13; DB98], the potential temperature range per general preferred thermal setting is defined as:

$$\xi_o = [min(T_{in}), max(T_{in})] = \begin{cases} \xi = [19, 23] : & \text{'}cooler\text{'} \\ \xi = [21, 25] : & \text{'}neutral\text{'} \\ \xi = [23, 27] : & \text{'}warmer\text{'} \end{cases} \tag{4.4}$$

Each occupant's stated preferred temperature range $[(t-1), (t+1)]$ is simulated with the range's mean t, which is drawn uniformly randomly from ξ_o. This limits the range and maintains variability across occupant preferences.

An occupant who usually prefers warm temperatures is less likely to feel comfortable at a lower air temperature than at a higher temperature, and vice versa. Thus, the overall distribution of occupant votes U is assumed as a bell-shaped curve (see Figure 4.4) that is moved along the x-axis – the respective scale K_{tc} – by the absolute difference between every scale point k and t. The probability of an occupant's vote on a scale point k is defined as the random variable $u \in U$:

$$\forall k \in K_{tc} :\ u = \frac{e^{-\lambda * (|k-t|)}}{\sum\limits_{k \in K_{tc}} \left(e^{-\lambda * (|k-t|)}\right)} \tag{4.5}$$

The stated preference is then defined based on the preferred temperature range's mean. The scale mapping K_{tc} moves the scale points according to the preferred temperature range's minimum and maximum values:

$$K_{tc} = \begin{cases} tc = ts\ \ (\textit{Thermal sensation}) : & \{-3, -2, -1, 0, 1, 2, 3\} \\ tc = tp\ \ (\textit{Thermal preference}) : & \{-2, 0, 2\} \\ tc = td\ \ (\textit{Thermal desirability}) : & \{-2.5, -1.5, 0, 1.5, 2.5\} \end{cases}, \tag{4.6}$$

The result of Equation (4.5) is a distribution of probabilities across all three scales. For example, Figure 4.4 visualizes this distribution on the 7-point thermal sensation scale, from *cold, -3* to *hot, +3*. Each bin's size indicates the probability that the respective occupant will vote for this point on the scale – under consideration of the indoor air temperature and their respective preferred thermal setting. Notably, the values for thermal preference and thermal desirability were adapted to the thermal sensation scale's values so that the distribution probabilities remain similar. The occupant's vote is chosen randomly according to this distribution.

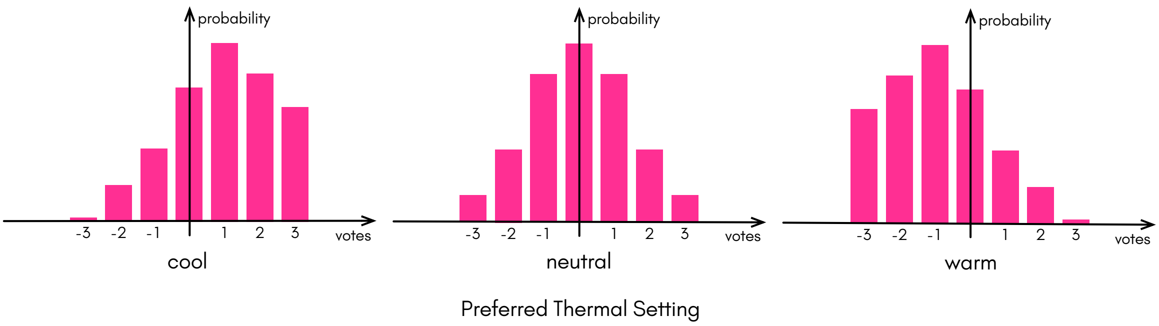


Figure 4.4: **Vote Generation Bin Distribution**

4.2.4 Conflict Resolution Model

After assessing the individual occupant's context factors in Section 4.2.3, these factors are evaluated on a group level using solution strategies. Figure 4.5 presents an overview of the group assessment.

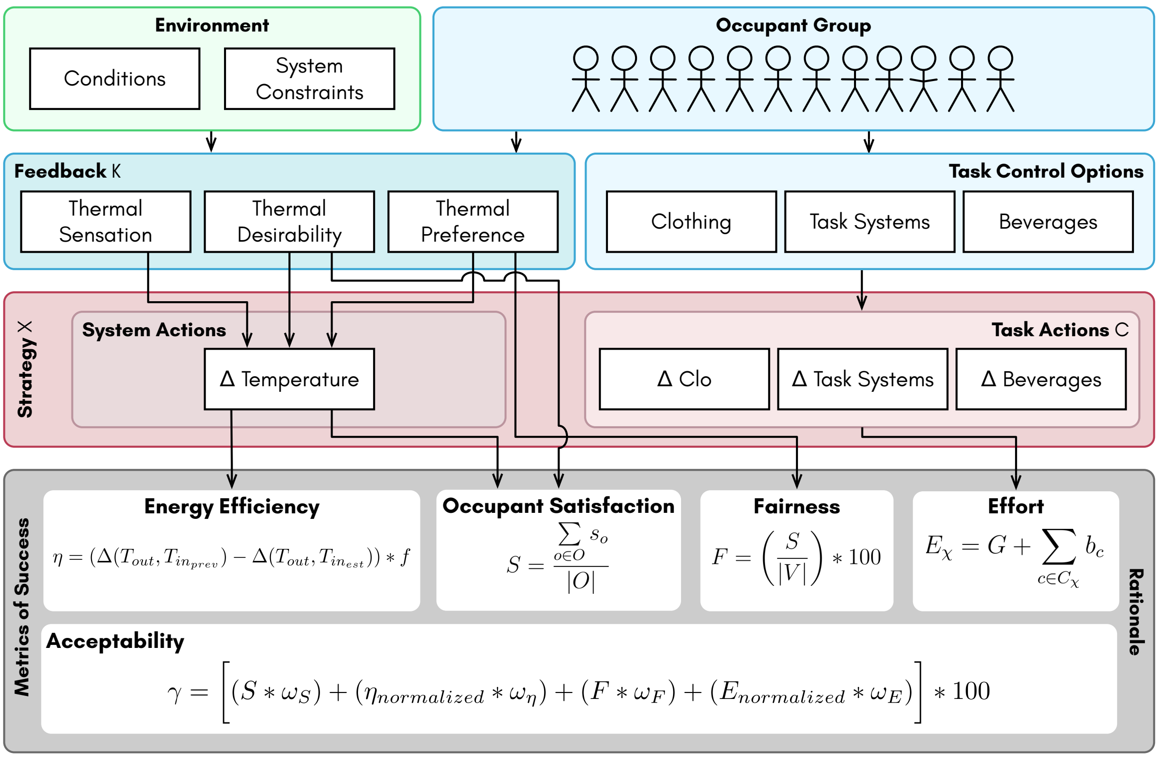


Figure 4.5: **Overview of TREATI's Group Assessment**

All submitted occupant votes are observed within a conflict period to identify potential conflicts. A conflict period is defined as the time frame after the last conflict has ended or when an occupant has submitted a new vote. The conflict is then evaluated utilizing the solution strategies, and the most acceptable decision is determined. The solution strategies generate either a system action or task actions which are assessed using the metrics of success. The description of the metrics of success is presented in Section 4.2.5 and the solution strategy evaluation in Section 4.2.6.

Environmental Context & Impact

A thermal conflict is defined as a disagreement among two or more occupant votes [Fra21] or a disagreement between occupant votes and energy conservation relative to the outdoor environment (Definition 2.12). Therefore, the environmental context is defined as a *virtual vote* to be included in the conflict identification and solution strategies. This allows the control system to relativize occupant votes to the energy-conserving environmental vote and to target a global thermal equilibrium. The environment's vote is defined as the difference between indoor and outdoor air temperatures. The greater the difference, the lower the energy savings to maintain the indoor air temperature [LC11]. If both temperatures are identical, this will result in high energy savings. The environment's energy conserving vote env_{tc} is mapped to each of the three comfort scales $tc \in ts$, tp, td to provide comparability to occupant votes, given $k_{max} = max(K_{tc})$ as the absolute maximum value of the respective scale K_{tc}:

$$env_{tc} = \begin{cases} k_{max} & : \Delta(T_{in}, T_{out}) > k_{max} \\ (-1) * k_{max} & : \Delta(T_{in}, T_{out}) < -k_{max} \\ \Delta(T_{in}, T_{out}) & : \Delta(T_{in}, T_{out}) > 0.5 \\ (-1) * \Delta(T_{in}, T_{out}) & : \Delta(T_{in}, T_{out}) < -0.5 \end{cases} \tag{4.7}$$

The environment's energy efficiency vote uses the imposed system constraints described in Section 4.2.6 as a boundary to prevent temperatures below the minimum or above the maximum constraints:

$$t(env_{tc}) = \begin{cases} T_{in} - \max(T_{in}) & : T_{in} < T_{out} \wedge T_{in} - env_{tc} > \max(T_{in}) \\ T_{in} - \min(T_{in}) & : T_{in} > T_{out} \wedge T_{in} - env_{tc} < \min(T_{in}) \end{cases}$$

For instance, given an outdoor temperature $T_{out} = 16\,°C$ and indoor temperature $T_{in} = 19\,°C$, the environment's energy efficiency vote would be mapped to a *cooler* thermal preference, driving indoor conditions to 16 °C. If this were, however, applied, the indoor temperature would fall below the minimum temperature constraint. Instead, the current and minimum temperature difference is adjusted, and the resulting vote is mapped to *no change*.

Conflict Identification

The TREATI framework categorizes and evaluates events, as detailed in Section 3.3.4. This simulation investigates time-independent scenarios. Thus, TREATI's event categorization has been adapted: Entropy of the occupant votes governs the presence of a conflict. Information entropy is a measure to quantify information [Sha48; VN32]. It is often used to construct decision trees or neural networks [Set90]. Entropy and other similar methods of measuring uncertainty have been used in decision theory to address and resolve conflicts [Yua+16; GP96]. For instance, George and Pal introduced a total conflict measurement based on the Dempster-Shafer theory [GP96]. Yuan et al. imposed data fusion in wireless sensor networks, adapting the Deng entropy to measure the uncertain information using the evidence distance to determine the conflict degree [Yua+16].

To identify thermal conflicts, the level of disorder or disagreement distance among occupant votes is determined using the entropy $H(V_{tc})$ of a discrete random variable $V_{tc} = tp$. The discrete random variable V_{tc} represents all possible votes tp that occupants can submit. The entropy is calculated using Shannon's entropy formula [Sha48], where $p(v)$ denotes the empirical probability of a vote $v \in V_{tc}$, indicating the percentage of occupants who have submitted the particular vote v. The Shannon entropy is applied to measure this empirical probability and quantify the uncertainty or variability of occupant votes:

$$H(V_{tc}) = -\sum_{v \in V_{tc}} p(v)\, log_2\, p(v) \tag{4.8}$$

The disagreement distance identifies the percentage of occupants with a conflicting vote. The closer the disagreement distance is to 1, the more conflicts and the bigger the need for resolving them. Table 4.7 presents example conflicts regarding the group voting behavior scenarios (Table 4.5). For instance, split scenarios have a high voting entropy ($H(V_{tc}) >= 1$), but the first majority vote scenario has a relatively low entropy ($H(V_{tc}) = 0.41$).

Since TREATI also addresses conflicts between occupants and the environment, the entropy needs to be at least $H(V_{tc}) = 0.4$ to initiate any required action.

Scenario	Vote Distribution			Vote Entropy
	warmer	*no change*	*cooler*	$H(V_{tc})$
Random	**3**/10	**5**/10	**2**/10	1.49
	–	**5**/5	–	0
Split	**2**/4	-	**2**/4	1
	3/9	**3**/9	**3**/9	1.58
Majority vs. Minority	**1**/12	-	**11**/12	0.41
	10/12	**2**/12	-	0.65
	1/12	**1**/12	**10**/12	0.82
	8/12	-	**4**/12	0.91
	8/12	**1**/12	**3**/12	1.19

Table 4.7: **Example Conflicts and their Vote Entropies** based on thermal preference votes

Task Actions and System Actions

Gail Brager et al. propose three categories of adjustments to raise comfort levels [BDD98]: Personal, environmental (or technological), and cultural. The TREATI simulation model distinguishes between personal and environmental strategies. Cultural strategies, such as scheduling breaks or adapting dress codes, are out of scope. Personal adjustments are defined as local solution strategies that are mapped to individual occupants and influence the occupant's task space. They are henceforth referred to as *task actions*. The conflict resolution model uses clothing, task conditioning system, and beverages as available task actions.[6]

Environmental adjustments, or *global system actions*, are realized in global solution strategies which influence the ambient indoor air temperature.

A *solution strategy* is either a local task action, a global system action, a composition of a set of task actions, or a combination of system actions and task actions. In total, ten strategies are compared against each other to determine the most suitable strategy, see Figure 4.6: PMV, Task Action, Mean Sensation, Mean Preference, Mean Desirability, Mean Sensation Composite, Mean Preference Composite, Mean Desirability Composite, Dynamic Temperature, and Static.

The Predicted Mean Vote (**PMV**) is the most commonly used temperature model in building control [Ame20; Fan70], adjusting indoor air temperatures based on international standards of occupant comfort for 80% satisfaction. PMV establishes a temperature setpoint without the use of on-site occupant votes. For office calcula-

[6] Since the availability of operable windows is contingent upon the individual building and changes in activity and location depend on the occupant's occupation, these adjustments can only be suggested within an extended context model and in coherence with the prevailing workplace regulations. Therefore, they are not directly mapped to the simulation model.

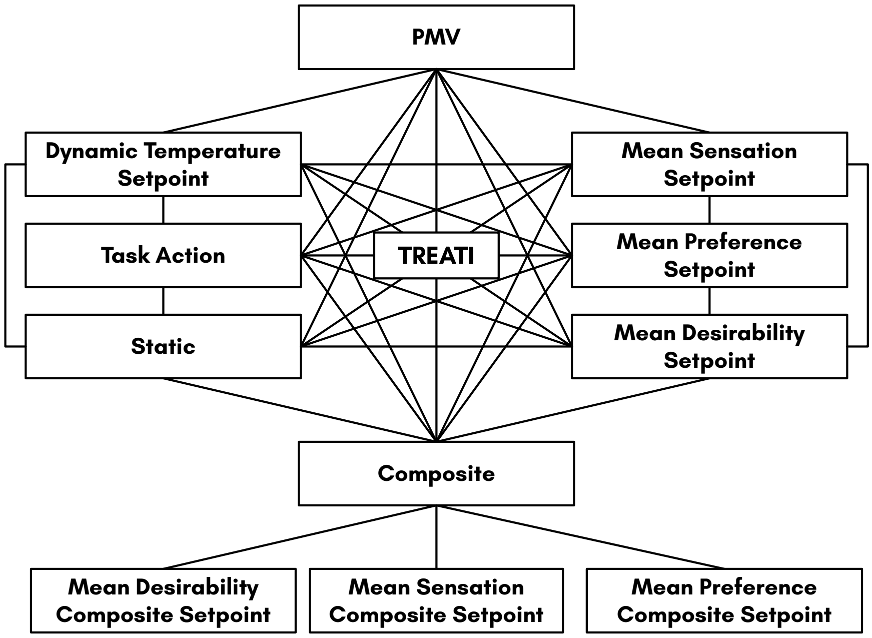


Figure 4.6: **Simulation Matrix** of TREATI's actions

tions, the metabolic rate is assumed to remain constant at 1 MET[7] for a sedentary, typing activity, as defined in Table 4.6. The mean radiant temperature is assumed to match the indoor temperature, and air flow is nominal.[8]

Task Actions offer local control choices to occupants if their vote is not in alignment with the respective decision. Task actions are defined as low-effort behavioral thermoregulation activities or behavioral adjustments that occupants can perform to raise their own comfort [BDD98; Woh72]. Typical behavioral adjustments include change of clothing, activity, or location, or consuming hot or cold beverages [BDD98]. Local environmental adjustments can also influence an occupant's task climate, for instance, through the use of task conditioning systems or operable windows. The conflict resolution model uses clothing, task conditioning systems, and beverages as available task actions.

Task actions are suggested depending on the occupant's context – their votes on thermal sensation, preference, desirability, and current and additionally available clothing items – and the impact on their comfort level. The main goal is to reach the state where an occupant is comfortable and does not require a change in air temperature. Task actions support the thermal equilibrium (see Definition 2.10), which

[7] MET (Metabolic Equivalent of Task) is a measure that quantifies the ratio of a human's working metabolic rate relative to their resting metabolic rate.

[8] The source code for the PMV calculation is based on Tartarini et al. [TSCH20].[9]

[9] `https://github.com/CenterForTheBuiltEnvironment/comfort_tool/blob/master/docs/documentation/pmv.md`.

describes the balance between heat gain and heat losses. The following paragraphs describe the three task action options in more detail: clothing, task conditioning (fans and heaters), and hot and cold beverages.

Since clothing has a significant impact on the perception of temperature [Par07], the Task Action strategy first explores clothing options. Precedent research has presented comprehensive mathematical models that define the exact effect of environmental factors and clothing on human physiology under various controlled conditions [Par07; AZ06; Ste79]. Subsequent research has drawn from these findings to develop simplified models with fewer factors [JDB20; Rij+08]. Commonly, thermal insulation provided by clothing is expressed in clo units: $1\,clo = 0.155m^2K/W$, i.e., the thermal resistance needed at which a body resists a heat flow. ASHRAE defines the value of $1\,clo$ as the amount of insulation needed for a person at rest to maintain thermal equilibrium at 21 °C [70 °F] in a normally ventilated room with $0.1m/s$ air velocity and an estimated body surface area of $1.8m^2$ [Ame20]. ASHRAE 55 provides a table with common garment items and their respective average clo values [Ame10, Addendum h].

The TREATI simulation introduces three different clothing items to reflect possible additions by occupants during different scenarios and seasons: a sleeveless vest or dress ($0.15\,clo$), a sweater ($0.25\,clo$), and a jacket ($0.4\,clo$). These values are based on the garment insulation values from ASHRAE 55 [Ame10, Addendum h], where the respective values for thick and thin garments of the same type are combined into one value for simplicity reasons. For instance, thin sleeveless vests have $0.10 - 0.13\,clo$, a thick sleeveless sweater vest has $0.17 - 0.22\,clo$ [Ame10, Addendum h]. Combining those values, the simulation model uses a value of $0.15\,clo$ for a sleeveless vest. If an additional clothing item has been chosen, its insulation is added to the overall occupant's clo. For spring, winter, and fall, where the daily maximum outdoor temperature does not exceed 20 °C, the overall clo value is assumed at $1\,clo$, i.e., a typical business attire including a shirt, undershirt, trousers, and a jacket, or long-sleeved wool dress, thick tights, and a jacket. For summer, $0.5\,clo$ is assumed for moderate outdoor temperatures and $0.35\,clo$ for hot outdoor temperatures, where the daily minimum exceeds 28 °C.

To identify the most appropriate clothing choice, the difference between the occupant's state to a thermal equilibration state needs to be determined. A formula presented by Morgan and de Dear estimates that the selected clothing insulation I_{clu} worn indoors will be based on the outdoor air temperature [MD03]. This formula is built on the assumption that occupants generally choose clothing based on the previous day's mean outdoor air temperature and the maximum temperature of the weather forecast for the current day:

$$I_{clu} = 1.15 - 0.0164 * T_{out_{prev.\,day}} - 0.0178 * T_{out_{max\,forecast}} \quad (4.9)$$

Since this experiment assumes a constant daily average outdoor air temperature per reported conflict, T_{out} is used:
$I_{clu} = 1.15 - 0.0164 * T_{out} - 0.0178 * T_{out} = 1.15 - 0.0014 * T_{out}$.

The required clothing insulation ΔI_{clu} is hence defined as the difference of the necessary clothing insulation I_{clu} and the occupant's present clothing insulation I_{clu_o}:

$$\Delta I_{clu} = (1.15 - 0.0014 * T_{out}) - I_{clu_o} \quad (4.10)$$

Insulation provided by the occupant's chair is not considered. This value varies depending on the type of chair and amount of body contact [Ame20]. In addition, many offices nowadays offer standing desk opportunities, which would nullify the chair's insulation.

If a recommendable change in clothing insulation approximately[10] matches available clothing, the item is suggested to the occupant:

$$\Delta I_{clu} \approx I_{item} \quad (4.11)$$

A change in clothing insulation influences the occupant's satisfaction s_o and is defined as the percentage of the clothing insulation reached:

$$s_o = \frac{I_{clu_o} + I_{item}}{I_{clu}} * 100 \quad (4.12)$$

If no clothing item matches, the actuation of a task conditioning option is suggested. Two types of task conditioning systems are considered available per occupant: a desk fan and a task heater. Task conditioning systems are assumed to influence a single-point change regarding the occupant's thermal vote for thermal preference and desirability and a change of 1 to 2 points for thermal sensation, following the scale mapping shown in Figure 2.8. Other task conditioning options, such as occupant access to and control of operable windows or shading devices, were not included in this simulation. While task conditioning requires electricity, the overall energy use is generally lower compared to the heating or cooling of a space. The simulation model disregards this additional consumption in the overall energy efficiency calculation for task conditioning.[11] If task conditioning choices are not available, the occupant is di-

[10] The tolerance value used is $\delta = 0.05\,clo$.

[11] Task conditioning systems typically have a localized impact on the occupant's individual thermal comfort rather than affecting the entire space and have varying power consumptions across different

rected to consume a hot or cold beverage. Hot beverages provide short-term comfort when occupants find spaces too cool, and cold beverages provide short-term comfort when occupants find spaces too hot. The consumption of beverages assumes a change of 0.5 points for thermal preference and desirability and a single-point change for thermal sensation. Temperature needs can also be short-term, such as when entering an office from outdoors or following a period of exercise.

Dynamic Temperature aims at correcting the difference between the indoor air temperature and the collective occupants' comfort temperature using simplified adjustments. It is based on Griffiths' method [Gri90] with modifications by Nicol et al. [Nic+94] and Rijal et al. [Rij+08]. Griffiths' method predicts the comfort temperature by a regression slope across ASHRAE's thermal sensation scale k_{ts} and the indoor air temperature T_{in}. With Nicol et al.'s modifications, an occupant's comfort temperature ct_o is defined as the sum of the mean indoor air temperature $\overline{T_{in}}$ and the difference of the scale's neutral vote k_n and the occupants' mean vote $\mathbb{E}[V_{ts}]$ divided by the regression coefficient α:

$$ct_o = \overline{T_{in}} + \frac{k_n - \mathbb{E}[V_{ts}}{\alpha}$$

Instead of solely using thermal sensation, the dynamic temperature strategy uses the product of thermal sensation and thermal preference to prevent unsolicited changes, $\mu = \mathbb{E}[V_{ts} * \mathbb{E}[V_{tp}$. Thermal preference indicates the direction of change and has a maximum absolute value of $V_{tp} = 1$, thermal sensation determines the amplitude of the change [Ame20]. Given the neutral vote $k_n = 0$, the overall change in temperature T_c is defined as:

$$\Delta T_c = \frac{0 - (|\mathbb{E}[V_{ts}]| * \mathbb{E}[V_{tp}])}{\alpha} = -\frac{|\mu|}{\alpha} \tag{4.13}$$

Following Rijal et al.'s suggestion to "allow for an effect of random error in the [indoor] globe temperature" [Rij+08], the regression coefficient $\alpha = 0.5$ is chosen. The comfort temperature of an occupant is the sum of the indoor air temperature and the temperature change, $ct_o = T_{in} + \Delta T_c$. The proposed total temperature change is the sum of the estimated temperature change values of all voting occupants divided by the number of votes.

Existing thermal control models often compute the average across all thermal sensation votes to determine temperature changes [DD04; Gag71; Fan70]. In TREATI, the **Mean Sensation**, **Mean Preference**, and **Mean Desirability** are diversified

device models. By excluding the electricity consumed by task devices, the simulation model aims to provide a more accurate assessment of the energy efficiency of a generic space's control system.

vote strategies that each compute the mean across all votes regarding the respective scale. The temperature change for each is modeled as the sum across all votes divided by the number of votes.

Composite actions include task actions in order to reduce occupant dissatisfaction relative to the thermal sensation, preference, or desirability scales, that may be imposed by the respective strategy. The following strategies allow composites: ***Mean Sensation Composite***, ***Mean Preference Composite***, ***Mean Desirability Composite***, and ***Dynamic Temperature Composite***. The resulting occupant satisfaction for composite actions is calculated by the respective global strategy's satisfaction and satisfaction derived from task actions, see above.

The **Static** strategy, or Static control, does not apply any changes to the air temperature. It is intended to be used in the event that a conflict cannot be resolved, for example, a change in air temperature would exceed the maximum air temperature and there are no available task actions.

4.2.5 Metrics of Success

Four metrics are used to assess each solution strategy, ranked in order of priority: *Occupant Satisfaction*, *Energy Efficiency*, *Fairness*, and *Effort*. Each strategy's *Acceptability* score is determined as the sum of these prioritized metrics and compared to all other strategies' acceptability scores. The highest score concludes the decision, and the respective system or task action will be applied by TREATI for thermal comfort.

Occupant Satisfaction

Given the importance of indoor environments for human health and productivity, the highest priority in thermal conditioning is occupant satisfaction. The occupant satisfaction metric is a measure that indicates the overall contentment of all occupants regarding the proposed decision. ASHRAE defines $\geq 80\%$ of occupant satisfaction as the overall target [Ame20]. An occupant satisfaction of $\geq 60\%$ is far more frequent in the field [HAZA06] and may still be considered acceptable.

Occupant satisfaction is measured on a 5-point satisfaction scale, ranging from *very satisfied* to *very dissatisfied* [Ame20]. Satisfaction alone reveals little about the direction or quantity of thermal change that might be needed. Hence, thermal sensation scales are included to assess satisfaction. ASHRAE's 7-point thermal sensation scale, from *cold (-3)* to *neutral (0)* to *hot (+3)*, captures a percent satisfaction for all occupants who score -1, 0, and +1 on the sensation scale. Thermal preference also captures satisfaction and includes more occupant input into the requested action. Occupants may report a sensation *slightly cool* or *slightly warm* but want no action, whereas a 3-point thermal preference scale offers a definitive call for action (*warmer* or *cooler*).

Occupant satisfaction defined through a thermal desirability scale provides for a more refined and nuanced estimate than relying solely on thermal sensation or thermal preference [FLB21]. To estimate an individual occupant's satisfaction, their thermal desirability vote is compared to the proposed solution's temperature change. An occupant is more likely to be satisfied if their vote supports the proposed temperature change, rather than if it does not. Drawing from the vote mapping table from [FLB21], the sum of the occupant's thermal desirability vote v_{td} and the proposed solution's temperature change $\Delta t = T_{in} - T_c$ estimates the difference to a satisfied occupant: $\Delta(-v_{td}, -\Delta t) = v_{td} + \Delta t$.[12] The occupant's satisfaction s_o is defined as the difference between the maximum occupant satisfaction, which is set at 100%, and the difference factor multiplied by the satisfaction factor y:

$$s_o = 100 - |\,\Delta(v_{td}, \Delta t)\,| * y \tag{4.14}$$

The satisfaction factor $y_{\xi,td_o,\Delta t}$ is based on the presumption that $|\Delta(td_o, \Delta t)|$ can maximally be 5 ($|v_{td}|= 2$, $|\Delta t|= 3$). Assuming that 0 is also an option, this results in $(100 - (5 - 1) * y) \Rightarrow y = 25$. To account for individual occupant differences, $y_{\xi,td_o,\Delta t}$ differs based on the estimated difference and the occupant's general preferred temperature ($\xi \in \{$'*cooler*', '*neutral*', '*warmer*'$\}$):

$$y_{\xi,v_{td},\Delta t} = \begin{cases} 30: & \Delta(td_o, \Delta t) > 0 \ \wedge \ \xi = \text{‘}warmer\text{’} \\ 20: & \Delta(td_o, \Delta t) < 0 \ \wedge \ \xi = \text{‘}cooler\text{’} \\ 25: & else \end{cases} \tag{4.15}$$

For instance, when an occupant asks for a slightly warmer temperature $td_o = -1$, and the actual change is $\Delta t = +3\,°C$, depending on the occupant's general temperature preferences, the respective occupant might be unsatisfied with this change if they generally prefer cooler temperatures rather than warmer ones.

The overall solution's percent of occupant satisfaction S is the sum across all individual occupant's satisfactions divided by the number of occupants:

$$S = \frac{\sum\limits_{o \in O} s_o}{|O|} \tag{4.16}$$

[12] A sum operation is used to normalize the sign changes since both variables can be either positive or negative, hence: $(-1) * (-v_{td} - \Delta t) = v_{td} + \Delta t$.

Energy Efficiency & Savings

Given today's challenges in addressing climate change, the second highest priority in thermal conditioning is energy efficiency. In the built environment, energy efficiency is defined as the extent to which the energy consumption of $1m^2$ of floor area compares to energy consumption benchmarks for a specific building under specific environmental conditions. There are globally recognized benchmarks for energy efficiency depending on building climate, function, occupant density, and hours of use.

The energy efficiency η of a building's thermal conditioning is defined as the combined annual cooling C and heating ϕ energy combined into Q generated divided by the annual energy efficiency ratio of the energy production process ϵ [Kal10]:

$$\eta = \frac{C + \phi}{\epsilon} = \frac{Q}{\epsilon}$$

In the commercial sector, buildings maintain complex non-linear energy models that map control actions to energy consumption. It is out of scope of this dissertation to define a realistic energy model of the modeled space's thermal energy demand, given the variability in building envelope construction and operation, climate, as well as occupancy patterns, and activity. Instead, an estimate of energy efficiency given the specified building's characteristics is used to validate the outcome of TREATI's conflict resolution process, disregarding the annual energy efficiency ratio ϵ. In this simulation, energy efficiency is interpreted as an energy savings score and is defined as the energy gain or loss for the respective solution strategy compared to the system's prior state. The following illustrates the derivation of this score. For simplicity reasons, the terms energy efficiency and energy savings are used interchangeably hereafter.

Generally, thermal energy Q is defined as the product of the specific heat capacity of dry air c_p, mass of air m, and the temperature difference $\Delta(T_{prior}, T_{est})$:

$$Q = c_p * m * \Delta(T_{prior}, T_{est}) \tag{4.17}$$

With the parameter assumptions presented in Table 4.8, this results in:

$$Q = 1.006kJ/kgC * 514.5kg * \Delta(T_{prior}, T_{est}) = 517.587kJ/C * \Delta(T_{prior}, T_{est})$$

The characteristics c_p and m in Equation (4.17) are assumed to remain constant throughout the simulation and are not considered in the energy efficiency calculation, hence: $Q \approx \Delta(T_{prior}, T_{est})$.

Parameter		Value
Specific heat capacity of air[13]	c_p	1.006 kJ/kgC
Air density	ρ	1.225 kg/m^3
Mass of air[14]	m	514.5 kg
Floor area	A	140 m^3
Room height	h	3 m

Table 4.8: **Thermal Energy Parameter Assumptions**

To account for differences in energy use between heating and cooling [RA18], the thermal energy is multiplied by the seasonal factor f. A distinction between heating and cooling energy is modeled depending on the difference between indoor and outdoor temperatures. Table 4.9 presents the seasonal dependencies that are assumed during the energy evaluation. The closer the indoor temperature preference is to the outdoor temperature, the higher the energy savings possible, and thus efficiency.

There is no universally accepted factor for heating and cooling energy savings per 1 °C due to the differences in climate and building layouts. The U.S. Department of Energy (DoE) advises to "turn the thermostat back 7 °F–10 °F [3.8 °C – 5.5 °C] for 8 hours a day from its normal setting" to achieve up to 10% of energy savings a year on heating and cooling in residential homes.[15] This means that a 1 °C difference between the indoor air temperature and outdoor air temperature could lead to a 1% increase or decrease in energy efficiency. Nest suggests that by using their smart thermostat, an annual 10% – 12% of heating usage and electric savings or 15% of cooling usage can be achieved with 3.8 °C[10 °F] setbacks in winter and 3.8 °C[10 °F] increased set-points in summer during periods of no occupancy.[16] Buildings in Germany can achieve 3% – 16% of energy savings using an eight-hour night setback (from around 20 °Cto less than 16 °C) during the heating season, depending on the building envelope and design [Pet12]. An office study in Singapore targeting offices has shown that using a learning-based thermostat can lead to 11.4% cooling energy savings when increasing the temperature by 1 °C from 23 °C to 24 °C and 21.3% cooling energy savings when increasing the temperature by 2 °C (23 °C to 25 °C) [Hu+18].

Drawing from these reports and studies, the energy savings per increased 1 °Care estimated at 10% during the cooling season. During the heating season, a 1 °C tem-

[13]The specific heat capacity of air in the simulation is estimated at 20 °C air temperature with an air pressure of 1 bar.

[14]With $m = \rho * A * h = 1.225\,kg/m^3 * 140\,m^2 * 3m = 514.5\,kg$.

[15]U.S. Department of Energy. *Thermostats*. 2022. `https://www.energy.gov/energysaver/thermostats`.

[16]Nest Labs. *Energy Savings from the Nest Learning Thermostat: Energy Bill Analysis Results*. White Paper, 2015.

perature decrease results in 5% of energy savings. Assuming a temperate climate and the temperature dependencies in Table 4.9, the seasonal factor f is defined as:

$$f = \begin{cases} +5\% \text{ per lowered } 1\,°C & : \textit{if heating } (T_{out} < T_{in}) \\ +10\% \text{ per raised } 1\,°C & : \textit{if cooling } (T_{out} > T_{in}) \\ +1\% \text{ per } 1\,°\text{C difference} & : \textit{else} \end{cases} \tag{4.18}$$

A solution's estimated global energy savings η gain or loss is defined as the difference between the prior state's energy savings $\Delta(T_{out}, T_{in_{prior}})$ and the proposed solution's estimated energy savings $\Delta(T_{out}, T_{in_{est}})$ multiplied with the seasonal factor f.

$$\eta = (\Delta(T_{out}, T_{in_{prior}}) - \Delta(T_{out}, T_{in_{est}})) * f \tag{4.19}$$

$$\text{with } \eta = \begin{cases} \text{temperature decrease, energy efficiency increase} & : > 0 \\ \text{temperature increase, energy efficiency decrease} & : < 0 \\ \text{no change} & : \ 0 \end{cases}$$

The closer the estimated temperature is to the outdoor temperature and the greater the difference between the outdoor temperature and prior indoor temperature, the greater the energy savings.

Dependency	$\Delta T_{out,in_{prior}}$	$\Delta T_{out,in_{est}}$	**Energy Savings**	f
$T_{in_{prior}} < T_{in_{est}} < T_{out}$	↘	↗	↗	$+10\%\ /\ 1\,°C$
$T_{in_{est}} < T_{in_{prior}} < T_{out}$	↘	↘	↘	$-10\%\ /\ 1\,°C$
$T_{in_{prior}} < T_{out} < T_{in_{est}}$	↘	↗	↘	$-10\%\ /\ 1\,°C$
$T_{in_{est}} < T_{out} < T_{in_{prior}}$	↘	↗	↗	$+\ 5\%\ /\ 1\,°C$
$T_{out} < T_{in_{est}} < T_{in_{prior}}$	↗	↗	↗	$+\ 5\%\ /\ 1\,°C$
$T_{out} < T_{in_{prior}} < T_{in_{est}}$	↗	↗	↘	$-\ 5\%\ /\ 1\,°C$

↗ $\widehat{=}$ increase, ↘ $\widehat{=}$ decrease

Table 4.9: **Temperature Dependencies**

Fairness

Given the ongoing dominance of executive control of thermal conditions, the third highest priority is thermal conditioning fairness. A strategy's fairness expresses how occupant votes are distributed in accordance with the decision, considering the inclusion of opposing votes that have not been fairly supported in previous decisions. The fairness score's intent is to avoid a series of unfair decisions that exclusively favor one group of occupants. If a decision is supported by a vote, the occupant is considered satisfied $s_{o,h} = 1$. All satisfied occupants' satisfaction scores are added up.

If a vote opposes a decision, the occupant's mean historic satisfaction $s_{o,h} \in [0,1]$ is derived from the past ten historic decisions. In the simulation, historic decisions are randomly generated to introduce a noise factor, aimed to reflect the uncertainty of reality. The historic satisfaction score $s_{o,h}$ is deducted from the maximum fairness of $max(F) = 100\%$ to determine the dissatisfaction score. The sum of all dissatisfaction scores is then subtracted from the number of satisfied occupants to determine the overall occupant satisfaction S:

$$S = \sum_{o \in O, s_{o,h}=1} 1 - \sum_{o \in O} (1 - s_{o,h})$$

The overall solution's fairness score F is defined as the occupant satisfaction score S divided by the number of all submitted votes V.

$$F = \left(\frac{S}{|V|} \right) * 100 \tag{4.20}$$

Effort & Task Actions

The final priority in thermal conditioning is to ask for occupant effort to pursue a task action. Strategies can include a set of task actions ranging from changing clothing levels to turning on fans and heaters, i.e., $C_\chi = \{c : \exists c \in \chi\}$. Applying a strategy requires effort from either the building's control system (global), the occupant (local), or both. The main focus is on occupant effort, i.e., how much effort it takes an occupant to apply the solution. The goal is to achieve low effort, as this could impact the overall system acceptance among occupants. Each global strategy has a system effort of 1, as the simulation uses one system control option, i.e., indoor air temperature. Table 4.10 shows the estimated effort values b per solution strategy χ.

Strategy χ	**Effort** b_χ	
Mean Sensation	b_{ms}	1.0
Mean Preference	b_{mp}	1.0
Mean Desirability	b_{md}	1.0
Dynamic Temperature	b_{dyt}	1.0
PMV	b_{pmv}	1.0
Static	b_{nc}	0.0
Task Action	b_c	[0,1]

Table 4.10: **Solution Strategy Effort Values**

Table 4.11 presents the effort values per subset of task actions considered in this dissertation and the respective implications on occupant satisfaction and energy impacts. Task actions that include beverages add or deduct 0.5 from the occupant satisfaction, as they only provide short-term satisfaction whereas clothing and task conditioning options provide long-term satisfaction, i.e., +1 or −1.

Task Action c	**Effort** b	**Occupant Satisfaction** s	**Energy Cost***
Put on clothing	0.5	+1.0	0
Take off clothing	0.5	−1.0	0
Have a hot beverage	0.75	+0.5	very low
Have a cold beverage	0.75	−0.5	very low
Turn on task heater	0.5	+1.0	low
Turn on desk fan	0.5	−1.0	low

**compared to central HVAC*

Table 4.11: **Task Action Effort Values**

The overall effort of a strategy E_χ is the sum of the respective system action's effort G and the sum of all task actions' effort values:

$$E_\chi = G + \sum_{c \in C_\chi} b_c \tag{4.21}$$

4.2.6 Solution Strategy Evaluation

Each solution strategy is evaluated by its acceptability and in compliance with the system constraints. System constraints describe the physical and logical limits imposed on the respective strategy. Temperature control systems already specify an acceptable temperature control range to avoid unhealthy conditions and unforeseen energy costs. The same applies to limiting the temperature change steps that are applied in response to each occupant's request. Thus, the temperature control range is defined at ASHRAE's proposed range 19 °C − 27 °C , and maximum steps are $\pm 3\,°C$ [Ame20]. Occupant satisfaction should be $> 80\%$ [Ame20] − if that goal cannot be achieved, occupant satisfaction should be at least $> 60\%$ [HAZA06]. Each strategy should not consist of more than 50% of task actions to prevent low occupant acceptability and additional energy implications when task conditioning systems are used.

Each metric is assigned a prioritization weight ω. The weights are chosen to ensure that strategies with lower occupant satisfaction values, relative to other strategies, are not selected. The metrics fairness F, considered an arbitrary factor, and the effort E, representing a neutral factor as task actions are regarded as a positive addition, are both assigned the least influential weights.

The metrics are prioritized as follows:

1. **Occupant Satisfaction** is the most influential determinant of whether a strategy may be accepted by occupants ($\omega_S = 0.6$)
2. **Energy Efficiency** is often the overriding goal in building control as it influences heating and cooling costs and overall sustainability. However, because TREATI is an occupant-in-the-loop system, the occupant has the first priority ($\omega_\eta = 0.2$)
3. **Fairness** influences the overall occupant satisfaction and prevents the formation of favored groups of occupants ($\omega_F = 0.1$)

Task Actions or effort is the last priority as humans are generally used to determine ways to make themselves comfortable ($\omega_E = 0.1$)

The **acceptability** score defines how acceptable a strategy is with regard to the system constraints and to the prioritization of the metrics. The prioritization weights for occupant satisfaction ($\omega_S = 0.6$), energy efficiency ($\omega_\eta = 0.2$), fairness (ω_F=0.1), and task action effort ($\omega_E = 0.1$) are multiplied with the respective metric's output, forming the overall strategy's acceptability $\gamma \in \mathbb{R}$:

$$\gamma = \Big[(S * \omega_S) + (\eta_{normalized} * \omega_\eta) + (F * \omega_F) + (E_{normalized} * \omega_E)\Big] * 100 \qquad (4.22)$$

Since energy efficiency (-30% to 30%) and task action effort scores (0 to 6) use scales with different amplitudes than the other metrics, they are normalized to a scale of 0 to 100%.

All solution strategies are compared based on their acceptability, and the best strategy is selected. If a strategy fails to meet a constraint, the acceptability score is reduced by the product of the respective metric's factor and its prioritization factor.

4.2.7 Simulation Model Validation & Verification

An empirical validation based on simulations requires both validation and verification of the simulation model to ensure the findings' validity. The validation of the simulation model determines whether the specifications and requirements are met. The verification of the simulation model is the process of confirming its correctness regarding its conceptual model.

The validation and verification of the simulation model occur throughout its design and development process, including *theory validation*, i.e., comparing theory against the system, *conceptual model validation*, as the process of confirming the model's correctness regarding its conceptual model, *specification* and *implementation verification*, i.e., confirming the model and implementation against its specification, and *operational validation* to ensure that the simulation model's correct behavior [Sar99].

Several techniques verify and validate the simulation model, as introduced by Robert Sargent [Sar99] and presented in Table 4.3. The following summarizes the results of the validation and verification efforts.

Validation of the Simulation Model

Data Relationship Correctness. While the simulation model is a simplification and abstraction of reality, the relationships between the environmental and human parameters need to mimic the real world to allow generalizable conclusions. Real-world relationships are modeled after findings from anecdotal evidence, field research, and literature, as described in Section 4.2.3. The existing conditions model focuses on the relationships between the occupant's persona and environmental factors that are necessary to generate thermal sensation, preference, and desirability votes – since these votes are the main input parameter for determining thermal satisfaction. Figure 4.7 illustrates the influence of the parameters on the occupant's individual assessment.

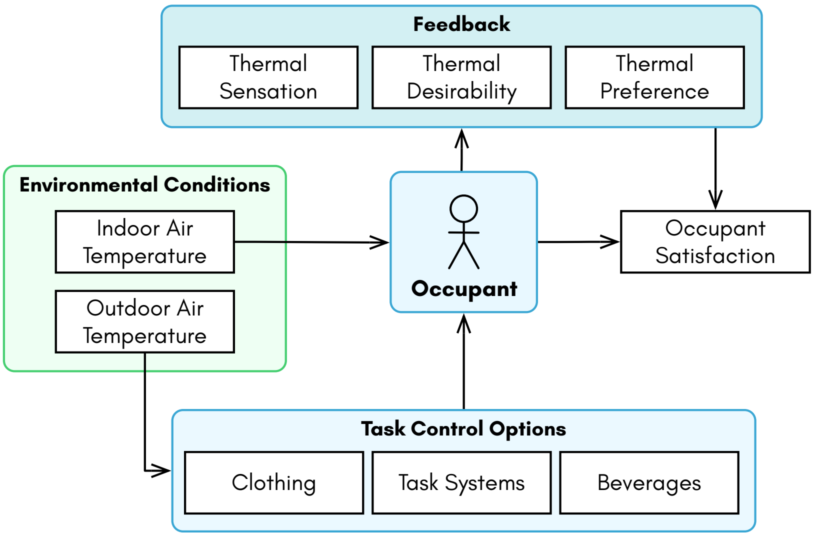


Figure 4.7: **Individual Assessment**

Event Validity. Events in the simulation model are compared against real data. ASHRAE 55 includes examples of environmental and human factors and their respective PPD (Predicted Percentage Dissatisfied) and PMV (Predicted Mean Vote) output [Ame10]. The scenarios that were tested are presented in Table 4.12. The input parameters from the first three rows were taken from ASHRAE and were chosen based on the varying clothing insulation and humidity levels. The last four rows depict representative demonstration scenarios to investigate how TREATI behaves under temperature and clothing insulation changes with a consistent relative humidity (rh) at 50%. An identical group voting behavior was assumed during each run.

	T_{in}	rh	Clo	PMV ASHRAE	PMV TREATI
ASHRAE	19.6 °C	86%	1.0 clo	−0.5	−0.47
	26.8 °C	56%	0.5 clo	0.5	0.52
	21.2 °C	20%	1.0 clo	−0.5	−0.47
Demo	19.0 °C	50%	1.0 clo	–	−0.81
	23.0 °C	50%	1.0 clo	–	0.14
	23.0 °C	50%	0.5 clo	–	−0.79
	27.0 °C	50%	0.5 clo	–	0.53

Table 4.12: **Event Validity Scenario Configuration and Results**

The simulation was conducted 336 times to assess the validity of each event scenario. The rounded simulation results matched ASHRAE's PMV; with each row representing the average of the results. Consequently, the event validity test scenarios validate the expected behavior regarding the resulting PMV value.

Internal Validity. Table 4.13 shows four test scenarios for evaluating internal validity.

Input Parameter	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Outdoor Air Temperature	23 °C	23 °C	25 °C	23 °C
Indoor Air Temperature	23 °C	23 °C	23 °C	23 °C
Task Action Choices	All	All	All	All
Persona Type	Cooler	Cooler	Combination	Combination
Group Voting Behavior	Random	Random	Random	Identical
Occupants	12	Random	12	12

Table 4.13: **Scenario Configurations to Test Face, Internal, and Predictive Validity** of the simulation model.

Scenario #1 was run 100 times to determine the level of internal stochastic variability regarding vote distribution and decision outputs. Outdoor and indoor air temperatures were set at 23 °C to reduce other influences, and because 23 °C is often seen as a 'neutral' temperature [Cui+13; DB98]. Occupants were configured to 'wear' all available clothing items to test their effect on task actions and composite actions without randomization. This scenario was expected to primarily achieve a negative change in air temperature with a vote distribution curve leaning towards *cooler*. These expectations, using thermal preference votes as indicator, are confirmed: The overall vote distributions for *cooler* and *no change* are bell-shaped, with the peak for *cooler* higher than for *no change* votes, and only a few *warmer* votes, see Figure 4.8.

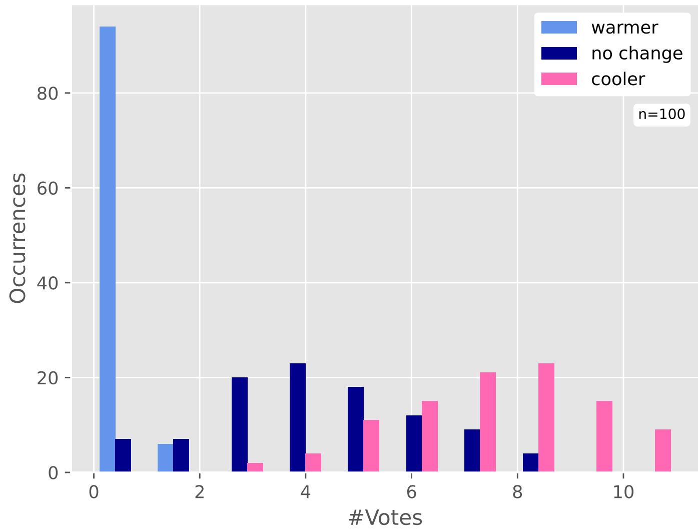


Figure 4.8: **Stochastic Variability Histogram** for occupants who generally prefer cooler temperatures

The expectation for TREATI's actions was that the majority of conflicts would result in an air temperature change, which is also confirmed: Task Action was chosen for 28% of the conflicts with an average of 5.5 task actions (1.54 in total), 55% of conflicts resulted in a temperature decrease of $-1\,°C$, and 17% led to a temperature decrease of $-2\,°C$, mostly by the Mean Preference Setpoint (42%), see Table 4.14.

	warmer	*no change*	*cooler*
Mean	0.43	4.29	7.28
Std	0.61	1.80	1.79
Min	0	0	3
25%	0	3	6
50%	0	4	7
75%	1	5	8
Max	2	8	11

$n = 100$

Table 4.14: **Stochastic Variability Results** testing the internal validity of the simulation model.

The simulation model purposefully adds noise via randomization to the number of votes and the actual votes to add a nondeterministic aspect to the conflict resolution process. The overall expectations of the simulation results are met, demonstrating that the internal validity of the simulation model has been validated.

Face Validity. The predefined scenarios (outlined in Table 4.13) were established for the purpose of testing the system's behavior when parameters are changed to ensure that the resulting metrics are correct. Therefore, the influence of changes in persona types and voting behavior on decisions is evaluated.

Each scenario was run 100 times, the results are summarized in Table 4.15, including the decision type and vote distribution.

	Scenario			
	1	2	3	4
Decision Type				
Static	6	–	–	–
Task Action	27	52	9	–
Mean Sensation	12	1	2	–
Mean Preference	38	40	18	37
Mean Desirability	12	4	40	56
Dynamic Temperature	5	2	18	7
Mean Sensation Composite	–	–	1	–
Mean Desirability Composite	–	1	–	–
Dynamic Temperature Composite	–	–	12	–
Occupant Satisfaction $\overline{x}$	80.78	83.07	75.19	100
Thermal Preference Vote				
warmer	3.75	0.83	51.00	68
no change	35.08	42.54	28.92	0
cooler	61.17	56.63	20.08	32
Change in Temperature				
increase +2 °C	–	–	4	40
increase +1 °C	–	–	87	27
no change 0 °C	33	52	9	–
decrease $-1\,°C$	51	48	–	17
decrease $-2\,°C$	16	–	–	15
Meets Expectations?	✓	✓	✓	✓

units in [%], $n = 100$ *per scenario*

Table 4.15: **Face and Predictive Validity Test Results** show the decision type distribution and thermal preference vote distribution by scenario.

Scenarios #1 '*chilli-milli*' is comprised of personas that generally prefer cooler temperatures, which is reflected in their voting behavior, with overall 61% of votes asking for a temperature decrease, 35% for no change, and only 3.75% for a warmer temperature. For scenario #2 '*sporadic occupancy*', the results are similar, while the number of occupants submitting votes varies between 5 and 12, with 8 votes as the average per conflict. Scenarios #3 and #4 test mixed persona types. In scenario #3 '*thermal* *blend*', where mixed temperature preference persona types are considered, there is a noticeable increase in the overall spread of decision strategy types and votes compared to the other scenarios. This scenario also exhibits a more distinct and varied vote distribution. The actual preferences in the mixed persona type were randomly selected, which resulted in personas that mostly preferred warmer conditions. Thus, overall 51% of votes were in favor of a temperature increase.

Scenario #4 '*synced concensus*' uses mixed temperature preference personas with identical voting behavior. The simulation aims to confirm whether an acceptable decision is reached if all occupants vote for the same option. As expected, TREATI solely used basic actions and predominantly applied the Mean Desirability Setpoint strategy (56%). Task actions were not expected in this scenario, since all 12 occupants submitted identical votes – 12 task actions would impose excessive effort on the occupants. To conclude, this test revealed no inconsistencies.

Predictive Validation. The same scenarios were used to test both face and predictive validity for simplicity. This approach allowed for the simultaneous confirmation of the expected results while verifying the correctness of the logic and behavior. The non-deterministic generation of occupant votes cannot lead to concrete defined values for the vote distribution and metric outcomes – hence, the focus of this test was more on approximations of the vote distributions by persona type and the resulting outcome, based on the input temperatures. In comparison, the scenarios used to test event validity use concrete numbers as predicted outcomes to correlate with given the PMV values from ASHRAE [Ame20].

The results for all four scenarios, presented in Table 4.15, reveal that the expectations for the overall vote distribution and resulting occupant satisfaction with the decisions are met. On average, Scenario #1 and #2 result in occupant satisfaction levels above 80%. In Scenario #3, 76% of conflicts yield occupant satisfaction levels between 64% and 79%, with the mean at 75.19%, which is still considered acceptable. The reason for the lower occupant satisfaction lies in the vote distribution: A change in air temperature leads to higher dissatisfaction in the cohort that was not supported by the decision. Half of the votes are in favor of a warmer air temperature, which means that if the air temperature is lowered, dissatisfaction increases.

The expectation for Scenario #4 was that if the resulting temperature change and all votes are in line, all occupants would be satisfied. Scenario #4 uses personas with identical voting behavior and, thus, results in an average of 100% occupant satisfaction. The temperature was changed according to the average votes and no persona was disfavored by the temperature change.

Concluding predictive validation, the expected outcomes have been confirmed; there is variability in occupant satisfaction outcomes based on the different persona types. The resulting change in air temperature matched the persona types at a neutral air temperature (23 °C): scenarios with personas who prefer cooler temperatures will frequently result in air temperature decreases, and scenarios with personas who prefer warmer temperatures will frequently lead to air temperature increases.

Verification of the Simulation Model

To verify the simulation model, TREATI's concepts (detailed in Chapter 3) – are were to the simulation model to ensure bilateral completeness. The class names from the AOM were mapped to respective elements of the simulation model to reduce ambiguities. The simulation model was implemented using object-oriented programming languages, i.e., for the existing condition model Javascript and for the conflict resolution model Java. The implemented concepts from the AOM were mathematically formalized and have been verified by a domain expert. The verifiability of the concrete implementation was addressed by means of the methods mentioned in Table 4.3.

Sensitivity Analysis. To analyze and verify the impact of the existing conditions model's input parameters (Table 4.4) on the system's behavior, a rudimentary sensitivity analysis was conducted. The sensitivity analysis allowed for further confirmation of the robustness of the system by testing minor variations in individual parameters and comparing the results. While a detailed analysis would be necessary to verify every potential change in each parameter and its effect on the results, this analysis was limited to seven variations of a base scenario of a workday, each was run 100 times.[17] Per simulation run, one parameter was changed to identify the implications of the change on the results. Therefore, this sensitivity analysis rather focused on comparing selected changes to the overall result. The configurations are presented in Table 4.16.

	Scenario						
Input Parameter	Base	1	2	3	4	5	6
Indoor Air Temperature	22 °C	22 °C	22 °C	22 °C	22 °C	22 °C	19 °C
Outdoor Air Temperature	12 °C	22 °C	25 °C	12 °C	12 °C	12 °C	12 °C
Task Action Choices	All	All	All	None	All	All	All
Persona Type	Neutral	Neutral	Neutral	Neutral	Cool	Warm	Neutral
Voting Behavior	Random						

Table 4.16: **Sensitivity Analysis Configurations**

[17]The actual conflict resolution experiment is already set up to provide a total of 360 scenarios, which represent all relevant parameter changes in the scope of this validation.

The relationship between indoor and outdoor temperature is explored by testing the three cases $T_{in} > T_{out}$, $T_{in} = T_{out}$, and $T_{in} < T_{out}$. The base configuration uses a higher indoor air temperature than outdoor air temperature; the other two cases are mapped in scenarios #1 and #2. The task action configuration is configured with two options, 'all' available task actions and 'none', which are tested in scenario #3. There are three main persona types which are named based on their general preferred temperature preferences, i.e., 'neutral', 'warmer', and 'cooler'. The base configuration applies neutral personas, the other two types are tested in scenarios #4 and #5.

Table 4.17 presents the results of the sensitivity analysis.

		Scenario						
		B	1	2	3	4	5	6
Decision Type								
	PMV	68	–	52	63	23	–	1
	Static	–	3	3	–	18	–	–
	Task Action	11	30	28	–	49	–	–
	Mean Sensation	9	7	13	–	–	8	1
	Mean Preference	–	24	–	28	1	–	–
	Mean Desirability	5	29	–	9	4	92	–
	Dynamic Temperature	7	7	4	–	3	–	98
	Dynamic Temperature Composite	–	–	–	–	2	–	–
Occupant Satisfaction $\overline{x}$		81.33	81.98	82.86	79.47	79.34	92.87	96.02
Thermal Preference Vote								
	warmer	61.0	59.00	58.0	64.17	23.83	88.83	98.5
	no change	35.5	37.42	38.0	32.08	39.00	11.00	1.5
	cooler	3.5	3.58	4.0	3.75	37.17	0.17	–
Change in Temperature								
increase	$+2\,°C$	21	10	17	63	–	100	99
	$+1\,°C$	68	57	52	37	25	–	1
no change	$0\,°C$	11	33	31	–	67	–	–
decrease	$-1\,°C$	–	–	–	–	8	–	–
	$-2\,°C$	–	–	–	–	–	–	–

units in [%], $n = 100$ *per scenario*

Table 4.17: **Sensitivity Analysis Results** show the decision type distribution, occupant satisfaction, vote distribution, and temperature changes by scenario.

Temperature changes of the outdoor temperature compared to the indoor temperature only show minor changes in the proposed temperature change. Identical indoor and outdoor air temperatures (#1) and a lower outdoor air temperature but relatively neutral indoor air temperature (#2) lead to fewer changes in temperature than a neutral indoor air temperature and lower outdoor air temperature. A low indoor air temperature coupled with a neutral persona type results in almost all occupants asking for an increase in air temperature. The neutral persona type's preferred air temperature range is between 21 °C and 25 °C , which aligns with the general simulation model. Occupant satisfaction was relatively consistent across the base scenario and scenarios #1 through #4. Scenario #5 showed the highest occupant satisfaction, which is consistent given the respective vote distribution and temperature changes. The vote distributions per scenario were compared using thermal preference votes. The differences among the persona types are as expected and in line with the simulation model's assumptions. Warmer personas overall lead to a majority of *warmer* votes, whereas personas that prefer cooler temperatures cast more *cooler* and *no change* votes, for a neutral indoor air temperature on the lower bound.

Overall, no significant unexpected differences were identified. The simulation model is considered robust, providing valid results for the purpose of this experiment.

Extreme Condition Test. Generally, it is unlikely for extreme conditions, such as indoor air temperatures of 10 °C, to occur by design in shared spaces in the western hemisphere. Considering the defined parameters, there are no 'extreme' values per se regarding the defined parameters. Hence, the extreme condition test investigates the composition of parameters that lead to a contradiction of the building constraints. Four scenarios were tested and their effect on the expected indoor air temperature change was evaluated. Two baselines were included to ensure the correct output of non-contradicting parameter compositions. Table 4.18 presents the parameter composition and the respective results.

Input Parameter	**Value**					
	Baseline		Lower		Higher	
Outdoor Air Temperature	23 °C	23 °C	1 °C	1 °C	30 °C	30 °C
Indoor Air Temperature $T_{in_{prior}}$	23 °C	24 °C	19 °C	20 °C	26 °C	27 °C
Voting-Induced Temperature Change	-2 °C	+3 °C	-1 °C	-2 °C	+2 °C	+2 °C
Implications for T_{in}	21 °C	27 °C	18 °C	18 °C	28 °C	29 °C
Meets Building Constraints?	✓	✓	×	∼	∼	×
Indoor Air Temperature Change	-2 °C	+3 °C	0 °C	-1 °C	+1 °C	0 °C
Indoor Air Temperature $T_{in_{est}}$	21 °C	27 °C	19 °C	19 °C	27 °C	27 °C
Result	✓	✓	✓	✓	✓	✓

Table 4.18: **Extreme Condition Test:** Scenario configuration and results

Chapter 5

Simulation Results and Discussion

> The science of operations, as derived from mathematics more especially, is a science of itself, and has its own abstract truth and value.
>
> Ada Lovelace

Based on the validation steps described in the previous chapter, this chapter summarizes the power of TREATI to improve occupant satisfaction, energy efficiency, fairness, and effort in a range of scenarios. Section 5.1 describes the simulation data analysis in detail, while Section 5.2 discusses the findings and threats to validity.

5.1 Simulation Data Analysis

The simulation's results are presented in the following. The overall dataset is described in Section 5.1.1 and the descriptive statistics are detailed in Section 5.1.2.

The dataset is analyzed and the results are presented in three sections, in alignment with the dissertation's hypotheses 1 and 2 and the validation goals (Table 4.2): Different scenario types regarding occupant voting behavior (Section 5.1.3); occupant voting types (Section 5.1.4); and consistent occupant involvement (Section 5.1.5).

5.1.1 Simulation Settings, Controls & Dataset Description

Generally, office workers spend 50-75% of their day sitting at their desk [CPMG14; WS+13], totaling 20 to 30 hours per work week; hence, the simulation model assumes 24 hours of total work time at the desk in a work week to ensure comfort using TREATI. Every 30 minutes, the conflict resolution model checks whether a new conflict has occurred, which amounts to up to 48 conflicts per scenario. In each time period, the environmental and human factors are modeled continuously to produce results independent from the previous time periods, which creates additional noise and randomization and leads to different input parameters per simulation run. 360 scenarios (see Table 4.4) were evaluated, producing a total of 10 849 conflicts, with an average of 30 conflicts per scenario. The resulting dataset represents one conflict per row and contains critical context – scenario configuration and vote distribution – and conflict resolution data, including the resulting output's metrics per conflict.

Local & System Actions. A conflict's output describes the local or system action that was applied. Local actions are *Task Actions*, i.e., clothing changes, fans or heaters, and beverages. System actions are algorithms that compute a temperature setpoint by means of different inputs. *PMV* (Predicted Mean Vote) [Fan70] is based on static assumptions about air velocity, humidity (RH), activity, the current conditions of indoor and outdoor air temperature, and each occupant's dynamic clothing insulation. *Static* maintains the indoor conditions as they are and does not apply a new temperature setpoint. *Dynamic Temperature Setpoint* determines a temperature setpoint from the averaged occupants' feedback and the difference to the current temperature by using the 3-point thermal preference and 7-point thermal sensation scales as the temperature change amplitude. Three system actions compute an average temperature setpoint derived from occupant feedback (thermal sensation, preference, and desirability votes): *Mean Sensation Setpoint*, *Mean Preference Setpoint*, and *Mean Desirability Setpoint*. Composite setpoint system actions apply a combination of an average feedback setpoint action with *Task Action*: *Mean Sensa-*

tion Composite Setpoint, *Mean Preference Composite Setpoint*, and *Mean Desirability Composite Setpoint*. The set of task and system actions are referred to as **strategies**. The computation of the task and system actions are detailed in Section 4.2.4.

Controls. TREATI's impact is compared against the traditionally used PMV and Static controls, which constitute the *baselines*.

Dataset Description. Table 5.1 presents the number of identified conflicts based on the individual scenarios, which range from 1 to 48 conflicts per scenario.

Conflict Occurrences					
≤ 10	≤ 20	≤ 30	≤ 40	> 40	$= 48$
10.00	8.06	12.50	16.67	14.72	38.06

units in [%], $n = 360$

Table 5.1: **Conflict Count per Scenario**

The number of conflicts per scenario depends on the scenario and the likeliness of a conflict occurring. For instance, a neutral persona type, random voting behavior, and identical indoor and outdoor air temperatures lead to fewer conflicts ($n = 94$) than the same configuration with differing air temperatures ($n = 1419$). Notably, 36 scenarios resulted in less than 10 conflicts, with 6 scenarios leading to only one conflict each. 43.1% of all scenarios lead to a conflict in each run, totaling 48 conflicts each.

5.1.2 TREATI's Impact: Overall Descriptive Statistics

Overall, the actions proposed by TREATI produce better metrics than each of the baseline thermal control strategies (Static- and PMV-driven), as shown in Table 5.2.

Overall Distribution. TREATI achieves the overall highest occupant satisfaction mean (89.26%) and the lowest standard deviation (8.52%). Both Static and PMV-driven controls result in mean occupant satisfaction at least 20% lower than TREATI; PMV has the highest standard deviation (17.54%). However, compared to the previous conditions before the respective control's proposed change, PMV's energy efficiency mean is +1.72% while TREATI's energy efficiency mean is −0.69%, although both medians are 0%. Since Static control does not result in a new setpoint, there is no change in energy efficiency. TREATI is, on average, 42% fairer than PMV and 64% fairer than Static control. All strategies (the respective local or system action chosen by TREATI) offer overall occupant satisfaction greater than 65%, as shown in Table 5.2, although neither Static nor PMV achieves 80% occupant satisfaction.

TREATI's Applied Action	$\overline{x}$	$med(x)$	SD	Var	Min	Max
Static	65.54	62	13.08	171.0	40	100
PMV	69.29	73	15.9	252.82	0	100
Task Action	83.19	83	8.59	73.73	42	100
Mean Sensation SP	79.81	79	11.47	131.53	34	100
Mean Sensation SP Composite	81.62	82	10.9	118.85	34	100
Mean Preference SP	76.84	77	10.48	109.93	35	100
Mean Preference SP Composite	77.16	78	10.49	110.08	35	100
Mean Desirability SP	82.83	84	11.69	136.58	40	100
Mean Desirability SP Composite	83.88	85	11.18	125.03	40	100
Dynamic Temp. SP	69.31	70	12.31	151.47	10	100
Dynamic Temp. SP Composite	71.96	74	11.74	137.71	10	100

$\overline{x}$ *indicates the mean*, $med(x)$ *indicates the median* – SP = 'setpoint' – *units in* [%], $n = 10849$

Table 5.2: **Occupant Satisfaction Means and Medians** by action types

Overall, TREATI's most frequent action is Task Action ($n = 3445$), followed by the Mean Desirability Setpoint ($n = 3067$), as shown in Figure 5.1.

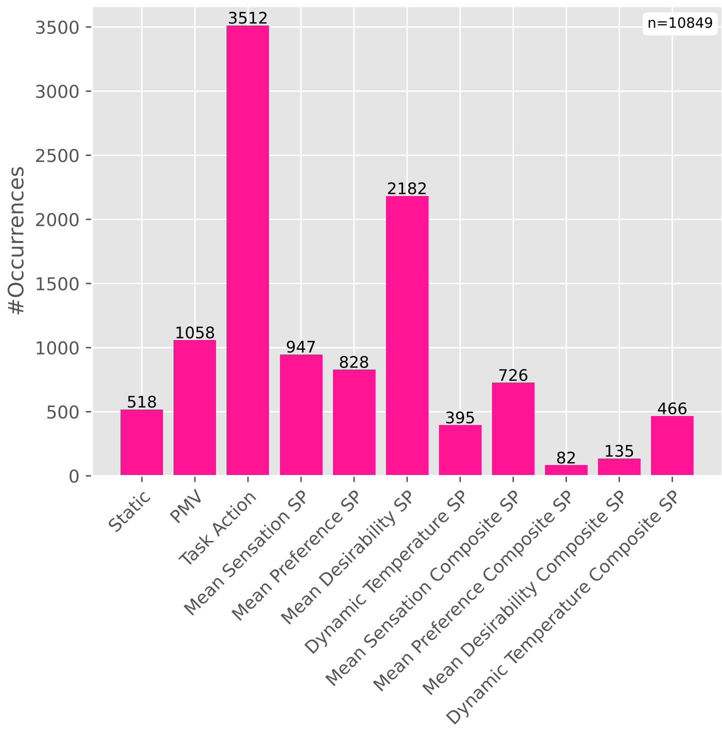


Figure 5.1: **Distribution of TREATI's Actions**

Dissimilarity between TREATI and the Baselines. An independent t-test with $H_0 : \mu_{\text{TREATI}} - \mu_{\text{Baseline}}$ validates that TREATI and the baselines produce different results regarding occupant satisfaction, with the test statistics $t_{\text{TREATI},PMV} = 121.2566$ ($p_{\text{TREATI},PMV} = 0.0$) and $t_{\text{TREATI},Static} = 180.8800$ ($p_{\text{TREATI},Static} = 0.0$), see

Table 5.3. Cohen's d reveals large effect sizes ($d_{PMV} = 1.5360$ and $d_{Static} = 2.2913$), which further shows that TREATI and baselines are dissimilar to each other. The differences of TREATI to the baselines are both positive, which confirms that TREATI produces better results than the baselines alone.

Independent T-Test	**Baselines**	
	PMV	**Static**
Difference (TREATI - *Baseline*)	19.9747	23.7247
Degrees of Freedom	21696.0000	21696.0000
Test statistic	115.3247	158.3156
p-value (Two-Sided T-Test)	0.0000	0.0000
p-value (Difference < 0)	1.0000	1.0000
p-value (Difference > 0)	0.0000	0.0000
Cohen's d	1.5658	2.1495
Pearson's r	0.6165	0.7321

$n = 10849$

Table 5.3: **Independent T-Test Comparing TREATI to the Baselines** validates the difference between TREATI and the baselines' occupant satisfaction results

Robustness of TREATI's Occupant Satisfaction. Around 75% of TREATI's actions result in an occupant satisfaction higher than 85%; 25% of TREATI's actions yield at least 97% occupant satisfaction, see Table 5.4. 25% of PMV's occupant satisfaction is higher than 80% and 25% of Static control is higher than 74%. A visualization in the form of a box-and-whisker plot can be found in Figure B.1.[1]

Quartile	**TREATI**	**PMV**	**Static**
0.25	85	60	56
0.50	89	73	62
0.75	97	80	74

$n = 10849$

Table 5.4: **Occupant Satisfaction Quartiles**

Pearson Correlation. The Pearson correlation method does not yield conclusive correlations among the context and TREATI's chosen action's metrics for the full dataset (see Figure B.3) – but rather further confirms and extends the simulation model's validity regarding the parameters' relationships as described in Section 4.2.7. For instance, the indoor air temperature has a moderate positive correlation with

[1] These results comprise the full dataset. In addition, the individual scenarios' mean and median occupant satisfaction are evaluated using box-and-whisker plots and show comparable results, see Appendix B Figure B.2.

TREATI's proposed temperature change ($r = 0.58$), and the outdoor air temperature moderately correlates with TREATI's energy efficiency ($r = 0.47$). The voting behavior moderately correlates with the number of votes ($r = 0.56$), which is expected as the number of votes only changes in random voting behavior scenarios.

5.1.3 Voting Types

Occupant voting behavior has an impact on occupant satisfaction and energy efficiency: TREATI achieves better occupant satisfaction and fairness than PMV and Static controls for each voting type. Three types of voting behavior have been explored (as specified in Section 4.2.2): *random* (51.94%), *split* (30.73%), and *majority* (17.33%). The outcome of non-trivial vote scenarios depends on the type of votes: Split voting behavior conflicts are divided into conflicts with 50% voting for 'no change' (SV1) and contradicting temperature changes (SV2). Majority vote conflicts are split into two types: (1) The majority prefers *no change* and (2) the minority prefers *no change* regarding the air temperature. The first case is expected to yield only a few temperature changes for most actions[2]. Thus, majority vote conflicts are divided into conflicts with majority *no change*-votes (MV1) and conflicts excluding a *no change* majority (MV2). Table B.1 shows the overall descriptive distributions for each voting type and Table B.2 presents the independent t-test results for each voting behavior.

Random Voting Behavior. Random voting behavior scenarios represent non-deterministic conflicts regarding the number and direction of votes. Figure 5.2 shows the action distribution of TREATI. The most frequently chosen actions are the Mean Desirability Setpoint and Task Action, followed by the Mean Sensation Setpoint and Mean Sensation Composite Setpoint actions. TREATI's temperature change demonstrates a strong positive correlation with the indoor air temperature (0.73), see Figure 5.3. Occupant satisfaction does not correlate with any other feature, emphasizing its subjective and random nature. The two correlations of TREATI's energy efficiency and outdoor air temperature (correlation coefficient of 0.57) and temperature change (correlation coefficient of 0.43) are each slightly higher compared to the full dataset.

[2]For instance, for the Mean Preference Setpoint, nine votes for *no change* (0) and three votes for *warmer* (1) results in an average of 0.25, i.e., no change in air temperature.

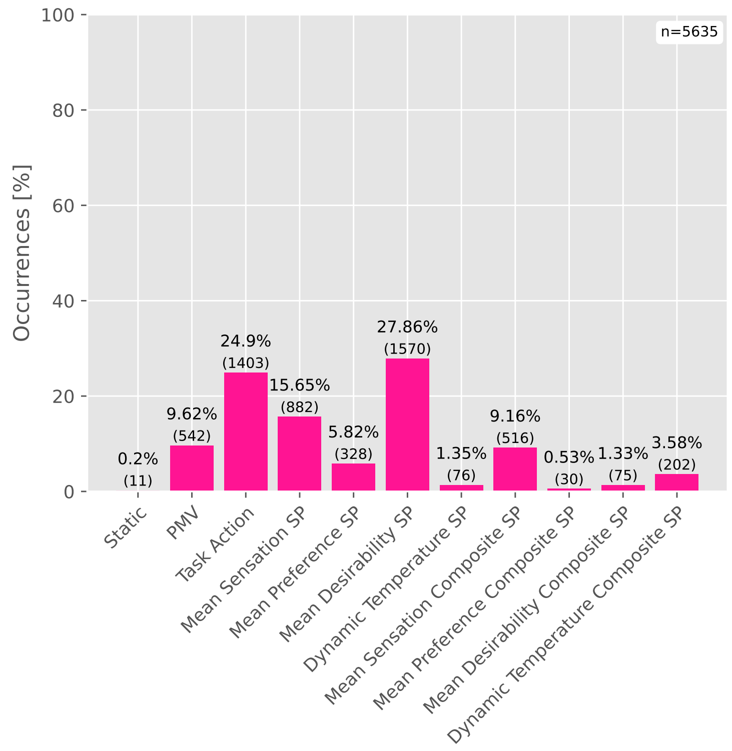


Figure 5.2: **Random Voting Behavior Action Distribution**

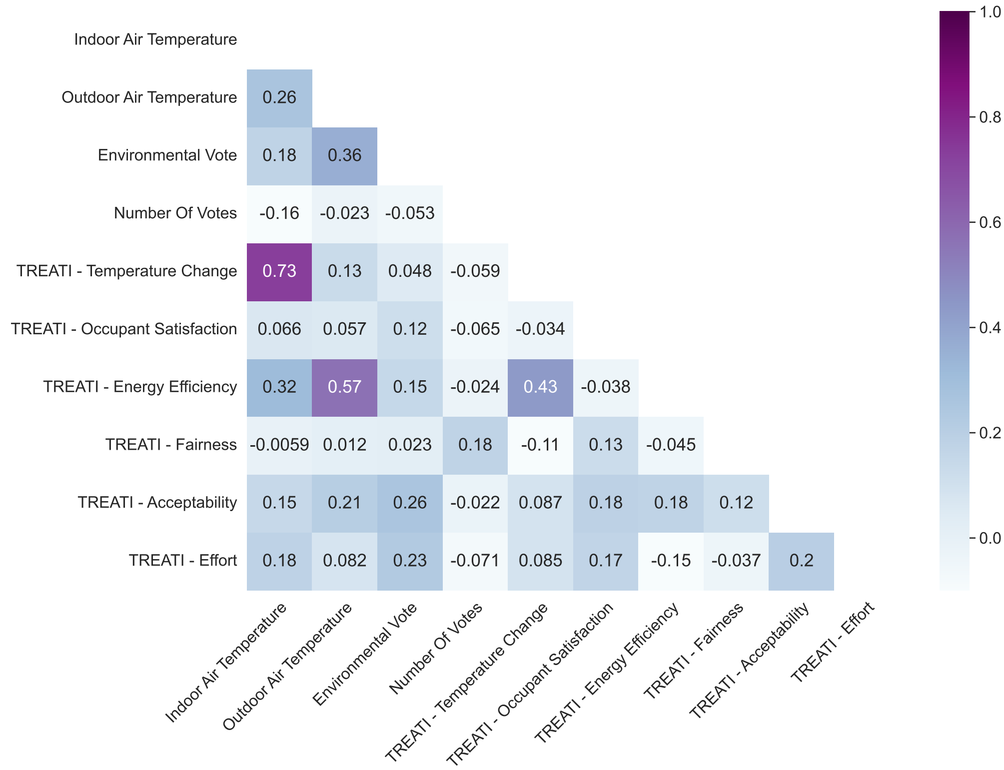


Figure 5.3: **Random Voting Behavior Correlation Matrix** (Pearson)

Split Voting Behavior. Conflicts with the split voting behavior configuration reveal that TREATI's energy efficiency has a positive correlation with acceptability ($r_{split} = 0.49$), see Figure 5.4.

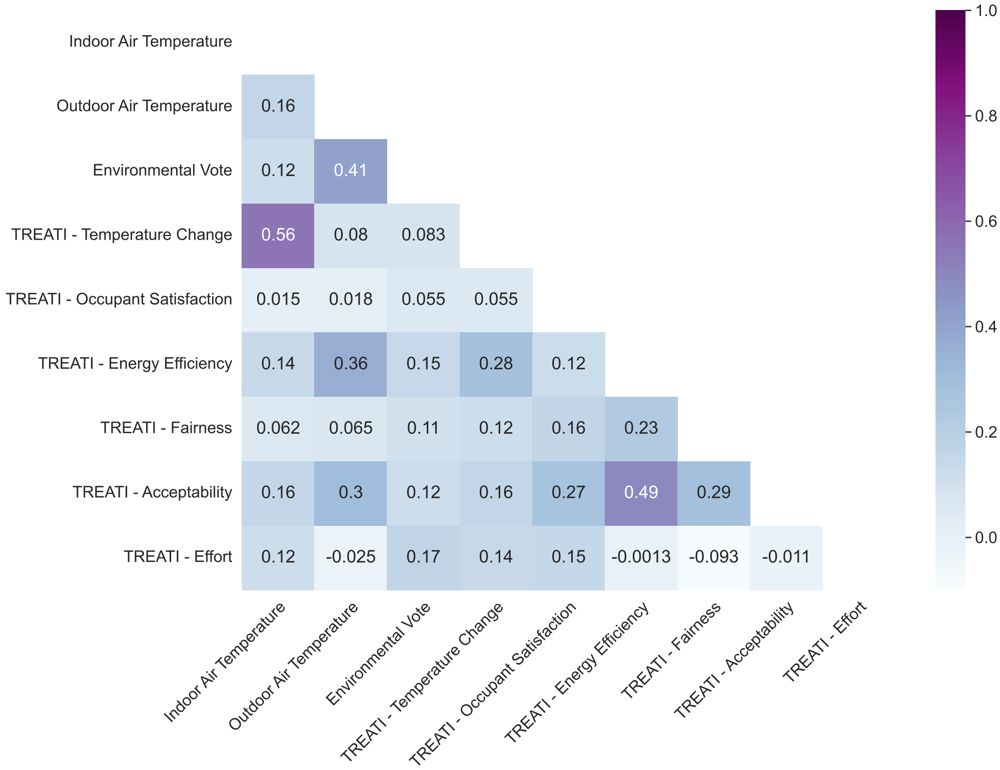


Figure 5.4: **Split Voting Behavior Correlation Matrix** (Pearson)

A split voting scenario can result in either 50% of occupants voting for an increase or decrease in air temperature (on each of the three scales, thermal sensation, preference, and desirability), for the opposing temperature change, or for no change in temperature. The split voting behavior dataset is filtered for conflicts in which 50% of votes are *no change* (SV1, $n_{SV1} = 1684$) and opposing votes (50% warmer vs. 50% cooler) (SV2, $n_{SV2} = 1650$). The action distribution for both types is shown in Figure 5.5 and shows that if half of the occupants are comfortable (SV1), conflicts are mostly addressed by either task actions (53.33%) or doing nothing (27.85%).

The correlation between TREATI's energy efficiency and the outdoor air temperature is lower (0.36) than for the full dataset (0.47). Since SV1 and SV2 have differences regarding TREATI's action distribution, their individual correlations are examined. SV1's temperature change strongly correlates with energy efficiency, whereas SV2 shows only a slight correlation ($r_{SV1} = 0.71$, $r_{SV2} = 0.28$). SV2 presents a strong positive correlation between TREATI's acceptability and energy efficiency ($r_{SV2} = 0.66$, $r_{SV1} = 0.51$). Both can be explained through TREATI's action distribution: In SV1, more than 81% of actions do not result in any energy efficiency changes, in SV2, 77%

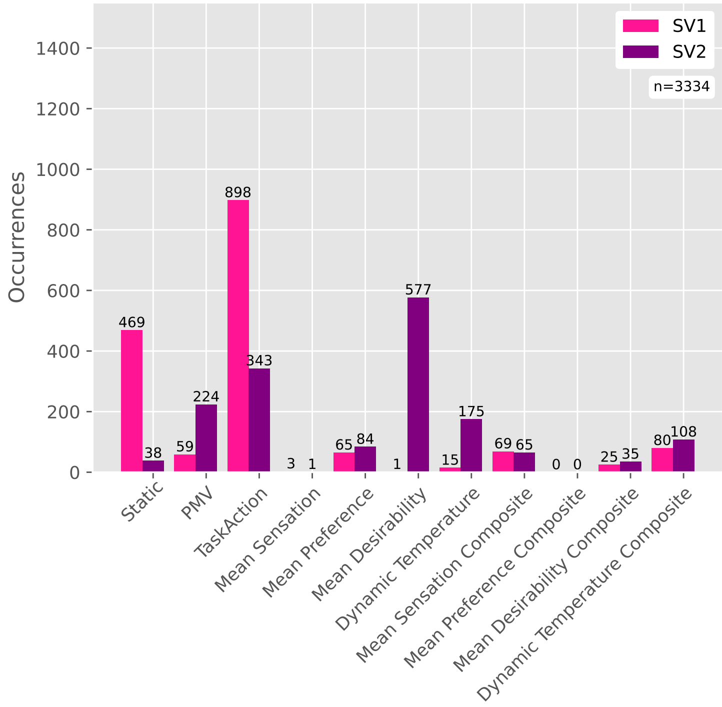


Figure 5.5: **Split Voting Behavior Action Distribution**

of actions lead to a change in energy efficiency. Changes in air temperature impact the energy efficiency score and, thus also, the acceptability score. If there is no change in air temperature, the energy efficiency remains the same, hence the different correlation coefficients. The correlation matrixes for both subsets can be found in Figure B.5.

Majority Voting Behavior. Per conflict – since majority vote conflicts are modeled with a $75\% - 25\%$ vote distribution – there are either zero, three, or nine votes per step on the thermal preference scale. Figure 5.6 shows the distribution of TREATI's actions compared by both majority voting types. MV1 – the majority voting for no temperature change – solely applies Task Actions ($n = 632$). For MV2 ($n = 1248$), Mean Preference Setpoint is the most frequently selected action (28.12%), followed by Task Action (18.91%) and PMV (16.67%). Overall, MV1 has stronger correlations compared to MV2, as illustrated in Figure B.6. MV1 reveals a strong correlation between TREATI's acceptability and fairness ($r_{MV1} = 0.78$, $r_{MV2} = 0.38$, $r_{all} = 0.1$). Task Actions do not favor particular occupants and therefore do not impact the fairness score negatively. MV2 shows moderate correlations between the environmental energy efficiency vote and three other features: The action's fairness ($r_{MV2} = 39$), TREATI's acceptability ($r_{MV2} = 0.38$), and the outdoor air temperature ($r_{MV2} = 0.43$, $r_{MV1} = 0.45$). This indicates that the environmental energy efficiency vote has a positive impact on TREATI. There are no other relevant correlations.

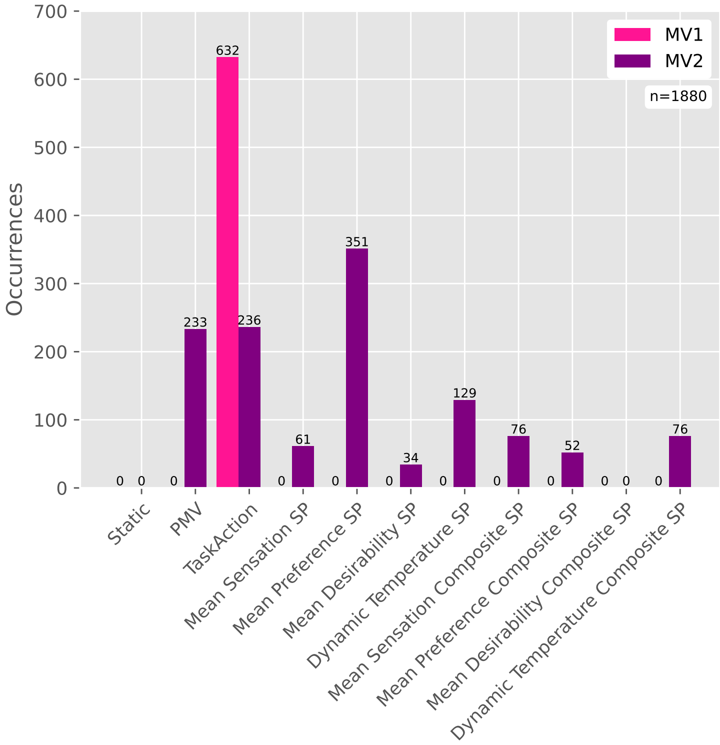


Figure 5.6: **Majority MV1 and MV2 Action Distribution**

5.1.4 Occupant Participation

To address VQ2 and analyze the effects of voting behavior on TREATI, occupant vote participation is examined. Non-trivial votes, i.e., split and majority votes, are not considered, since they were modeled with 100% occupant involvement. Table 5.5 presents an overview of the occupant vote participation distribution regarding occupant satisfaction for different participation rates in comparison: $\geq 75\%$, $\geq 50\%$, and $\geq 25\%$.

Participation		$\overline{x}$	$med(x)$	**SD**	**Var**	**Uncertainty Score**	
$\boldsymbol{n}$	**Rate**					$\overline{x}$	$med(x)$
1717	$\geq 75\%$	93.0	95	6.53	42.71	10.28	8.33
3918	$< 75\%$	87.21	87	7.15	51.19	42.55	41.67
4169	$\geq 50\%$	89.91	91	7.39	54.62	23.82	25.00
1466	$< 50\%$	86.31	87	7.01	49.21	58.04	58.33
5492	$\geq 25\%$	89.03	90	7.41	54.85	31.55	33.33
143	$< 25\%$	86.90	90	9.16	83.88	77.86	75.00

$\overline{x}$ indicates the mean, $med(x)$ indicates the median *units in [%], $n = 5635$*

Table 5.5: **Influence of Vote Participation on Occupant Satisfaction**, filtered by random voting behavior conflicts.

Since TREATI only takes the submitted votes into account, there are no significant differences regarding occupant satisfaction when comparing the different rates. The standard deviation and variance increase by decreasing participation. The uncertainty score $u \in U$ describes the percentage of potentially dissatisfied occupants of a specific participation rate r regarding an action a – assuming full occupancy:

$$\begin{aligned} \forall v \in r : u_a = v + 1 - \frac{\#v}{12} \\ U_a = \sum u \end{aligned} \tag{5.1}$$

The goal is to achieve a low uncertainty score, which would decrease the risk of an action leading to another conflict. For occupant participation of $\geq 75\%$, the uncertainty score is low ($\overline{x} = 10.28\%$, $med(x) = 8.33\%$) but above 40% for lower participation. A participation rate of less than 25% has a high mean of 86.90%, but also a high uncertainty rate, $\overline{x} = 77.86\%$. While these numbers do not have an actual impact on TREATI, they provide insights into how reliable an action is and show implications for future adjustments. Including the uncertainty score in the acceptability definition could, for instance, prevent unreliable actions. The occupants' general preferred thermal settings could also be incorporated. However, more knowledge about the occupant is needed to generate added value to the uncertainty score.

5.1.5 Consistent Occupant Involvement

To address the question of whether TREATI can achieve a minimum of 80% occupant satisfaction over time, three scenarios with different configurations were evaluated. The independent variable across the three scenarios was the voting behavior. The base configurations are outlined in Table 5.6.

One scenario imitates one workday, assuming an average of 5 hours spent at the occupant's workstation. Each run has 10 cycles, where the data were continuously modeled using the output air temperature from the previous action as input for the next cycle. The input votes are based on the previous cycle's resulting temperature change and persona type as described in Section 4.2.5. Using three scenarios with ten cycles, each tests the robustness of the system against randomness in human factor changes (the persona type distribution). Table 5.7 summarizes the resulting indoor air temperatures and vote distribution. Overall, two cycles resulted in 79% occupant satisfaction, all others led to at least 80% of satisfied occupants. All three scenarios are converging towards using the task action strategy after reaching an acceptable air temperature, which is indicated by the dashed line.

Factor	Value
	Dependent Variables
Outdoor Air Temperature	12 °C
Occupancy	Full (12 occupants)
Fairness	$F \in (1, 0.7, 0.5, 0.3)$
Task Control Options	Random distribution of clothing items
	Independent Variable
Indoor Air Temperature	19 °C (initial setting)
Voting Behavior	Semi-random, the first votes are generated randomly; the output is used as input to the next conflict, etc. **Scenario 1** – Random voting: Equally distributed general temperature preferences (4x warmer, 4x neutral, 4x cooler) **Scenario 2** – Random voting: Randomly mixed general temperature preferences **Scenario 3** – Majority voting: Randomized cohorts

Table 5.6: **Closed-Loop Scenario Configurations**

5.2 Validation Discussion

Section 5.2.1 provides a summary of the findings with respect to the validation goals (VG) and validation questions (VQ) defined in Table 4.2. Section 5.2.2 discusses the threats to validity with respect to construct, internal, and external validity.

5.2.1 TREATI Improves Occupant Comfort

VG1 – TREATI's Impact on Thermal Comfort Conflicts.
TREATI achieves levels of higher occupant satisfaction and fairness compared to PMV and Static controls. To evaluate TREATI's actions regarding thermal comfort conflicts, TREATI's metrics were compared with the baselines' metrics. In addition, different parameters and their effect on TREATI were analyzed.

VQ1 investigates the use of local actions in combination with system actions, comparing them to PMV and Static controls. The overall descriptive statistics (see Table 5.2) for TREATI, PMV, and Static controls indicate that TREATI outperforms PMV by 20% and the Static controls by 24% regarding occupant satisfaction. Since TREATI's actions also include both baselines, a t-test was performed (see Table 5.3), which revealed that TREATI's actions are dissimilar to the baselines. When comparing the different types of voting behavior (outlined in Table B.3), the means and medians show that the occupant satisfaction levels for the baselines are, on average, above 60%. TREATI results in occupant satisfaction levels between 82% (MV2) to 96% (MV1) and performs at least 6.39% better than the best baseline (MV1).

Sc.	Cycle	Indoor Air Temperature		Occupant Satisfaction	Vote Distribution				
					much warmer	slightly warmer	no change	slightly cooler	much cooler
1	1	–	19	94	8	3	1	0	0
	2	(+2)	21	83	6	5	0	1	0
	3	(+1)	22	79	6	3	3	1	0
	4	(+1)	23	84	2	3	3	2	2
	5	–	23	81	4	1	3	2	2
	6	–	23	82	4	3	2	0	3
	7	–	23	80	5	2	1	2	2
	8	–	23	81	3	4	2	1	2
	9	–	23	80	4	1	2	4	1
	10	–	23	81	4	3	1	3	1
2	1	–	19	98	11	0	1	0	0
	2	(+2)	21	85	6	1	3	2	0
	3	(+2)	23	75	4	3	3	2	0
	4	(+1)	24	88	0	0	4	1	7
	5	(−1)	22	85	4	1	5	0	2
	6	–	22	85	3	6	2	1	0
	7	(+1)	23	88	2	2	6	0	2
	8	–	23	81	3	2	3	1	3
	9	–	23	80	0	3	3	4	2
	10	–	23	84	4	1	2	2	3
3	1	–	19	85	4	5	3	0	0
	2	(+1)	20	79	3	6	0	2	1
	3	(+1)	21	81	0	0	3	3	6
	4	(−1)	20	81	1	2	0	7	2
	5	(−1)	19	91	1	2	0	6	3
	6	–	19	87	2	1	0	5	4
	7	–	19	85	3	0	0	5	4
	8	–	19	80	2	1	0	3	6
	9	–	19	90	0	0	3	5	4
	10	–	19	93	2	1	0	8	1

- - - *represents the setting after which only task actions are selected to address conflicts*

Table 5.7: **Closed-Loop Cycles** – Summary of the input and output from the manual object-event simulation, emphasizing the resulting occupant satisfaction levels and vote distributions

The PMV performs slightly better regarding the average energy efficiency (+1.72%) than TREATI (−0.69%) – however, both have a median of 0%. Since energy efficiency is measured on a scale of $[-30\%, 30\%]$, the positive and negative values are likely to neutralize each other. To confirm this assumption, TREATI's energy efficiency values are compared by voting behavior using box-and-whisker plots in Figure B.4. These box-and-whisker plots show that TREATI overall yields a broader range along the energy efficiency scale with a lower minimum value but an equal mean compared to PMV. Split voting behavior in particular shows the biggest differences: 25% of TREATI's actions lead to −5% energy efficiency ($Q1_{PMV} = 0\%$), the PMV results in 5% for the 75% quartile ($Q3_{\text{TREATI}} = 0\%$). For majority votes – where the majority requests a change in air temperature (MV2) – TREATI results in a larger spread ($Q1_{\text{TREATI}} = -5\%$, $Q2_{\text{TREATI}} = 0\%$, $Q3_{\text{TREATI}} = 5\%$) than the PMV ($Q1_{PMV} = 0\%$, $Q2_{PMV} = 0\%$, $Q3_{PMV} = 5\%$). MV1 results solely in non-temperature changing strategies, keeping the energy efficiency unchanged.

TREATI's fairness score surpasses the baselines by at least 40% for all voting behavior types. Notably, is that when applying the Static strategy to random vote conflicts and MV2 conflicts, the average fairness is less than 4% (($\overline{x_{F_{Static}}} = 3.7\%$, $\overline{x_{F_{MV2}}} = 2.62\%$) with a median of 0%. The fairness score factors in the previous 10 actions and varies by conflict, as it is randomly generated. Therefore, this finding has limited significance and necessitates further examination with real human occupants.

To conclude VQ1, the observations show that evaluating multiple strategies outperform the baselines for occupant satisfaction and fairness, but not energy efficiency. Considering that occupant satisfaction contributes 60% to the acceptability score during evaluation and action selection, while energy efficiency accounts for only 20%, this outcome is expected. However, for human subject experiments or in a real-world setting, the overall requirements need to be evaluated first to achieve acceptable actions.

The aforementioned findings also address **VQ2** to investigate whether solving non-trivial conflicts using TREATI leads to higher occupant satisfaction and energy efficiency than compared to the baselines. The dataset was filtered for split and majority voting behavior conflicts. For conflicts with split voting behavior, TREATI's energy efficiency values are slightly more spread than those of the PMV, see Figure B.4 and Table B.6. For split votes that include 50% *no change* votes (SV1), TREATI's energy efficiency is 0% for all quartiles (minimum value is −10%, maximum value is 25%); PMV is spread more ($Q1_{PMV} = 0\%$, $Q2_{PMV} = 0\%$, $Q3_{PMV} = 5\%$, minimum value is −10%, maximum value is 30%). This difference between the two types of split votes is explained by the distribution of action types: SV1 conflicts are primarily resolved through Task Action and Static control, which do not result in temperature changes.

To conclude VQ2, non-trivial conflicts lead to higher occupant satisfaction and higher fairness, but lower energy efficiency as compared to the baselines – with the exception of split votes where 50% of votes are '*no change*' (SV1) and which have a similar energy efficiency to that of the PMV.

To further analyze how different parameters influence TREATI's results (**VQ3**), the context parameters 'persona' and 'indoor air temperature' were examined.

All persona types (cooler, neutral, warmer, and neutral) have a strong correlation between the indoor air temperature and TREATI's temperature change ($r_{cooler} = 0.84$, $r_{neutral} = 0.88$, $r_{warmer} = 0.85$, $r_{mixed} = 0.83$) and a moderate correlation between the outdoor air temperature and TREATI's energy efficiency ($r_{cooler} = 0.61$, $r_{neutral} = 0.29$, $r_{warmer} = 0.54$, $r_{mixed} = 0.22$). Personas who prefer cool temperatures show a moderate correlation between TREATI's energy efficiency and temperature change ($r_{cooler} = 0.56$, $r_{neutral} = 0.88$, $r_{warmer} = 0.38$, $r_{mixed} = 0.83$) Conflicts with warm personas also show a moderate correlation between indoor air temperature and occupant satisfaction (0.56). These observations confirm that – given all occupants' general preference of the air temperature – a change in indoor air temperature affects TREATI's temperature change and energy efficiency.

A moderate or neutral indoor air temperature ($22\,°C$ to $25\,°C$) predominantly results in Task Actions (40.1%). For warm and cooler temperatures, the Mean Desirability Setpoint ($x_{Warm} = 28.8\%$. $x_{Cool} = 27.6\%$) and Task Action ($x_{Warm} = 27.3\%$. $x_{Cool} = 24.2\%$) occur most frequently in the whole dataset. Filtering for random voting behavior reveals fewer task actions for warm ($x_{Warm} = 6.3\%$) and cool ($x_{Cool} = 12.6\%$) temperatures but 42% of task actions for neutral temperatures. In other words, if the indoor temperature is kept at a neutral level, TREATI can address ~50% of all conflicts by applying Task Actions or by the Static strategy (6.7%). This observation supports the findings from other studies that have already suggested the application of neutral temperatures to increase occupant satisfaction [Cui+13; DB98].

VG2 – Occupant Involvement in TREATI.
A key aspect of TREATI is involving the occupant in the decision-making process. While the simulation does not address occupant feedback regarding the resulting action, occupant votes, and occupant satisfaction form the basis of evaluating a conflict.

To address **VQ4**, occupant vote participation was analyzed in Table 5.5. If solely considering the absolute number of submitted votes and no abstentions, there is no significant difference in occupant satisfaction among different participation configurations. The voting behavior of the simulation model depends on a randomly generated number of submitted votes, aiming to investigate whether the number of votes has an impact on TREATI. An uncertainty score was introduced to indicate the average number of missing occupant feedback, assuming a total of 12 occupants in the respective zone, which may impact TREATI's actions.[3] Ideally, actions have a low uncertainty

[3]This was not addressed during the simulation runs to prevent any distortion of the results.

score to avoid unsuitable changes in air temperature, which may lead to new conflicts.

The PMV and Static strategy do not rely on active occupant involvement in the form of votes but instead on often pre-defined or assumed human factors – metabolic rate and clothing insulation. TREATI considers occupant votes to determine the most suitable action, which was compared to both baselines in detail above. Thus, to conclude VQ4, occupant involvement leads to higher occupant satisfaction rates.

The expectation for composite actions was that they would be chosen more frequently than their basic action counterparts – given that non-satisfied occupants can improve their own comfort using task actions. **VQ5** was addressed by analyzing the occurrences of composite and basic actions and their resulting metrics.

Surprisingly, composite actions account for only 13% of all actions in total – 24.5% when comparing them to their basic counterparts. This overall low percentage of composite actions is due to two reasons: First, the addition of task actions for composite actions depends on the type of conflict and TREATI's temperature change. When filtering for scenarios that allow task actions – i.e., 7921 conflicts in total[4] – 17.79% of actions are comprised of composite actions, as outlined in Table 5.8.

Scenarios involving random voting behavior yield a composite action rate of 20.83%. Split voting behavior scenarios are approached by overall 15.3% composite actions, 12.57% if one cohort prefers no change in temperature (SV1), and by 18.71% for contrary votes (SV2). When filtering for the majority vote (MV2) strategy, composite actions comprise 24.23% of TREATI's actions. Since Task Actions are used most frequently for non-trivial conflicts to avoid more discomfort for the disfavored group, it is logical that composite actions are used less frequently.

Second, all task actions lead to an increase in effort. Depending on the number of task actions, the normalized effort score is lower than for basic actions. Since the Mean Desirability Setpoint was most frequently chosen out of all composite actions, it is compared to its composite alternative's metrics by random voting behavior, using only task action scenarios. In total, 81 scenarios match this filter. There are only slight differences between the basic action's acceptability score ($\overline{x}_{basic} = 82.24\%$, $\overline{x}_{basic} = 83.9\%$) to the composite counterpart ($\overline{x}_{composite} = 81.03\%$, $\overline{x}_{composite} = 82.5\%$) and the occupant satisfaction ($\overline{x}_{basic} = 90.2\%$, $\overline{x}_{basic} = 93\%$ and $\overline{x}_{composite} = 91.05\%$, $\overline{x}_{composite} = 92\%$). The energy efficiency score is identical. 87.65% composite actions include one task action, and 12.35% include two. The mean effort score for the

[4] 5476 conflicts with task actions requiring additional items; 2445 conflicts with beverage task actions.

Proposed Action	All	Random	Split SV1	Split SV2	Majority MV1	Majority MV2
Static	3.31	0.15	16.98	1.89	0.0	0.00
PMV	6.51	6.00	2.60	10.79	0.0	14.61
Task Action	44.34	35.51	64.88	30.85	100.0	28.03
Mean Sensation SP Basic	6.31	11.79	0.14	0.09	0.0	3.68
Mean Sensation SP Composite	9.17	13.06	4.99	5.85	0.0	9.03
Mean Preference SP Basic	4.87	3.70	2.38	3.69	0.0	19.71
Mean Preference SP Composite	1.04	0.76	0.00	0.00	0.0	6.18
Mean Desirability SP Basic	14.18	20.80	0.00	25.63	0.0	1.90
Mean Desirability SP Composite	1.70	1.90	1.81	3.15	0.0	0.00
Dynamic Temp. SP Basic	2.69	1.21	0.43	8.36	0.0	7.84
Dynamic Temp. SP Composite	5.88	5.11	5.78	9.71	0.0	9.03
Total Basic SP Strategy	28.05	37.5	3.95	37.77	0.0	33.13
Total Composite SP Strategy	17.79	20.83	12.58	18.71	0.0	24.24
Total Occurrences n	7921	3951	1384	1112	632	842
			2496		1474	

Filtered for conflicts that allow task actions *units in* [%], $n = 7921$

Table 5.8: **Comparison of Basic vs. Composite Action Distributions compared by Voting Behavior** filtered by conflicts that allow task actions

composite action is 0.56 higher than the basic action's. A higher effort score leads to a slightly lower acceptability score compared to the basic action, which results in the basic action being selected over the composite action. This leads to the deduction that an adjustment of the acceptability score is required to allow more composite actions.

Vice versa, 75 actions that use the Mean Desirability Composite Setpoint action using the same filter as above are compared to their basic actions' metrics. The acceptability score of the composite actions is, on average, 1.11% higher than the basic action ($\overline{x}_{basic} = 85.9\%$). The composites' occupant satisfaction mean is 94.4% ($\overline{x}_{composite} = 95\%$), the basic actions' mean is 90.43% ($\overline{x}_{basic} = 91\%$). Interestingly, the composites' fairness score is 94.49% ($\overline{x}_{composite} = 100\%$), which makes it 14.31% higher than the basic actions' fairness score ($\overline{x}_{basic} = 80.19\%$, $\overline{x}_{basic} = 85\%$). 80% of the composite actions include one task action, 17.3% include two task actions, and 2.67% include three task actions, which results in the mean effort score of 1.61%.

Similarly, split and majority voting behavior were compared in view of basic and composite actions. The results can be found in Table B.5. These observations show that by including composite actions in the solution strategy set, compared to their basic actions, TREATI was able to increase occupant satisfaction by 4% (Mean Desirability) to 8.7% (Dynamic Temperature) for random voting behavior, around 13% for each strategy[5] using split voting behavior, and around 7% for majority voting behavior (except for Mean Desirability strategies). While a 4% increase in occupant satisfaction may not be a significant difference, including task actions with basic actions is a low-cost way to allow occupants to choose their own way of improving their comfort in a thermal conflict. However, real occupants' acceptance and comfort implications regarding task actions need to be investigated to establish a more applicable effort score and adjust the acceptability score's priorities accordingly.

The results for VQ1 – VQ5 have already confirmed that TREATI can lead to high occupant satisfaction (> 80%) in individual non-contiguous conflicts. **VQ6** was conducted to ascertain whether a closed-loop scenario, where the output of an action is used as input to the next cycle, can still result in high occupant satisfaction. Section 5.1.5 suggests that after a few cycles, TREATI's actions stabilize as the only chosen solution strategy is the task action strategy. As soon as either the majority of occupants are satisfied or the occupants' votes continuously lead to a split conflict and no change in air temperature can satisfy the majority of occupants, the only reasonable control option is to propose task actions to all unsatisfied occupants. Nonetheless, this finding needs to be confirmed in a human subject experiment, as human subjectivity and their acceptance of task actions may have a significant influence on these results.

Baseline Analysis.
Contrary to expectations and findings from other studies [KSB18; Che+19; BP09; DB98], the PMV and Static strategies have a relatively high average regarding occupant satisfaction across the full dataset ($\overline{x}_{PMV} = 69.29\%$ and $\overline{x}_{Static} = 65.54\%$). When examining the dataset by voting behavior, one result is that split voting conflicts which include *no change* votes ($n_{SV1} = 469$), lead to an average of 91.1% occupant satisfaction. This is unexpected at first glance since split voting behavior and no change in air temperature would indicate that 50% of the occupants are dissatisfied. However, because votes across the three thermal comfort scales are generated with some degree of randomness, one comfort scale may represent split voting behavior but 100% of identical votes for another. Observing this type of split voting behavior conflicts – in view of the Static strategy – indicates that conflicts with inconsistent votes across different scales are addressed and relativized by using the thermal desirability scale, as occupant satisfaction is evaluated through the thermal desirability votes.

[5] There were no Mean Preference Composite actions, as they were generally not applied to many conflicts, accounting for a total of only 0.76% of all conflicts.

Scale Comparison.
Thermal sensation, thermal preference, and thermal desirability are scales that measure occupant satisfaction. The system actions that rely on scales (Mean Sensation Setpoint, Mean Preference Setpoint, Mean Desirability Setpoint, and the respective composite actions) use occupant votes as a determinant to compute a temperature setpoint. Overall, the Mean Desirability basic and Mean Desirability Composite actions were chosen more frequently (21.4%) than Mean Thermal Sensation (15.4%) and Mean Thermal Preference (8.4%), although Mean Sensation Composite (6.7%) was chosen more often than Mean Desirability Composite (1.2%). If a conflict is comprised of the majority of votes towards either end of the respective scale, the amplitude is larger for thermal sensation than for thermal desirability. While this discrepancy was by design to determine whether TREATI can support multiple scales and thus different types of feedback, it is interesting that the distributions tend more towards thermal desirability than thermal sensation. As mentioned, in the real world, it is unlikely that all three types of scales are used collectively. The results do show that if the thermal desirability scale is applied, the probability is slightly higher that TREATI has higher acceptability than thermal sensation and thermal preference. The Mean Desirability Setpoint actions also maintain a higher minimum value for occupant satisfaction than the other strategies (see Table 5.2).

5.2.2 Threats to Validity

To achieve an empirical validation that targets the aforementioned goals and yields generalizable results, it would be necessary to conduct numerous long-term human subject experiments to test different configurations during all seasons. In such studies, the outcome depends on the environmental setup and available building controls, leading to threats to external and conclusion validity. A human subject experiment presents anecdotal evidence but is not generalizable and does not describe the complexity of real environmental changes. Human involvement introduces inevitable bias and, thereby, threats to the internal validity of such studies. Study participants are exposed to constantly changing environmental conditions, which may affect their health, overall satisfaction, and productivity, leading to ethical controversies. The selection of participants merely yields evidence that applies to very narrow application domains. Environmental parameters, like the weather or geographical location, have a big influence on the results, which introduces significant threats to external validity.

In addition, during the SARS-CoV-2 pandemic, the feasibility of studies involving more than one human participant for a longer time period has been restricted in many countries, including Germany[6], rendering an experiment with multiple participants in a shared space impossible.

A computer simulation addresses these issues: Different configurations and parameters were investigated without human health risks, human bias, or other constraints of the real world. The following summarizes the threats to validity of this validation according to the classification presented by Runeson et al. [RHRR12].

Construct Validity

The simulation model is not entirely realistic, but rather an abstract approximation of the real world. Its aspects are based on research and observations from different sources and different contexts. Consequently, the findings can only be regarded as a first confirmation of the hypotheses, but not as universally valid evidence.

While the simulation model was validated in Section 4.2.7, there are aspects that could not be modeled to perfectly imitate reality, such as the cause-effect relationship between outdoor air temperature and indoor air temperature, and their effect on energy efficiency. Since outdoor and indoor air temperatures were modeled as input parameters to the existing conditions model and hence change for every scenario, this relationship does not reflect the real environment. Energy efficiency, as mentioned in Section 4.2.5, expresses an estimated change in energy after applying the respective strategy and not the actual space's energy consumption. Energy consumption depends on the respective building's envelope, which depends on each individual building and thus varies substantially. The validation's intent was not to recreate a perfect model of a real-world building, its envelope, and exact control options but rather to avoid geographical and resource limitations to investigate relationships among metrics and their potential impact on decisions. Consequently, the resulting energy efficiency values need to be re-evaluated on an individual building's basis.

Similarly, occupant satisfaction, fairness, and effort also need to be further analyzed. In the simulation, the prior vote of the thermal desirability scale and the occupant's general temperature preference estimate the resulting action's occupant satisfaction. This might not be the case for real occupants: Occupant voting behavior can be inconsistent with the respective scale's intent [HH07], which is not addressed in the simulation model. The simulation model uses all three thermal comfort scales - which is improbable in a realistic setting. It shows, however, that – based on the

[6]Bayerisches Staatsministerium für Gesundheit und Pflege, *Bayerische Verordnung über Infektionsschutzmaßnahmen anlässlich der Corona-Pandemie (Bayerische Infektionsschutzmaßnahmenverordnung – BayIfSMV)*, BayMBl. 2020 Nr. 158 – BayMBl. 2022 Nr. 816. Valid from March 27, 2020, until April 2, 2022.

assumption that the three scales provide different degrees of control – thermal desirability does offer more fine-grained control options than thermal preference. As stated in Section 4.2.5, occupant satisfaction is modeled based on the assumptions that the thermal desirability scale is calibrated 1:1 to a change in air temperature and that the occupant's general temperature preference remains consistent. In reality, there may be differences in real-world situations and inconsistencies regarding the general temperature preferences. Occupant satisfaction may be considered too high, therefore the results may not be conclusive. However, since the same mathematical model is used throughout VQ1 – VQ6, which relativizes the results, the exact values are not relevant – the results still show, that TREATI performs better than the baselines.

If two or more strategies yield the same and the highest acceptability score, a strategy is selected on a first-come-first-serve approach – with the exception of the Task Action or Static control, which are preferred in this case. This influences the overall distribution of actions (Figure 5.1). There may be an impact on real occupants' acceptance of a control decision, requiring occupant effort to carry out a task action. It, therefore, poses a threat to the overall construct validity and needs further research.

Internal Validity

By not considering other temperature control variables see Table 4.6, the results cannot guarantee that they do lead to the same outcomes if more parameters are considered. The choice of sample size for the input parameters (Table 4.4) is restricted to five with a few options each, leading to a total of 360 scenarios. While the variables and parameter definitions are based on common knowledge, literature, and an expert's knowledge, they reflect limited points of view, which introduces instrumentation bias. However, the findings do show that TREATI can achieve significant improvements compared to the applied baselines – using only these general and easy-to-measure parameters that were added (in addition to the PMV's required parameters). This indicates that these parameters may also be sufficient for real-world situations; further investigation into the influence and possible relationships among additional parameters, such as skin temperature [Cho10] or human body shape [Fra+19], in TREATI is still necessary to further support this assumption.

As personas with synthetic attributes were used as proxies for real occupants, other potential threats to internal validity are diminished, e.g., experiential mortality (no loss of subjects) or selection-maturation interaction caused by differing groups and interaction with them. It can, however, be argued that selection bias is introduced through the selection of attributes for the personas – such as their general temperature preference or persona characteristics. These attributes only contribute to the generation of occupant votes for random voting behavior conflicts – where the intent was not necessarily to reproduce real occupants but rather test the limits of the system towards different non-deterministic voting distributions. Therefore, this threat needs to be examined in more detail with regard to real occupants and their voting behavior in real-world situations.

External Validity

There are several shortcomings of the simulation model which limit the generalizability of the results. First, the simulation model assumes a moderately continental climate; other climatic zones were not considered. Second, the simulation time is modeled as time-independent to reduce additional influential factors such as time zones or shift work. Non-working hours, such as night, breaks, or location changes, are not considered. Third, causal dress attire was assumed but depending on the space's context, the dress code might differ. This aspect influences the task actions' outcome, whether a clothing task action can be suggested or not. Even though these shortcomings hint at low generalizability, they do not impose major constraints on the results, as their influence has been kept low. A further investigation of the influence of these factors is still necessary to improve the generalizability of the simulation's results.

The most important threat to external validity is that synthetic personas cannot replace real human occupants and their habits. Their acceptance of an action – in particular one that includes tasks – needs to be assessed, which a simulation is unable to accomplish. The system may be able to replicate approximately the results from the simulation in a real-world situation, but if occupants do not accept and trust the system, the system's validity cannot be achieved. Therefore, further analysis of occupant interaction needs to be conducted.

Chapter 6

Conclusion

> The end, then, being what we wish for, the means what we deliberate about and choose, actions concerning means must be according to choice and voluntary.
>
> Aristotle,
> *Nicomachean Ethics: III*

Building control systems often fail to achieve occupant comfort and satisfaction due to variations in occupant clothing and preferences, which are compounded by variations in building enclosure and mechanical system design [PN18]. Yet optimal thermal comfort ensures high levels of satisfaction to maintain productivity, motivation, and health among occupants [Fis02]. Moreover, thermal preferences are often conflicting among occupants in shared spaces and reaching a consensus is difficult or is not supported by existing control systems.

TREATI applies decision management methodologies to address conflicts in thermal comfort control and identify a suitable solution strategy based on a set of context indicators. It utilizes rationale management to capture decisions, proposed alternatives, and their arguments, as outlined in Figure 6.1.

This dissertation's contributions are detailed in Section 6.1. Section 6.2 discussed the limitations and directions for future work. Section 6.3 presents an outlook.

6.1 Contributions

The main contributions of this dissertation include the definition of the TREATI framework, the design of its simulation model, the validation of TREATI, and the quantification of the benefits associated with various strategies for improving thermal satisfaction while maintaining energy efficiency.

These five main contributions are summarized as follows:

1. Identification of the **levels of thermal control typically available for modern offices**, ranging from ambient level to task level, and their respective impact on occupant thermal comfort and energy, with respect to occupant feedback

2. Identification of **scales for thermal comfort evaluation**, using thermal sensation, preference, and desirability, and their respective impact on occupant thermal comfort and energy

3. Identification of **hypotheses and metrics of success for negotiated thermal control**. The identified metrics are occupant satisfaction, energy efficiency, fairness, and effort

4. Development of **TREATI**, an innovative thermal control framework that is based on rational decision-making. TREATI delivers greater thermal comfort in a shared thermal environment with a single global controller – where negotiation is critical for occupant satisfaction, energy efficiency, fairness, and effort – than comparable traditional controls

5. Validation and verification of the **impact and benefits of TREATI** against standard controls with Predicted Mean Vote (PMV) and static setpoints

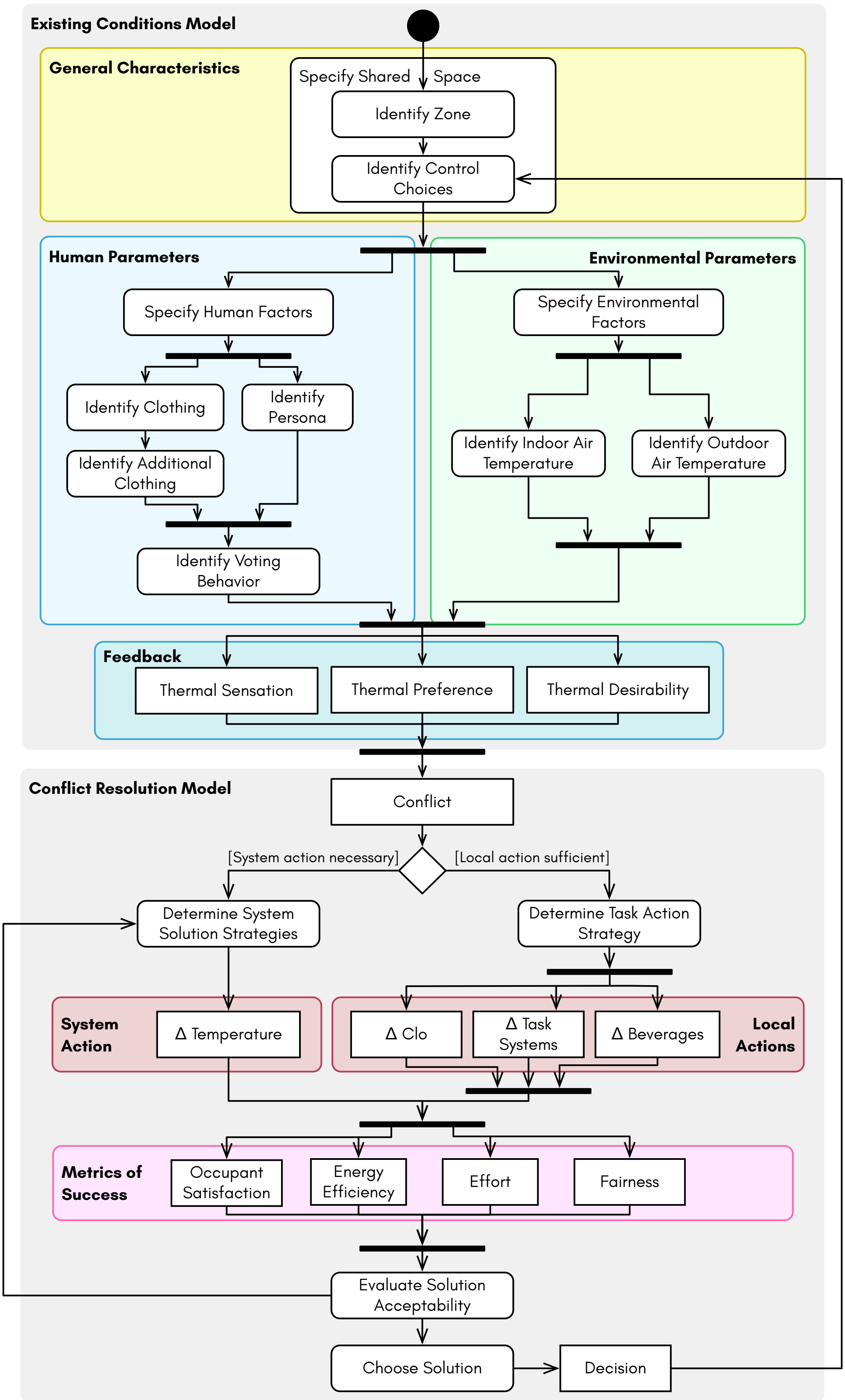


Figure 6.1: **Simulation Process Model** (UML Activity Diagram)

6.1.1 Levels of Thermal Control Typically Available for Modern Offices

Three types of building control actions can be considered for delivering thermal comfort in buildings with a variable climate and occupant loads (see Figure 6.2):

1. **Automated Actions** incorporate generic PMV (Predicted Mean Votes) and Static controls

2. **Interactive Actions** incorporate occupant feedback (through thermal sensation, preference, or desirability votes) into dynamic thermostatic changes for ambient conditioning

3. **Task Actions** incorporate occupant task actions, including clothing changes, task conditioning systems, or consumption of hot or cold beverages

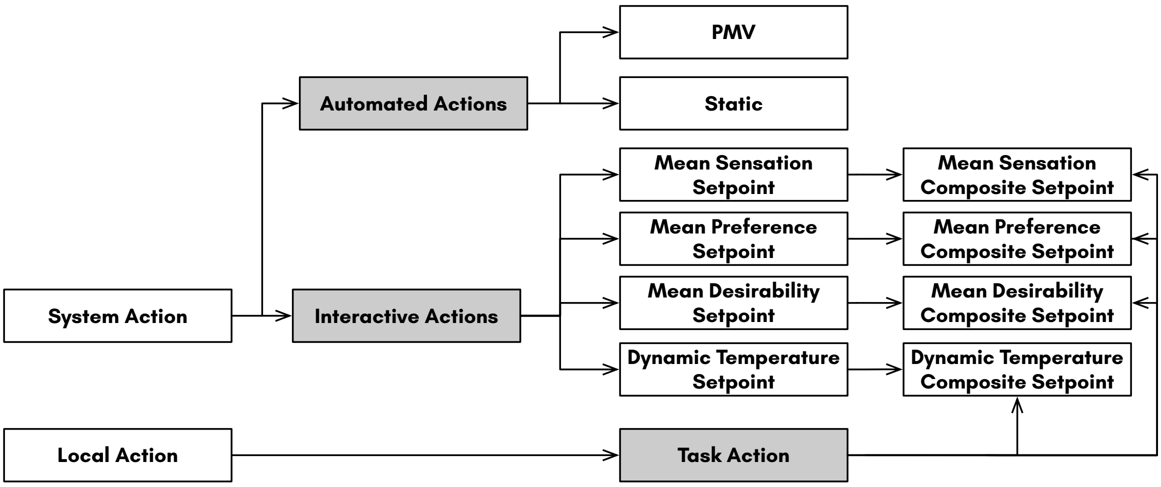


Figure 6.2: **TREATI's Action Types**

When evaluating a thermal conflict, TREATI combines these three action types to determine the most acceptable control action or set of actions. A control decision evaluation process was designed based on findings from knowledge and decision management research with transparency as the primary requirement (Figure 3.10).

6.1.2 Scales of Thermal Comfort Evaluation

TREATI is based on the assumption that human factors, particularly occupant feedback, must drive temperature control decisions for achieving thermal comfort. This dissertation evaluates the common thermal comfort scales, namely thermal satisfaction, sensation, and preference, and introduces and evaluates the new thermal desirability scale. These scales rely on occupant interaction to determine thermal discomfort, identify thermal conflicts, and support the negotiation of a suitable control decision. Instead of using thermal satisfaction as an interactive scale, occupant satisfaction regarding thermal conditions in a space is measured through thermal sensation, preference, and desirability.

Thermal sensation indicates an occupant's perception of temperature but gives no direct request for control, while thermal preference indicates whether an increase or decrease of the temperature is actually being requested. Thermal desirability is a 5-point scale that targets control and is more fine-grained than thermal preference.

This dissertation successfully demonstrated that the 5-point thermal desirability scale is a better control determinant and occupant satisfaction measure than thermal sensation or thermal preference.

6.1.3 Hypotheses & Metrics of Success for Negotiated Thermal Control

This dissertation advances two hypotheses and develops critical metrics of success:

> **Hypothesis 1 – Rationale Management Solves Thermal Conflicts**
> A computational rationale management approach that supports collective decision-making techniques will resolve thermal conflicts in shared spaces with higher levels of thermal satisfaction and higher levels of energy savings compared to conventional thermal control.

> **Hypothesis 2 – Rationale Management Ensures Occupant Involvement**
> Engaging the individual occupant in thermal control decision-making processes and continuously integrating the individual occupant's thermal preferences provides a higher level of thermal satisfaction through all seasons and spatial changes.

The metrics for measuring success are crucial for advancing the design of building control systems, most importantly: occupant satisfaction, energy efficiency, fairness, and effort. They have been quantified for measuring the impact of control decisions, as illustrated in Figure 6.3.

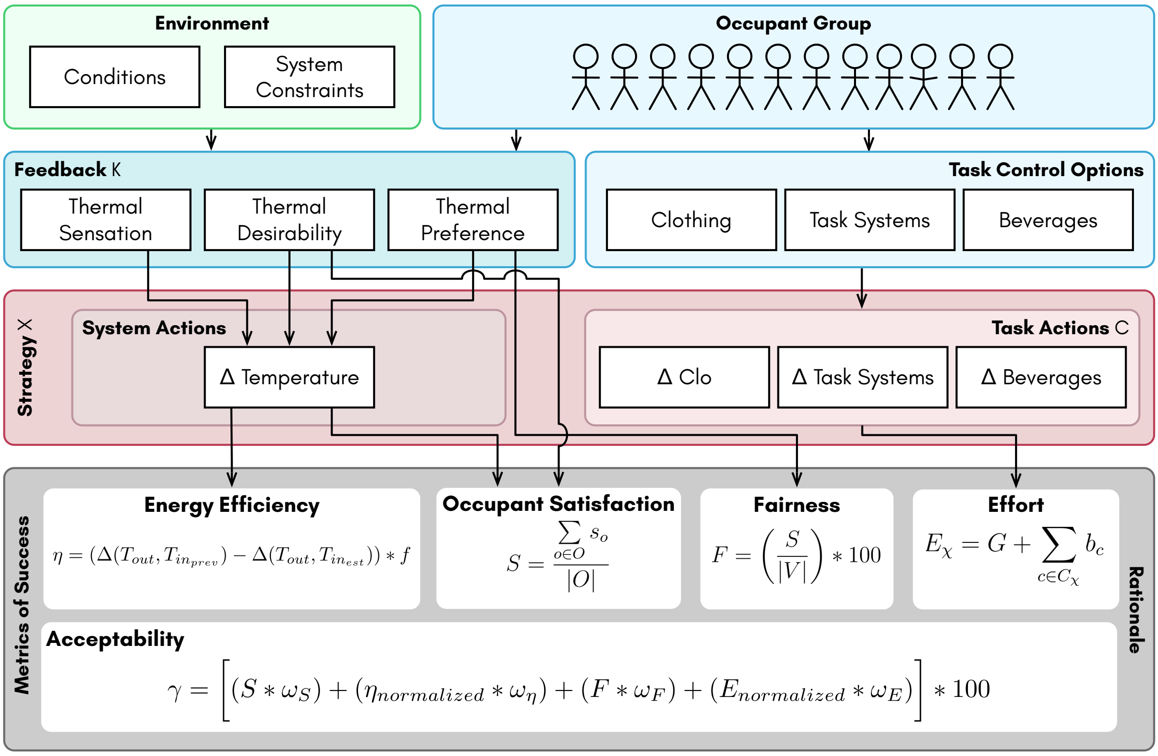


Figure 6.3: **Input Parameters, Actions, and Metrics of Success for Negotiated Thermal Control**

6.1.4 TREATI – Thermal Control Decision-Making using Rationale Management

The main objective of this dissertation was the development of a robust human-in-the-loop thermal control framework that supports negotiated control in shared office environments. The TREATI framework borrows from rationale management to describe the resolution of thermal conflicts. These conflicts are conceptualized in the TREATI metamodel (see Figure 3.1) and extended with concepts related to indoor environmental quality (see Figure 3.2).

Six packages have been identified: Environment, Building Management, Occupant, Event, Context, and Rationale. Each package represents a critical concept that needs to be considered when attempting to resolve thermal conflicts.

Object-event simulations were used to imitate thermal conflicts, environmental factors, and human factors. The simulations verify and validate TREATI with respect to hypotheses H1 and H2. The simulations test the impact of TREATI on the metrics of success and evaluate the conflict resolution boundaries, with particular emphasis on non-trivial conflicts, such as split or majority vote conflicts.

6.1.5 Impact & Benefits of TREATI

10 849 iterative simulation runs explored the four metrics of success against multiple outdoor temperature conditions reflecting the seasons, five possible indoor ambient temperature settings, a diverse set of occupant personas, diversified voting behavior, and the full suite of task actions, see Table 6.1.

<table>
<tr><th>Outdoor Air Temperature</th><th>Indoor Air Temperature</th><th>Task Action Choices</th><th>Persona Types</th><th>Voting Behavior</th></tr>
<tr><td rowspan="2">1 °C
11 °C
21 °C
31 °C</td><td rowspan="2">19 °C
21 °C
23 °C
25 °C
27 °C</td><td rowspan="2">No Actions
All Actions:
Clothing Change
Hot/Cold Beverage
Task Fan or Heater</td><td>Cooler
Neutral
Warmer
Combination</td><td>Randomized
Split</td></tr>
<tr><td>Cohort Split</td><td>Majority</td></tr>
</table>

360 *permutations*

Table 6.1: **Simulation Input Parameters**

For thermal comfort in hypothesis H1, the results were conclusive: TREATI leads to higher occupant satisfaction and fairness than PMV and Static controls, with nominal energy cost, as shown in Table 6.2.

Controls		$\overline{x}$	$med(x)$	SD	Var	Min	Max
Occupant	TREATI	89.26	89	8.52	72.62	46	100
Satisfaction	PMV	69.29	73	15.9	252.82	0	100
[0 to 100]	Static	65.54	62	13.08	171.0	40	100
Energy	TREATI	-0.69	0	8.64	74.61	-20	30
Efficiency	PMV	1.72	0	7.51	56.41	-10	30
[-30 to +30]	Static	0.0	0	0.0	0.0	0	0
Fairness	TREATI	79.06	87	17.9	320.34	0	100
[0 to 100]	PMV	36.64	32	34.62	1198.27	0	92
	Static	15.54	0	23.75	563.98	0	92

$\overline{x}$ *indicates the mean,* $med(x)$ *indicates the median* *units in* [%], $n = 10849$

Table 6.2: **TREATI outperforms the Baselines** (PMV and Static controls) regarding occupant satisfaction and fairness

TREATI achieves at least 20% more occupant satisfaction and is 42% fairer than the alternative controls. In 75% of all conflicts, TREATI results in more than 85% occupant satisfaction, above present goals and standards. In addition, TREATI has significantly lower variability in satisfaction as revealed in Figure 6.4.

TREATI consistently outperforms the baselines PMV and Static control in terms of occupant satisfaction across all filters, regardless of voting types (random, split,

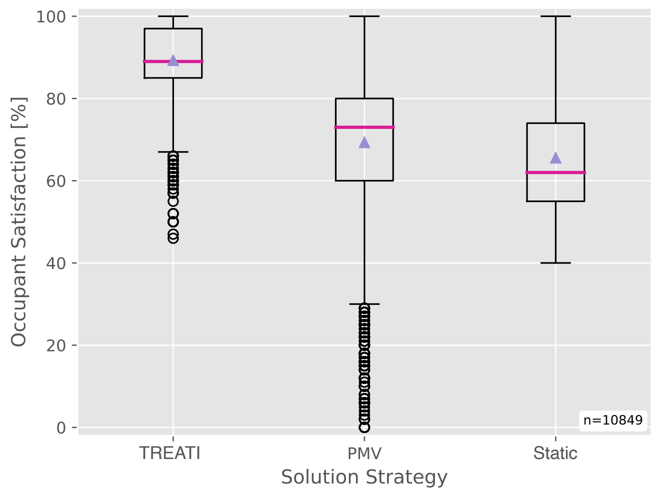


Figure 6.4: **Overall Occupant Satisfaction** comparing TREATI versus the baselines

majority) and persona types (cooler, neutral, warmer, combination). Additionally, there were no significant differences observed in energy demands, which did not align with the hypothesis of energy savings. In addition, there were no significant differences observed in energy demands, which did not align with the assumptions of energy savings in Hypothesis 1.

Hypothesis 2 was addressed by comparing voting participation rates and conducting three closed-loop scenarios to determine if continuous occupant involvement can consistently achieve > 80% occupant satisfaction over time. This hypothesis was not confirmed as there was little variation in occupant satisfaction with increases in voting participation rates. However, the higher the voting participation rate, the more stable the control actions. The closed-loop scenarios show that TREATI can achieve consistent occupant satisfaction of > 80% after three to five iterative feedback loops.

The simulation has revealed that task actions are critical to TREATI. They were the most frequently selected type of action for resolving thermal conflicts, accounting for 32.4% of the 10 849 simulation scenarios. In total, actions that involving task actions addressed 45% of all thermal conflicts.

This dissertation's results establish the benefits of the thermal desirability scale over other scales used to measure thermal satisfaction. Thermal desirability was used to estimate overall occupant satisfaction over thermal preference and thermal sensation, as it allows for a more reliable and fine-grained understanding of control requests. TREATI has a higher acceptability rate with thermal desirability votes than with thermal sensation and thermal preference votes. Few conflicts were addressed using Mean Sensation Setpoint (8.7%) and Mean Preference Setpoint (7.6%) actions, whereas Mean Desirability Setpoint actions were the second most frequently applied actions (20.1%).

6.2 Limitations & Directions for Future Work

Five limitations of the TREATI research effort form the basis of future research:

- The need for field testing using human subject experiments
- The exploration of seasonal energy benefits of TREATI and humans in the loop
- Expansion of the fairness metric and evaluation of occupant acceptance
- Investigation of the relationship of thermal comfort to other indoor environmental variables such as air quality
- Evaluation of controls in building facades (shading, operable windows, air tightness) and selection of mechanical system types (micro-zoning, integrated task conditioning) to thermal satisfaction and energy savings

While TREATI can be applied in human subject experiments, the validation in this dissertation was based on simulations due to empty workplaces and restrictions throughout the SARS-CoV-2 pandemic.

The simulation model was verified against the environment by means of existing data, literature, and expert knowledge. In the future, TREATI should be validated and refined with long-term human subject experiments in a shared space with variations in environment, occupancy schedules and loads, task control options, and personas. Particular attention should be paid to seasonal energy loads, miscellaneous electric loads, and their effect on TREATI.

Fairness is a critical aspect of thermal control due to the prevalence of traditional office layouts and hierarchies. If the fairness score only considers a limited amount of occupant feedback, as modeled in the validation, it may result in lower fairness scores for occupants who spend more time at the office. To address this limitation, future research could expand the fairness score to consider the occupant's context, in particular, their office presence. Occupant acceptance also needs to be further analyzed, in particular, whether decisions lead to additional conflicts and which decisions lead to less acceptance over time to identify new areas for improvement.

TREATI's primary focus is on advancements in thermal comfort and energy savings. However, it could be expanded to other IEQ indicators, most notably indoor air quality. While thermostats traditionally only measure and modulate in response to temperature, mechanical systems carry the responsibility of delivering both thermal comfort and air quality. By incorporating human-in-the-loop controls, such as TREATI, there is a significant potential for improving both environmental outcomes.

6.3 Outlook

As TREATI introduces human-in-the-loop control with task and ambient control actions, the actual thermostatic control and task control choices are limited. Future research could explore a more comprehensive suite of task control systems, including shading devices and operable windows, along with innovative mechanical systems that integrate task controls or deploy micro-zoning to replace larger thermal zones with individual thermal control zones – either water or air-based.

The potential of future research does not diminish the scale of the impact of a TREATI control system that fully engages humans in both ambient thermal conditions and task thermal conditions. TREATI has successfully demonstrated that human-in-the-loop and iterative decision-making can enable negotiated setpoints for larger mechanical zones and task control actions. This approach achieves over 85% thermal satisfaction without any additional energy costs, replacing the broad-brush, unfair, and unsatisfactory approach to thermal control in existing buildings.

Glossary

Acoustic Quality Measures the surrounding sound situation on auditory events

Air Quality Measures how clean or polluted the air is in a space

Closed-Loop A concept or system that relies on the interaction with humans and even prioritizes them

Cohort Comfort Comfort of a subset of a group of occupants sharing a space who experience the same level of comfort

Control Choice A specific control option applied by a strategy

Control Option A means of control to influence the comfort of an individual or cohort

Decision The solution strategy with the highest acceptability

Energy Efficiency Measure that indicates the use of less energy to perform a task
Def. in Simulation: Difference between the current state compared to a proposed new state

Group Comfort Accumulated comfort of a number of occupants sharing a space

Human-in-the-loop (HITL) A concept or system that relies on the interaction with humans and even prioritizes them

IEQ The Indoor Environmental Quality (IEQ) refers to the quality of a building's environment in relation to the health and wellbeing of its occupants

Local Action or **task action**; describes a change that affects the environmental conditions for a single occupant's task space

Persona A fictitious representation used in place of a real occupant

Setpoint or **temperature setpoint**; a specific point on the thermostat at which it has been set

Shared Space A zone shared by multiple occupants

Simulation Imitation of environmental and human factors that generate and address thermal conflicts

Analogue: human-in-the-loop simulation that models humans and human input parameters

Simulation Model Logical and mathematical model for the simulation, consists of the existing conditions and the conflict-resolution model

Strategy or **solution strategy**; a Local Action, system action, or a combination of both, with specific characteristics that can be applied to resolve an issue

System Action or **global action**; describes a change that affects the environmental conditions in a zone

Thermal Comfort Describes the satisfaction with the thermal environment. The term thermal comfort is used as the overall umbrella term to describe an individual's or cohort's overall perception towards the prevailing thermal conditions

Thermal Comfort Conflict or **Thermal Conflict**; is a disagreement among at least two occupants or an occupant and the environment regarding the prevailing thermal conditions

Thermal Desirability Measure for thermal comfort that indicates the occupant's desire for a change in temperature on a 5-point scale

Thermal Preference Measure for thermal comfort that indicates the occupant's preference towards a temperature change on a 3-point scale

Thermal Sensation Measure for thermal comfort that indicates the occupant's feeling regarding the thermal environment on a 7-point scale

Thermal Voting Scale Measure for thermal comfort relying on occupant interaction

Visual Quality Measures the illuminance and glare levels of a workstation depending on the respective occupant's task

Zone or **thermal zone**; area in an enclosed space that is controlled by a single thermostat

Nomenclature

α	Regression coefficient
C	Set of task actions
c	Single task action that targets an individual occupant
χ	Solution strategy
E	Effort score [%]
env	Environment
env_v	The environment's energy conserving vote $env_{tc} \in k_{tc}$
η	Change in energy efficiency compared to the prior state [%]
F	Accumulated fairness score of a solution strategy [%]
f	Seasonal factor [%], determines the energy penalty, dependent on the state (heating or cooling)
G	System action's effort score [%]
γ	Solution acceptability [%]
I_{clu}	Overall clothing insulation [clo]
I_{item}	Clothing insulation of a specific item [clo]
K	Set of thermal comfort scales
k_{tc}	Thermal comfort scale, $k \in K$ and $tc \in ts$, tp, td
O	Set of occupants
o	Individual occupant

ct_o Air temperature at which an occupant o is estimated to be comfortable

ω Prioritization weights [%]

s_o Individual occupant's satisfaction

S Overall occupant satisfaction [%]

$s_{o,h}$ Individual occupant's historic occupant satisfaction [%]

T_c Resulting change of the indoor air temperature to reach an occupant's comfort temperature [°C]

tc Thermal comfort scale, $tc \in \{ts, tp, td\}$

td Thermal desirability, $K_{td} = \{-2, -1,\ 0,\ 1,\ 2\}$

T_{in} Indoor air temperature [°C]

$max(T_{in})$ Upper indoor temperature bound in the respective context [°C]

$min(T_{in})$ Lower indoor temperature bound in the respective context [°C]

T_{op} Operative temperature [°C]

T_{out} Outdoor air temperature [°C]

tp Thermal preference, $K_{tp} = \{-1,\ 0,\ 1\}$

ts Thermal sensation $K_{ts} = \{-3, -2, -1,\ 0,\ 1,\ 2,\ 3\}$

V Set of all occupant votes

v Individual vote

ξ A persona's generally preferred thermal setting, $\xi \in$ '*cooler*', '*neutral*', '*warmer*'

Appendices

Appendix A
Model Validation Scenarios

A.1 Fairness Validation

To validate the output of the fairness metric, a non-trivial scenario was defined including the expected fairness for each solution strategy. The results were then compared to the expected fairness score. The demo scenario assumes the following conditions:

1. Indoor air temperature: 21 °C
2. Outdoor air temperature: 1 °C
3. Environmental vote: *cooler*
4. Thermal preference votes: 3x *warmer* (-1), 9 x *cooler* (+1)

Table A.1 shows the results: each solution's proposed temperature change, the percentage of satisfied occupants after the change, and the fairness score. Only one is displayed since the expected and actual fairness scores are identical. For task actions, the score before applying task actions and after deviates, thus, both scores are shown.

Solution Strategy	Temperature Change	Satisfied Occupants	Fairness
Static	0 °C	0%	0%
Task Action	0 °C	92%	0% | 90%
PMV	0 °C	0%	0%
Dynamic Temperature	-2 °C	77%	71%
Mean Sensation	-1 °C	77%	71%
Mean Preference	-1 °C	77%	71%
Mean Desirability	-1 °C	77%	71%
Dynamic Temperature Composite	-2 °C	77%	71%
Mean Sensation Composite	-1 °C	77%	71%
Mean Preference Composite	-1 °C	77%	71%
Mean Desirability Composite	-1 °C	77%	71%

Table A.1: **Fairness Model Validation Results** for a demo scenario

A.2 Occupant Satisfaction Validation

Different permutations of thermal desirability votes, temperature changes, and personas were tested to validate that each solution strategy yields the expected occupant satisfaction. The resulting occupant satisfaction was compared against each occupant's expected satisfaction.

To cover all scenarios, all types of thermal desirability votes ([-2, -1, 0, 1, 2]) and available temperature changes ([-3, -2, -1, 0, 1, 2, 3]) were permuted. For instance, a -2 vote and a $-2\,°C$ change in air temperature is expected to yield a satisfaction of 0%. Vice versa, a -2 vote and a $+2\,°C$ change in air temperature are assumed to satisfy the occupant (100%).

Three kinds of personas' generally preferred thermal settings provide for a more fine-grained estimation of occupant satisfaction. The settings used are: cool (occupants who prefer cooler temperatures, $\xi = 0.5$), warm (occupants who prefer warmer temperatures, $\xi = 1.5$), and neutral (occupants who have neither preference, $\xi = 1$). An occupant ($v_t d = -1$) who generally prefers a cooler environment ($\xi = 0.5$) is more likely to be unsatisfied with an air temperature change of $+3\,°C$ than an occupant who prefers a warmer environment. Table A.2 presents the tested values and the validated resulting occupant satisfaction.

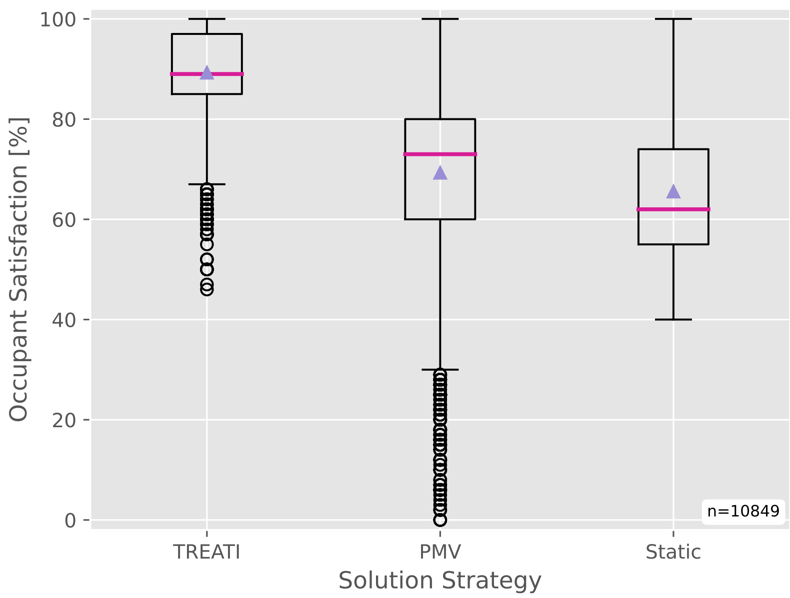
ξ	td_o	T_c	Δ	S	ξ	td_o	T_c	Δ	S	ξ	td_o	T_c	Δ	S
0.5	-2.0	-3.0	-5.0	0.0	1.5	0.0	-1.0	-1.0	75.0	1.5	1.0	1.0	2.0	40.0
1.0	-2.0	-3.0	-5.0	0.0	1.5	1.0	-2.0	-1.0	75.0	0.5	2.0	1.0	3.0	25.0
1.5	-2.0	-3.0	-5.0	0.0	0.5	-2.0	2.0	0.0	100.0	1.0	2.0	1.0	3.0	25.0
0.5	-2.0	-2.0	-4.0	0.0	0.5	2.0	-2.0	0.0	100.0	1.5	2.0	1.0	3.0	10.0
1.0	-2.0	-2.0	-4.0	0.0	1.0	-2.0	2.0	0.0	100.0	0.5	0.0	3.0	3.0	25.0
1.5	-2.0	-2.0	-4.0	0.0	1.0	2.0	-2.0	0.0	100.0	0.5	1.0	2.0	3.0	25.0
0.5	-1.0	-3.0	-4.0	0.0	1.5	-2.0	2.0	0.0	100.0	1.0	0.0	3.0	3.0	25.0
1.0	-1.0	-3.0	-4.0	0.0	1.5	2.0	-2.0	0.0	100.0	1.0	1.0	2.0	3.0	25.0
1.5	-1.0	-3.0	-4.0	0.0	0.5	-1.0	1.0	0.0	100.0	1.5	0.0	3.0	3.0	10.0
0.5	-2.0	-1.0	-3.0	10.0	0.5	0.0	0.0	0.0	100.0	1.5	1.0	2.0	3.0	10.0
1.0	-2.0	-1.0	-3.0	25.0	0.5	1.0	-1.0	0.0	100.0	0.5	2.0	2.0	4.0	0.0
1.5	-2.0	-1.0	-3.0	25.0	1.0	-1.0	1.0	0.0	100.0	1.0	2.0	2.0	4.0	0.0
0.5	-1.0	-2.0	-3.0	10.0	1.0	0.0	0.0	0.0	100.0	1.5	2.0	2.0	4.0	0.0
0.5	0.0	-3.0	-3.0	10.0	1.0	1.0	-1.0	0.0	100.0	0.5	1.0	3.0	4.0	0.0
1.0	-1.0	-2.0	-3.0	25.0	1.5	-1.0	1.0	0.0	100.0	1.0	1.0	3.0	4.0	0.0
1.0	0.0	-3.0	-3.0	25.0	1.5	0.0	0.0	0.0	100.0	1.5	1.0	3.0	4.0	0.0
1.5	-1.0	-2.0	-3.0	25.0	1.5	1.0	-1.0	0.0	100.0	0.5	2.0	3.0	5.0	0.0
1.5	0.0	-3.0	-3.0	25.0	0.5	-2.0	3.0	1.0	75.0	1.0	2.0	3.0	5.0	0.0
0.5	-2.0	0.0	-2.0	40.0	0.5	2.0	-1.0	1.0	75.0	1.5	2.0	3.0	5.0	0.0
1.0	-2.0	0.0	-2.0	50.0	1.0	-2.0	3.0	1.0	75.0					
1.5	-2.0	0.0	-2.0	50.0	1.0	2.0	-1.0	1.0	75.0					
0.5	-1.0	-1.0	-2.0	40.0	1.5	-2.0	3.0	1.0	80.0					
0.5	0.0	-2.0	-2.0	40.0	1.5	2.0	-1.0	1.0	80.0					
0.5	1.0	-3.0	-2.0	60.0	0.5	-1.0	2.0	1.0	75.0					
1.0	-1.0	-1.0	-2.0	50.0	0.5	0.0	1.0	1.0	75.0					
1.0	0.0	-2.0	-2.0	50.0	0.5	1.0	0.0	1.0	75.0					
1.0	1.0	-3.0	-2.0	50.0	1.0	-1.0	2.0	1.0	75.0					
1.5	-1.0	-1.0	-2.0	50.0	1.0	0.0	1.0	1.0	75.0					
1.5	0.0	-2.0	-2.0	50.0	1.0	1.0	0.0	1.0	75.0					
1.5	1.0	-3.0	-2.0	50.0	1.5	-1.0	2.0	1.0	80.0					
0.5	-2.0	1.0	-1.0	80.0	1.5	0.0	1.0	1.0	70.0					
0.5	2.0	-3.0	-1.0	80.0	1.5	1.0	0.0	1.0	70.0					
1.0	-2.0	1.0	-1.0	75.0	0.5	2.0	0.0	2.0	50.0					
1.0	2.0	-3.0	-1.0	75.0	1.0	2.0	0.0	2.0	50.0					
1.5	-2.0	1.0	-1.0	75.0	1.5	2.0	0.0	2.0	40.0					
1.5	2.0	-3.0	-1.0	75.0	0.5	-1.0	3.0	2.0	50.0					
0.5	-1.0	0.0	-1.0	70.0	0.5	0.0	2.0	2.0	50.0					
0.5	0.0	-1.0	-1.0	70.0	0.5	1.0	1.0	2.0	50.0					
0.5	1.0	-2.0	-1.0	80.0	1.0	-1.0	3.0	2.0	50.0					
1.0	-1.0	0.0	-1.0	75.0	1.0	0.0	2.0	2.0	50.0					
1.0	0.0	-1.0	-1.0	75.0	1.0	1.0	1.0	2.0	50.0					
1.0	1.0	-2.0	-1.0	75.0	1.5	-1.0	3.0	2.0	60.0					
1.5	-1.0	0.0	-1.0	75.0	1.5	0.0	2.0	2.0	40.0					
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮					

Table A.2: **Occupant Satisfaction Validation Results** – Permutation configurations and results

Appendix B

Validation Results

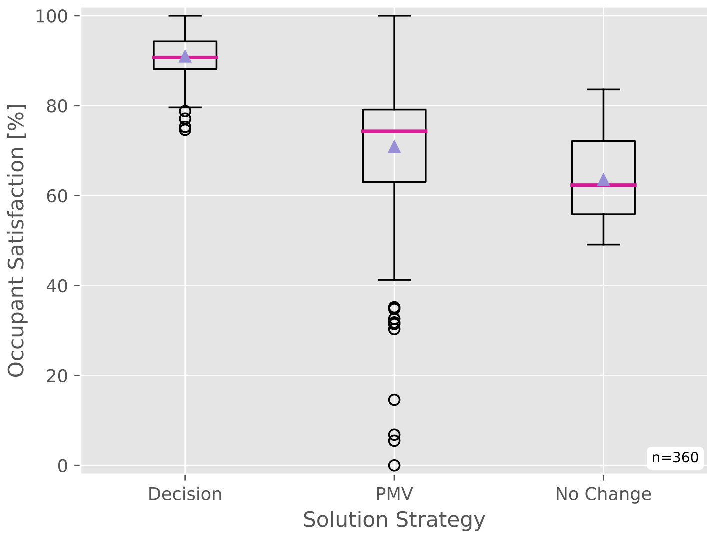
B.1 Descriptive Statistics



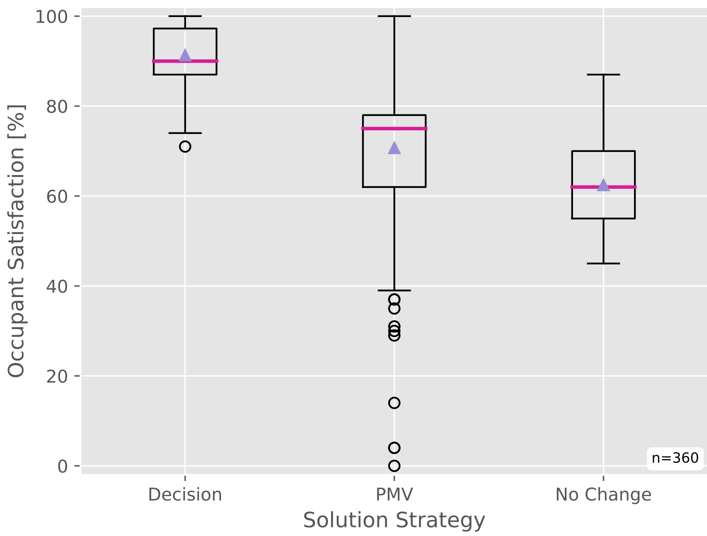
▲ *marks the median.*

Figure B.1: **Occupant Satisfaction Box-and-Whisker Plots** of all scenarios' actions initiated by TREATI ($\overline{x} = 90\%$) compared against the PMV ($\overline{x} = 74\%$) and Static ($\overline{x} = 62\%$) controls

To gain further insights, the individual scenarios were investigated on an averaged individual basis, i.e., using the average outcome per scenario. Each individual scenario's overall mean and median value were used to determine the quartiles for Figure B.2. The results are comparable to the full dataset.



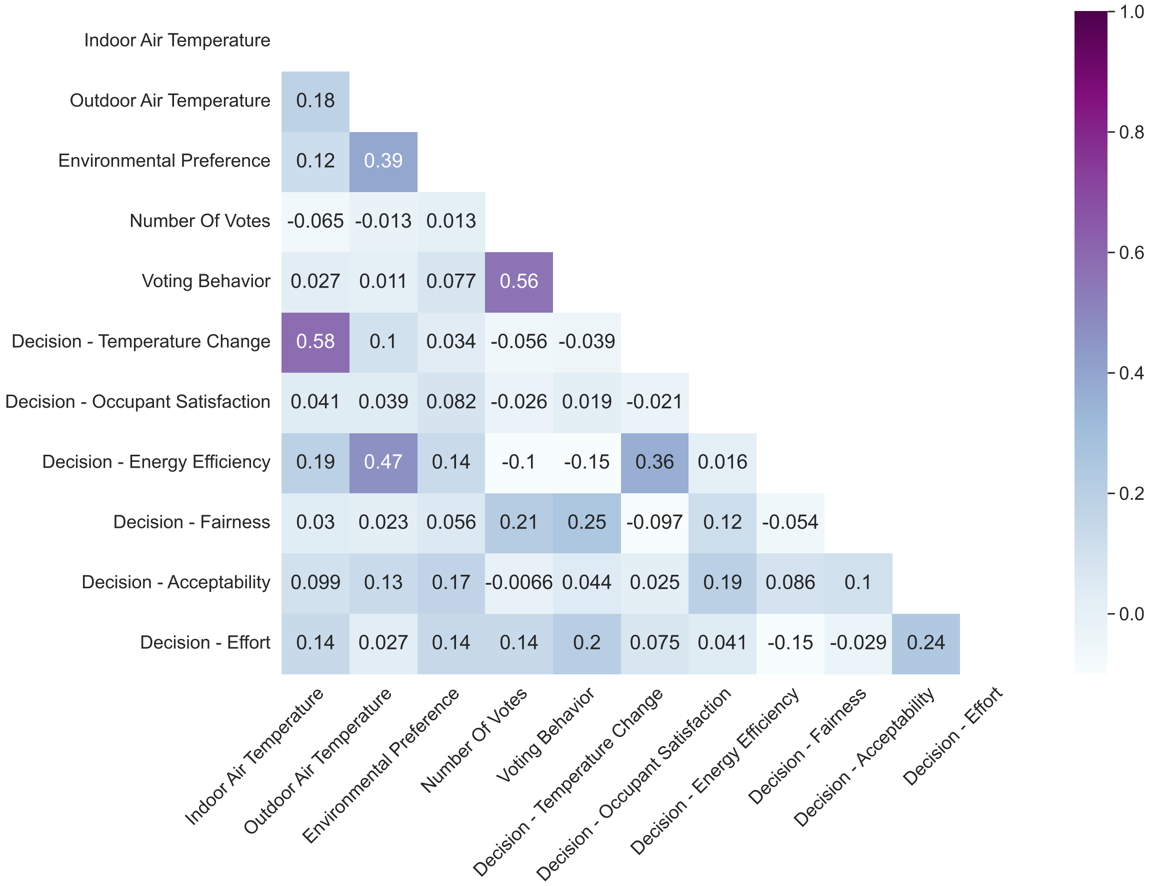
(a) Mean Occupant Satisfaction: TREATI ($\overline{x}$ = 90.9%), PMV ($\overline{x}$ = 70.9%), Static ($\overline{x}$ = 63.5%)



(b) Median Occupant Satisfaction: TREATI ($\overline{x}$ = 90.7%), PMV ($\overline{x}$ = 74.3%), Static ($\overline{x}$ = 62.3%)

▲ *marks the median*, $n = 360$

Figure B.2: **Occupant Satisfaction Box-and-Whisker Plot** using the average outcomes per scenario



$n = 10849$

Figure B.3: **Pearson Correlation Matrix** of all scenarios' actions

B.2 Voting Style

Controls		$\overline{x}$	$med(x)$	SD	Var	Min	Max
Random ($n = 5635$)							
Occupant Satisfaction	TREATI	88.98	90	7.46	55.7	50	100
	PMV	69.27	71	14.34	205.71	0	100
	Static	59.51	58	8.29	68.66	40	100
Energy Efficiency	TREATI	-1.26	0	9.94	98.79	-20	30
	PMV	1.32	0	7.33	53.69	-10	30
	Static	0.0	0	0.0	0.0	0	0
Fairness	TREATI	80.75	84	12.39	153.63	0	100
	PMV	41.9	40	37.98	1442.85	0	92
	Static	3.69	0	9.21	84.81	0	81
Split ($n = 3334$)							
Occupant Satisfaction	TREATI	91.18	90	9.87	97.43	46	100
	PMV	71.78	75	16.66	277.53	0	100
	Static	71.25	73	14.81	219.41	40	100
Energy Efficiency	TREATI	-0.6	0	7.29	53.17	-20	25
	PMV	1.72	0	7.06	49.86	-10	30
	Static	0.0	0	0.0	0.0	0	0
Fairness	TREATI	76.27	90	25.69	659.85	0	100
	PMV	34.3	33	28.94	837.58	0	92
	Static	31.32	32	26.39	696.32	0	92
Majority ($n = 1880$)							
Occupant Satisfaction	TREATI	86.73	85	8.13	66.17	64	100
	PMV	64.93	67	17.89	320.16	2	93
	Static	73.49	70	12.72	161.89	45	93
Energy Efficiency	TREATI	0.84	0	6.07	36.83	-20	20
	PMV	2.9	0	8.62	74.31	-10	30
	Static	0.0	0	0.0	0.0	0	0
Fairness	TREATI	78.9	73	13.98	195.53	58	100
	PMV	25.0	7	29.61	876.71	0	74
	Static	23.11	4	29.08	845.57	0	75

$\overline{x}$ indicates the mean, $med(x)$ indicates the median *units in* [%], $n = 10849$

Table B.1: **Descriptive Statistics for Each Voting Behavior Type**

	Independent T-Test	Baselines PMV	Static
Random ($n = 5635$)	Difference (TREATI - *Baseline*)	19.9239	29.7299
	Degrees of Freedom	11318	11318
	t-value	93.2875	202.7846
	p-value (Two-Sided T-Test)	0.0000	0.0000
	p-value (Difference < 0)	1.0000	1.0000
	p-value (Difference > 0)	0.0000	0.0000
	Cohen's d	1.7536	3.8119
	Hedge's g	1.7535	3.8117
	Glass's delta	2.7395	4.0879
	Pearson's r	0.6593	0.8855
Split ($n = 3334$)	Difference (TREATI - *Baseline*)	21.5390	26.6198
	Degrees of Freedom	9846	9846
	t-value	78.7237	105.1358
	p-value (Two-Sided T-Test)	0.0000	0.0000
	p-value (Difference < 0)	1.0000	1.0000
	p-value (Difference > 0)	0.0000	0.0000
	Cohen's d	1.5866	2.1189
	Hedge's g	1.5865	2.1187
	Glass's delta	2.4789	3.0636
	Pearson's r	0.6215	0.7272
Majority ($n = 1880$)	Difference (TREATI - PMV)	26.8021	13.2957
	Degrees of Freedom	3758	3758
	t-value	46.3760	38.0737
	p-value (Two-Sided T-Test)	0.0000	0.0000
	p-value (Difference < 0)	1.0000	1.0000
	p-value (Difference > 0)	0.0000	0.0000
	Cohen's d	1.5126	1.2418
	Hedge's g	1.5123	1.2416
	Glass's delta	3.2732	1.6237
	Pearson's r	0.6033	0.5276

$n_{total} = 10849$

Table B.2: **T-Test Results for Each Voting Behavior Type**

Variable	Mean	SD	SE	95% Conf.	Interval
	Random ($n = 5635$ | 51.94%)				
TREATI	88.98	7.46	0.10	88.78	89.17
PMV	69.27	14.34	0.19	68.90	69.64
Static	59.51	8.29	0.11	59.29	59.73
	All Split ($n = 3334$ | 30.73%)				
TREATI	91.18	9.87	0.17	90.84	91.51
PMV	71.78	16.66	0.29	71.21	72.35
Static	71.25	14.81	0.26	70.74	71.75
	Split – SV1 ($n = 1684$ | 15.52%)				
TREATI	90.95	8.06	0.20	90.57	91.34
PMV	75.36	14.87	0.36	74.65	76.07
Static	82.34	8.95	0.22	81.91	82.76
	Split – SV2 ($n = 1650$ | 15.21%)				
TREATI	91.41	11.42	0.28	90.86	91.96
PMV	68.12	17.58	0.43	67.27	68.97
Static	59.92	10.405650	0.26	59.42	60.43
	All Majority ($n = 1880$ | 17.33%)				
TREATI	86.73	8.14	0.19	86.37	87.10
PMV	64.93	17.90	0.41	64.12	65.74
Static	73.49	12.73	0.29	72.92	74.07
	Majority – MV1 ($n = 632$ | 5.83%)				
TREATI	96.17	1.95	0.08	96.02	96.32
PMV	72.05	17.61	0.70	70.67	73.42
Static	89.78	1.86	0.07	89.63	89.92
	Majority – MV2 ($n = 1248$ | 11.5%)				
TREATI	81.96	5.47	0.15	81.65	82.26
PMV	61.32	16.94	0.48	60.38	62.26
Static	65.25	6.31	0.18	64.90	65.60

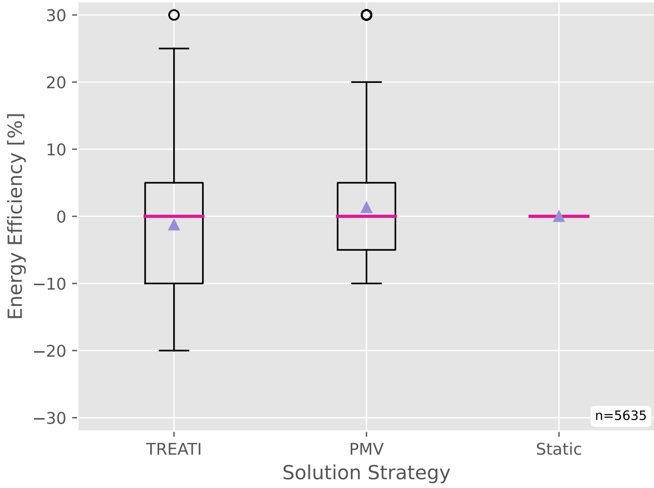
units in %, $n = 10849$

Table B.3: **Comparison of Descriptive Statistics for Occupant Satisfaction based on Voting Behavior**

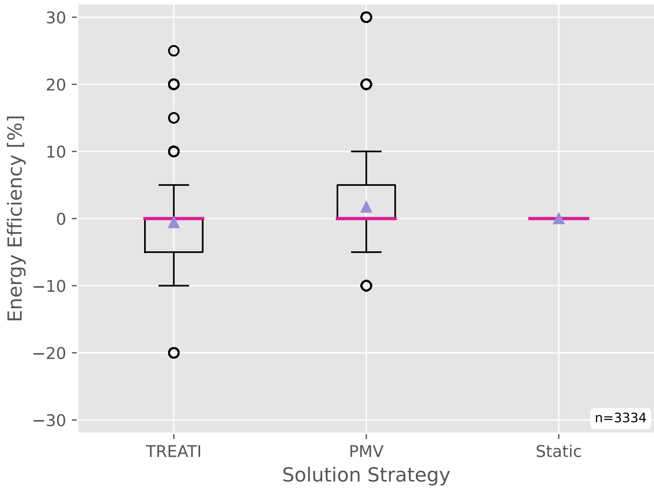
Controls		$\overline{x}$	$med(x)$	SD	Var	Min	Max
Split − SV1 ($n = 1684$)							
Occupant Satisfaction	TREATI	90.95	87	8.06	65.0	70	100
	PMV	75.36	75	14.86	220.93	23	100
	Static	82.34	85	8.94	79.98	70	100
Energy Efficiency	TREATI	0.65	0	4.38	19.15	-10	25
	PMV	2.51	0	7.4	54.83	-10	30
	Static	0.0	0	0.0	0.0	0	0
Fairness	TREATI	83.5	90	21.21	449.74	0	100
	PMV	33.63	33	27.72	768.61	0	92
	Static	41.05	34	27.05	731.45	0	92
Split − SV2 ($n = 1650$)							
Occupant Satisfaction	TREATI	91.41	100	11.42	130.42	46	100
	PMV	68.12	72	17.57	308.81	0	100
	Static	59.92	60	10.39	108.0	40	75
Energy Efficiency	TREATI	-1.88	0	9.2	84.65	-20	25
	PMV	0.92	0	6.6	43.5	-10	30
	Static	0.0	0	0.0	0.0	0	0
Fairness	TREATI	68.9	90	27.69	766.64	0	100
	PMV	34.99	33	30.12	907.04	0	92
	Static	21.39	29	21.57	465.22	0	92
Majority − MV1 ($n = 632$)							
Occupant Satisfaction	TREATI	96.17	97	1.95	3.79	92	100
	PMV	72.05	77	17.6	309.68	7	93
	Static	89.78	90	1.86	3.45	85	93
Energy Efficiency	TREATI	0.0	0	0.0	0.0	0	0
	PMV	2.87	0	8.91	79.39	-10	30
	Static	0.0	0	0.0	0.0	0	0
Fairness	TREATI	92.31	90	3.94	15.5	89	100
	PMV	23.1	12	27.09	734.0	0	73
	Static	63.58	62	4.14	17.15	58	75
Majority − MV2 ($n = 1248$)							
Occupant Satisfaction	TREATI	81.96	83	5.46	29.86	64	100
	PMV	61.32	64	16.94	286.8	2	91
	Static	65.25	66	6.31	39.85	45	81
Energy Efficiency	TREATI	1.27	0	7.41	54.94	-20	20
	PMV	2.92	0	8.47	71.74	-10	30
	Static	0.0	0	0.0	0.0	0	0
Fairness	TREATI	72.11	70	12.23	149.48	58	100
	PMV	25.96	7	30.76	946.24	0	74
	Static	2.62	0	3.99	15.89	0	18

units in [%], $n_{total} = 10849$

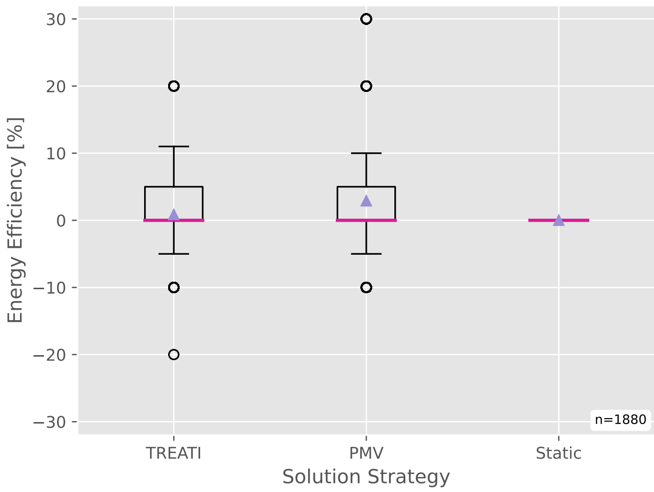
Table B.4: **Detailed Descriptive Statistics of Split and Majority Voting Behavior**



(a) **Random**

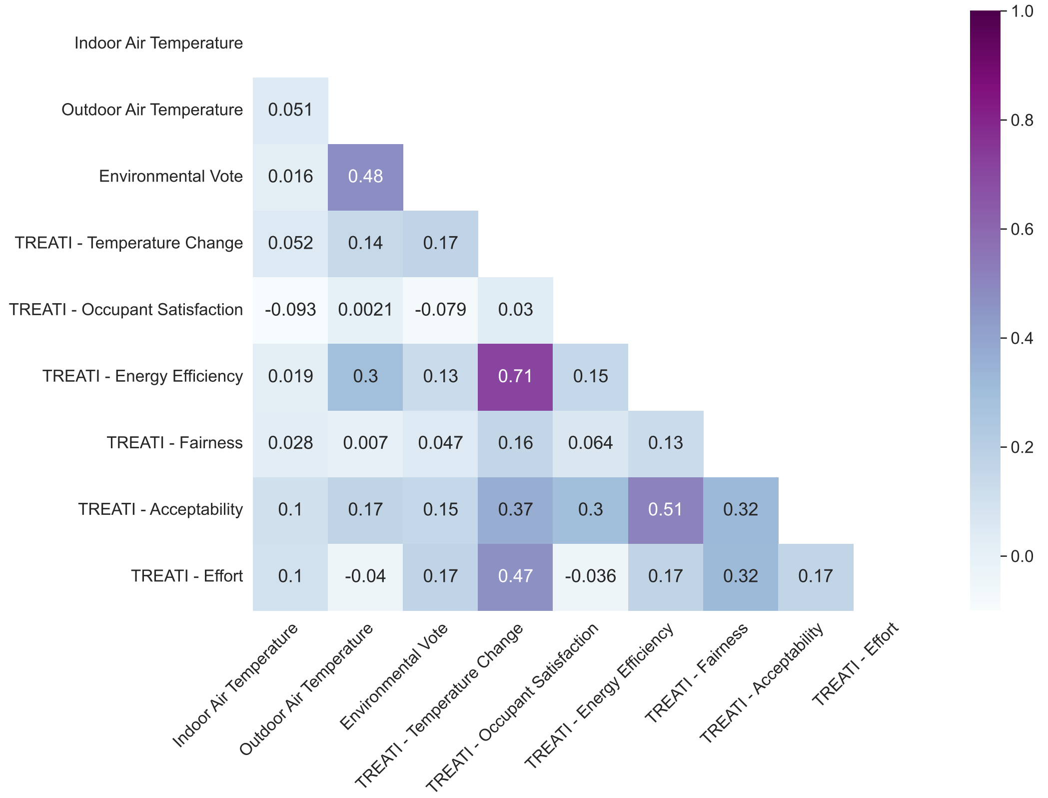


(b) **Split**

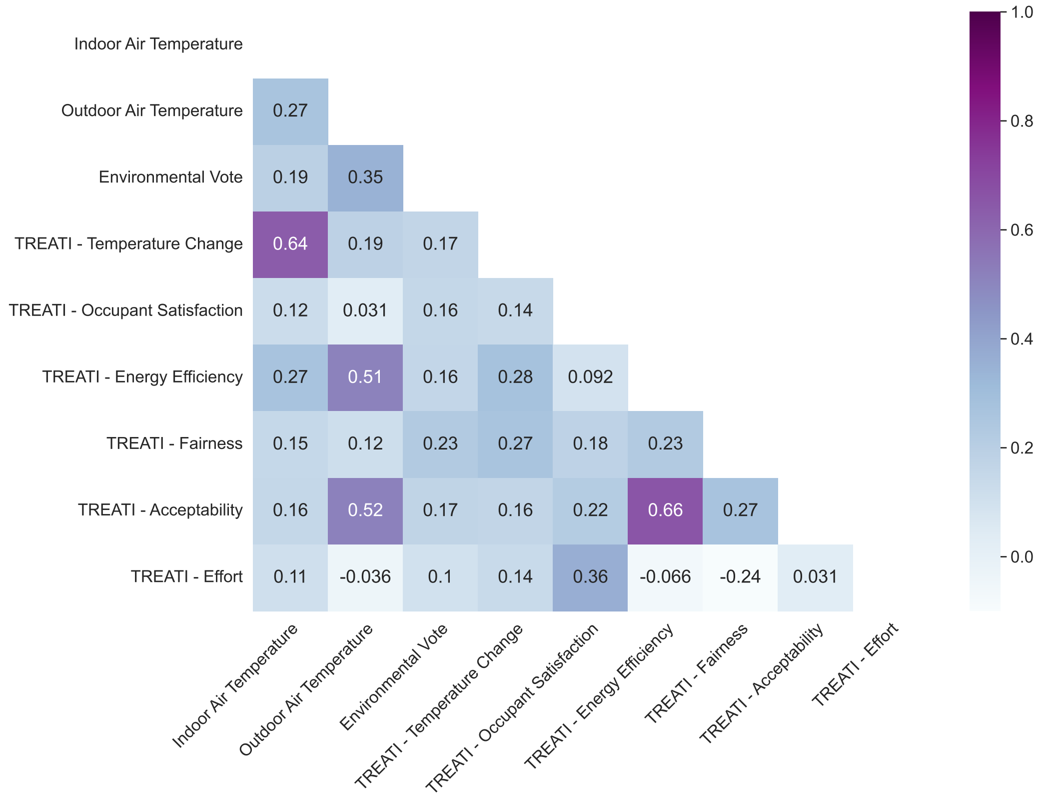


(c) **Majority**

Figure B.4: **Energy Efficiency comparing TREATI to the Baselines by Voting Behavior**

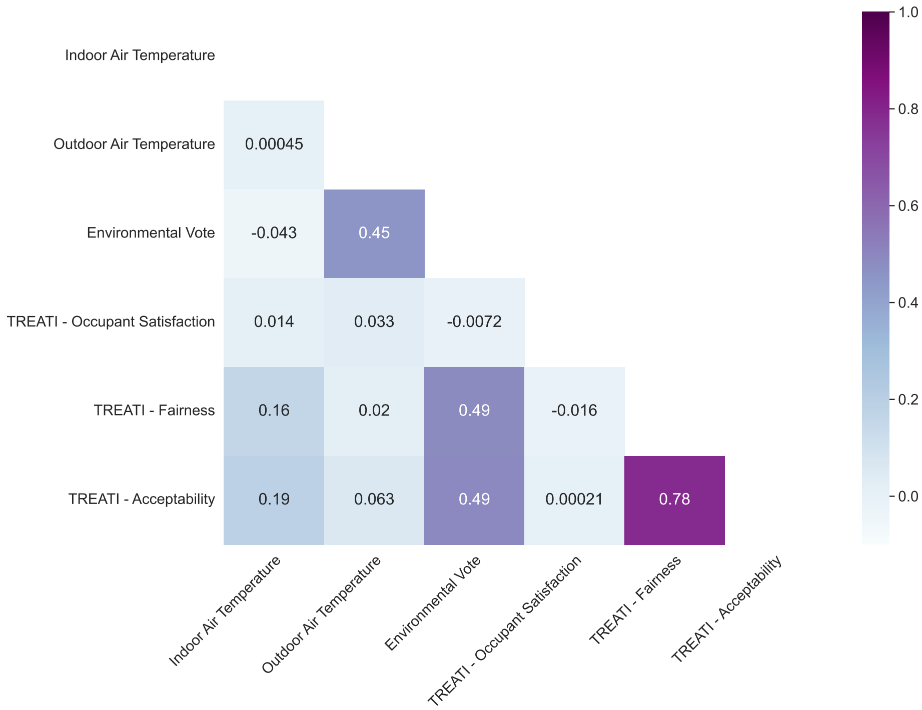


(a) **SV1** – 50% of votes are *no change* ($n = 1684$)

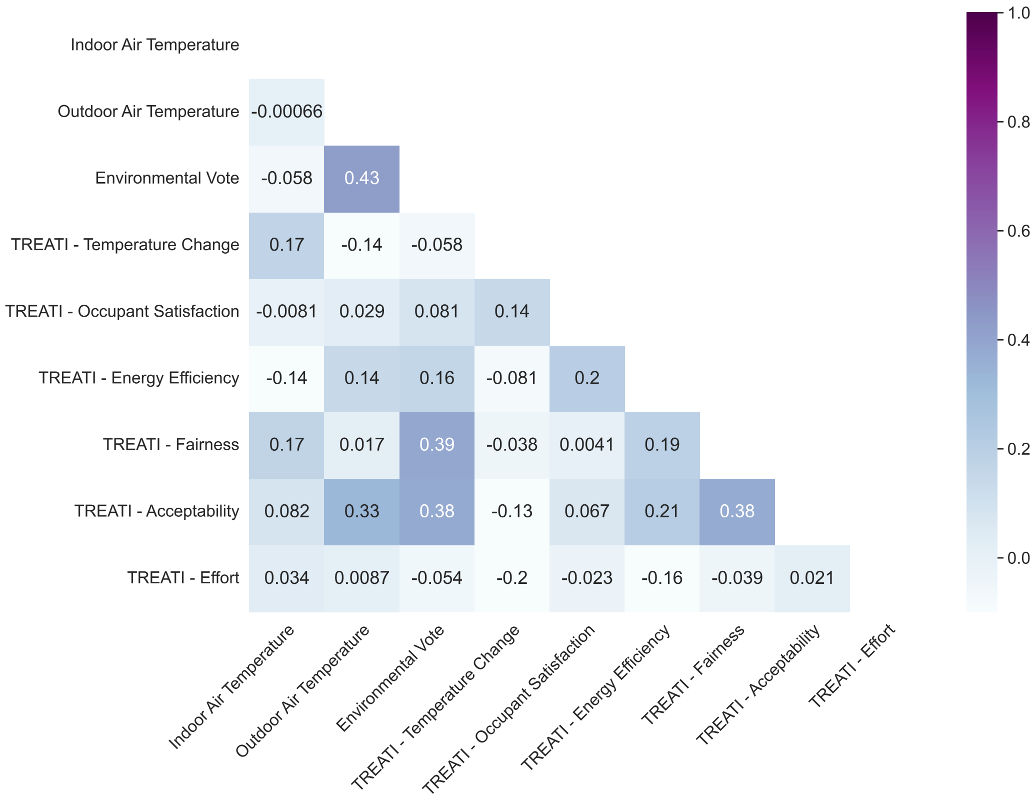


(b) **SV2** – Contradicting votes with 50% *warmer* vs 50% *cooler* ($n = 1650$)

Figure B.5: **Split Voting Behavior Correlation Comparison of SV1 and SV2**



(a) **MV1** – Majority vote is *no change*, $n = 632$



(b) **MV2** – Minority vote is *no change*, $n = 1248$

Figure B.6: **Majority Voting Behavior Correlation Comparison between MV1 and MV2** – in MV1, TREATI's temperature change, energy efficiency, and effort score are constants and thus omitted

B.3 Basic & Composite Actions

	Random		Split		Majority	
Metric	**Basic**	**Comp.**	**Basic**	**Comp.**	**Basic**	**Comp.**
Mean Sensation						
n	516		134		76	
Acceptability $\overline{x}$	78.38	80.28	73.03	78.5	69.97	70.58
$med(x)$	78.8	80.5	72.5	78.9	68.15	68.15
Occ. Satisfaction $\overline{x}$	83.4	88.77	77.9	90.39	73.86	80.93
$med(x)$	84.0	90.0	75.0	87.0	72.0	79.0
Fairness $\overline{x}$	69.74	87.24	39.94	84.14	63.47	69.17
$med(x)$	71.0	88.0	40.0	100.0	62.0	62.0
Mean Preference						
n	30				52	
Acceptability $\overline{x}$	75.33	76.02	–	–	73.25	73.47
$med(x)$	75.6	75.9	–	–	73.25	73.5
Occ. Satisfaction $\overline{x}$	76.8	82.73	–	–	73.1	80.46
$med(x)$	77.0	82.0	–	–	72.0	79.0
Fairness $\overline{x}$	72.3	72.3	–	–	71.02	71.02
$med(x)$	72.5	72.5	–	–	71.0	71.0
Mean Desirability						
n	75		60			
Acceptability $\overline{x}$	85.9	87.02	71.81	74.61	–	–
$med(x)$	86.3	87.7	73.5	74.9	–	–
Occ. Satisfaction $\overline{x}$	90.43	94.37	76.57	89.85	–	–
$med(x)$	91.0	95.0	85.0	100.0	–	–
Fairness $\overline{x}$	80.19	94.49	37.25	52.55	–	–
$med(x)$	85.0	100.0	42.0	42.0	–	–
Dynamic Temperature						
n	202		188		76	
Acceptability $\overline{x}$	68.53	70.76	69.92	74.03	69.46	69.74
$med(x)$	68.35	71.1	70.8	74.95	68.1	68.3
Occ. Satisfaction $\overline{x}$	70.87	79.54	73.48	86.6	72.61	79.68
$med(x)$	71.0	79.0	74.0	87.0	72.0	79.0
Fairness $\overline{x}$	49.84	58.03	40.22	68.54	64.13	65.63
$med(x)$	51.0	57.0	40.0	60.0	62.0	62.0

$\overline{x}$ indicates the mean, $med(x)$ indicates the median *units in* [%]

Table B.5: **Metric Comparison between Basic and Composite Actions** by type and voting behavior

B.4 Energy Efficiency

	Quartile	TREATI	PMV
Random	0.25	-10	-5
	0.50	0	0
	0.75	5	5
All Split	0.25	-5	0
	0.50	0	0
	0.75	0	5
Split – SV1	0.25	0	0
	0.50	0	0
	0.75	0	3
Split – SV2	0.25	-10	0
	0.50	0	0
	0.75	2	3
All Majority	0.25	0	0
	0.50	0	0
	0.75	5	5
Majority – MV1	0.25	0	0
	0.50	0	0
	0.75	0	5
Majority – MV2	0.25	-5	0
	0.50	0	0
	0.75	5	5

units in [%], $n_{total} = 10849$

Table B.6: **TREATI's Energy Efficiency Metric Compared to the PMV Baseline**

B.5 Personas

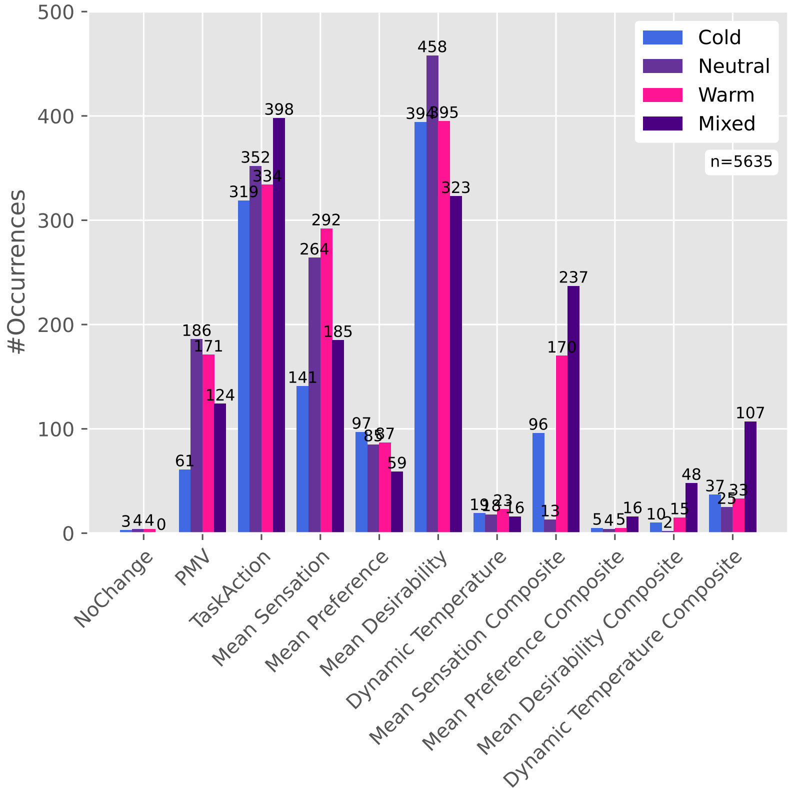


Figure B.7: **Action Distribution by Persona**

Controls		Mean	Median	SD	Var
Cold ($n = 1189$)					
Occupant Satisfaction	TREATI	89.75	91	7.56	57.19
	PMV	64.11	66	18.65	347.97
	Static	58.03	57	9.3	86.53
Energy Efficiency	TREATI	-0.86	3	11.5	132.29
	PMV	2.66	0	9.3	86.44
	Static	0.0	0	0.0	0.0
Fairness	TREATI	81.39	84	12.05	145.16
	PMV	37.82	25	37.63	1416.01
	Static	4.73	0	11.73	137.57
Neutral ($n = 1412$)					
Occupant Satisfaction	TREATI	89.46	90	6.18	38.25
	PMV	72.92	75	12.03	144.79
	Static	61.58	60	8.28	68.53
Energy Efficiency	TREATI	0.11	3	10.12	102.46
	PMV	0.84	0	6.39	40.83
	Static	0.0	0	0.0	0.0
Fairness	TREATI	80.57	84	9.61	92.36
	PMV	46.02	58	38.49	1481.14
	Static	3.59	0	8.67	75.23
Warm ($n = 1546$)					
Occupant Satisfaction	TREATI	90.59	91	7.04	49.51
	PMV	69.65	71	13.52	182.67
	Static	59.23	57	8.47	71.8
Energy Efficiency	TREATI	-0.2	2	9.99	99.71
	PMV	0.75	0	5.89	34.65
	Static	0.0	0	0.0	0.0
Fairness	TREATI	83.38	86	12.05	145.09
	PMV	39.93	29	38.3	1467.09
	Static	4.42	0	9.83	96.67
Mixed ($n = 1513$)					
Occupant Satisfaction	TREATI	87.09	87	7.74	59.89
	PMV	69.54	70	11.79	138.97
	Static	58.86	58	6.75	45.63
Energy Efficiency	TREATI	2.0	5	10.03	100.66
	PMV	1.21	0	7.56	57.2
	Static	0.0	0	0.0	0.0
Fairness	TREATI	81.49	84	11.63	135.18
	PMV	43.78	49	37.15	1379.85
	Static	2.15	0	5.94	35.24

Table B.7: **Personas Descriptive Statistics**

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