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SUMMARY

This study aimed to gather information, together with the researchers working on Work Package 1 (error detection and error diagnosis) and Work Package 2 (flexibilization), about the views of the market regarding the integration of user data and feedback to their services and products: what is the market already doing in this area and what are their plans. The perspective from the market can help the researchers in WP1 and WP2 to align their developments better with what the market's current efforts demands. This report documents the steps taken to achieve this and summarises the knowledge that has been collected. As sources of information, we undertook a literature study to establish the state of the art in academia on the role of user data in building systems and user interfaces (occupants and facility managers). In addition, we gathered input from the industry partners in our B4B project, where the aim was to find out how they currently integrate user data in their products and what their ambitions are for the future.

This resulted in the following conclusions:

Occupant-related data and occupants' behaviour models to facilitate building management and control

The literature study showed that many occupancy models had been developed to integrate different types of occupant-related data into building control and performance models. However, the investigation with companies shows that these models are not yet currently used in practice.

The interviewed companies gather some occupant-related data, but the use of the data is still limited to satisfaction with the indoor conditions or complaints about it. However, some partners are working towards gathering better user experiences in the buildings, for example, the Mood Box in development by Strukton and the plans from O-Nexus to understand occupants' satisfaction and mood through the analysis of existing building data.

The interviewed partners perform fault detection and diagnosis based on rules (rule-based) of indicators such as sensor ranges and trends. Furthermore, energy prediction and optimization are performed using black box models using the available building sensors. Here, some partners opt for a minimal sensor approach to reduce costs, whereas others prefer placing extra sensors to achieve better data for their models.

The partner's user interfaces provide feedback to the occupant on a high-level (narrowcasting) or not at all, whereas feedback to the professional end-user is typically not used yet. Regarding the occupants, there exists a general interest in user models. Specifically, partners are interested in exploring the relationship with perceived comfort to determine comfort ranges for energy flexibility and optimization.

Feedback interfaces for building occupants

For the state of the art, scientific articles related to feedback interfaces were sought. The investigation showed that although interfaces for building occupants are considered promising to decrease energy use using understandable information for users, there are still many limitations to their use, mostly related to their validity, replicability, and acceptance.

On the other hand, the interfaces (dashboards and platforms) developed by the involved B4B partners involved in this study mainly focus on providing information to the facility managers and the building owner. Thus, they focus on energy and indoor environmental quality (IEQ) control and building performance. Partners seem interested in collecting more self-reporting data from occupants, for which the development of interfaces to collect such data is under development. However, none of these partners aims to focus on interfaces to provide information to the occupants of the buildings.

The results from the Clima workshop with academics and practitioners identified similar requirements for the occupants' interfaces as those found in the literature, such as the need for more understandable, accessible, and easier-to-read interfaces for the layperson.

Interfaces for facility managers

The state of the art study on interfaces for facility managers mainly focused on using BIM and other emergent smart technologies, their opportunities, and challenges. These technologies are seen as having great potential in increasing the effectiveness of FMs work and improving building performance. The main shortcomings of these technologies to support FMs are the lack of data integration and accessibility to data, lack of clear and understandable information, and lack of awareness and skills in the industry to use these technologies. These challenges were in line with the requirements identified during the workshop at the Clima conference. Further research will be aimed at working with FMs to determine these requirements.

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1 INTRODUCTION

This study aimed to gather information, together with the researchers working on Work Package 1 (fault detection and fault diagnosis) and Work Package 2 (flexibilization), about the views of the market regarding the integration of user data and feedback to their services and products: what is the market already doing in this area and what are their plans. The perspective from the market can help the researchers in WP1 and WP2 to align their developments better with what the market's current efforts demands. This report documents the steps taken to achieve this and summarizes the knowledge that has been collected.

The following sources of information were used:

- Literature: a literature study was performed to establish the state of the art in academia on the role of user data in building systems and on user interfaces (occupants and facility managers). The focus was on existing knowledge gaps and data integration challenges in building management and control. The literature study is described in chapter 2.
- The industry partners in our B4B project: Input from our industry partners was gathered in several ways. The aim was to find out how they currently integrate user data in their products and what their ambitions are for the future. To gather this information, the following activities were organised (described in chapter 3):
- Initial (physical) workshop (chapter 3.1.1)
- A questionnaire was distributed among the industry partners in the project (3.1.2)
- Industry partners in the project were asked to present their current products during workgroup sessions (3.1.2)
- In depth interviews were conducted with our industry partners (3.1.3)
- Information was collected from market perspective from a wider group during a workshop at the CLIMA conference 2022 in Rotterdam. The scope here was both on the integration of user interaction and on user feedback (3.2).

The conclusions of the undertaken steps are summarized in chapter 4.

2 STATE OF THE ART

In this section, we present a literature review on the state of the art on the two main issues investigated in this research: 1) current developments in occupancy models and occupants' behaviour models for building control; and 2) current insights into the role of feedback interfaces to reduce energy consumption in buildings.

2.1 The role of occupants-related data in building systems

Occupants-related data comprises all possible information provided implicitly or explicitly by occupants in a smart building, such as presence, clothing, activities, interaction with the building (behaviour), comfort and satisfaction. Incorporating, assessing, interpreting, and applying these data in building systems is crucial for maintaining a healthy indoor environment and reducing energy consumption. In the past decade, several studies have focused on using occupants-related data to control office building systems and reported enhanced energy performances. These studies differed in terms of sensor technologies used, modelling techniques, control type and performance evaluations. Table 1 compiles a selection of the distinct studies conducted in the last ten years. For the scope of this project, the compilation is restricted to only studies conducted in office buildings. Comfort evaluation has been the scope of the study for only a few papers. In the rest, thermal comfort is only considered between a specified air temperature range for all occupants. Models like the predicted mean vote (PMV) and the adaptive model are used widely, but their accuracy has been criticised in the literature, indicating high subjectivity of thermal comfort. To tackle this subjectivity, self-reporting of thermal comfort has been introduced. In the following sections, the different types of occupants-related data currently used in building systems are summarised.

2.1.1 Occupancy

One of the most common and widely used sensors for occupancy detection is the passive infrared (PIR) sensor. These sensors can detect infrared radiation changes caused by occupant's motion and thus can detect presence. Several studies have used PIR sensors for occupancy detection in buildings but accurately determining occupancy levels and zones is challenging. In 2006, Dodier et al. [1] presented a PIR sensor belief network for occupancy detection using Bayesian probability theory. Wahl et al. [2] proposed an occupancy counting system using pairs of PIR sensors to detect their moving directions. In 2016, Raykov et al. used only a single PIR sensor to estimate the occupancy count. They implemented an infinite hidden Markov model (HMM) to extract motion patterns and then statistical regression methods to infer the number of occupants up to an accuracy of 80%. Motion sensors-based machine learning models have also been presented by studies to determine occupancy with increased accuracy of up to 90%.

Measuring power consumption using smart meters has also been used to predict occupancy with reasonable accuracy. Chen et al. [4], Kleiminger et al. [5], Kleiminger et al. [6] obtained accuracy between 60-80%, whereas Akbar et. al.[7] and Becker and Kleiminger [8] claimed to achieve an accuracy of 94% and 90% respectively.

Another popular non-intrusive sensor is the CO_2 sensor. Initial studies were only able to detect whether occupants were present in a zone [9-11], but recent studies use machine learning techniques to predict occupancy levels as well [12-15]. To further increase the accuracy of this prediction, a network of multiple sensors which measure humidity, light, and pressure is also used in the literature [16-19]. However, the modelling techniques used are complex and difficult to reproduce.

All the technologies mentioned above require a setup of sensors and complex modelling techniques to accurately predict occupancy. The use of mobile networks, GPS, and Wi-Fi, though a bit intrusive, provide an accurate level of occupancy in offices without requiring to setup an expensive network of sensors. Balaji et. al. [20] presented an occupancy-based HVAC control using existing wi-fi infrastructure for office buildings. Several other studies use cellular networks, GPS for building control actuation [21-23]. Other technologies include cameras which provide an even higher accuracy (99%, Munir et al. 2017 [24]) but are either costly or highly intrusive.

2.1.2 Activity level

Metabolic rate is a significant parameter in the PMV thermal comfort model. One of the ways in which it can be determined for an occupant is by knowing or monitoring their activities. In buildings, methods have been proposed for detecting occupant activities through visual, acoustic, and CO_2 sensors. Lu et. al. [25] used a static RGB camera for classifying activity levels and used it for real-time HVAC control. The accuracy of this classification was claimed as 90%. Benzeth et al. [26] proposed a vision-based system for human detection and activity analysis based on video sequences using a static camera. Wolf et al. [27] presented a hidden Markov-Switching model using CO_2 sensors to determine activity levels with an average accuracy of around 85%. Zhang et al. [28] present a structural vibration-based occupant activity level estimation method by placing a sensing unit inside the floor.

2.1.3 Window opening/closing

Fritsch et al. [29] developed a mathematical model to predict window opening angles using the Markov chain model. They built four Markov chains to realise the link between outdoor temperature and occupant action concerning windows. Markovic et al. [30] used indoor air temperature; outdoor climate features such as outdoor air temperature, precipitation, wind velocity, wind direction, CO_2 and relative humidity (RH) to model window opening/closing actions. They used support-vector machines and random forest to predict window status up to 88% accurately. Cali` et al. [31] reported that the significant parameters influencing the opening action are the time of day and CO_2 concentration and that the most common driving factors for the closing action are the outdoor temperature and time of day. D'Oca and Hong [32] also documented that indoor air temperature, outdoor air temperature, arrival/leave time, time of day and occupancy are the top five features influencing window opening/closing. They further classified occupant behavior into three types: 1) thermal-driven, 2) time-driven, and 3) thermal-driven & time-driven, which depend on the type of building, activities carried out in the buildings, and building users.

2.1.4 Comfort/Satisfaction

One of the major functions of buildings is to maintain a comfortable indoor environment for its occupants, as it can affect their productivity and health. Thermal comfort is a much-studied topic and has been shown in the literature to be dependent on several environmental, physiological and psychological factors. In 1970, Fanger performed extensive experiments to study the thermoregulation of the human body and developed the predictive mean vote (PMV) model [33]. It has since become the basis for standards like ASHRAE 55 and EN 16798-1:2019 for conditioning indoor spaces in a building. Comfort evaluation has been the scope of the study for only a few papers. In the rest, thermal comfort is only considered between a specified air temperature range for all occupants. Models like PMV and the adaptive model are used widely. Still, their accuracy has been criticised in literature due to the high subjectivity of thermal comfort caused by the specific comfort preferences of individuals. To consider this subjectivity, some studies have focused on self-reporting of comfort. Erickson and Cerpa (2012) [34] [UN1] developed a mobile application for self-reporting and used the PMV model as the baseline for real-time HVAC control. Feldmeier and Paradiso (2010) [35] developed wearable actuation hardware for sensing indoor environmental conditions, occupants' location, and their physiological parameters. They used Fisher's linear discriminant analysis to model comfort based on self-reporting data gathered from the wearable device but employed only a 3-point scale (hot, neutral, cold) as opposed to a 7-point scale in PMV. Liu et al. also used a 3-point scale as an output for their neural network model of thermal comfort. For data collection, they kept the subjects in experimental conditions for 30 mins and asked them to fill out a questionnaire.

Table 1 Studies focused on occupant behaviour modelling in the last ten years.

Reference	Sensor Technologies used for Occupancy Detection	Control			Performance Evaluation		
		Control Type	HVAC Control	Temperature Control Strategy / Comfort objective	Evaluation Method	Energy savings (Upto)	Comfort Evaluation
Sentinel [20]	Wifi nework	Reactive	H/V/C	Setpoint/Setback (21°C-25°C)	Field evaluation	17.80%	X
Occupancy-driven EM for SMA [36]	Door Reed switches, PIR	Reactive	H/C	Setpoint/Setback (22.9°C-26.1°C)	Simulation	15.00%	X
Assessing the impacts of real-time occupancy state transitions on building heating/cooling loads [37]	Scheduled	Rule based Control	H/C	Setpoint/Setback (22.78°C/25.56°C)	Simulation	28.30%	X

Reference	Sensor Technologies used for Occupancy Detection	Control			Performance Evaluation		
		Control Type	HVAC Control	Temperature Control Strategy / Comfort objective	Evaluation Method	Energy savings (Upto)	Comfort Evaluation
Multiple perspectives of the value of occupancy-based HVAC control systems [38]	Scheduled	Rule based Control using occupancy probability	H/V/C	PNNL model	Simulation	50.00%	X
Using machine learning techniques for occupancy-prediction-based cooling control in office buildings [39]	Motion Sensors	Rule based Control using occupancy probability	C	Setpoint/Setback (22.5°C/35°C)	Field evaluation	52.00%	X
Occupancy prediction algorithms for thermostat control systems using mobile devices [21]	Cellular network, WiFi	Rule based Control using preconditioning time	H	(22.9°C/24°C)	Field evaluation	26.00%	X
ThermoSense: occupancy thermal based sensing for HVAC control [40]	Thermal sensors, PIR	Rule based Control using preconditioning time	H/V/C	Setpoint/Setback (20°C/24°C)	Simulation	25.00%	X
OBSERVE: occupancy-based system for efficient reduction of HVAC energy [41]	Cameras	Rule based Control using preconditioning time	H/V/C	Setpoint/Setback (21.11°C/27.78°C)	Simulation	42.00%	X
POEM: power-efficient occupancy-based energy management system [42]	Cameras	Rule based Control using preconditioning time	H/V/C	PMV	Field evaluation and Simulation	26% and 30% respectively	X
A Systematic Approach for Exploring Tradeoffs in Predictive HVAC Control Systems for Buildings [43]	PIR Ultrasonic sensors	Rule based Control using preconditioning time	H/C	Setpoint/Setback (20°C/24°C)	Simulation	28.00%	40% improvement in Thermal comfort
Importance of occupancy information for building climate control [44]	Bluetooth tags	Optimal Control	H/C	Setpoint/Setback (22°C/24°C)	Simulation	2%	50% decrease in thermal discomfort
Personalized HVAC Control System [35]	Scheduled	Optimal Control (MPC)	H/C	Setpoint/Setback (21°C/26°C)	Simulation	Negligible	X
Sentinel [20]	Wearable (watch)	Reactive	C/V	Self reporting	Field evaluation	24.00%	Self-reporting of thermal comfort
Thermovote: Participatory Sensing for Efficient Building HVAC Conditioning [34]	Cellular network, WiFi	Reactive	H/V/C	PMV - AMV (actual mean vote)	Field evaluation	10.10%	Interview for assessing satisfaction

Reference	Sensor Technologies used for Occupancy Detection	Control			Performance Evaluation		
		Control Type	HVAC Control	Temperature Control Strategy / Comfort objective	Evaluation Method	Energy savings (Upto)	Comfort Evaluation
User-led decentralized thermal comfort driven HVAC operations for improved efficiency in office buildings [45]	X	Reactive	H/V/C	f (Self-reporting, Current room temperature)	Field evaluation	26.00%	Self-reporting of thermal comfort
A neural network evaluation model for individual thermal comfort [46]	X	X	X	Predefined values	Field evaluation	N.A.	Self-reporting of thermal comfort
A personalized measure of thermal comfort for building controls [47]	Fixed occupancy (6)	MPC	L	X	Field evaluation	X	Self-reporting 3 point scale
Human-Building Interaction Framework for Personalized Thermal Comfort-Driven Systems in Office Buildings [48]	Motion Sensors, PIR, Indoor temperature, CO2, humidity, door status, light and sound	Reactive	V/C	f (Self-reporting, Current room temperature)	Field evaluation	X	Mobile application for self-reporting of thermal comfort (7-point scale)
A data-driven method to describe the personalized dynamic thermal comfort in ordinary office environment: From model to application [49]	Fixed occupancy (9)	X	X	X	Field evaluation	6%	desktop application for self reporting of thermal comfort (5-point scale)
iLTC: Achieving Individual Comfort in Shared Spaces [50]	Wifi nework	Reactive	H/C/L	f (Self-reporting, Current room temperature)	Field evaluation	39%	Mobile application for self-reporting of thermal comfort (7-point scale)
Personalized human comfort in indoor building environments under diverse [51] conditioning modes	Mobile application	Reactive	H/V/C	f (Self-reporting, Current room temperature)	Field evaluation	X	Mobile application for self-reporting of thermal comfort (7-point scale) Uncomfortable reports reduced by 53.7%
Model-free HVAC control using occupant feedback [52]	Mobile application	Reactive	H/V/C	f (Self-reporting)	Simulation	50%	Self reporting 3 point scale
Personal comfort models: Predicting individuals' thermal	Fixed	Manual	H/C	Manual	Field evaluation	X	Developed comfort models using heating/cooling behaviour data

Reference	Sensor Technologies used for Occupancy Detection	Control			Performance Evaluation		
		Control Type	HVAC Control	Temperature Control Strategy / Comfort objective	Evaluation Method	Energy savings (Upto)	Comfort Evaluation
preference using occupant heating and cooling behavior and machine learning [53]							
Integrating occupants' voluntary thermal preference responses into personalized thermal control in office buildings [54]	Fixed	Reactive	H/V/C	f (Self-reporting, Current room temperature)	Field evaluation	X	Interface for self-reporting
Improving occupancy presence prediction via multi-label classification [55]	Motion Sensors	SVM, Random forest, Decision tree kNN	Predictive Control	X	X	X	X
PROMT: predicting occupancy presence in multiple resolution with time-shift agnostic classification [56]	PIR	kNN-DTW, Random forest, SVM	Predictive Control	V	f (Occupancy)	X	X
A context-aware method for building occupancy prediction [57]	PIR motion and acoustic sensors	Markov model, Semi-Markov model	Predictive Control	X	X	X	X
Modeling occupancy behavior for energy efficiency and occupants comfort management in intelligent buildings [58]	Motion sensors	Genetic programming	Predictive Control	X	X	X	X
Modeling regular occupancy in commercial buildings using stochastic models [59]	Camera	Markov model	Predictive Control	X	X	X	X
Occupancy prediction model for open-plan offices using real-time location system and inhomogeneous Markov chain [60]	RTLS (Real time location sensors)	Markov model	Predictive Control	H/V/C	Setpoint/Setback	X	X
Optimizing energy consumption	RTLS (Real time	Proportional model	Predictive Control	H/V/C	Setpoint/Setback	Simulation	2%

Reference	Sensor Technologies used for Occupancy Detection	Control			Performance Evaluation		
		Control Type	HVAC Control	Temperature Control Strategy / Comfort objective	Evaluation Method	Energy savings (Upto)	Comfort Evaluation
and occupants comfort in open-plan offices [61] using local control based on occupancy dynamic data	location sensors)						

2.2 Interfaces for building occupants

The end users of buildings interfaces can be categorized in: building/real estate owner, facility managers and building occupants (e.g. office workers and students). In this section we present a non-exhaustive literature review on the role of interfaces for building occupants and facility managers.

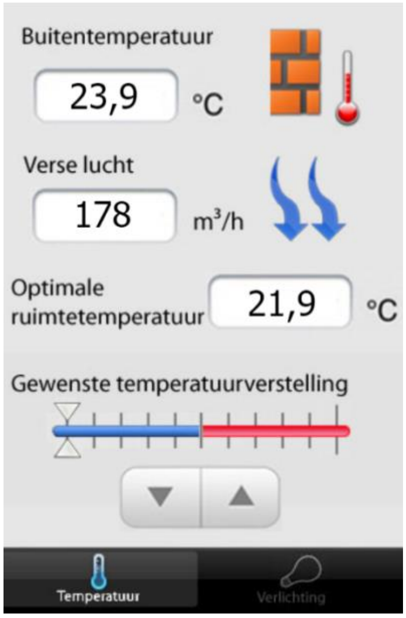
2.2.1 Energy efficiency and energy savings in buildings

Building owners and energy providers rely on the final consumers (building users) to decrease and balance their energy consumption. Consumers have been identified as the main actor in influencing the energy transition towards post-carbon societies [62-64]. Consumers are encouraged to contribute to higher energy efficiency in cities by focusing their efforts on energy saving or load shifting to periods when energy sources are cleaner [65-68].

In this regard, smart data-driven technologies have great potential for energy reduction and management. Recent technological developments in sensors, energy meters and data transport and storage have enabled possibilities to monitor the actual and real-time performance of buildings to help occupants to use buildings more efficiently and sustainably [69-73].

However, it is not yet understood how far feedback to building users can support the transition towards more energy-efficient behaviours in the long run [74], and which groups of people can benefit the most from them [75-78]. Large differences in the amount of energy saved (from 0% to 32%, but usually between 5% and 12%) have been found in recent studies [67,79-84]. An often-seen shortcoming of these solutions is participants returning to old behaviours after the end of the program [74,85-89].

A major constraint in the impact of such data-driven solutions is the great diversity of final users with different lifestyles [74,90]; preferences and changing energy requirements make these advances difficult [71,91].



Building users can influence temperature in a room by using app. In this case, users prefer the max cooling setting. Information on fresh air ("178m3/h") will not mean anything to most building users. (DGBC office, The Hague).

2.2.2 Energy feedback and visualisations

Energy is a concept that, for many people, is difficult to understand, and most people find it difficult to link the impact of everyday activities to energy use or to environmental impacts [92-94]. Authors have found that people hold misperceptions around energy use [89,92,95,96], often underestimating saving associated with building energy efficiency measures and overestimating savings produced by curtailment behaviours, or not understanding how much energy different actions require [96]. For example, Photovoltaics are often introduced and perceived as free and green electricity, causing a rebound effect even among careful energy consumers [97]. Furthermore, with the incorporation of smart technologies in buildings, occupants are faced with complex systems that are difficult to operate, which can lead to an increase in energy consumption and a decrease in overall satisfaction [98-102].

Energy feedback and visualizations based on real-time information have been identified as an opportunity to increase energy awareness and understanding of daily practices' effect on energy use [68,74,94,103,104]. But so far, the effect of smart meter feedback alone on reducing energy demand have been questioned [105-

109] for example, due to the difficulties of keeping long-term interest in it [94,76,110] but also due to lack of understanding of displays [111]. According to Boomsma [94], there is still the need to develop educational tools to understand the concept of energy in daily activities that can engage people in energy-saving actions in the long term.

Furthermore, data collection and analysis have proven difficult to maintain, given the large amount of data, the great diversity of occupancy patterns, financial barriers for large-scale monitoring, privacy concerns, and lack of reliability of the systems [112-116]. For example, Csoknyai [112] and AlSkaif [69] have emphasised that metered data is insufficient to draw conclusions about energy consumption habits or engage users in energy-efficient practices.

2.2.3 The underlying problem of feedback interfaces

The role of the context and the user

Most data-driven solutions tackling behavioral change target energy reductions without considering: 1) energy-related daily practices and technologies and systems present at home, and 2) the type of user. Human-building interactions are highly context-dependent [117]. Evidence suggests that human-building interactions are driven by contextual factors such as building conditions and characteristics [118-120]. Identifying the contextual factor (building characteristics and building technology) is critical for designing behavioral change interventions that support actual user needs and preferences [73,121,122]. However, most studies fail to provide a systematic analysis of the contextual factors [73] especially those related to social and psychological dimensions [123]. The type of building technology available and other building characteristics will affect how people use the buildings, and thus, any behaviour change will also be determined by them.

Research implementation and confounding factors

Past research has focused on determining the effectiveness of interventions for behavioral change to reduce energy consumption in buildings. Only some interventions have shown a moderate level of success. For example, many studies measure or report on variables that can be affected by many other factors. For example, total energy consumption and indoor air temperature are often used as indicators without considering that these are influenced by other variables such as weather, the efficiency of building systems, etc. In other cases, the 'intention' for behavioral change is measured and not the real outcomes. For example, Ro [124] designed an applied game intervention but did not verify whether the players actually engaged in the sustainable actions they claimed credit for. In this regard, the research implementation might also affect the lack of certainty in the outcomes. According to Johnson [125], "the reliability on the interventions is partially undermined by shortcomings identified in the methodology including small sample sizes, poorly described methodologies, limited use of validated measures to quantify outcomes, absence of controls, presentation of descriptive statistics only and narrow data collection timeframes". Morganti [126] agrees on the need to identify of a common methodology and standard measures to evaluate the outcomes of these interventions, since uncertain results might be explained by the measures used to assess their effect.

Another reason for the lack of certainty in outcomes in applied games interventions are confounding factors overlooked during the research implementation. For example, Csoknyai [112] reported to have more than 50 communication actions to stimulate the participants to use their app, but no control group was used to determine the effect of such communications in the intervention outcomes.

2.3 Interfaces for facility managers

According to Carreira et al [127], facility managers (FM) practitioners have started adopting computerized tools, which help automate routine tasks, manage information, monitoring building's performance and assist in decision-making processes. Among these tools, BEMS, BAS, and BIM seem to be the most widely known and used. However other emerging (also called disruptive) technologies such as Virtual Reality (VR), gamification and serious games approach, and AI, are often mentioned in research papers.

2.3.1 FM-information systems

One of the roles of a FM is the maintenance of the building. In current practice, FMs make use of two different types of information systems 1) **building energy management systems (BEMS) and building automation systems (BAS)** to monitor and optimize the performance of the building, based on the reports of failures from **direct digital controllers (DDC)**, and 2) **computerized maintenance management system (CMMS)** where facility maintenance data are typically stored and managed. These two types of systems are however not (well) integrated. Ideally, these systems should be able to share information with each other in an automated manner, as well as to optimize the process for gathering maintenance-related information [128].

According to Shalabi & Turkan [128], the shortcomings of Facility Management Information Systems have been identified as:

- Building sensors and controllers are connected to the BEMS or BAS system, where they input data and report any flaws or equipment failures. However, current practices depend on manual data input during the O&M phase.
- Sensors reporting data (DDCs) are typically numbered and organized based on their location in the building and presented in list format. However, data about their exact locations, the equipment affected by them, and their maintenance history information are not stored in BEMS.
- Sensor outputs, energy performance metrics, and other building performance metrics are presented in two-dimensional (2D) histograms, tables, and lists of tasks or in similar formats, which require manual data extraction and interpretation.

The shortcomings of computerised maintenance management systems (CMMS) have been identified as:

- CMMSs have a data structure incompatible with BEMS [129].
- The CMMS interface lacks easy and direct access to the different resources needed by FMs for the maintenance process, such as: documentation, equipment, personnel, and availability of spare parts.[128].
- The quality of maintenance data is highly dependent on the users' interaction with the system since typical users are: FM personnel, including operators, technicians, and facility managers [130,131].
- CMMS often lacks the capability to communicate the output data and support the user needs because it does not provide with a user-friendly interface or good visualization of data [128, 131, 132], and because they are not designed for the facility managers' specific needs [130,132].

In this regard, BIM is sought to improve the interoperability, visualization, and data fragmentation challenges [128]. Some of the advantages that BIM can offer to FM, identified by Matarneh et al. [133] are the following:

- BIM can provide FMs with access to digital information about facility components and equipment from one unified source [134].
- BIM can reduce the time to locate facility assets [136-138], improve fault detection and diagnosis in all construction phases, and it supports collaboration and enhances data visualization [139-141].
- BIM can provide comprehensive and accessible real-time information through the building life cycle [134, 141, 144].
- BIM can support other FM activities, such as market intelligence and satisfaction surveys [142], and prepare rental contracts [143].
- BIM can enhance building energy performance and occupant value [140, 145].

2.3.2 Application fields of emerging technologies within FM

Marocco and Garogolo [146] identified four main application fields of emerging technologies within FM, which include: information management, maintenance management, energy management and emergency management. In the same line, Matarneh et al [133] identified 7 research patterns in the field of BIM for FM: information management, opportunities for BIM in facility management, maintenance management, energy management, existing building audits and surveys, engagement of FM in design stage through BIM, refurbishment/retrofit, and health and safety management. Within the scope of the B4B, the applications for maintenance management and energy management are relevant. Information management can be considered within both energy and maintenance management.

Maintenance management

Maintenance can be reactive/corrective, programmed/preventive and predictive [51]. While the first one responds to a cause of failure or breakdown [147], programmed and predictive maintenance aims to act in advance to prevent possible deteriorations and failings [146]. There are two main challenges in maintenance management: automation and data integration.

Developments in this area focus on automatic detection and identification of potential operational faults by exploiting real-time data.

FMs with managerial roles are likely to interact with computer-aided facility management systems (CAFM) and computerized maintenance management systems (CMMS) to manage the characteristics of space and equipment [127]. On the other hand, FMs with operational roles are more likely to interact with building managements systems (BMSs) and energy management systems (EMS) to manage real-time information regarding spaces and equipment. Therefore, there is a need for the information from these different tools to be brought together more efficiently and effectively [127,148].

Current solutions include integrating BIM and FM systems' information using different technologies, such as semantic web technology, “to help maintenance personnel to efficiently track and control the whole maintenance management process” [149], and “integrating BIM and knowledge systems in a case-based reasoning module to enable maintenance information retrieval and knowledge sharing to solve maintenance problems” [147, 150]. Other attempts focused on developing automated approaches to define possible causes and retrieve related information to facilitate the process of HVAC troubleshooting [151,152].

Energy management

According to Marocco and Garogolo [146], current research on disruptive technologies for energy management focuses on real-time energy monitoring and assessing and optimising energy building performance. Within the B4B project we consider these applications as a single one since real-time energy monitoring is necessary to assess and optimise energy performance [146]. A review from Matarneh et al [133] showed that current studies focus on different approaches to implementing BIM in energy management, such as:

1) using BIM for monitoring, analysing and optimising the performance of systems and on developing and implementing an operational strategy;

2) building energy consumption assessment to support management decision-making, and

3) visualizing sensor data in 2D and 3D BIM environments to support energy-saving management decision-making.

Information management

According to Matarneh et al [133], BIM offers opportunities to improve facility management by providing a unified platform for various data sources needed for daily Operation and Management. However, the FM teams continue to struggle with information management, mainly because of the various FM information systems, which lack interoperability. According to Matarneh [133] the future research agenda involves:

1) integrating different energy information streams, including BIM models, to enhance the visibility of facility performance and to promote better energy management,

2) utilizing information collected by capturing actual facility energy data in BIM-based simulations for more efficient energy performance analysis to support energy retrofit decisions, and

3) identifying the required energy data from BIM models from an FM perspective.

2.3.3 Opportunities and challenges of emerging technologies within FM

The following opportunities and challenges of emerging technologies such as BIM, AI and IoT have been found in the literature:

Opportunities / advantages

- **Data entry efficiency** - **BIM** acting as a central data repository for the whole building’s lifecycle from design to operation and maintenance could eliminate redundancy in data re-entry ([128, 153].
- **Data accessibility** - **BIM** can increase the efficiency of work order executions by providing faster access to data and by improving the process of locating various facility elements [128, 154].
- **Data accessibility** - **GIS** applications can be used to access information [127, 155].
- **Data integration** – For BIM to be the basis for constructing digital twins requires data integration from other resources. **Cloud computing, BIM and IoT** technologies can provide high-fidelity operable datasets in real-time, allowing advanced analysis through **AI agents** [146].
- **Data integration/understanding** - BIM applied to operation and maintenance provides the ability to extract and analyze data for various needs that could support and improve decision-making [128, 156].
- **Data understanding** - Data visualization can allow the analysis and presentation of data using **computer graphics and interactive technologies** [157].
- **Data understanding** - Using **BIM** models plus appropriate **algorithms** instead of paper blueprints, FMs can reconcile real components with the corresponding three-dimensional models [157].
- **User engagement** - **Game-based systems** could be applied to FM activities to increase engagement for building managers [146].

Challenges / shortcomings of FMs activities

- **Awareness and skills** - Responding and repairing systems’ failures in a timely fashion remains a challenge for facility managers [128, 158].
- **Awareness and skills** - Lack of the technical skills to manage the systems in the operational phase. Modelling and maintaining the models, along with collecting and analysing accurate maintenance data need knowledge, competencies and processes which are not standard in the FM context [146].

- **Data understanding** - FM information systems lack interoperability and visualization capabilities ([128]).
- **Data integration** - Energy performance of buildings can deteriorate overtime because of lack of prompt response to faults/alarms reported by BAS and BEMS systems, imprecise commissioning, and BEMS/BAS malfunctioning ([128]).

Challenges / shortcomings of current systems

- **Awareness and skills** - Limited awareness of BIM benefits among facility management professionals, lack of data exchange standards, and unproven productivity gains illustrated by case studies, as well as lack of real cases for validating approaches and systems. [128,146].
- **Data accessibility** - Data about the exact locations of BEMS and BAS microcomputer systems, the equipment affected by them, and their maintenance history information are not stored in BEMS [128].
- **Data integration** - Computer Maintenance and Management System (CMMS) have their data structure that is not compatible with BEMS [128, 129] and often lacks the capability to communicate the output data and support the FMs specific needs (lack of inoperability, visualization, user friendliness) [128, 130, 131, 132].
- **Data integration** - There is a need to combine up-to-date and living data with static information. Computer Aided Design (CAD) systems cannot store and manage data as a centralised and unique repository and do not allow instant updates of all sources when some parts are modified [146].
- **Data understanding** - BEMS' and BAS' sensor outputs and performance metrics are presented in two-dimensional (2D) histograms, tables, and lists of tasks or in similar formats, which require manual and tedious data extraction and interpretation [128]

Challenges / shortcomings related to the deployment of Digital twin platforms

- **Data integration** – Different data collection devices store information into different formats and databases, leading to the issue of lack of interoperability and separated data silos [146].
- **Data understanding** - Visual outcomes in tables and graphs can facilitate the understanding and interpretation of data, especially for non-experts of data analysis [146].
- **Awareness and skills** - Considering the experience and knowledge of workers are critical to guide decisions but often neglected. Defining performance indicators for strategic decision methods based on data and worker expertise could be a topic of interest [146].

3 INPUT FROM A MARKET PERSPECTIVE

In this section, we report the findings from our interaction with market parties. Most of the information came from our partners in the consortium (see 3.1), but we also used the CLIMA2022 conference to gather information from stakeholders outside the consortium (see 3.2).

3.1 Input from the industry partners in our consortium

Input from the industry partners in our consortium was collected on various activities. First, a face-to-face workshop with partners was carried out to provide an overview of the interests, goals and current developments of the partners in the consortium and, more specifically, of the WP3 partners (see 3.1.1). Based on the workshop, we developed a questionnaire to be sent out to consortium partners to map out the current situation and objectives of the different partners, as well as to further define the use cases in WP3 (See 3.1.2). Furthermore, during the monthly WP3 meetings, relevant industry partners presented their products/services, followed by questions from other WP3 partners (also in 3.1.2). With these activities, we sought to answer the following questions:

- What is the current approach used by the industry regarding the role of occupants in the performance/management of buildings?
- How do companies consider the occupant in their product/services?

This information led to more in-depth interviews with several partners (See 3.1.3). The aim was to find out in more detail how the partners perform fault detection and diagnoses, energy prediction and optimization, and feedback to the end-user at this moment and what they might be looking for in the future.

In the following sections, we summarize the results of these activities.

3.1.1 Workshop

A workshop with consortium partners was organized during the first face-to-face consortium meeting in Delft, in November 2021. The workshop was intended to start a discussion with the project partners concerning occupancy data and its use in building control platform systems. The following questions were selected to be used via Mentimeter.

- What is the aim of your product/service?
- Who is your end user?
- What kind of occupant-related data do you use?
- What type of feedback do you give to the occupant?
- What type of feedback do you give to the professional end user?
- Which statement is closest to your philosophy?
- What are your (short-term) plans or vision regarding user-centric systems and interfaces?

First, the partners were asked about the aim of their product or service, and we provided 5 options, according to different topics identified for the B4B project: fault detection, energy management, building control, and energy flexibility. The results of the Mentimeter showed that most partners' products or services focus on more than one aspect.

> *Q1 - What is the aim of your product/service? Answers (N=10):* fault detection (2), energy flexibility (4), energy management (5), building control (4), other (3).

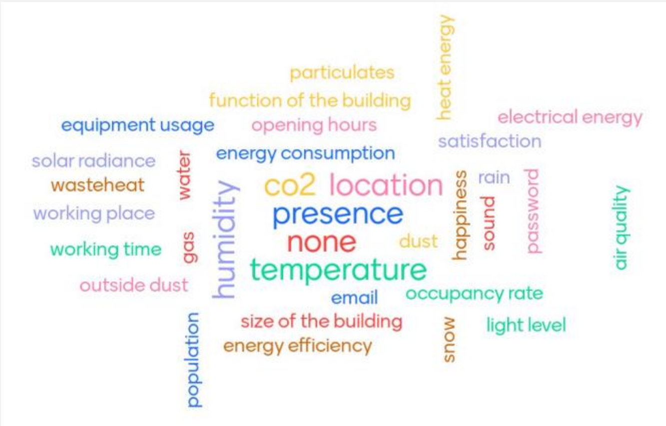
The second question was regarding the end user of the partners' product. With this question, we also intended to make clear that we are not only focusing on the end user as the building occupants. The possible answers were: facility manager, building manager (gebouwbeheerder), building owner, company owner, and building occupants. Just as the previous question, the results show that the products are intended to be used by more than one type of end user.

> *Q2 - Who is your end user? Answers (N=9): facility manager (5), building manager (gebouwbeheerder) (5), building owner (6), company owner (5), occupants (5), others (3).*

The third question concerned the type of occupant-related data used by the partners. In this case, the participants were left free to use any word they wanted, which resulted in the figure below. The results point at some differences in what is considered occupant-related data. The words used can be categorized as indoor parameters/conditions (particulate matter, CO2 level, sound, temperature, light level and humidity), external conditions (solar radiance, rain, snow, particulate matter), building information (function, size, time schedule, workplaces, occupancy), resources consumption (heat, gas, water, electricity, equipment usage), occupants' feedback (satisfaction and happiness) and personal data (email, passwords).

The answers showed that most often, data collected is only indirectly related to the user (indoor/outdoor conditions and resource consumption). The only direct aspects considered are the presence of occupants in the building (occupancy), and satisfaction/happiness.

Q3 - What kind of occupant-related data do you use? N=16



The next two questions were about the type of feedback given to the end users, starting with the occupants. The responses were very varied from changing behaviour (i.e. through gamification, positive feedback, suggestions on how to adjust energy consumption behaviour and compliance reporting) to visual feedback on wellbeing (i.e. happy faces) based on the state of the building (CO2, air quality, etc.). The means to reach the occupants were also mentioned, for example push notifications and specific information in occupants' screens (e.g. screens in meeting rooms).

Q4- What type of feedback do you give to the occupant? N= 9

- *Not just straight data. Data linked to outcome on a screen. Meeting room and other screens are ideal.*
- *Badges and awards*
- *How to adjust energy consumption behaviour*
- *None*
- *Well-being index including simple gauges or happy faces on air quality, CO2 and so on.*
- *Positive feedback on the impact they have had on energy and carbon saving and a reduction in a climate change rate.*
- *Push notifications*
- *Compliance reporting.*

The last question focused on the feedback provided to a professional end user (facility manager, building manager (gebouwbeheerder), building owner, company owner). The answers indicate that the feedback provider is about 1) regarding information about the building itself and its installations, the status of installations, 2) the performance of the building (energy efficiency related to target, normalized benchmarking, compliance reporting), and 3) strategies to improve the performance outcomes.

Q5- What type of feedback do you give to the professional end user? N=9

- *Building use. Installation type.*
- *Status reports of the installations*
- *Data monitor*
- *None*
- *Insights on how to improve based on targeted outcomes*
- *Energy efficiency related to target*

- *Compliance reporting*
- *Normalized benchmarking*
- *Business case of measures*

During the discussion of these two questions, the partners discussed the shortcomings seen in their own products/services. The main problem faced was that the end-users do not always use their platforms as intended.

3.1.2 Questionnaire and workshop presentations

During the WP3 meetings, industry partners were asked to talk about their products/services, as well as their ambitions concerning the B4B project. Furthermore, a questionnaire was sent to WP3 and other relevant partners with the same questions. The following information comprises a summary of five industry partners. Figure 1 shows an overview of the characteristics of the partner's systems.

Client, main end-user and use by end-user

A difference has been made between the client of the companies (the party who pays for the product or service), and the final end-user. Within this project, we consider the main end users to be either the facility managers or the occupants of the buildings (i.e., the office workers).

The questionnaires and the presentations/interviews with partners showed that the client for most partners were the real estate/building owners, and in one case, the project developers. The main user falls in two categories: the real estate/building owners, and the facility managers. None of the partners focuses on the building occupants as end-user for their product or service.

Feedback/info to the professional user

The professional users are, in all cases, the building owner or the facility manager. The companies (all except Peutz) offer different dashboards for different users. Some dashboards can be customised according to the needs of the end-user. The information in the dashboard/platforms fall within all studied purposes: FDD, asset management, energy production, systems control, and so on.

Model for energy prediction and rule-based algorithms to analyse data

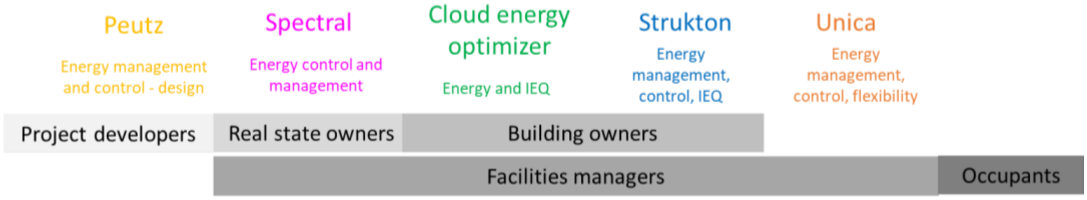
Both white box and (AI-based) black box models are used to predict energy use, energy productions, system setpoints and indoor conditions.

How is occupants-related data collected?

Only two partners currently collect data directly for the occupants (Unica and Spectral). The data collected, via email or apps consists of complaints and satisfaction with the indoor environment. Strukton is currently developing and testing a Mood Box also to gather data from the occupants. The occupants' data is used for better management of the building in terms of energy efficiency and/or comfort. While Spectral makes use of the occupants' data for better energy efficiency, Cloud Energy Optimizer only makes use of indoor environmental data to predict indoor comfort. Strukton and Unica use both types of data (indoor environment and occupants) for both purposes (energy and comfort).

Feedback/information to and from the occupants

As mentioned before, only three companies collect data from the users: Unica, Spectral and, in the future Strukton. These data are mostly related to satisfaction with the indoor environment and complaints. On the other hand, the only company whose systems communicate back with the occupants is Unica, which thanks the occupants for their input. None of the partners currently have a direct interface to communicate with the occupants.



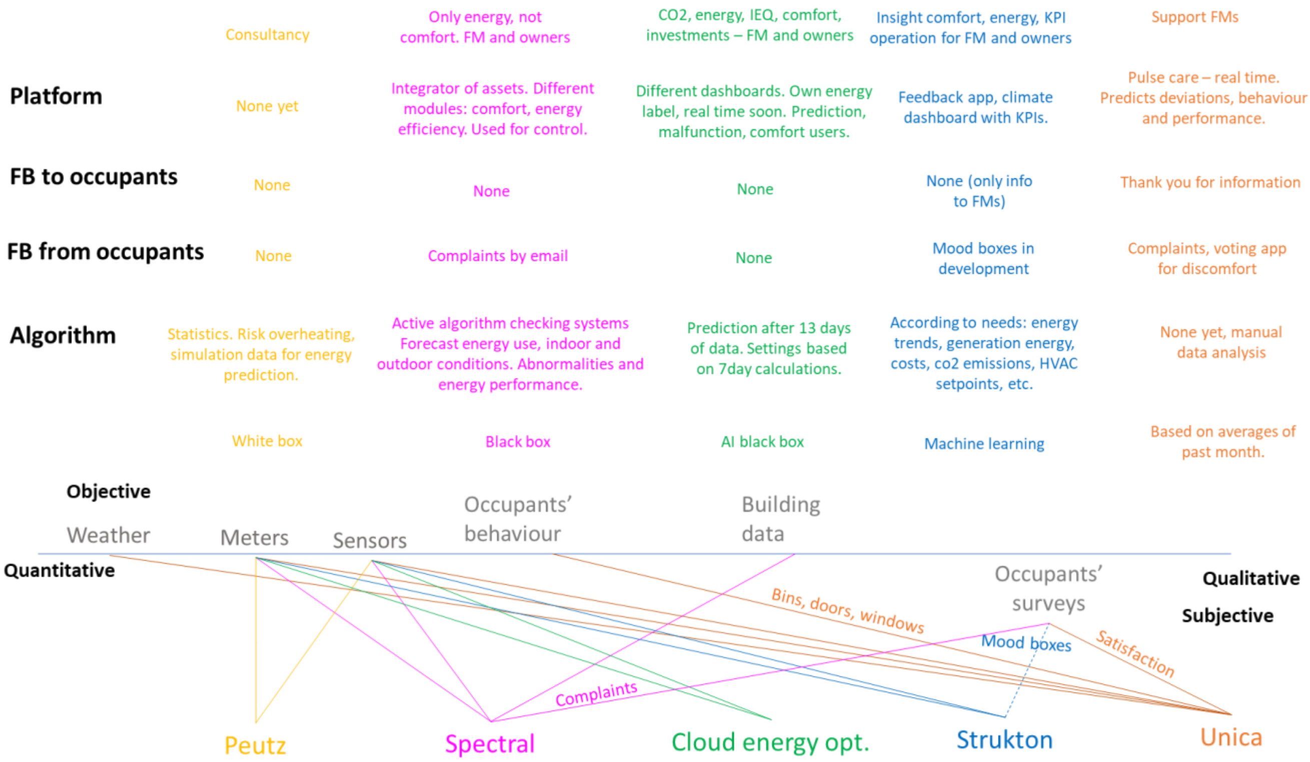


Figure 1 Characteristics of B4B partners' products/services

3.1.3 In-depth interviews with the industry partners

This section describes the results from interviews with B4B partners on end-user requirements for fault detection and diagnosis and energy flexibility control systems and interfaces.

TNO conducted a series of interviews with B4B partners to add input to WP1 and WP2, and obtain information regarding interaction with interfaces for WP3. When analyzing these results, it should be considered that interviewed partners have clients with buildings ranging from big utility buildings to small and medium enterprises (SME) buildings and focus on clients with different levels of (building-) knowledge. The input from the partners was analyzed and this resulted in a summary matrix. The summary matrix can be found in Annex 2. From the summary matrix the following conclusions were derived:

The aim of the product and services of all partners is energy and comfort optimalisation. Additionally, (energy)-reporting, building insights (e.g., occupancy of spaces), and fault detection are often named alongside this. End-users of these partners' platforms and services can be grouped into the facility/property managers level (Unica, SPIE, Simaxx) and the building owners' level (Cloud Energy Optimizer, O-nexus). The interviewed partners primarily use dashboards to serve end-users regarding consultancy and control. Specifically, Spectral is working towards flexible dashboards for building owners and facility managers. On the other hand, O-Nexus' end-users amount to SME buildings and facility managers that are not specifically targeted.

For some partners' clients, the key selling points are approximated promised energy and cost savings (Cloud Energy Optimizer, O-Nexus). In contrast, others mention reducing the man-hours of facility managers (Spectral), reducing the initialization time of installing external building control (Cloud Energy Optimizer), or combining data streams and portals into one place (Unica) as their key selling point. Besides, most partners mention that tenant occupant comfort is an added benefit to their primary business.

Regarding fault detection and diagnosis, all interviewed partners perform fault detection via rule-based systems based on operating-ranges or trends.

Prediction models for optimizing energy primarily comprise data-driven black-box models. Cloud Energy Optimizer and Spectral include physical properties like return temperatures of Air Handling Units (AHU) and the thermal mass of buildings as input for their models. Furthermore, Spectral uses Energy+ to generate synthetic dummy/training data to tune their energy black box prediction models. If data is not sufficient, usually extra sensors are placed. Additionally, it is often mentioned that the biggest uncertainty in these models is occupant behaviour.

Occupant-related data is either inferred from submetering, like time schedules, space utilization, room reservations (SPIE, Simaxx, Spectral), from directly measured parameters like tap-water and electricity use (O-Nexus) or return temperatures of the AHU (Cloud Energy Optimizer). Extra occupancy-related sensors are sometimes placed, such as infrared sensors (O-Nexus) and motion sensors (Spectral). Third-party reservation apps are also looked at to gather occupant-related data. Moreover, the occupancy data is also sometimes integrated as input for the energy-prediction model (Spectral, O-Nexus, CEO).

Occupants and sensors do not always live

Feedback to professional end-users occurs via dashboards, whereas feedback to building occupants is currently not performed. However, SPIE does use narrow-casting by showing building performance on monitors in certain spaces.

Feedback from occupants to the partners' systems is gathered via ordinary complaint handling by email/customer service software (Cloud Energy Optimizer, Spectral). This complaint handling is, however not yet used in energy prediction models or fault detection. On top of that, SPIE is currently testing mood-boxes to receive user feedback, and Unica is testing a QR-scanning feedback app with 5 questions about comfort, coupled with sensors in that room.

Most interviewed partners are generally interested in having insights into the relationship between perceived and measured comfort. Here, the relationship between occupant satisfaction and realizing economic savings (Cloud Energy Optimizer) by determining comfort ranges to save energy is mentioned as a solid business-incentive.

Additionally, SPIE would like to stimulate occupants to provide feedback and would like to have automated improvements based on feedback values and energy flexibility opportunities. One mentioned value-proposition from a comfort improvement could be that tenants are likely to stay longer in buildings (Spectral). In line with this, O-Nexus would like to see a robust connection between occupant experience of comfort and data already present in a building, such as setpoint changes, expecting to see a correlation between e.g. setpoint changes and the occupant and their behaviour.

In sum: The interviewed partners perform fault detection and diagnosis based on rules (rule-based) of indicators such as sensor ranges and trends. Furthermore, energy prediction and optimization are performed using black box models using the available building sensors. Here, some partners opt for a minimal sensor approach to reduce costs, whereas other partners prefer placing extra sensors to collect more data to achieve more accurate insight/control.

The partner's user interfaces provide feedback to the occupant on a high-level (narrowcasting) or not at all. In contrast, feedback to the professional end-user is typically not used yet. Regarding the occupants, there exists a general interest in user models. Specifically, partners are interested in exploring the relationship with perceived comfort to determine comfort ranges to use for energy flexibility and comfort optimalization.

3.2 Input from a wider audience

We benefited from the opportunity to discuss the market perspective with a wider audience at the CLIMA Conference 2022 in Rotterdam. During a 2-hour workshop on May 23, a group of around 30 participants discussed the need for more interaction between building energy systems and the users of the building during the session: "Smart buildings & interfaces for managers of buildings and facilities, and intelligence needed for occupant-HVAC interfaces at room level". The session was hosted by Mirjam Harmelink (TU Delft), Marleen Spiekman (TNO), Sander van der Harst (Unica) and Frans Joosstens (HHS). Present during the session were facility managers (2), installation and design engineers (8), representatives from academia (19) and participants with other backgrounds (3). The discussion covered two topics:

– Information and interaction for end users, facility managers and designers (3.2.1)
– And the role and design of feedback (3.2.2)

3.2.1 Input on information and interaction for end users, facility managers and designers

During the workshop, stakeholders provided input via a Mentimeter session on the following two questions:

– What information do you need to ensure that the building is energy efficient?
– What interaction do you need with the building?

Because some stakeholder groups were overrepresented and others were underrepresented, we asked all participants to put themselves in the position of a facility manager, a design engineer and an end-user and answer the questions accordingly.

Facility managers

In the result of the *information* needed by the facility manager, the following information pops out (see Figure 2 for the whole overview):

- Occupancy
- Energy consumption
- Benchmark
- Temperature
- User satisfaction
- Energy usage
- Real-time data dashboard

Figure 2: Mentimeter result of the question: Put yourself in the position of a facility manager. What information do you need as a facility manager to ensure your building is energy efficient?

It must be said that there were only two facility managers present, so most of the data come from participants that think this is what facility managers need. Based on these results, a real-time data dashboard with information on how many people are in the building (and where), the energy consumption and temperatures in the various rooms were seen as useful, probably this type of information could be used to have a good overview of the building performance (energy and indoor quality) in relation to the number of occupants. Accompanied by benchmarking on when energy consumption and temperatures are fine and when more attention is needed and accompanied by information on user satisfaction which also could indicate the need for attention.

In the result of the *interaction* between facility managers and buildings that facility managers could help, the following information pops out (see Figure 3 for the whole overview):

- As little as possible
- Error messages

Figure 3: Mentimeter result of the question: Put yourself in the position of a facility manager. What interaction do you want with the building?

Most of the input given by the participants was actually on information from the building or systems, not on interaction with each other. This is consistent with the lack of need for interaction (‘as little as possible”). Either there is no wish for interaction between the building and the facility manager, or the added value of interaction is not yet clear. Both options are plausible: during the discussion, we learned that facility managers have many tasks and handling the energy use of the building is often not their highest priority. That can explain the feeling that no interaction is wanted since that would mean attention that can’t be given elsewhere. On the other hand, interaction with the building could mean that problems are more easily solved, so also less time is needed for this.

Installation and design engineers

In the result of the *information* needed by the installation and design engineers, the following information pops out (see Figure 4 for the whole overview):

- User feedback
- Occupancy
- Sensors – monitoring
- Installation performance

These findings show a wish for both information based on monitoring with sensors and information directly from the building users. How many, when and where users are present in the building, clearly is an important aspect for engineers to control indoor comfort. And also, to monitor the performance of the systems seems an important factor.

Figure 4 Mentimeter result of the question: Put yourself in the position of an engineer at an installation company. What information do you need to provide a good indoor climate comfort?

In the result of the *interaction* between installation and design engineers and buildings that installation and design engineers could help, the following information pops out (see Figure 5 for the whole overview):

- Occupancy
- User feedback
- System performance

Figure 5 Mentimeter result of the question: Put yourself in the position of an engineer at an installation company. What interaction do you want with the building?

It is striking that these results are similar as when asked about what information was needed. Most of the input from participants were related to information instead of interaction. So maybe also here the concept of interaction and the added value of it is not yet clear.

End-users (office workers)

Finally, we asked the participants so put themselves in the role as end-user. In the result of the *information* needed by the end-users, the following information pops out (see Figure 6 for the whole overview):

- Feedback
- Possibilities (action perspectives)
- Respect

It is clear that end-users like feedback. The most prominent feedback they want is feedback on possibilities, which could be interpreted as the action possibilities for adapting the building to their comfort wishes. The more detailed input gives a lot of aspects that might be additional helpful feedback to end-users, such as current energy usage, CO_2 and the effect of setpoint change. 'Respect' could be interpreted as: the building should have respect for the wishes of the end-user. As opposed to what is often heard: "the user just should not do that". Combining this all: it might be helpful that an end-user gets feedback on alternative possibilities for action to reach the desired comfort instead of actions that result in a less efficient or effective situation.

Figure 6 Mentimeter result of the question: Put yourself in the position of an office worker. What information *do you need to contribute to a building which is energy efficient and healthy?*

In the result of the *interaction* between end-users and buildings, the following information pops out (see Figure 7 for the whole overview):

- None
- Comfort
- Control
- (Possibility for) feedback

Figure 7 Mentimeter result of the question: Put yourself in the position of an end-user. What interaction do you want with the building?

That no interaction is desired could be interpreted from the perspective that end-users think that the building should handle the indoor climate by itself and when it does a good job, no interaction is needed. This makes sense realizing that office workers are at the office to work and not to be troubled with controlling the building. There are others that state they like interaction on comfort at their workplace an on the control of their indoor climate. Feedback that goes two ways might be a way to enable this.

3.2.2 Input on the role and design of feedback

In addition to the Mentimeter questions, we also held a post-it session.

We posed 5 questions and asked the participants to stock post-its with their ideas. The post-its were color-coded: blue for facility managers, purple for installation and design engineers, yellow for academics and green for others. An example of the result is given in Figure 8.

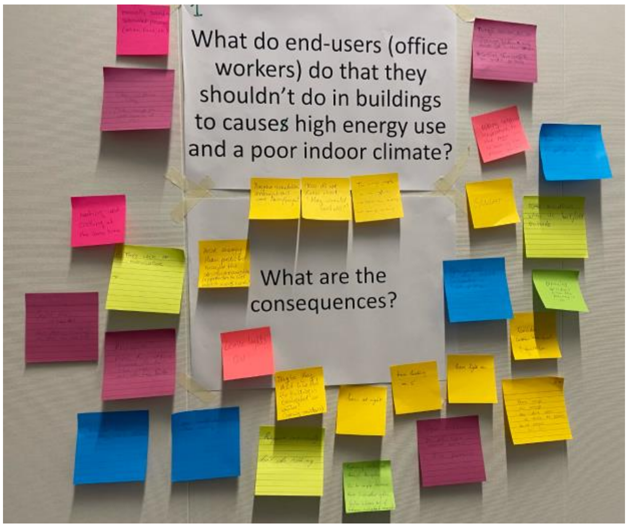


Figure 8 example of the post-it session result.

The questions and post-it content are given in the table below.

Table 2 Post-it content on the workshop questions

1 What do end-users (office workers) do that they shouldn't do in buildings which causes high energy use and a poor indoor climate? And what are the consequences?	
Facility managers	Open windows to 'solve' outside condensation on triple glazing Block doors so they can't close Open the window when it is hot outside; it is getting hot inside
Installation/design engineers	Heating and cooling at the same time Wear insufficient clothing Make changes for short amount of time Manually overriding automated processes (valves, fans, etc.) Upping setpoint temperature to the max, just to heat up the room quicker Forgot devices, AC on Opening windows and doors for hidden smoke Setting thermostats on the max or min Open windows Do not care about systems Give feedback Fight over thermostat Leave heating/cooling on when not occupied Leave lights on Disagree: people do something because they don't like something: it is not their fault! Open sunshade when cooling
Academics	Open windows when it is hot/cold outside Too many people in an office: bad air quality opening windows How do we know what 'they should do"? Maybe simulation assumptions where insufficient? Respond internally: don't do anything Turn heating on 5 More energy than predicted. Maybe the design assumptions do not match user's needs Consider same individual preferences Heat at night Don't change any setting. They don't want to touch the system No one present but lights on Maybe they don't like that the building is overheated in winter? (Opening windows) Sweat They lack knowledge

Others	Opening windows when the heating is on Bypassing control, not through the system. Can be simply because there is no other option. System is thrown out of balance and starts compensating
2 How could we avoid these unwanted situations? By what means?	
Facility managers	Provide insight in control of the building Instruction Not allowing different scenarios
Installation/design engineers	Teach/train users, workshop Info dashboard Creating better buildings Energy use indicator at the thermostat On/off schedule to prevent unoccupied heating and cooling Display impact Training Information Automation User feedback Don't build windows in a way that the user can open them Assure a comfortable indoor climate: if users feel comfortable they won't touch anything
Academics	Real time occupancy monitoring (to limit wasted energy) Occupant -centered ventilation strategies To give meaning To promote a challenge between end-users Post messages on a wall Design installation to purpose occupants Fast feedback on user actions More m2 per worker, fewer desks / chairs per office, system of higher capacity Easy to read, real time, infographics on energy feedback environment impact informing Show real time energy bill (cost) to end users Better informing users about the building systems Information Usable buildings Expectation management Use automation to switch off
Others	Information at once Let users define comfort Give users control through the climate system
3 How do we provide effective feedback to the building occupants?	
Facility managers	Desk or pc inbuild dashboard
Installation/design engineers	VR? Dashboard simple no technical Someone will ask them Screens on meeting points Periodic surveys Feedback. What is good IAQ what is bad IAQ Simplified infographic Projection of impact if everyone does the same Information in dashboards
Academics	Warning sigh + suggested action Simplified reports, graphs, schemes Semaphore light red, orange, green Realtime data drive dashboard Digital communication + face to face communication Occupant personal history with the building to rase awareness Avoid; you should not... Suggest an action based on the measured metric Behaviour recommendations which reply to actual real needs Feedback on what the building does Offer a guide to 'diverse' environments 'try the atrium its fresh and cool'
Others	Via an app or edge device Insight in their own data coupled to objective measurements Benchmarking By email
4 What are the requirements for user-interfaces?	
Facility managers	Simple to use User friendly Explanation about what you see If you can fill in value's; an example of what the value could be
Installation/design engineers	Human centered design No room for wrong choice (prevention by design) Simple Easy to connect Fast working In the future with mobile app Remotely connected
Academics	Easy interpretable (not 1500 ppm, but: bad) Easy usage

	Usable for lay persons No information overload Situated in daily practices (cooking e.g.) Tuned to user knowledge See e.g. CANAIRI.IO Standardized Good indictor Simplicity Build on existing knowledge and skills Ergonomics Challenging Targeted to actual needs of user Related to user aims (e.g. find a comfortable room) Feedback Know the targeted users' activity: this affects how to operate the interface
Others	(no input given)
5 When do user-building interfaces become a business case?	
Facility managers	When you can provide comfort as a service
Installation/design engineers	When they are stable/reliable/resist long enough to output learning Link it to the performance of the employees Integrated with BMS and energy management Scalability Easy to install Cheap
Academics	When personalized IAQ technology is in place When its application is generating economic profits (on the long-time) (e.g. higher satisfaction and productivity, lower energy expenditure More productive workers Low energy costs More maintenance instead of replacement When they are still effective after one year Occupancy complaints When we understand how to deal with individual preferences of occupants' effective operation
Others	Whenever money comes into play

The input from the post-it session gives us information that is very useful in a later stage of the project when we will design feedback to end users:

- It provides us with many situations based on the participants' experience where users and building systems interfere with each other, or where due to lack of knowledge users act less effective than they could (such as: heat at night, open window when it is too hot outside, so it gets hot inside, upping temperature to the max to heat up the room quicker, opening windows when the heating is on)
- It provides us with ideas how this could be helped by feedback to users (such as: expectation management, real time information, fast feedback on user actions, to give meaning, provide insight in the control strategy)
- Gives us ideas about how to give feedback (such as: via app, simple dashboard, with semaphore lights (red, orange, green), warning signs + suggested action, benchmarking)
- Gives us input for requirements for user interfaces (such as: simple to use, explanation about what you see, tuned to user knowledge, related to user aims, a nice example see: CANAIRI.IO)
- Gives us ideas about when user building interfaces become a business case (such as: when they can provide comfort as a service when they are stable/reliable, easy to install, cheap, when it leads to more productivity when they lead to fewer occupant complaints

Visual feedback: If CO_2-levels are too high, the canary will 'die' and fall down from its stick.

On the last topic (when does it become a business case) we had an additional discussion. The most interesting remarks during the discussion were the following:

- How do you measure the success of feedback?
- Improvement of productivity
- Do you measure negative impact or positive impact: e.g. happiness?
- Don't give feedback too often
- Climate is something people do not notice when it is good enough
- The explanation why the situation is as it is or why it is not possible what you want: manage expectations
- Feedback can show what is not there and where the system will lead to (e.g. when the system reacts slow)

- Facility managers have a lot of tasks and no time to interact with the building.
- Every building is different, feedback system needs to be flexible
- Users do not want too much interaction: they are in the office for other reasons

Part of these remarks will be taken into account in further phases of the research activities of B4B project.

3.2.3 Conclusions from the CLIMA2022 workshop:

The CLIMA 2022 workshop was a big success and gave us a lot of input for designing feedback systems for professionals and end-users.

Firstly, we learned that facility managers have many tasks, so they don't have time to investigate energy and comfort. They want to solve problems quickly, preferably by calling someone. So, there may be more demand for a service that anticipates problems or tracks things down for them than for them to do it themselves. Since there were not many facility managers present, it is unclear whether this applies to all facility managers or whether it is different for large companies with specialised departments dedicated to this.

Installation and design engineers are most helped with information on specific system performance via sensors and user feedback about their comfort.

End-users could be helped by getting information on their option: when they are not happy, what are their options, and what would be the consequence of these options?

The feedback design could gain when it focuses on situations where users and building systems interfere with each other or where, due to lack of knowledge, users act less effectively than they could. Possible feedback could be focused on expectation management, real-time information, fast feedback on user actions, giving meaning, providing insight into the control strategy etc. And it would probably work best when it is simple to use; there is an explanation about what you see, and it is tuned to user knowledge and related to user aims.

4 CONCLUSIONS

Occupant-related data and occupants' behaviour models to facilitate building management and control

The literature study showed that many occupancy models have been developed to integrate different types of occupant-related data into building control and performance models. However, the investigation with companies shows that these models are not yet currently used in practice.

The interviewed companies currently gather some occupant-related data, but the use of the data is still limited to satisfaction with the indoor conditions or complaints about it. However, some partners are working towards gathering better user experiences in the buildings, for example the Mood Box in development by Strukton, and the plans from O-Nexus to understand occupants' satisfaction and mood through the analysis of existing building data.

The interviewed partners perform fault detection and diagnosis based on rules (rule-based) of indicators such as sensor ranges and trends. Furthermore, energy prediction and optimization are performed using black box models using the available building sensors. Here, some partners opt for a minimal sensor approach to reduce costs, whereas other partners prefer placing extra sensors to achieve better data for their models.

The partner's user-interfaces provide feedback to the occupant on a high-level (narrow casting) or not at all. In contrast, feedback to the professional end-user is typically not used yet. Regarding the occupants, there exists a general interest in user models. Specifically, partners are interested in exploring the relationship with perceived comfort to determine comfort-ranges to use for energy flexibility and comfort optimalization.

Feedback interfaces for building occupants

For the state of the art, scientific articles related to the use of feedback interfaces were sought. The investigation showed that although interfaces for building occupants are considered promising to decrease energy use through understandable information for users, there are still many limitations to their use, mostly related to their validity, replicability, and acceptance.

On the other hand, the interfaces (dashboards and platforms) developed by the B4B partners involved in this study mostly focus on providing information to the facility managers and the building owner. Thus, they focus on energy and indoor environmental quality (IEQ) control and building performance. Partners seem interested in collecting more self-reporting data from occupants, for which the development of interfaces to collect such data are in development. However, none of these partners aim to focus on interfaces to provide information to the occupants of the buildings.

The results from the Clima workshop with academics and practitioners identified similar requirements for the occupants' interfaces as those found in the literature, such as the need for more understandable, accessible, and easier-to-read interfaces for the layperson.

Interfaces for facility managers

The state of the art study on interfaces for facility managers focused mainly on using BIM and other emergent smart technologies, their opportunities and challenges. These technologies are seen as having great potential in increasing the effectiveness of FMs work and improving building performance. The main shortcomings of these technologies to support FMs are the lack of data integration and accessibility to data, lack of clear and understandable information, and lack of awareness and skills in the industry to use these technologies. These challenges were in line with the requirements identified during the workshop at the Clima conference. Further research will be aimed at working with FMs to determine these requirements.

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APPENDIX 1 –QUESTIONNAIRES

Added in pdf

APPENDIX 2 – IN-DEPTH INTERVIEWS

Summary of the results of the in-depth interviews with the industry partners

	1. Products and services	2. Aim of products	3. End user	4. Key selling point
Cloud energy opti	energieoptimalisatie (congestiemanagement) en predictive maintenance	energie en kostenbesparing, comfortoptimalisatie	gebouweigenaren en vastgoedbeheerders	20% energiebesparing, tijdsbesparing zelf inregelen gbs systeem
Strukton	Gebouwprestatie analyse platform met consultancy diensten. Foutdetectie middels sensordata.	Gericht op comfort en energiebesparing, asset prestatie (installaties) en predictive maintenance, fout detectie en diagnose en energie management	Facility manager, property manager en facility tenants	Building value, having insights and consu
Simax	Simax is a software as a service cloud based analytics platform that use historic data and data models of mechanical equipment. The basic architecture is around abstract models of mechanical equipment: boilers, chillers, hvacs etc.	To provide useful insights to end user costumers. Using KPI's to indicate the performance of a building.	Operationmanagers, facilitymanagers	energy monitoring, predictive maintenance, providing a cloud infrastructure.
Unica	Een feedback app (gekopped aan Buliding Inisght) en occupancy/climate model. Unica heeft op dit moment Living labs draaien om informatie (alle soorten gebouwedata komt hier binnen: bezetting, temperatuur, bevochtiging, energieconsumptie, waterconsumptie, etc.) te vergaren om die modellen te gaan ontwikkelen.	Momenteel kijkt Unica hoe gebruikers bepaalde waardes ervaren, om een bandbreedte te kunnen bepalen als veilige marge om iets met de installatie te kunnen gaan doen. Dit zou vervolgens gebruikt kunnen worden voor energieflexibiliteit. Ook zou dit gekoppeld kunnen worden aan een binnenklimaatlabel.	Eindgebruikers zitten op facility management niveau. Daarnaast zijn de klanten ook gebruikers van gebouwen, waarbij de focus nu is op utiliteitsgebouwen. (kantoorpanden en multi-use panden).	Het creëren van extra inzichten voor het gebruik van consultancy tak van Unica. Facility managers hebben vaak 20 verschillende portalen om in te loggen. Building insight geeft overzicht en doet daarnaast anomaly detection (of er in bepaalde processen iets verkeerd gaat). Daarnaast maakt het energiereportages.
Spectral	GRESB reporting, predictive energy optimization, abnormality detection	Reporting, energy-optimalisation, comfort optimalisation, anomaly detection	building owners and facility managers (flexible dashboards for both)	Reducing amount work facilitiy managers. Saved energy consumption. Making building more comfortable for tenants. Predict system faults
O-Nexus	O-Nexus analyseert historische en actuele gebouwdata door middel van black box modellen en optimaliseert daarmee energievraag en comfort van (MKB) gebouwen. O-Nexus bepaalt alleen wanner energie gebruikt moet worden en past regelsystemen niet zelfstandig aan. Aansturing gebeurt doorgaans met weerstandsapparaten, bv warmtepomp. Deze gebouwen hebben geen gbs (bv brandweerkazernes, kleine kantoortjes), waardoor de installatie zelf	Energie en comfort optimalisatie van (MKB) gebouwen	In het algemeen gebruikers van de gebouwen (grotendeels MKB gebouwen)	Energiegebruik sturen om circa 30% energie te kunnen besparen. Door energieverbruik in de tijd te verleggen, kan zelfconsumptie worden vergoot van 30 tot 60%.
Summary	*The aim of the products of all partners is energy, cost and comfort optimalisation. Additionally, (energy)-reporting, building insights, and fault-detectection are often named along side this. End-users of their platform and services can be grouped into the facility/property managers level (Unica, Strukton, Simax) and the building owners level (Cloud Energy Optimiser). Spectral's targets both groups and is working towards flexible dashboards for both building owners and facitlity managers. O-Nexus end-users are MKB buildings. For these clients the key selling points are sometimes quantified/approximated energy and cost savings (Cloud Energy Optimiser, O-Nexus). Others mention reducing man-hours of facitlity managers (Spectral), or combining datastreams and portals into one place (Unica) as their key-selling point. Most partners mention that tenant comfort is an added benefit.*			

	5. Which model for energyprediction	6. which rule-based algorithms	7. is data sufficient, or extra physical relation needed	8. knowledge gaps
Cloud energy opti	blackbox op basis van thermische energie van de lucht en thermische massa	boundary rules voor foutdetecties	Ja, alleen relatie thermische massa en restwarmte is enige	Ontbrekende relatie tevreden houden klanten en toch economische besparing halen
Strukton	data driven models in combination with occupancy, control data and weather data	Yes, there are a lot of algorithms based on expert rules based on a variety of data from the BMS, comfort data (external sensors), such as: are setpoints being reached, availability, integral performance,	Nvt	Nvt
Simax	Data driven model using the abstract mechanical equipment models at its core.	rule-based algorithms to check whether equipment operates within a range are used for fault-detection	Physical relationships could be added, but are currently not a constituent part of the data model.	User occupancy is currently not an area of focus for Simaxx, but would require a relation between perceived and measured comfort.
Unica	Ja, gebaseerd op gemiddeldes van afgelopen tijd. Op dit moment worden er geen gebouwmodellen gebruikt	Ja, dat zijn op dit moment eenvoudige modellen voor foutdetectie, rule-based. Dit betreft energieconsumptie afgezet tegen de bezetting in gebouwen.	Nvt	Nvt
Spectral	Energyprediction: lightweight data-driven model, using energy+ for extra dummy/training data. Fault-detection by changes in of abstract coefficients of AHU	A rule/trend-based model is used for fault-detection.	If data is not informative, Spectral places its own-sensors: motion sensors, temperature, humidity and illumination and CO2	Standardization of occupant related data and modelling.
O-Nexus	Ja, black box model met een minimale set aan parameters.	Ja, er worden regels gebruikt voor het bepalen van redelijke waardes waarin sensorwaardes zich doorgaans moeten bevinden.	O-Nexus probeert met zo min mogelijk data een zo goed mogelijke voorspelling van energiegebruik te maken. Daarvoor zijn de aanwezige sensoren vaak afdoende, en liggen de grootste onzekerheden in gebruikersgedrag.	Nvt
Summary	*Models from energy prediction are primarily data-driven black-box models. Cloud Energy Optimiser uses thermal air-energy and thermal mass of building. Energy+ as dummy/training data. Rule-based for fault detection: sensor ranges, trend-based model. If data is not sufficient, usually extra sensors are placed, biggest uncertainty in user behaviour (O-Nexus)*			A knowledge gap is the relation between perceived and measured comfort.

	9. Occupancy related data	10. How collect user related data	11. How is occupancy data used in model	12. What feedback/information to professional end-user
Cloud energy opti	Occupancy bepaald uit restwarmte. Meer data betaalt zich niet uit	Nvt	Met restwarmte wordt blackbox model getuned	Operatiestatus gebouw in vorm van dashboard
Strukton	Yes, occupancy related data is gathered from space utilisation, room reservation & work space reservation data from third party.	Occupancy sensors (counters, pir), second-party reservation apps, (work orders based on comfort complaints)	Occupancy related data is presented in a dashboard and in energQ for energy assessment.	We can provide this information through narrow casting.
Simax	Typically, information of BMS is used such as timeschedules. Simaxx is now looking at presence detection in the form of desk utilization and room utilization together with Xovis (a people-flow monitoring company). This could be used for example to optimizing cleaning schedules to create value for the end user.	Currently via BMS only.	There exists no user-satisfaction feedback at the moment.	The end-user has access to a dashboard.
Unica	Nvt	Voor de living labs wordt zo veel mogelijk data vergaard. Daarna gaat gekeken worden wat de set aan data is die relevant is voor gebruikersgedrag.	Nvt	Energieverbruik en huidige gebouwprestatie (via building insight).
Spectral	Motion sensors used as additional input for model. Also submetering like monitor use	Submetering	Integrated as input in energymodel	Dashboards with technical and historic data visualizations.
O-Nexus	Door de historie van een gebouw met haar gebruikers in te leren kan de energievraag voorspeld worden. Hierbij wordt bv een lichtschakelaar ook als gebruikers gerelateerde data gezien, alsmede het electriciteits en tapwater gebruik. Hierbij wordt gebruikersgedrag meegenomen in de voorspelde energievraag (zelfs als er vaak met verwarming en open ramen wordt gewerkt).	Ja, door het plaatsing infraroodsensoren kan een beter beeld van daadwerkelijk gebruikers-aanwezigheid worden geschetst. Echter is verwarming/koeling doorgaans te traag om op gebruikers-aanwezigheid te sturen vanwege de traagheid. Een koppeling met aan agenda is in de realiteit doorgaans niet een betrouwbare optie.	Dit zit doorgaans in het black box model zelf. Door extra sensoren wordt het systeem minder robuust.	Alle relevante informatie beschikbaar in het dashboard. Het liefst wil O-Nexus zo min mogelijk actie vereisen van de end-user.
Summary	*Occupant related data is either inferred from submetering, like timeschedules, space utilisation, room reservations (Strukton, Simaxx, Spectral). O-Nexus gebruikt tapwater electriciteitsverbruik, lichtschakelaars also as occupancy related data. This way occupancy is incoorportated in predicted energy-use. Placing extra sensors: infrarood sensoren (O-Nexus), motion sensors (Spectral). Thrid party reservation apps are also looked as for occupant-related data. Cloud Energy Optimiser uses risidual heat as occupant related data. Occupancy data is integrated as input in energymodel (Spectral, O-Nexus).*			*Feedback to professional end-user is usually occupants: currently none. Strukton uses narr groups: ordinary complaints (Cloud Energy O scanning feedback app with 5 questions abou*

	13. Feedback of system towards occupants	14. Feedback of occupants to system	15. Short term vision user centric interfaces	16; Other active development plans or WP3 ideas
Cloud energy opti	Nvt	Registratie klachten (vaak onbetrouwbaar gevonden)	relatie tussen tevredenheid van bewoners en het halen van economisch besparingen. Marktbreed en schaalbaar op basis van waargenomen comfort	Nvt
Strukton	At the moment not, work in progress.	Currently such a direct connection is not present. In the scope of B4B a connection with moodboxes will be tested	We would like to add an incentive for occupants to provide feedback. In addition we would like to have automated improvements based on feedback values and energy flexibility opportunities	Analysis workflow in the Pulse Core. Makes it possible to improve the advice, data configuration. Integrate workflow of maintenance into pulse core.
Simax	Nvt	Nvt	Simaxx is currently working on a way to feedback relevant information back into the BMS.	Simaxx is trying to validate the connectivity of equipment that is being brought on to a project. This expands the capacity of Simaxx to become more of a digital-twin. Specifically, this is about a validation tool for the inclusion of equipment on a smart building project to validate the BIM (architect's plan) and compare that to equipment that is currently physically installed. Regarding WP3, Simaxx would like to have a more clear picture about perceived and measured comfort.
Unica	Nvt	De feedback app is gekoppeld aan het buildingInsight platform. Je scant een QR code die in de ruimte staat, die een web-app opent met een aantal scores die over de ruimte te geven zijn: b.v: hoe luchtkwaliteit ervaren wordt, hoe temperatuur ervaren wordt, hoe de noise-level ervaring is. Dit zijn maximaal 5 scores en 1 open veld. Dit wordt vervolgens gekoppeld aan de sensorwaardes van die ruimte. Er draait momenteel een pilot met twee situaties: situatie 1. eerst ruimtecondities laten zien en dan feedback vragen. Situatie 2. eerst	Verdere ontwikkeling feedback app en integratie in Building Insight	De toekomstvisie is om gebouwen kunnen in te kunnen zetten als energiebuffer en onderhoud aan te sturen dmv van data. Binnen WP3 zoekt Unica een model dat kan ondersteunen in de keuze maken om op of af te schalen qua energieverbruik, waarmee de bandbreedtes bepaald kunnen bepalen. Een criteria zou kunnen zijn dat het model zo open mogelijk model is. (open-source) Van daaruit zou dit model verfijnt kunnen worden door het gebouwspecifiek te maken.
Spectral	Currently none	Comlaint reporting via Zendesk	Working on application to enhance the process of direct feedback, challange in filtering user feedback	From WP3 Spectral would like to have more insight into what users find important in buildings and how the connection between occupants and the building is made. Valueproposition could be. If there is a connection with the users, tenants are likely to stay longer in buildings, which adds a value to
O-Nexus	NVt	Nvt, regelsystemen worden niet aangepast.	Nvt	O-Nexus is in WP3 op zoek naar meetbare parameters die zinvolle informatie geeft over energiegedrag. Het gaat hier niet per definitie gebruikersgedrag, maar juist het resultaat van de gebruiker op de energievraag. O-Nexus zou graag willen weten hoe er een robuuste link te leggen is met comfortbeleving en de data die al in het gebouw aanwezig is (bv het gedrag van setpointveranderingen).
Summary	*n dashboard: containing all relevant data to professional end-user. Towards ow-casting. Feedback of occupants to system can be distinguished into to ptimiser, Spectral). Strukton is testing moodboxes. Unica is testing QR- t comfort, coupled to sensors in that room.*		*relatie tussen tevredenheid van bewoners en het halen van economisch besparingen. (CEO). We would like to add an incentive for occupants to provide feedback. In addition we would like to have automated improvements based on feedback values and energy flexibility opportunities (Strukton). Regarding WP3, Simaxx would like to have a more clear picture about perceived and measured comfort. (Unica) Verdere ontwikkeling feedback app en integratie in Building Insight. Binnen WP3 zoekt Unica een model dat kan ondersteunen in de keuze maken om op of af te schalen qua energieverbruik, waarmee de bandbreedtes bepaald kunnen bepalen. Een criteria zou kunnen zijn dat het model zo open mogelijk model is. (open-source) Van daaruit zou dit model verfijnt kunnen worden door het gebouwspecifiek te maken. (Spectral) Working on application to enhance the process of direct*	