User perspectives in smart office environments

A stated choice approach to determine user preferences and expectations regarding smart office features

GRADUATION PROJECT

S. Guendouz (1519581)
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A stated choice approach to determine user preferences and expectations regarding smart features

Author
Sara Guendouz
1519581
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MSc Construction Management and Engineering
Department of the Built Environment
Eindhoven University of Technology

Graduation Committee

Chair
Prof. Dr. Ir. Bauke de Vries
Information Systems in the Built Environment
Eindhoven University of Technology

First supervisor
Dr. Dujuan Yang
Information Systems in the Built Environment
Eindhoven University of Technology

Second supervisor
Alex Donkers MSc
Doctoral Candidate
Information Systems in the Built Environment
Eindhoven University of Technology

External advisor
Priya Shankar
Head of product
EDGE Next

External advisor
Frank Vieveen
Programmamanager
Gemeente Rotterdam Stadsontwikkeling

Preface

After months of hard work, I am proud to present to you my master thesis. I am grateful that during this graduation project, I got the opportunity to combine the knowledge and skills I obtained during my master's degree, Construction Management & Engineering (CME), at the Eindhoven University of Technology.

This thesis would not have been here without the help of wonderful people around me who have assisted me to get the most out of this research. Your critical view has positively influenced the quality of this thesis. The development of this research has come to a joyful end with the help of my main supervisor, Alex Donkers. I would like to thank you for your professional guidance, continuous support, constructive feedback and motivation to make this thesis a beautiful piece. I would also like to thank Dujuan Yang for her guidance at the beginning of this project. Furthermore, my thanks go to Peter van der Waerden for helping me conduct the analysis. In addition, my appreciation goes to Priya Shankar and her team for their support and business insights within Edge-Next. Thank you, Frank Vieveen and the steering committee, for your assistance within the Municipality of Rotterdam.

Not to forget my profound gratitude to my mentor René Heller, friends, parents, and sister for their unconditional love, understanding, and support to achieve my ambitions. Without them, I would not have been able to accomplish this.

I hope you will enjoy reading this thesis.

Sara Guendouz

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Summary

Smart office concepts have become popular due to the increasing use of technology that will help measure and improve the environment for the user. The goal is to provide efficient and effective workplaces that respond to work dynamics and user needs (Zhou et al., 2020; Tuzcuoglu et al., 2021). A better understanding of office users' preferences and expectations plays an important role in designing an office environment and promotes users' experience, satisfaction, and work performance (Voordt et al., 2004; Hongisto et al., 2016). However, the primary focus on smart office concepts is developing technology. Few studies have addressed the user perspective regarding preferences and expectations (Tuzcuoglu et al., 2021; Noceraet al., 2015). The emphasis from previous studies is mainly on collecting indoor environment quality and user behaviour (mainly the occupancy rate) through the sensor data or smart building control system by connecting sensor data. Those studies do not give a clear insight into whether these related functions provide the right smart office development regarding the users' preferences. It is unclear what users prefer and expect from a smart office environment (Haapakangas et al., 2018; Tuzcuoglu et al., 2021). Therefore, this study's main research question is: '*What kind of smart features in smart offices meet user expectations and preferences?*'

An investigative study was conducted to gain insight into smart features that meet the knowledge worker. As a result, seven smart features meet the user's daily activities and consider the user's needs: smart indoor location tracking of colleagues, smart parking, smart workspace booking, smart meeting room booking, smart indoor climate control of temperature, smart indoor climate control of air quality and smart lighting control. However, to meet the user, it is important also to understand which attributes of the smart features should be designed to contribute to the users' expectations and preferences (Haapakangas et al., 2018). Therefore, a framework for creating a smart feature aligned to users' perspectives is provided based on the following five attributes; control (type of decision support), information sharing (type of information), communication (way of receiving information), knowledge acquisition (purpose of the collected data) and personal information for research efficiency (willingness to share personal or sensitive data) (Yang et al., unpublished; Memoori, 2019; Mikulecky, 2012).

An online survey has been used to determine users' expectations and preferences regarding those smart features and their attributes. The respondents were questioned about socio demographic-, personality-, work-, attitude-, and experience-related characteristics to examine if there is a relationship with user preferences. The survey also contained a stated choice experiment. A stated choice experiment is a statistical technique that considers individuals' choices between alternatives. By decomposing the alternatives into different attributes, the value of how respondents perceive the value can be measured (Louviere et al., 2010).

A total of 245 respondents have started the online survey. After noise reduction, 137 surveys were used for data analysis. In the stated choice experiment, the respondents were asked in 9 choice situations to choose between two theoretical smart feature packages. All smart

feature packages contained the five attributes. In addition, each survey includes two smart features to prevent survey fatigue.

After the data preparation, a Multinomial Logit Model (MNL) was used to estimate the overall utility of each attribute level among the whole sample. In addition, a Latent Class Model (LCM) was used to find groups or "latent classes" that had similar smart feature preferences. Eventually, using different statistical analyses (e.g. Chi-square), the differences between the classes were investigated.

Based on the analysis results, it shows that 75.50% of knowledge workers prefer a smart feature. Knowledge workers prefer a smart feature that includes decision support, sharing basic information such as calendar and work activities, having a dashboard, and sharing personal data to receive more suitable services. Further, respondents are not concerned if their data is used to analyze usage patterns in the whole system. However, it is also found that 24.50% of the knowledge workers do not want smart features if they have to share personal data or if their collected data is used for analysis. Therefore, to meet this group of knowledge workers, it is important to take this into consideration.

This research also reveals that knowledge workers mainly prefer certain smart features. Within a smart office concept, smart meeting room booking, smart indoor temperature control and smart indoor air quality control are most preferred by the respondents. The least preference among this group of respondents was for smart parking.

Furthermore, the most interesting finding of this research is that the results of all smart features are very different from each other. This means that each smart feature should be approached separately since each smart feature contributes to different daily tasks or users' needs. This gives a clear insight into the relevance of including office users in developing smart features rather than just focusing on the technology.

Finally, this study is a starting point for more research. It is recommended that this research be conducted for other smart features that were not included. Also, it is recommended to perform the same research for other types of users (think of facility staff members). Another interesting aspect is conducting qualitative research to understand how knowledge workers think about smart features and attribute levels. Understanding of respondents' trade-offs and decisive choices can be achieved.

Samenvatting

Slimme kantoorconcepten zijn populair geworden door het toenemende gebruik van technologie. Deze nieuwe concepten hebben als doel om efficiënte en effectieve werkplekken te bieden die inspelen op de werkdynamiek en de behoeften van de gebruiker (Zhou et al., 2020; Tuzcuoglu et al., 2021). Bij het ontwerpen van een kantooromgeving speelt een beter begrip van de voorkeuren en verwachtingen van kantoorgebruikers een belangrijke rol. Inzicht hierin draagt bij aan de ervaring, tevredenheid en werkprestaties van de kantoorgebruikers (Voordt et al., 2004; Hongisto et al., 2016). Momenteel is de primaire focus van smart officeconcepten het ontwikkelen van technologie. Weinig studies richten zich op het gebruikersperspectief met betrekking tot voorkeuren en verwachtingen (Tuzcuoglu et al., 2021; Noceraet al., 2015). De nadruk van eerdere studies ligt vooral op het verzamelen van gegevens met betrekking tot de kwaliteit van het binnenklimaat en het gebruikersgedrag middels sensoren. Deze studies geven geen duidelijk inzicht op de vraag of deze gerelateerde functies zorgen voor de juiste smart officeontwikkelingen met betrekking tot de voorkeuren van de gebruikers. Het is onduidelijk wat gebruikers prefereren en verwachten van slimme kantooromgevingen (Haapakangas et al., 2018; Tuzcuoglu et al., 2021). Daarom richt deze studie zich op de volgende onderzoeksvraag: *"Welke slimme functies in slimme kantoren voldoen aan de verwachtingen en voorkeuren van gebruikers?"*

Om inzicht te krijgen in slimme functies die de kenniswerker tegemoet komen is een inventarisatie onderzoek gedaan. Hieruit is gebleken dat de volgende zeven slimme functies voldoen voor de dagelijkse activiteiten en behoeftes van het gebruik: slimme locatiebepaling van collega's, slim parkeren, slimme werkplekreservering, slimme vergaderruimtereservering, slimme regeling van de binnentemperatuur, slimme regeling van de binnenluchtkwaliteit en slimme lichtregeling. Het is echter ook belangrijk om te onderzoeken welke attributen van deze slimme functies ontworpen dienen te worden, wat bijdraagt aan de verwachtingen en voorkeuren van de gebruikers (Haapakangas et al., 2018). Hierom zijn deze slimme functies afgestemd op de perspectieven van de gebruikers, gericht op de volgende vijf attributen; controle (type beslissingsondersteuning), informatie delen (soort informatie), communicatie (manier van informatie ontvangen), kennisverwerving (doel van de verzamelde gegevens) en persoonlijke informatie voor onderzoek efficiëntie (bereidheid om persoonlijke of gevoelige gegevens te delen) (Yang et al., ongepubliceerd; Memoori, 2019; Mikulecky, 2012).

Om de verwachtingen en voorkeuren van de gebruikers ten aanzien van die slimme functies en hun kenmerken te bepalen is gebruik gemaakt van een online-enquête. De respondenten ontvingen vragen met betrekking tot sociaal-demografische, persoonlijkheids-, werk-, attitude- en ervaringen gerelateerde kenmerken om na te gaan of er een verband is met de gebruikersvoorkeuren. Ook bevat de enquête een *stated choice experiment*. Een stated choice experiment is een statistische techniek die de keuzes van individuen tussen alternatieven beschouwt. Door de alternatieven in verschillende attributen te ontleden, kan worden gemeten hoe de respondenten de waarde percipiëren (Louviere et al., 2010).

In totaal zijn 245 respondenten begonnen aan de online-enquête. Na het opschonen van data, zijn 137 enquêtes gebruikt voor data-analyse. In het keuze-experiment zijn de respondenten

in 9 keuzesituaties gevraagd te kiezen tussen twee theoretische slimme functiepakketten. Alle slimme functiepakketten bevatten de vijf attributen. Elke enquête bevat twee slimme kenmerken om enquêtemoeheid te voorkomen.

Na de voorbereiding van de data werd een Multinomiaal Logit Model (MNL) gebruikt om het algemene nut van elk attribuutniveau onder de hele steekproef te schatten. Daarnaast werd een Latent Class Model (LCM) gebruikt om groepen of "latente klassen" te vinden die vergelijkbare slimme functies hebben. De verschillen tussen de klassen zijn met behulp van diverse statistische analyses (bv. Chi-kwadraat) onderzocht.

Op basis van de analyseresultaten blijkt dat 75,50% van de kenniswerkers de voorkeur geeft aan een slimme functie. Kenniswerkers geven de voorkeur aan een slimme functie met beslissingsondersteuning, het delen van basisinformatie zoals agenda en werkactiviteiten, het hebben van een dashboard en het delen van persoonlijke gegevens om meer geschikte diensten te ontvangen. Verder hebben deze respondenten blijkbaar geen bezwaar als hun gegevens worden gebruikt om patronen van het gehele systeem te analyseren. Daarentegen blijkt dat 24,50% van de kenniswerkers bezwaarlijk vindt om persoonlijke gegevens te delen als hun verzamelde gegevens worden gebruikt voor analyses. Om deze laatste groep kenniswerkers tegemoet te komen is het dus belangrijk om hiermee rekening te houden.

Uit dit onderzoek is ook gebleken dat kenniswerkers vooral de voorkeur geven aan bepaalde slimme functies. Binnen een slim kantoorconcept hebben slimme vergaderruimtereservering, slimme regeling van de binnentemperatuur en slimme regeling van de binnenluchtkwaliteit de meeste voorkeur van de respondenten. De minste voorkeur onder deze groep respondenten ging uit naar slim parkeren.

Binnen de resultaten van dit onderzoek is naar voren gekomen dat slimme functies sterk van elkaar verschillen. Hierom dient elke slimme functie apart te worden benaderd omdat deze van dagelijkse taken of behoeftes van gebruikers verschilt. Het betrekken van kantoorgebruikers bij het ontwikkelen van de slimme functies staat hier centraal in plaats van alleen de focus te leggen op technologie.

Ten slotte biedt deze studie mogelijkheden voor vervolgonderzoeken. Het is aan te bevelen om vervolgonderzoek uit te voeren voor andere slimme functies die bij deze studie nog niet zijn meegenomen. Ook is het aan te bevelen om hetzelfde onderzoek uit te voeren voor andere typen gebruikers (denk aan facilitaire medewerkers). Een ander interessant aspect is het uitvoeren van kwalitatief onderzoek om inzicht te krijgen in hoe kenniswerkers denken over slimme functies en attribuutniveaus. Dit zorgt voor het verkrijgen van een beter beeld van de overwegingen van de respondenten.

Abstract

Smart office concepts have become popular due to the increasing use of technology that will help measure and improve the environment for the office user. The goal is to provide efficient and effective workplaces that respond to work dynamics and user needs (Zhou et al., 2020; Tuzcuoglu et al., 2021). However, the primary focus on smart office concepts is developing technology. Few studies have addressed the user perspective regarding preferences and expectations (Tuzcuoglu et al., 2021; Noceraet al., 2015). Those studies do not give a clear insight into whether these related functions provide the right smart office development regarding the users' preferences. It is unclear what users prefer and expects from smart office environments (Haapakangas et al., 2018; Tuzcuoglu et al., 2021). Therefore, this study aimed to get insight into user expectations and preferences regarding seven smart features. In addition, it also tried to determine how the attributes of smart features should be designed to contribute to the users' needs. Therefore, a stated choice experiment is used to evaluate five attributes that meet the user expectations and preferences. The Multinomial Logit models show that smart meeting room booking, smart indoor climate control of temperature, and smart indoor climate control of air quality are the most preferred smart features. In addition, the analysis conducted with the Latent Class model indicated two classes, namely *Adapters* and *Rejecters*. The main difference between those classes is that the Rejecters do not want to share personal data with the smart feature. Furthermore, the study gives a clear insight into the relevancy of including the office users in developing the smart feature rather than just focusing on the technology.

Keywords:
Smart office environments, Smart features, User expectations and preferences, Stated Choice Experiment

Abbreviations

BFI Big Five Inventory Personality Test
CBS Company for measurement of statistics (Dutch: Centraal Bureau van Statistiek)

DCE Discrete choice experiment

GDPR General Data Protection Regulation

IOT Internet of Things

LC Latent Class

LCM Latent Class Model

MNL Multinomial Logit Model

RUT Random Utility Theory

SCE Stated choice experiment

KBO Knowledge-Based Organizations

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Chapter 1. Introduction

This chapter introduces the research topic, starting with the increasing interest of companies in improving the productivity of their employees by implementing technologies that have resulted in a new office concept. Then, the specific problem statement for this topic is described in the research gap paragraph, followed by the research questions answered in this thesis. Further, the outline of the thesis will be explained as well.

1.1 Background

In the last decades, the great value of human capital has been recognized, especially in the field of knowledge work (Remes et al., 2021). As a result, more and more companies are interested in building solutions that are focused on helping knowledge workers rather than just concentrating on improving the efficiency of the building. In the past, solutions were mainly focused on improving sustainability and increasing the energy efficiency of buildings (Remes et al., 2021; Rönka, 2019). However, there is a growing demand to go further and focus on employee experience elements to improve employee performance and productivity (Rönka, 2019). A key driver for this is that personnel costs are approximately 90% of total operating costs (Alker et al., 2015). Using JLL's (2016) 300-30-3 strategy rule can provide better insight into cost allocation. This rule represents a breakdown of organizational costs per square foot in terms of total occupancy costs of $3 for utilities, $30 for rent, and $300 for personnel costs (JLL, 2016). Although these numbers are not the fixed standard numbers, they indicate how an organization typically allocates its company costs. This rule captures the main driver for the increasing interest in knowledge workers. Since interest is growing in this particular group of users, this research will focus on knowledge workers as the main users of offices (WorldGBC, 2014).

The development of the Internet of Things (IoT) is the next step that takes advantage of the recent interests related to improving the productivity of knowledge workers. The rapid deployment of IoT, artificial intelligence, and sensing technologies in the office environment contributes to the overall development of the so-called smart office. The intelligence capability of the smart office allows it to understand the context of the users and adapt to their needs to improve the work experience through the integration of innovative techniques (Zhang et al., 2022; Papagiannidis et al., 2019; Tuzcuoglu et al., 2021). This concept is becoming popular with the profound use of technology in providing efficient and effective workplaces for its users (Tuzcuoglu et al., 2021). This has led to more companies wanting to implement the concept of smart offices.

The increased application of the smart office concept has caused users' preferences and expectations of office environments to change (Tuzcuoglu et al., 2021; Kašpárkováa et al., 2018; Appel-Meulenbroek et al., 2015; Haapakangas et al., 2018). Understanding the user preferences and expectations is important; it plays a major role in influencing user satisfaction and productivity in office environments (Hongisto et al., 2016; Voordt, 2004). Several studies have identified it and show the importance of meeting the user perspectives (Hartog et al., 2017; Lee et al., 2005; Rothe et al., 2011). For instance, Hartog et al. (2017) analyzed the importance and influence of personality on user satisfaction with multi-tenant office characteristics. Lee et al. (2005) examined the effects of personal control over the work environment on perceived job performance, job satisfaction, group cohesiveness, and inclinations to work alone or in an enclosed space and their interrelationships. Rothe et al.

(2011) investigated the preferences of office users based on their age, gender, and mobility to understand the preferences of the users in work environments. Even so, this investigation is concerned with a 'regular' office environment. Little is known about the experience from the user's perspective when considering smart offices.

Currently, the literature about smart offices has investigated workplaces from a mostly technological standpoint. Those studies largely focus on collecting user behaviour through sensors to understand user preferences. For example, Noceraet al. (2015) increase workplace efficiency in a smart office by using user occupancy data to identify user behaviour. Also, Dong et al. (2019) provide insights into how indoor sensors influence the user and create an overview of the importance of energy-saving and occupant comfort in smart building environments. However, these studies do not take the user perspectives into account. Only a few studies addressed the user perspective on smart offices (Noceraet al., 2015; Dong et al., 2019; Tuzcuoglu et al., 2021). These earlier studies focus on collecting indoor environmental quality and user behaviour, especially occupancy, through sensor data or a (smart building) control system linking sensor data. Despite these studies, there is still little understanding of how the user experiences the effects of a smart work environment and their expectations and preferences regarding this new office environment. Since the literature is quite consistent in suggesting that user preferences and expectations are crucial in an office environment, it is important to understand their preferences in smart office concepts (Vischer et al., 2007; Kwon et al., 2019; Tuzcuoglu et al., 2020).

1.2 Research gap

Smart office concepts have become popular due to the increasing use of technology that will help measure and improve the environment for the user. The goal is to provide efficient and effective workplaces that respond to work dynamics and user needs (Zhou et al., 2020; Tuzcuoglu et al., 2021). A better understanding of office users' preferences and expectations plays an important role in designing an office environment and promotes users' experience, satisfaction, and work performance (Voordt et al., 2004; Hongisto et al., 2016). However, the primary focus on smart office concepts is mainly on developing technology. Few studies have addressed the user perspective regarding preferences and expectations (Tuzcuoglu et al., 2021; Noceraet al., 2015). The emphasis from previous studies is mainly on collecting indoor environment quality and user behaviour (mainly the occupancy rate) through the sensor data or smart building control system by connecting sensor data. Those studies do not give a clear insight into whether these related functions provide the right smart office development regarding the users' preferences. Therefore, it is unclear what users *prefer and expect* from smart office environments (Haapakangas et al., 2018; Tuzcuoglu et al., 2021).

The main research question that will be answered within the graduation thesis is:

‘What kind of smart features in smart offices meet user expectations and preferences?'

In order to answer this main research question, several sub-questions need to be reviewed. These will be:

> **SQ1:** What defines a smart office environment, and which smart features can be identified?
> **SQ2:** Which attributes of smart features do users expect?
> **SQ3:** Which preferences do users have for the different attributes of smart features?
> **SQ4:** To what extent do personal-, socio demographic-, work-, attitude-, experience-related characteristics influence the users' preferences for a particular smart feature?

This study will contribute to smart buildings' knowledge domain in the built environment by answering these questions. The main objective of this study is to provide an overview of smart features that meet user expectations and preferences. Also, the influence of personal-, socio demographic-, work-, attitude-, and experience-related characteristics on preferences will be considered. This will be achieved by understanding the user needs in an office environment. Moreover, the relationship between the user and the smart office environment will optimize the work environment and provide insight into the critical aspects of designing a smart office.

1.3 Outline

This thesis consists of seven chapters (see Figure 1). The literature related to the smart office concept, smart features, and users' expectations and preferences will be explained in the next chapter. The third chapter explains the methodology of this research. It discusses several considerations, such as the stages of the stated choice experiment (SCE), type of survey instrument, and data analysis methods. In the fourth chapter, the data preparation will be explained and also the descriptive statistics of the survey will be examined. In the fifth chapter, the data collected from the SCE will be analyzed using the multinomial logit and latent class models. The obtained results will be compared to previous findings of other research, and the research approach will be critically discussed in the sixth chapter. The seventh chapter of this research provides conclusions and will answer the main question of this research. Additionally, it emphasizes the scientific and social relevance and discusses the limitations of this research. Finally, recommendations for further research will be presented.

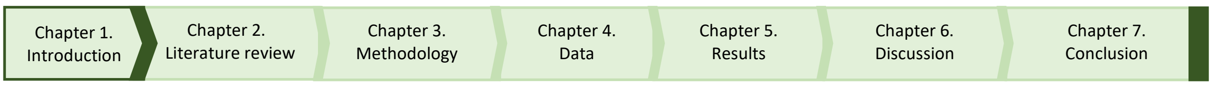


Figure 1: Outline of the thesis

Chapter 2. Literature review

The literature review will answer sub-questions one and two. In this chapter, the concepts of a smart office will be presented. With the acquired knowledge, the definition of smart systems will be discussed to get insight into the capabilities. Also, smart features and their essential attributes will be considered. Those attributes are based on the expectations and preferences of office users. Furthermore, the role of the General Data Protection Regulation within the smart office and its relationship with privacy concerns will also be a part of this review.

2.1 Smart office environment

Technological developments play an important role and contribute to the revolution within the built environment sector. The development of IoT is a major contributor to the technological revolution. Different kinds of machines and devices can be interconnected via the Internet (Tuzcuoglu et al., 2021; Munoz et al., 2018). Such physical objects are called *things,* and their purpose is to offer information about the surrounding environment and respond appropriately based on external stimuli. The possibility of connecting physical objects and virtual space enables a new range of services and applications in buildings. One of the technological innovations where these principles lay the foundation is the smart office (Bogdan et al., 2021).

2.1.1 Smart offices

The smart office is a relatively new concept within the built environment sector (Brugmans et al., 2017; Ghaffarianhoseini et al., 2016; Mikulecky, 2020). Due to the profound use of technologies, smart office concepts have become very popular by aiming to provide efficient and effective workplaces that respond to work dynamics and user needs (Tuzcuoglu et al., 2021). Tehseen et al. (2018) define a smart office as "a place/environment established to integrate physical devices, people, and computing technologies to provide a healthy, conducive, interactive, and smart environment for employees". Workplaces are equipped with sensors connected to the Internet and mobile devices (Tuzcuoglu et al., 2021). According to Brugmans et al. (2017) and Appel-Meulenbroek et al. (2011), these technologies should observe the environment and serve the user.

From the user's point of view, the integration of technologies contributes to work efficiency as well as user satisfaction in office environments (Ghaffarianhoseini et al., 2016; Danielsson, 2008). Therefore, a smart office is also seen as an environment that can adapt to user needs and support users in daily tasks (Tuzcuoglu et al., 2021). Moreover, it contributes to preventing health problems among users and improving the quality of life in the office environment (Zang et al., 2019). However, the core idea is to provide a working environment that responds to users' needs and minimizes environmental impact and wastage of natural resources (Ghaffarianhoseini et al., 2016). Smart office strategies thus overlap with sustainable office strategies (Verbeke et al., 2020).

2.1.2 Definition of smart systems

As can be noticed in the previous section, the implementation of technologies contributes to making an office smarter (Alter, 2019; Romero et al., 2020). As a result, those offices are equipped with all kinds of smart systems. To better understand the concept of a smart office, it is important to define a smart system first. With the rise of Industry 4.0, companies and governments are encouraging the development of new technologies (Schwab, 2016;

Hermann et al., 2016). These technologies are introduced to optimize strategies, create new products, reduce development times, and offer more personalized products (Romero et al., 2020). In particular, the increasing use of IoT has resulted in the recent rise of information communication technology in the built environment (Papagiannidis et al., 2020; Buckmans, 2014; Munoze et al., 2018). The diverse set of materials, structures, and technologies associated with this development are often called smart systems (Remes et al., 2021; Papagiannidis et al., 2020). However, there is currently no commonly accepted scientific definition of a smart system in the context of the built environment (Romero et al., 2020; Alter, 2019; Remes et al., 2021; Papagiannidis et al., 2020). This creates much confusion and brings with it vague connotations. For example, smart systems are often associated with computerized information and the original meaning of smart as a description of one's intelligence and practical ability (Medina-Borja, 2015; Alter, 2019; Romero et al., 2020). Technologies that use artificial intelligence, machine learning, and big data analytics to provide cognitive awareness to objects that were considered superhuman are especially related to smart systems (Alter, 2019; Romero et al., 2020).

To provide more insight into the similarities and differences of smart systems, 11 papers are reviewed that define smart systems in different contexts. The papers discuss a range of smart systems, including devices, services, cities, industry, buildings, offices, and homes. In addition, the capabilities of the smart system were collected for all papers. Through this comparison, an understanding of the development of smart systems will be gained. The results of the study have been summarized in Table 1.

Based on the comparison study, the following capabilities are fundamental for smart systems:

1) **Communication:** the system must be able to exchange data and provide information about the state of the environment. Interoperability is important between the elements and their environment (Romero et al., 2020; Alter, 2019, 2018; Silverio-Fernadez et al., 2018).
2) **Embedded knowledge:** the system is able to capture human experience and expertise. Knowledge can be conceived and implemented differently; for example, use can be built-up knowledge bases (e.g. Knowledge-based Systems) (Romero et al., 2020; Liu et al. 2016; Batov, 2015).
3) **Adaptive behaviour:** Various methods and algorithms can modify the knowledge of the system. This results in enabling adaptive behaviour. This makes it possible to deal with new situations. The 'learning' is carried out in an autonomous way, where knowledge can be modified without or with minimal help from outside. (Verbeke et al, 2020; Romero et al., 2020).
4) **Decision-making:** the system is able to make decisions with their knowledge. Various techniques enable strategic decision-making and flexible data processing, such as neural networks and fuzzy logic. Here the system is also enabled to predict future states of the environment (Romero et al., 2020; Verbeke et al., 2020; Wellener et al., 2018).
5) **Observing:** It must have a perceptive ability to collect, monitor, detect and analyze information from the environment (Alter, 2019; Tehseen et al., 2018 Silverio-Fernadez et al., 2018). It must be self-aware of performing a certain activity. It must perceive the environment and have built-in knowledge that can anticipate the environment. (Romero et al., 2020; Verbeke et al., 2020)

6) **Automated control:** It must recognize when tasks and decisions need to be performed without the direct command of the user (Romero et al., 2020; Verbeke et al., 2020).

The comparison study shows that communication, embedded knowledge, adaptive behaviour, decision-making, observing, and automated control are most frequently mentioned as capabilities of smart systems. Based on the comparison, smart systems must have at least the capability to observe the environment, control it, and allow communication between the system and user. Therefore, those three capabilities are considered as the base of the systems. Moreover, adaptive behaviour, decision-making, and embedded knowledge are commonly integrated into systems. According to Romero et al. (2020), adaptive behaviour and embedded knowledge make the system even smarter. Also, Alter (2014) considers systems containing over capabilities such as embedded knowledge and adaptive behaviour to add additional value to the smart system. This set of capabilities provides insight into the nature of smart systems.

Table 1: A comparison study of smart systems

	Romero et al. (2020)	*Alter (2019)*	*Batov (2015)*	*Verbeke et al. (2020)*	*Liu et al. (2016)*	*Silverio et al. (2018)*	*Lecomte (2019)*	*Buckman et al. (2014)*	*Tehseen et al. (2018)*	*Papagiannidis et al. (2020)*	*Mohamed et al. (2019)*	***Total***
Type of smart systems												
1) Communication	X	X	X	X	X	X	X	X	X	X	X	11
2) Embedded knowledge	X	X	X	X	X	X			X		X	8
3) Adaptive behaviour	X	X	X	X			X	X	X		X	8
4) Decision-making	X		X	X			X	X	X		X	7
5) Observing	X	X	X	X	X			X	X	X	X	9
6) Automated control	X	X	X	X			X	X	X	X	X	9

2.1.3 Components in smart office

A comparison study is conducted in the previous section to get insight into smart systems' capabilities. Those capabilities are converted into three main components that make a smart office possible: Hardware, software, and communication networks (Alter, 2019; Batov, 2015).

To enable the capabilities of a smart office, various types of *hardware* need to be installed. Literature mentions three kinds of hardware being sensors, actuators and computers. A sensor measures information from the smart office environment and users (Minerva et al., 2015). The collected data of the sensor will be sent to the connected actuators. It takes an electrical input from the sensor and turns it into physical action in the environment (Minerva et al., 2015). Finally, an autonomous computer is used to make the data exchange possible between the sensor and actuators (Silverio-Fernandez et al., 2018). Besides connecting devices, the context-aware computer can also process and store the collected information from the environment (Ahmed et al., 2019).

Next to hardware, smart offices use *software* to enable the capabilities mentioned in section 2.1.1. The software uses the hardware components for various purposes. Barisic et al. (2020) categorized them into three groups: monitoring, actuation, and visualization. Through monitoring, the state of the office could be determined. For example, sensors can monitor temperature, open or closed windows, and tell whether office appliances are defective. Outdoor sensors can monitor environmental variables related to temperature, wind, air pollution, and sunlight. Recent developments in occupant sensors enable monitoring of presence, activity type, location and body temperature. Actuation software can be used to control the state of the office environment based on those sensor measurements. Such software can either report to the user or control actuators directly. For instance, the software could warn the facility manager if the temperature in a room exceeds a threshold level and turn the heating system on or off to directly change the temperature itself. Actuators can use both historical data and real-time data. Historical data can be used to improve the order of the process and identify recurring patterns in the data. In contrast, real-time data can be used to take action on the collected data directly, increasing awareness of change in monitored systems or environments (Minerva et al., 2020; Dembski et al., 2020; Fuller et al., 2020). Finally, visualization software could be used to make data available in structured and human-readable formats, such as tables, graphs or reports. In addition, comprehensive data analysis tools could find patterns and correlations to predict future indoor environment states (Batov, 2015).

The office needs a stable *communication network* to exchange data between hardware and software components (Fudrik et al., 2013; Batov, 2015). Based on the amount of data and the distances, all these sensors, actuators and computers can be connected in different ways such as Bluetooth, Radio Frequency Identification (RFID), Near Field Communication (NFC), Long Range Low Power (LoRa) and WiFi. Bluetooth is a wireless connection between devices and reaches 100 meters. RIFD is a system that sends, stores, and reads information and reaches 12 meters. NFC technology is a derivative of RIFD. NFC is able to process signals and has a reach of 10 centimetres. This communication technology is mainly used in cards such as credit cards. WiFi wireless connection uses the Internet for data exchange and ranges 100 meters. LoRA is a telecommunications network suitable for low-power communication for longdistance data exchange. The range of a LoRa is between 2 and 21 kilometres (Al-Sarawi et al., 2017).

Moreover, Bluetooth, NFC, WiFi and LoRa can communicate two-ways, while RFID codes are a one-way communication medium (Akpakwu et al., 2017). Besides those communication technologies, 4G and 5G are upcoming communication-network means that can play a part in a smart office environment (Akpakwu et al., 2017). The emergence and development of all these network options are conducive to developing hardware and software essential for creating (new) features in a smart office.

2.1.4 Smart feature

The previous section described various components of a smart office. This section describes how combining these components introduces smart features in a smart office. However, to understand the definition of a smart feature, it is important to indicate what a feature is. As the literature is not always clear about the definition of features, this thesis uses the description formulated by Van Susante. According to Van Susante (2014), a feature is described as "a part of the workplace that presents itself directly to the users of the space". In addition to this definition, a feature is considered smart when it uses systems that take capabilities mentioned in 2.1.2 into account. Further, based on the smart office concept, a smart feature also has to meet and serve the user (Tuzcuoglu et al., 2021; Yang et al., Unpublished; Brugmans et al., 2017).

An investigative study was conducted to gain insight into smart features that meet the knowledge worker. As a result, several smart features were identified from papers and websites. In Table 2, an overview is provided of current smart features within a smart office.

Table 2: Investigation of smart features

Smart features	Flowscape (n.d.)	Pathak (2021)	Tyrberg (n.d.)	Ireland (2019)	MAPIQ (n.d.)	Gobright (n.d.)	Gira (n.d.)	Li et al. (2014)	Zhang et al. (2022)	Salosin et al. (2020)	Shinde et al. (2020)	Remes et al. (2020)	Brugmans (2017)	Memoori (2019)	**Total**
1) Smart indoor colleagues tracking	X	X	X		X	X					X	X	X	X	9
2) Smart parking	X									X	X		X		4
3) Smart workspace booking	X	X	X	X	X	X						X	X	X	9
4) Smart meeting room booking	X				X	X					X	X	X	X	6
5) Smart indoor air quality control		X	X	X	X		X	X	X	X	X		X	X	11
6) Smart indoor temperature control		X	X	X			X	X	X	X	X		X	X	10
7) Smart lighting control				X	X		X	X	X	X	X		X	X	9

Smart feature 1) Smart indoor location tracking of colleagues

The smart indoor location tracker focuses on finding colleagues in the office (Shinde et al., 2020; Remes et al., 2020). With this smart feature, the user can locate colleagues to see where they are currently working. Detecting the location of a colleague can be achieved in several ways, for example, by logging in to a fixed computer, using a desk check-in panel, or GPS (Flowscape, n.d.; Pathak, 2021; MAPIQ, n.d.). This reduces the time required to reach a colleague.

Smart feature 2) Smart parking

Smart parking offers the possibility to find suitable parking spots (Shinde et al., 2020; Remes et al., 2020). Usually, it is a time-consuming process for the user. However, information can be collected about occupancy rates using ground sensors and cameras. The data is then transmitted to a smart parking application, which communicates the availability to the user. (Salosin et al., 2020; Tyrberg, n.d.) Further, the system can also display the availability of parking spaces based on car type, preferences, and individual schedules (Li et al., 2014).

Smart feature 3) Smart workspace booking

Smart workspace booking helps users reserve a suitable (individual) workspace (Ireland, 2019; Budie et al., 2019). The user can use a workspace booking system to find a workspace that meets their agenda and preferences. The system provides an overview where users communicate their personal preferences, such as a standing desk, a focus area, or a seat near the window. Smart workspace booking ensures that they always have access to the space that suits their needs. (MAPIQ, n.d.; Gobright, n.d.).

Smart feature 4) Smart meeting room booking

Smart meeting room booking allows the reserve of suitable meeting rooms according to the user's needs (Ireland, 2019; Budie et al., 2019). This smart feature provides an overview of meeting rooms, scheduled meeting times, room characteristics, availability of equipment (e.g., video conference camera, projector, touch board), and extra services (e.g., catering). As a result, users can book all available meeting rooms that meet their preferences. This results in the users' ability to manage their time more efficiently and no longer search for a meeting room that fits their preferences (MAPIQ, n.d).

Smart feature 5) Smart indoor climate control – Temperature

Smart indoor climate control of temperature helps users to 'take control' and adapt to their preferred environment (Shinde et al., 2020). Temperature variation across building zones throughout the day is a common complaint of building occupants. With smart indoor climate control of temperature, individuals can adjust their personal heating/cooling preferences at their workplaces (Memoori, 2019). Further, the system is also capable of storing and learning from the data to indicate the usage patterns. Implementing this system will increase employee satisfaction regarding thermal comfort and translate into higher productivity (Remes et al., 2020).

Smart feature 6) Smart indoor climate control – Air quality

Smart indoor climate control of air quality creates the opportunity for individual monitoring (Shinde et al., 2020; Tyrberg, n.d). This system can detect usage patterns and also provides the possibility to control the air quality (Memoori, 2019). Using the collected data, insights and recommendations can be provided to the user to improve the air quality in the room. Implementing smart indoor climate control for air quality creates healthier indoor spaces and can increase employee productivity through better indoor air (Memoori, 2019).

Smart feature 7) Smart lighting control

Smart lighting offers the possibility to automatically determine the light intensity through sensors, which observe whether there is enough daylight inside. Also, smart lighting has the potential to adjust itself (Gira, n.d.; Zhang et al., 2020).

2.2 Smart office user

The impactful role of the knowledge workers in the smart office causes the growing interest in developing all kinds of smart features that contribute to the users' needs. However, little is known about the users' expectations and preferences regarding those smart features (Haapakangas et al., 2018). According to Tuzcuoglu et al. (2021) and Yang et al. (Unpublished), it is very important to gain insight into the users' expectations and preferences to understand which attributes of smart features are important for the user. For instance, smart features collect all kinds of personal data. This leads to privacy concerns among the users (Potoglou et al., 2017). So, the smart feature must take this attribute into account; otherwise, the user will not be interested in using the smart feature (Potoglou et al., 2017; Lee et al., 2019).

For this reason, it is essential to obtain an overview of which attributes within smart features are important to the users. Furthermore, it is also interesting to gain insight into the influence of personal, demographic, work, attitude, and experience-related characteristics on users' preferences. Those factors will help by designing a smart office that promotes users' experience, satisfaction, and work performance (Voordt et al., 2004; Hongisto et al., 2016).

2.2.1 Employee needs

As shown in the previous section, all different kinds of smart features can be implemented in a smart office to meet the needs of the knowledge worker. Therefore, it is important to understand the performance of the different tasks of the knowledge workers in an office. Various studies show that the need for concentration and communication often become essential needs for knowledge workers (Wohlers et al.,2019; Maarleveld et al., 2009; Heerwagen et al., 2004). In addition, knowledge workers need a workplace where they can interact with their colleagues and concentrate on utilizing their cognitive abilities to complete complex work tasks (Maarleveld et al., 2009; Heerwagen et al., 2004). However, these are not the only needs of knowledge workers. Therefore, Budie et al. (2019) conducted a study to understand the different needs of knowledge workers in office environments (see Figure 2).

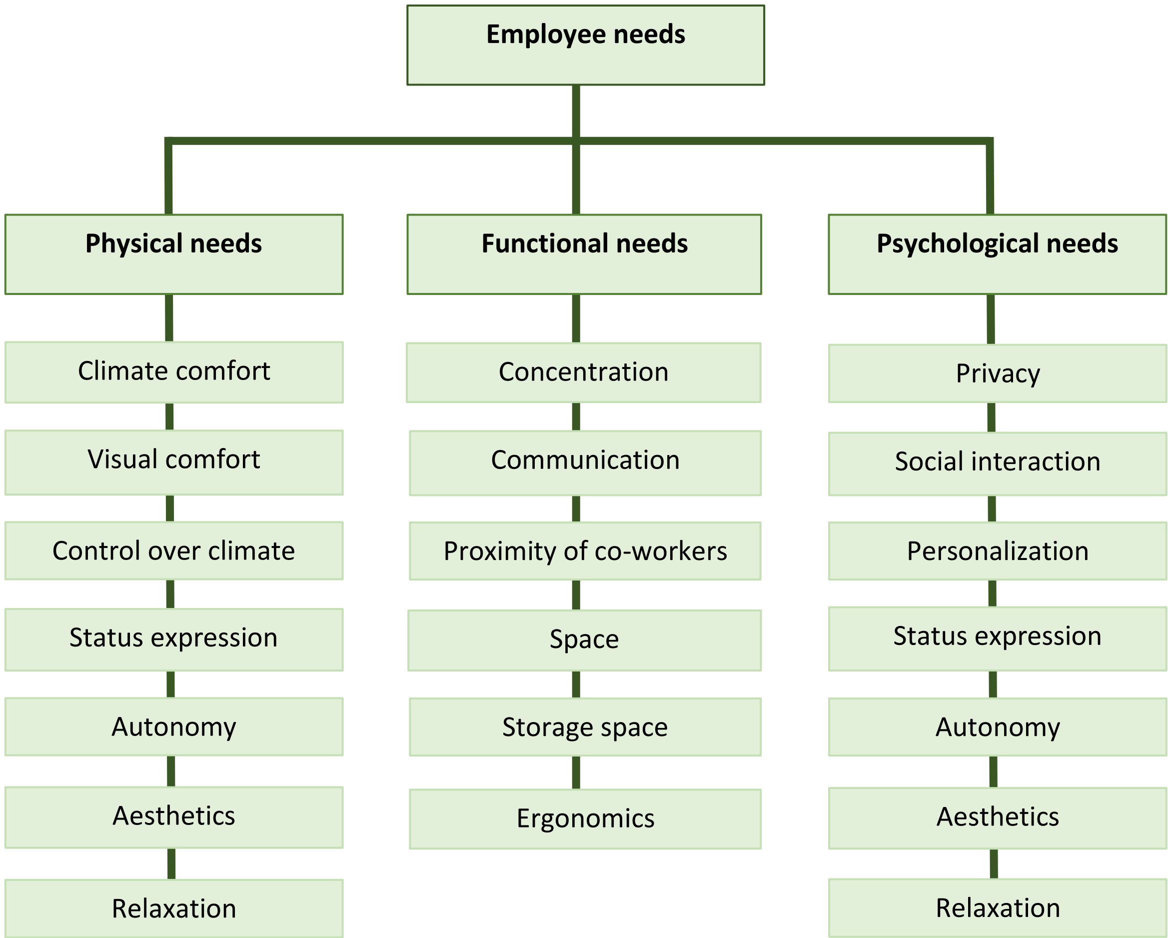


Figure 2: Overview Employee needs (Budie et al., 2019)

As shown in Figure 2, knowledge workers have three types of needs. The first need focuses on physical needs. Knowledge workers must-have comfort (e.g., climate and visual comfort) in the office environment for physical needs. The second, functional needs, refer to work-related needs, such as concentration and communication. The last one, the psychological needs of employees, refers to the need related to privacy and social interaction (Budie et al., 2019). Based on the collected smart features, each consists of one or more components that meet the employee needs in Figure 2. As a result, the collected smart features are expected to contribute to an efficient and effective workplace that also responds to the daily activity of knowledge workers (Tuzcuoglu et al., 2021).

2.2.2 Expectations and preferences

To meet the users' needs, it is also important to get insight into their expectations and preferences regarding attributes of smart features (Haapakangas et al., 2018). Nevertheless, literature shows that not much is known about the users' perspectives. For this reason, Yang et al. (Unpublished) conducted a study to investigate which attributes are important to the user. This research showed that *control*, *information sharing* and *communication* are important attributes for users to enhance interaction. Also, a study by Memoori (2019) suggested enhancing interaction as an essential component. Besides interaction related aspects, users also want to perceive the smartness of the environment (Yang et al., Unpublished). The study of Memoori (2019) and Mikulecky (2012) mentioned *knowledge* *acquisition* of usage patterns and *resource efficiency* by analyzing personal data as attributes that contribute. Therefore, a framework for creating a smart feature aligned to users' expectations and preferences can be provided based on the five attributes.

Attribute 1) Control

The first attribute is *controllability*. Kwon et al. (2019) and Schleich et al. (2017) showed that controllability in various office aspects affects satisfaction and work performance. For example, users like to adjust the indoor climate according to personal preferences. Memoori's (2019) research also shows that control is important. By providing control, users can optimize their workspace to suit their preferences. This contributes to user satisfaction and results in improving productivity within the office.

Attribute 2) Information sharing

The second attribute is *information sharing*. For office users, interaction with the system is a crucial aspect. This means that users need to share information with the system to receive specific information back. This was also shown in the study of Tuzcuoglu et al. (2020), which stated that users expect smart technologies to improve office interaction when users share information with the system. Furthermore, users expect to be better served when information is shared.

Attribute 3) Communication

The third attribute is *communication*. The study conducted by Yang et al. (Unpublished) shows that users would like to be more engaged with the information data their office environment collects. The users want to be involved by receiving real-time information from the office environment, for example, to gain insight into the indoor climate, location of colleagues, or the availability of office tools, workstations, and meeting rooms. Having the right office technologies can improve and reinforce the interaction between the user and the office (D'Oca et al., 2018). By using a dashboard, the office system can communicate with the user. It is also possible to create profiles in which users can share information with the system in order to receive more targeted feedback (Microsoft, n.d.).

Attribute 4) Knowledge acquisition

The fourth attribute is *knowledge acquisition*. This aims to improve services by acquiring knowledge based on general or individual usage patterns. Users expect smart office environments to adapt to their immediate needs by offering a variety of available spaces and resources, both for work and leisure (Mikulecky, 2012; Yang, Unpublished). The users expect the smart feature to learn from the usage patterns to improve the service (Microsoft, n.d.).

Attribute 5) Sharing personal information for resource efficiency

The fifth attribute is sharing *personal information for resource efficiency*. Users expect a smart office to provide office functions and tools to facilitate their daily activities (Tuzcuoglu et al. 2020). However, a lot of information needs to be shared to use the smart feature. Besides personal information (e.g. age), sensitive information (e.g. health data) has to be shared sometimes. Therefore, the smart feature can serve the user better and be more targeted (Kim et al., 2019).

2.2.3 Privacy concerns

As described in the previous section, smart features collect all kinds of data about the knowledge worker to improve the office environment. This collected data will identify the knowledge worker, recognize different usage patterns and personalize shared information to improve services in a smart office (Potoglou et al., 2017). However, the valuable data from a smart feature can contain personal data and even sensitive information such as health conditions and habits (Lee et al., 2019). Since this data includes personal information, there are potential risks if the data is not handled carefully (Potoglou et al., 2017). As a result, concerns about the privacy and security of personal information are increasing (Lee et al., 2019).

From the perspective of the user, data privacy is a rising topic. This will be an issue for some smart features, especially in a smart office where all smart features collect information. For example, think of smart indoor location tracking of colleagues; this system can collect real-time data about the user's location, which is quite sensitive. As the smart feature collects certain data, it may conflict with European privacy law. This legislation is named "General Data Protection Regulation" (GDPR) and puts control of personal data back in the hands of individuals. The six main principles of the renewed GDPR are shown in Figure 3.

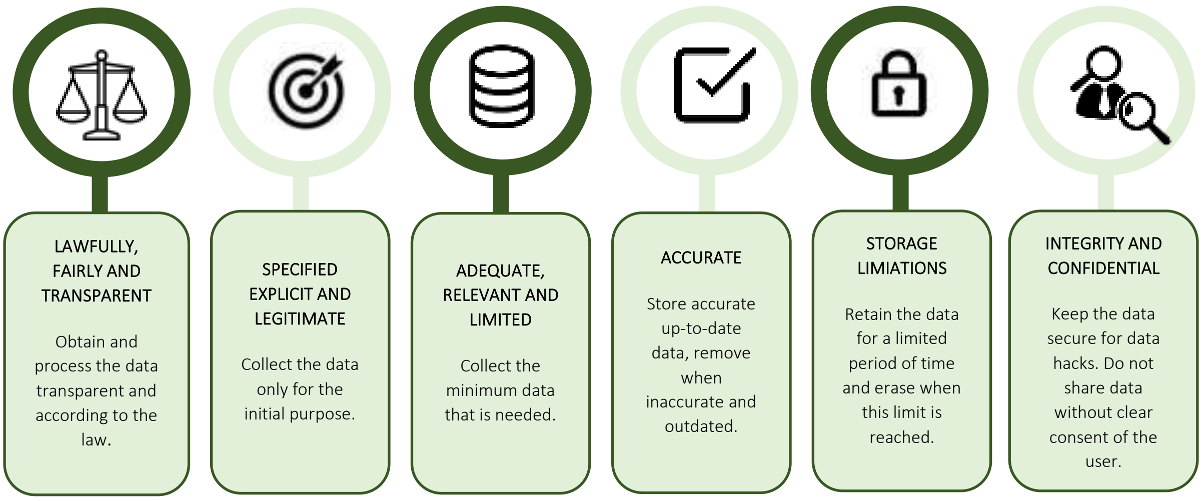


Figure 3: General Data Protection Regulation (Autoriteitpersoonsgegevens, 2019)

Under the GDPR, data must be collected transparently, accurately, and up to date. Furthermore, it must be used only for the stated purpose and deleted upon termination of the relationship. Every piece of "personal data" collected, stored, or shared by an organization must be processed according to the GPDR. The term personal data is defined as follows:

> *"Personal data means any information relating to an identified or identifiable natural person; an identifiable natural person is one who can be (in)directly be identified, by reference to an identifier such as a name, identification number, an online identifier or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that natural person* (Autoriteitpersoonsgegevens, *2019)."*

The GDPR gives room to local regulations to complement it. In the Netherlands, the GDPR has been incorporated into the 'Uitvoeringswet Algemene Verordening Gegevensbescherming'

(AVG). Employers must consider several aspects of collecting and processing personal data (Autoriteitpersoonsgegevens, 2019). For instance, personal data may only be processed under the law if it is based on consent, agreement, legal obligation, the legitimate interest of the company or organization. Also, the purpose of collecting personal data must be clear. Moreover, it is important that the individual from whom the data is collected is informed and agrees with the data collection (Personal Data Authority, 2021). This means that a smart office that uses a smart feature containing personal information must first ask the user's permission.

Contradictory to the high levels of concern about privacy, individuals tend to act differently. Previous studies regarding social media show that individuals are quite willing to trade their personal information for a "benefit" (Kokolakis, 2017). On the other hand, Barth et al. (2017) claim that users tend to engage in privacy-compromising behaviour. If the benefits outweigh the risk, individuals are willing to "give up" their privacy. This inconsistency between privacy behaviour is referred to as the "privacy paradox" (Kokolakis, 2017; Williams et al., 2018). In this case, users have to make a trade-off about sharing personal information and the benefits associated with the service of a particular smart feature. However, this phenomenon of the privacy paradox has not (yet) been tested in conjunction with smart offices. As this is a growing market, this topic is becoming more relevant nowadays.

2.2.4 Influence of personal-, socio demographic-, work-, attitude-, and experience-related characteristics on preferences of users

The previous sections described the expectations, preferences and privacy concerns of the knowledge workers. However, to create a smart office environment that fits most of its knowledge workers' preferences, it is essential to get more insight into the characteristics that set them apart (Appel-Meulenbroek et al., 2015; Rothe et al., 2011). Therefore, the following sections focus on the influence of personal, socio demographic-, work-, attitude-, and experience-related characteristics on knowledge workers' preferences.

2.2.4.1 Socio-demographic related characteristic

The research found that differences in socio-demographics of office users influence their preferences in the office. Tuzcuoglu et al. (2020) found that age, gender and education level influenced the preferences of knowledge workers. The first demographic characteristic is age. There are five distinct generations in the workplace (Smith et al., 2020). The baby boomers (1940-1955), gen-X (1955-1970), the pragmatic generation (1970-1985), millennials (1985-2000), and gen-Z (2000-2015). It is shown that there are differences among these groups when it comes to perspectives related to concentration, privacy, and indoor climate perspectives within the organization (Rothe et al., 2011). The second demographic characteristic is gender. Although there are ongoing discussions about gender equality, research shows that there are indeed differences between the two genders (male and female). In the office area, differences occur mainly on the need for control over indoor climate and status (Rothe et al., 2012; Bodin et al., 2009). The third demographic characteristic is education. According to Been et al. (2014) and Smid (2016), education level has a significant influence on communication, the experience of interior design, and indoor climate, as well as product support, privacy, and concentration in an office. Therefore, this is essential for getting insight into the different knowledge workers.

2.2.4.2 Personality related characteristics

Research by Hartog (2015) and Oseland (2009) shows that personality influences the user and the appreciation of the (work) environment. To determine personality, the Big Five Inventory (BFI) method is an often-used concept and helps describe and divide the different personalities comprehensively. The distinguished personalities are extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience (Hartig, 2015). Each BFI consists of several statements rated on a five-point Likert scale (strongly disagree to agree strongly). The BFI aspects explain a lot about workplace preferences and influence related needs. For example, introverts like to work alone and have a greater need for privacy than extroverts who are more social and have a greater need for communication (Oseland, 2009). Furthermore, personality influences being open or closed to new experiences, leading to differentiation in acceptance levels for change (Haynes, 2017).

2.2.4.3 Work-related characteristics

The studies show that work-related characteristics such as working hours per week (Been et al., 2016) and work activities (Budie et al., 2019; Vos et al., 2001) influence certain preferences. According to those studies, the amount of time employees work per week is relevant to employee preferences. Someone who spends more time in the office may have different requirements than someone not in the office often (Been et al., 2016).

Also, work activities influence preferences. Each work activity will result in certain preferences (Budie et al., 2019). De Been et al. (2016) indicated “focused, concentrated work”, “knowledge sharing”, and “social interactions” as the three main activities of knowledge workers. Also, Budie et al. (2019) made a similar identification of the main activities of knowledge workers. They divided work activities into concentrated and non-concentrated work and used formal and informal communication as two separate activities. Also, making telephone calls was identified as a separate activity.

2.2.4.4 Attitude-related characteristics

Singh et al. (2018) have looked at the users' perspectives and attitudes towards smart home technologies. This revealed that users were found to have an open attitude towards smart technology, and they recognize the added value that contributes to the quality of life. However, there is a fear of being dependent on technology (Bo et al., 2014). Further, the attitude of respondents can be determined by using the Likert scale. It is also possible to measure attitude towards technology with the Technology Readiness Index (TRI). TRI is a 36-item scale measuring respondents' “technology readiness” regarding new technology concepts (Parasuraman et al., 2014).

2.2.4.5 Experience-related characteristics

According to Tuzcuoglu et al. (2020), it is suggested that examining a user's experience in a smart office environment is necessary. Also, Alraja et al. (2019) mention the importance of considering the knowledge workers' experience since it can influence their trust regarding a new aspect. This influence can positively impact the intention to adopt an aspect such as a smart feature (Komiak et al., 2006). Further, the users familiar with the aspect will increase the acceptants of knowledge workers (Proctor et al., 2018).

2.3 Conclusion

This chapter carried out the literature study, which answered the first two sub-questions. The main goal of the literature review was to gather knowledge on recent and relevant developments concerning the smart office environment and the smart features with their attributes.

From the literature, it has become clear that little is known about smart office environments. This has resulted in the fact that there is no clear definition for a smart office. Therefore, the focus was first on determining which capabilities make systems in an office smart. The comparison study clarified six capabilities that contribute to smartness. Communication, embedded knowledge, adaptive behaviour, decision-making, observing and automated control are essential components to the smart systems in offices. With the help of the capabilities, it is possible to integrate devices, people and computer technologies in an office environment. This explains the most recent definition for a smart office formulated by Tuzcuoglu et al. (2021): "a place/environment established to integrate physical devices, people, and computing technologies to provide a healthy, conducive, interactive, and smart environment for employees". However, note that the user is central and that the smart office must meet the user's needs.

Furthermore, there are all kinds of smart features in a smart office. Based on an investigation study, seven smart features take the user needs into account:

1) Smart indoor location tracking of colleagues focuses on finding colleagues in an office.
2) Smart parking offers the possibility to find suitable parking spots.
3) Smart workspace booking helps users reserve a suitable (individual) workspace.
4) Smart meeting room booking allows the reserve of suitable meeting rooms according to the user's preferences.
5) Smart indoor climate control of temperature helps users to 'take control' and adapt to their preferred environment.
6) Smart indoor climate control of air quality creates the opportunity for individual monitoring.
7) Smart lighting control offers the possibility to control the light to a personal preference, e.g., adjusting the light intensity, colour temperature, and colour range.

The second part of the literature study focused on the smart office user. The users have different expectations and preferences in a smart office than a regular office. The preferences have to do with improving the interaction and perceived smartness of the office. This is divided into the five attributes:

1) Control: This focuses on how the user wants to have control.
2) Information sharing: The type of information users wants to share with the smart feature.
3) Communication: The way users want to receive information from the smart feature.
4) Knowledge acquisition: This focuses on improving the services by acquiring knowledge based on general office usage patterns or individual usage patterns.
5) Personal information for resource efficiency: The smart feature focuses on sharing personal information (e.g., age) or sensitive information (e.g., health data).

These five attributes are important elements for the user regarding a smart feature. Unfortunately, the use of a smart feature also raises concerns. This is because smart features collect a lot of information about the user. Due to data collection, users can become more reluctant to share their data. However, users have also shown a different behaviour when the benefits of sharing data with a smart feature are clear to them. As a result, users are more likely to share information, the so-called privacy paradox. It is up to the user; they have to make a trade-off about sharing personal information and the benefits of a particular smart feature. Although, little is known about this phenomenon in the smart office environment.

Chapter 3. Methodology

In this chapter, the methodology of the research will be presented. In the first section, the discrete choice experiment will be explained. Also, the experimental design process with stages will be described. All stages of the stated choice experiment are discussed in the second section. The final section will explain the analyses conducted after the data collection.

3.1 Discrete choice experiment

The discrete choice experiment (DCE) theory will determine the smart features that meet the user's expectations and preferences. In addition, this theory provides insight into the choices that individuals make between alternatives of products and services (Louviere et al., 2010). As a result, a detailed understanding of how choices are related to different aspects of smart features and how these choices relate to individuals' privacy issues can be gained.

Two popular approaches to measure preferences are revealed choice modelling and stated choice modelling. The first method, revealed choice modelling, involves determining respondents' preferences to real market conditions. In contrast, the second method, stated choice modelling, focuses on respondents' preferences in a hypothetical situation. This methodology is most useful in cases where new phenomena are presented to the respondents (Haegeli et al., 2009). Since smart features are considered a rather new phenomenon, a stated choice experiment will be conducted.

The stated choice experiment can be divided into preference and choice modelling, as shown in Figure 4. In preference modelling, the respondent is asked to rate or rank the importance of alternatives (Louviere et al., 2010; Kemperman, 2000). In choice modelling, the respondent is asked to choose between the alternatives. Kemperman's (2000) research shows that choice modelling better reflects people's experiences. Therefore, choice modelling will be used. The stated choice modelling uses decompositional modelling. In decompositional modelling, respondents make a trade-off between levels of the attributes. By doing so, the relative importance of the levels can be estimated. This choice process, where respondents choose an alternative based on a trade-off of attributes, shows similarities with real-life choice processes (Hensher et al., 2015; Louviere et al., 1990).

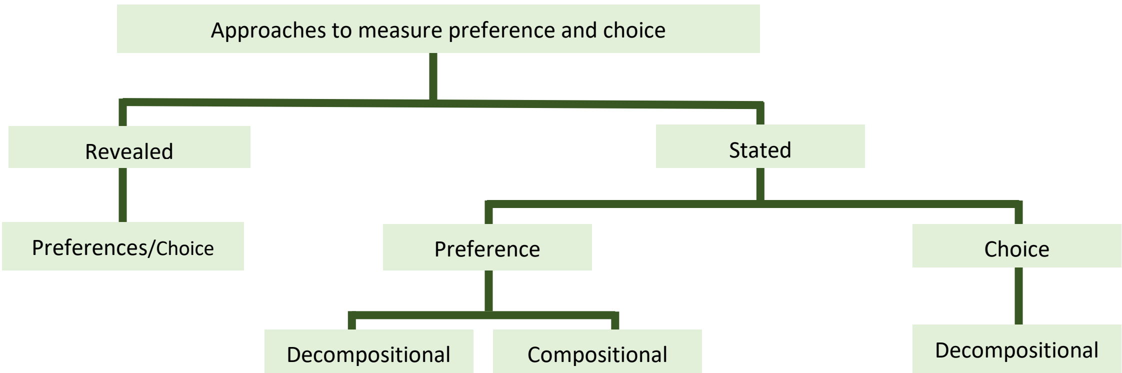


Figure 4: An overview of preference and choice measurement approaches Kemperman (2000)

3.1.1 Experimental design process

The experimental design describes all steps of the choice experiment. The experimental design framework of Hensher et al. (2015) is reused as it covers all the relevant steps of our experiment. Figure 5 presents the experimental design of Hensher et al. (2015).

The design process begins with a problem definition. The problem this research aims to tackle is described in the introduction. The rest of this chapter describes the remainder of the experimental design process.

Potential alternatives, attributes and levels are investigated using a literature review. The selection of these stimuli (stage 2) is described in section 3.2.1. After selecting those stimuli, choices are made regarding the design of the experiment (stage 3). These are described in section 3.3.1, after which the generation of the design (stage 4) is described in section 3.3.3. After the experimental design, in section 3.3.4, the attributes are assigned (stage 5). Different combinations of the choice sets (stage 6) are possible. These are determined in section 3.3.4, followed by randomization of these choice sets (stage 7) presented in section 3.4.1. After going through the previous seven phases, the final study (stage 8) can be designed in section 3.4.2-3.4.4, including the remaining variables needed to answer the research questions.

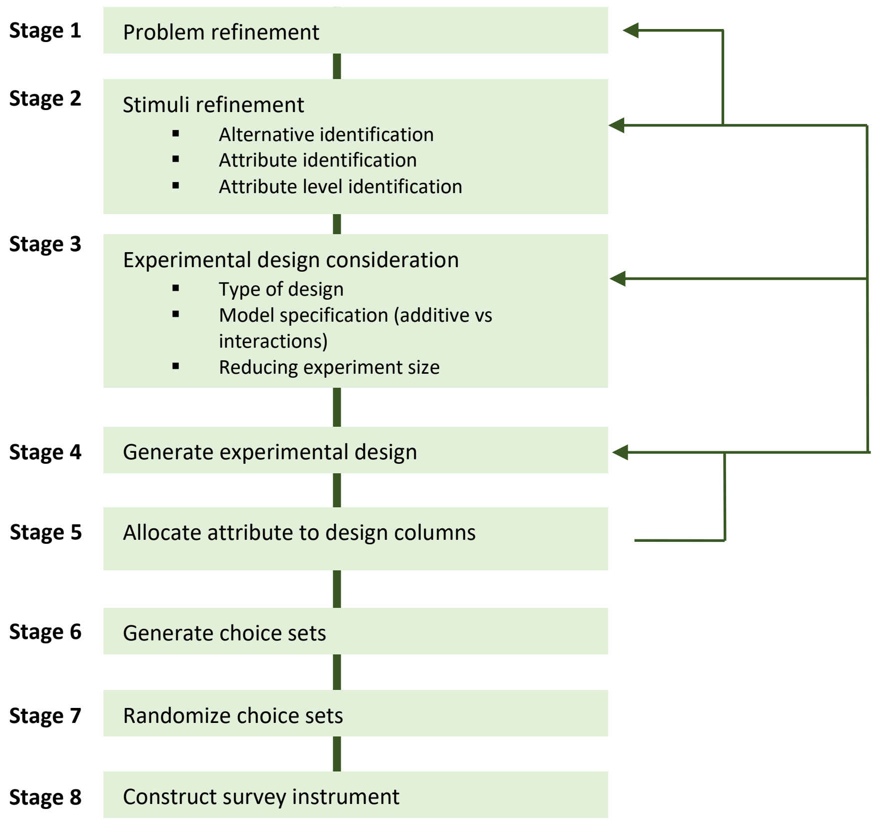


Figure 5: Experimental design process Hensher et al., (2015)

3.2 Attribute identification

This section will identify the attributes and attributes levels for the stated choice experiment of stage 2. This is a critical stage that determines the survey experiment's success and the validity of the results (Kløjgaard et al., 2021). Additionally, several socio-demographics-, work-personality, attitude- and experiment related questions and statements will also be discussed since the characteristics are also a part of the survey.

3.2.1 Input for Choice experiment

The experiment consists of choice sets. In this study, a choice set consists of two alternatives (Smart feature package A and Smart feature package B) which the respondent has to choose between. The alternatives contain several attributes. These attributes are characteristics of smart features. Each attribute has different levels, which can differ per alternative. Next to this, there is the 'No preference' option. This can be chosen when the alternatives are equal for the respondent or when no alternatives are preferred.

All attributes consist of two or three attribute levels. Regarding the attribute levels, all combinations of attribute levels have to be possible and not conflict with other attribute levels. Also, the attribute levels should be clear and understandable for the respondents. Otherwise, it will be too hard for the respondents to imagine the smart feature package alternatives. To identify the levels for each attribute, the levels used in previous studies were reviewed. Most levels were extracted from the literature. However, this is not the case for attribute five because it has not yet been examined in the literature. For this reason, these levels have been created based on common sense.

Table 3 shows the attribute levels for each attribute. The attribute and attribute levels of the table are the basis for all smart features. The attribute levels presented in the table are generically applicable. The attribute levels will be customized per smart feature since each is used for different needs and tasks. Appendix I includes a matrix in which all smart features are elaborated. In the following sections, the levels of each attribute are discussed.

Table 3: Experimental design attribute and level identification

No.	Attribute	No.	Attribute levels
A1	Control	L1 L2	▪ Decision support ▪ Automated decision support
A2	Information sharing	L1 L2 L3	▪ Not sharing information ▪ Basic information ▪ Basic information + Personal preference
A3	Communication	L1 L2 L3	▪ No dashboard ▪ Basic communication ▪ Advanced communication
A4	Knowledge acquisition (purpose of data use)	L1 L2 L3	▪ Knowledge acquisitions – No ▪ Knowledge acquisitions – Whole system ▪ Knowledge acquisitions – Individual system
A5	Personal information for resource efficiency	L1 L2 L3	▪ +0% efficiency (none) ▪ +15% efficiency (personal information) ▪ +35% efficiency (sensitive) information

3.2.1.1 Control

Within a smart office, users consider controlling their environment an important aspect (Kwon et al., 2019; Schleich et al., 2017). A smart feature can provide the user to have control over a choice in different ways (Appel-Meulenbroek et al., 2019; Reijula et al, 2011; Cook et al, 2009). Two attribute levels have been formulated. The first level is decision support; the smart feature uses a leading user system. The system automatically collects information about the environment and creates an overview for the user (Microsoft, n.d.). The user can make a choice based on the presented options. The second level is automated decision support; the smart feature uses a guiding system. The user shares their preferences with the system, and the smart feature automatically chooses the best alternative for the user (Microsoft, n.d.).

3.2.1.2 Information sharing

Users expect smart offices to contribute to their daily activities and needs (Tuzcuoglu et al., 2020). Information sharing with the office environment plays an important role in this context (Yang et al., Unpublished). The smart features can better support the users according to preferences, calendar, and work activities based on the shared data. The more information shared, the more targeted the smart feature can help and serve the user (Memoori, 2019; Microsoft, n.d.). Therefore, there are three attribute levels. The first attribute level is about not sharing information. The second level is about sharing basic information, which is not personal, such as calendar or type of work activity. The third level is sharing basic information and personal preferences; respondents can also share their preferences. In this way, the smart feature offers the users even more qualified assistance based on the needs of an individual.

3.2.1.3 Communication

According to Yang et al. (Unpublished), users want to be more involved with their office environment. Office users would like to know more about what is happening in the background and get feedback on a dashboard (D'Oca et al., 2018). Communication is, for this reason, an important attribute for users. The first attribute level is no dashboard; users who go for this option are not interested in feedback. The second level is basic communication; the current state is shared with the user. Finally, the third level is advanced communication, where users receive updates about the current state, tips and alerts from the system (Microsoft, n.d.).

3.2.1.4 Knowledge acquisition

Smart features collect various information about the users and office environment. Various analyses can be run with the collected data to better understand a smart office's usage patterns (Mikulecky, 2012; Microsoft, n.d.). The system can use knowledge acquisition to understand the usage pattern of the entire office and improve the service. Also, it is possible to get individual user patterns (Mahmoud et al., 2018). This attribute consists of three levels. The first level is no knowledge acquisition. The second level is knowledge acquisition for the whole system; data is used to create a general usage pattern in the office. The third level is on an individual level; data will be used to create individual user patterns.

3.2.1.5 Sharing personal information for resource efficiency

As described earlier, smart features collect many data about the users. By sharing data with a smart feature, the daily activity that the user has to perform becomes more efficient (Tuzcuoglu et al. 2020; Kim et al., 2019; Microsoft, n.d.). However, there is no insight into the extent to which respondents would like to share personal or sensitive data with the smart feature to get even more benefits from using the system. Therefore, this is related to the so-called privacy paradox (Kokolakis, 2017; Williams et al., 2018). Three levels measure the willingness to share personal information for better services. The first level is about not sharing personal information for resource efficiency. The second level is sharing personal information for 15% efficiency; the system will use the shared personal information to meet the users' needs. The third level is sharing sensitive information for 35% resource efficiency; the system will use the sensitive data to meet users' needs.

3.2.2 Input survey questions

Prior to the Stated Choice Experiment, the respondents will be asked about their socio-demographic-, work- and personality-related characteristics. Also, questions about familiarity with the seven smart features will be asked to gain insight into the respondent's experience. Furthermore, statements will be asked about how the respondent perceives the smart features.

3.2.2.1 Socio demographic variables

As found in the literature, several socio-demographic characteristics have significantly affected the individuals' preferences in the office. The most relevant characteristics are age, gender, and education. Therefore, the Dutch census called "Centraal Bureau voor de Statistieken" (CBS) is consulted to create the correct level of measurements. CBS provides reliable statistical information and data freely available (see Table 4). With their data, the survey results can be compared to the Dutch average and concluded if there is are any under- or overrepresented categories in the survey results.

Table 4: Socio-demographic variables and their representation amongst Dutch office workers according to CBS (2021)

Variables	Level	Dutch office workers (%)
Gender	Male	60.4
	Female	39.6
	Other	-
Age	15-24	15.8
	25-34	21.9
	35-44	19.9
	45-54	23.3
	55+	19.2
Education	Primary education	0.7
	Secondary education	10.3
	Vocational education	25.3
	Applied university	31.5
	Academic education	32.2

3.2.2.2 Work-related variables

Complementary to the socio demographic variables, two variables are included in the survey to address work-related variables. The first question is about working hours per week; respondents are asked to fill in how many hours they work per week at the office. The levels were determined using the CBS distribution. This question explicitly emphasized that it is about an estimated number of hours for the COVID-19 pandemic (see Table 5). The second question is focused on time spent on several work activities. This is based on De Been et al.'s (2016) distribution. However, the distribution has been renamed, and an option 'other work activities' has been added for activities that do not fall within the three levels (see Table 6).

Table 5: Work variable and their representation amongst Dutch office workers according to CBS (2021)

Variables	**Level**	**Dutch office workers (%)**
Work hours per week	<12h	11.0
	12h-19h	6.8
	20h-27h	13.7
	28h-34h	17.8
	≥35h	50.7

Table 6: Time spending related questions about work activities

Work activities	**Measurement**
Individual concentrated work	[Average time spend per week]
Formal communication work	
Informal communication work	
Other work activities	

3.2.2.3 Personality related variables

Personality will be measured using the Big Five Instrument (Hartog, 2015; Oseland, 2009). Based on 15 statements, the personality of the respondents will be indicated. There are five personality traits; extraversion, agreeableness, conscientiousness, neuroticism, and openness. Per personality traits, three statement related items will be presented. First, the respondent had to indicate to what extent they could identify themselves with the personality items. This is performed by using a Likert scale (see Table 7).

Table 7: Statements about personality

Personality	**Measurement**
Extraversion	[Five-level Likert Scale]
Agreeableness	
Conscientiousness	
Neuroticisms	
Openness	

3.2.2.4 Experience related variables

Three questions were asked to gain insight into the respondents' familiarity with the seven smart features. Per smart feature, respondents could select whether they were familiar with the smart feature or not. There is also a distinction between the extent to which the respondents have used the smart feature before. This ensures clear distinctions between the three questions (see Table 8).

Table 8: Experience related questions about smart features

Experience	Measurement
Smart indoor location tracking of colleagues	[Choosing a statement] ▪ Never heard about it before and never used it ▪ Heard about it and used it ▪ Heard about it but never used it
Smart parking	
Smart workspace booking	
Smart meeting room booking	
Smart indoor climate control for temperature	
Smart indoor climate control for air quality	
Smart lighting control	

3.2.2.5 Attitude related variables

It is important to understand how the respondents think about smart features. Based on the questions presented in Table 9, it can be concluded if there is a significant difference between the respondent's attitudes after the research is conducted. The questions are based on Technology Readiness Segmentation (Parasuraman et al., 2014). The attitude toward smart features will be measured with three survey questions. The question focuses on three aspects: productivity, quality, and occupation. To measure the attitude of the respondents, a 5-point Likert scale ongoing from 'Strongly Disagree' to 'Strongly Agree' were used. A 5-point scale is chosen since it is the most widely used size.

Table 9: Statements about the perception of smart features

Attitude	Measurement
Smart features (will) make me more productive at work.	[Five-level Likert Scale]
Smart features (will) contribute to a better quality.	
Smart features (will) make me more efficient in my occupation.	

3.3 Experimental design

This section creates choice sets using attributes and attribute levels (stage 3-6). Different choices have to be made in the different stages to make the choice set. The choices regarding the experimental design have a significant impact on the outcome of the experiment. It is therefore important that these choices do not limit the results.

3.3.1 Generate experimental design

The Statistical Analysis Software (SAS) is used to create the experimental design (SAS, 2022). With the help of this program, attributes and attribute levels can be translated into profiles. These profiles can then be used to generate the choice sets. Finally, the choice sets are applied to all seven smart features. To create this experimental design, four main macros are used to code in SAS: %MktRuns (suggesting reasonable sizes for experimental designs), %MktEx I(to create the experimental design), %MktLab (transformed the experimental design into textual attributes and level descriptions), and %ChoicEff (to estimate the fitness of the model). In Appendix II, the coding that is used in SAS is presented. Further in Appendix III, the output of SAS is shown.

3.3.2 Creating profiles

For the experimental design, it is important to evaluate the generated design of the stimuli refinement. To do so, the %MktRuns and %MktEx macros are used. The original design contains 162 possible profiles (full factorial). This is considered too large for the scope of this project. %MktRuns suggests reasonable design sizes for which an efficient design can be made. The %MktEx macro can then design efficient factorial designs based on the results of the %MktRuns macro.

Table 10 shows the output of the %MktRuns macro. It suggests two design sizes with 100% efficiency. The smallest number (18) is chosen, resulting in the least combinations necessary to achieve an efficient design. %MktEx is then used to create the factorial design.

Table 10: Output %Mktruns Macro - Reducing experiment size

```
                          Saturated      = 10
                          Full Factorial = 162
             Some Reasonable                   Cannot Be
             Design Sizes       Violations     Divided By
             18 *             0
             36 *             0
             27               5      2 6
             12               6      9
             24               6      9
             30               6      9
             15              11      2 6 9
             21              11      2 6 9
             33              11      2 6 9
             10 S            14      3 6 9
       * - 100% Efficient design can be made with the MktEx macro.
       S - Saturated Design - The smallest design that can be made.
```

Moreover, the experiment is generic, which means that all levels appear randomly over the profiles in the design. Blocking is used to prevent the levels from being the same across the choice sets; this is also called flagging in SAS. There are two flags coded, as each choice set has two profiles (alternatives) presented in the stated choice experiment (see Table 11). In short, every smart feature has a design size of 18 profiles; in each choice set, two profiles are presented as alternatives. This results in 9 choice sets being created for each smart feature.

Table 11: Output of %MktLab macro- Flags

Profile	Flag 1	Flag 2	A1	A2	A3	A4	A5
1	1	1	1	1	1	1	1
2	1	1	1	1	2	1	3
3	1	1	1	1	3	2	3
4	1	1	1	2	1	3	1

3.3.3 Goodness of fit

To provide efficient choice designs and evaluate the goodness of fit for the choice model design, %ChoicEff macro is used. The goodness of this design is determined by comparison with a hypothetical, optimal design. As shown in Table 12, the final design results have a relative D-efficiency of 58.93 on a score from 0 to 100. A value of 0 implies that one or more levels cannot be estimated, while a value of 100 suggests that the design is balanced and orthogonal. A D-efficiency of 100 cannot be achieved within this research since a full factional experiment was not conducted. However, it is possible to improve the D-efficiency by adjusting the design. Examples of this could be reducing the number of levels and increasing the profiles. Although if the choice is made to reduce the number of levels, the attributes of the study lose their level of detail. Also, if the choice is made to increase the number of choices, this will result in huge increases in the overall size of the study. Since all attributes can be estimated with a D-efficiency value of 58.93, and the covariance matrix showed no significant errors, the current experiment will be retained. According to Warren (2010), a D-efficiency value of 59% can be considered an acceptable average result.

Table 12: Output %ChoiceEff macro

```
            Final Results
Design                      12
Choice Sets                  9
Alternatives                 2
Parameters                   9
Maximum Parameters           9
D-Efficiency            5.3039
Relative D-Eff         58.9319
D-Error                 0.1885
1 / Choice Sets         0.1111
```

3.3.4 Creating choice sets

After verifying the goodness of fit, choice sets were created (see Table 13 for an impression of a choice set). Then, using %MktLab, these values in the choice sets can be transformed into textual attributes and level descriptions (see Table 14). This was performed for all nine choice sets. After that, the attribute levels of the choice sets were made smart feature specific for each smart feature. See Figure 6 for an example of the first choice set of smart indoor location tracking of colleagues.

After creating the choice sets per smart feature, stage 6 of the experimental design process has been completed. It is important to mention that there is no attention to the 'no preference' option during the process. In addition to the two alternatives, respondents are also given a choice to go for the "no preference" option. This option provides the respondent with the possibility of whether the alternatives are equally interesting or irrelevant. Since this choice option does not contain attributes and levels, it is excluded in the experimental design generation but included in the survey (See Figure 6).

Table 13: Choice set 1 – Values of attribute and attribute levels

Choice Set	Design	Efficiency	Index	Prob.	N	Flag 1	Flag 2	A1	A2	A3	A4	A5
1	12	5.30387	15	0.5	199	1	1	2	2	3	1	2
	12	5.30387	11	0.5	200	1	1	2	1	2	3	1

Table 14: Choice set 1 - An added textual description of attribute and attribute levels

Choice Set	Control	Information sharing	Communication	Knowledge acquisition	Resource efficiency
1	Automated decision support	Basic information sharing	Advanced communication	No knowledge acquisition	+15% efficiency
	Automated decision support	Not sharing information	Basic communication	Individual system	+0% efficiency

Choice set 1 **Characteristics**	**Package A**	**Package B**
Control	• Automatically guides you to colleagues based on the aggregated information.	• Automatically guides you to colleagues based on the aggregated information.
Information sharing	• Status busy/free	• None
Communication	• Map with locations of colleagues	• Colleague location list in outlook
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Time reduction of looking for colleagues)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choose one of the following answers:
Please choose only one of the following:

O Package A
O Package B
O None

Figure 6: Choice set 1 - Impression as in the survey (Smart indoor location tracking of colleagues)

3.4 Survey instrument

This section explains the randomization of the choice sets and the structure of the survey (stage 7-8). Limesurvey is used to designing the survey and share it with respondents (Limesurvey, n.d.).

3.4.1 Randomize choice sets

The experiment consists of multiple components. As a result, the phenomenon of survey fatigue can occur among respondents. Fatigue can occur when the survey takes too much time and effort, making the respondents' answers less accurate. This phenomenon carries the risk of reducing the quality of the experiment. According to Sanko et al. (2001), it is suggested to have a maximum of 9-16 choice sets per respondent. Therefore, two settings were applied in Limesurvey. The first setting ensures that a maximum of 2 smart features are displayed per respondent (each with nine choice sets). This prevents respondents from filling in choice sets from all smart features. The second setting allows the choice sets per smart feature to be presented randomly to a respondent. Every respondent starts with a different choice set. This will result that there is no bias in the choice order. This prevents risks of fatigue and confusion.

3.4.2 Privacy and Ethics

Due to GDPR and TU/e policies, it was decided to make the survey anonymous. In collaboration with the Ethical Review Board of the TU/e, the survey was checked, and agreements were made on how the data will be handled. It has been taken into account that no questions will be asked that could lead to the identification of the respondent. This also means that no traceable data will be stored, such as name or IP address. As a result, respondents cannot save the survey and finish it later. This can lead to respondents starting over if they accidentally close the survey.

Respondents are informed about data privacy and data processing in the consent section. Their data will only be used for the data analysis of this study and will be removed afterwards. Results of this analysis are presented in this thesis.

3.4.3 Information in the survey

The survey starts with a welcome message that contains information about the subject of the survey, the objective and the structure of the survey. This is followed by an introduction which is important as all respondents must have a certain level of knowledge about what smart office means in this survey. During the survey, respondents were provided with information about smart features. It was a conscious choice to provide the respondent with a small amount of information to ensure that the respondents were not overloaded with too much information.

To reduce the influence of possible learning rates, a short introduction explaining the stated choice experiment is shown just before the stated choice questions. An extra explanation is added to each choice set, explaining the purpose and meaning of the attributes to help the respondent in making a good trade-off. Appendix IV presents the complete survey.

3.4.4 Pre-testing

Before the survey was officially activated, it was tested among a test panel. The test can be divided into three phases (see Figure 7). Three office workers were asked to complete the survey in the first phase. These office workers are aware of the research and familiar with smart offices. The goal was to test the content of the survey to make sure the definitions were clear, and the choice experiment methodology was well described. In the first phase, it became clear that the content of the information was correct and that the randomization of the choice experiment also worked well. Five office workers were asked to fill out the survey in the second phase. These office workers work in companies outside the built environment sector. This was to understand if the survey is clear to employees who are not aware of the smart office trends to identify possible problems in the survey. Two issues were identified from the second phase. First, the test panel respondents considered that the survey was too large, caused by the provided information in the introduction section. Furthermore, respondents indicated that some parts were already familiar to them, and some were not. These two problems were solved by reducing the information in the introduction and adding information icons in the survey. In this way, the respondent can click on the icon when they think it is necessary. The same respondents were asked to review the survey again in the third phase. Moreover, all respondents indicated that the new version of the survey was clear. Finally, four other office workers were asked to review the survey in the fourth phase. This group experienced no problems or ambiguities. After the final review, the survey was ready to be activated.

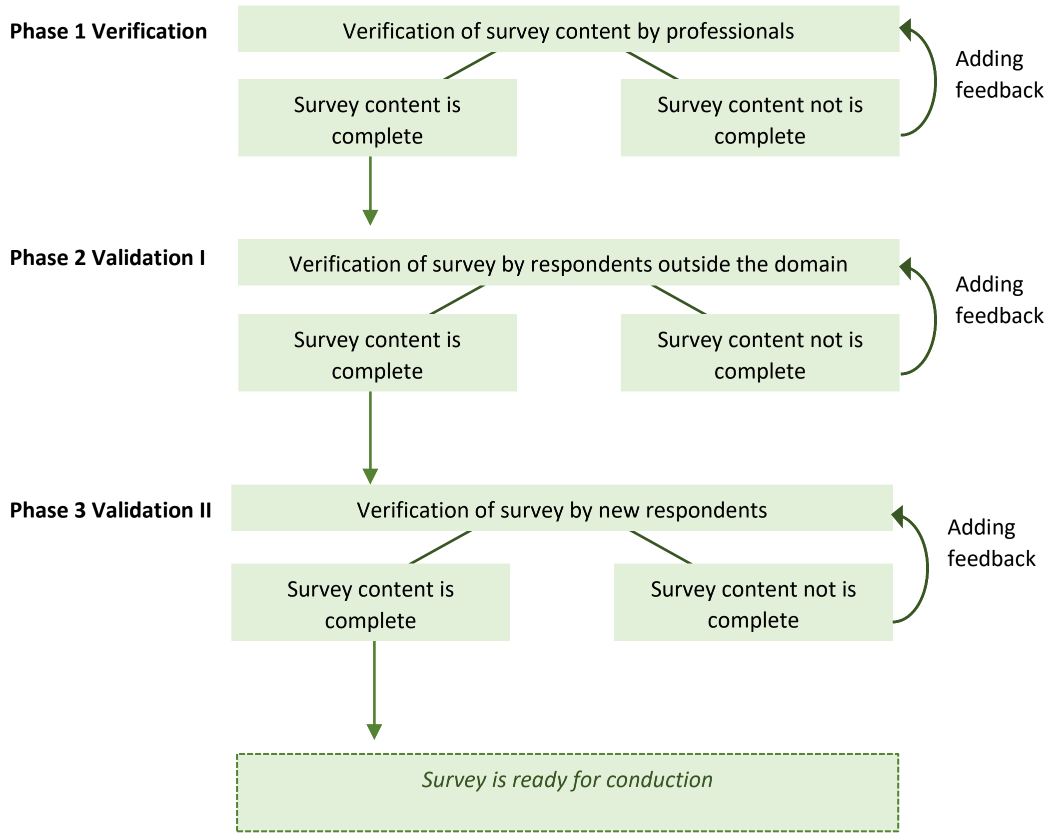


Figure 7: Pre-testing the survey

3.4.5 Noise reduction in survey results

Before analyzing the data, it will be checked for inaccurate or inconsistent results. Therefore, four noise reduction protocols have been established (Bhandari, 2021; Survey Monkey, n.d). The first protocol checks the data on missing values. Therefore, only fully answered surveys will be analyzed. The second protocol checks the survey on completion time. Five minutes is considered the bare minimum to read carefully through the information and answer the survey. Therefore, surveys with a completion time under 5 minutes are considered invalid. The third protocol verifies the dataset on duplication and deletes identical copies of data. Finally, the fourth protocol is to test for research outliers. This protocol focuses on respondents who choose the same answer for all the questions, also called straight-line. If this is the case, then the survey will also be removed.

3.4.6 Effect coding

To perform the analysis, the attribute levels of the choice experiment are coded. Coding allows for non-linear effects in the different levels of the attributes, which is necessary for accurate data analysis (Hensher et al., 2005). This can be done by using an effect coding scheme. In effect coding, each attribute is divided into parameters. In effect coding, attributes are coded using parameters. N-1 parameters (where N is the number of levels of an attribute) is sufficient to calculate the part value of each attribute level using a derived part-worth utility function (see Table 15). Then, through the derived part-worth utility, the part value of each attribute level can be estimated.

Table 15: Effect coding schema

Attribute	ID Level	Parameter I	Parameter II	Derived part-worth utility
1. Control	A1L1|Decision support	1		β1∗ 1
	A1L2|Automated decision support	-1		β1∗ -1
2. Information sharing	A2L1|Not sharing information	1	0	β1∗ 1 + β2∗ 0
	A2L2|Basic information	0	1	β1∗ 0 + β2∗ 1
	A2L3|Advance information	-1	-1	β1 ∗-1 +β2 ∗ -1
3. Communication	A3L1|No dashboard	1	0	β1∗ 1 + β2∗ 0
	A3L2|Basic communication	0	1	β1∗ 0 + β2∗ 1
	A3L3|Advanced communication	-1	-1	β1 ∗-1 +β2 ∗ -1
4. Knowledge acquisition	A4L1|No knowledge acquisition	1	0	β1∗ 1 + β2∗ 0
	A4L2|Whole system	0	1	β1∗ 0 + β2∗ 1
	A4L3|Individual system	-1	-1	β1 ∗-1 +β2 ∗ -1
5. Personal information for resource efficiency	A5L1|+0% efficiency	1	0	β1∗ 1 + β2∗ 0
	A5L2|+15% efficiency	0	1	β1∗ 0 + β2∗ 1
	A5L3+35% efficiency	-1	-1	β1 ∗-1 +β2 ∗ -1

3.5 Data Analysis Methods

The Multinomial Logit model (MNL) and a Latent Class Model (LCM) will be applied to get insight into the stated choice experiment data. Using the MNL model, an individual's overall preference for a choice option can be analyzed. The mean values for the total sample can be calculated with the results. The LCM will find groups of individuals who exhibit similar choice behaviour. These results will help to form the relationships between preferences and personal characteristics.

3.5.1 Explanation of Multinomial Logit

Discrete choice modelling is based on the Random Utility Theory (RUT). Using RUT, it becomes possible to analyze the choice of an alternative. For example, see the following formula (1) (Hensher et al., 2015; Kemperman, 2000):

$$\boldsymbol{U_{iq}} = \boldsymbol{V_{iq}} + \boldsymbol{E_{iq}} \quad \rightarrow \Sigma \boldsymbol{\beta_n} \boldsymbol{X_{inq}} + \boldsymbol{E_{iq}} \qquad \textbf{(1)}$$

$\boldsymbol{U_{iq}}$= the overall utility of alternative i for respondent q
$\boldsymbol{V_{iq}}$= the structural utility of alternative i for respondent q
$\boldsymbol{E_{iq}}$= the random utility component (error component)
$\boldsymbol{\beta_n}$= the utility weight of attribute n
$\boldsymbol{X_{inq}}$= the score of alternative i on attribute n for respondent

Using equation 1, the overall utility per alternative can be determined. The higher the utility value β, the higher the probability that the respondent chooses this alternative (Hensher et al., 2015; Kemperman, 2000). With the overall utility formula given in (1), the probability that an individual chooses a specific alternative can be measured with the Multinomial Logit Model. The MNL is the most commonly used method to estimate the utility value of a choice situation (Kemperman, 2000). The probability (P_i) of an alternative is calculated by equation (2) which returns a value between 0 and 1. (Hensher et al., 2015):

$$\mathbf{Pi} = \frac{\mathbf{exp(Vi)}}{\mathbf{\Sigma j\ exp\ (Vj)}} \qquad \textbf{(2)}$$

$\boldsymbol{P_i}$= the probability that alternative i will be chosen
$\mathbf{exp}(\boldsymbol{V_i})$= the structural utility of alternative i
$\Sigma\ \boldsymbol{j}\ \mathbf{exp}\ (\boldsymbol{V_j})$= the sum of the structural utility of all alternatives

3.5.2 Explanation of Latent Class

LCM help to identify different classes based on similar preferences. An LCM considers the heterogeneity in society (Hensher et al., 2015). Individuals can be divided into classes based on similar preferences through this method. With the following equation, the utility and probability can be estimated (the utility function (3), and the probability function (4)):

$$\mathbf{V}_{\boldsymbol{iq}} = \Sigma_{\boldsymbol{n}} \boldsymbol{\beta}_{nc} \boldsymbol{X_{inq}} \qquad \textbf{(3)}$$

$\boldsymbol{\beta}_{nc}$= the utility weight of attribute n for class c
$\boldsymbol{X_{inq}}$= the score of alternative i on attribute n for respondent

$$P_{iqt} = \frac{\exp(V_{iqt|c})}{\sum_{j=1}^{J} exp(V_{iqt|c})} \quad \textbf{(4)}$$

P_{iqt}= the probability of the individual q of class c will choose alternative i
$V_{iqt|c}$ = Structural utility for individual q of alternative i in choice set t given class c

Further, insight can be gained by performing statistical tests that can identify the differences between classes by considering socio-demographic and work-related characteristics. Those characteristics with nominal/ordinal variables can be measured with a Chi-square test, and internal/ratio characteristics can be measured by conducting an independent sample t-test. The results of the tests show the distribution among the classes

3.5.3 Goodness of fit

To use the MNL and LCM, it is important to check the model's goodness of fit. The performance can be verified by measuring the McFadden Rho-squared Test (McFadden, 1974). Using McFadden Rho-squared Test, the model's overall fit can be determined. McFadden suggests Rho-squared values of between 0.2 and 0.4 should represent an excellent model. However, a value below 0.2 is considered acceptable (McFadden, 1974).

$$\rho^2 = 1 - \frac{LL_{Estimated\ model}}{LL_{Null\ model}} \quad \textbf{(5)}$$

LL (β) = Log-likelihood of estimated model
LL (0) = Log-likelihood of null model

The Rho-squared is dependent on the log-likelihood of the estimated model LL(β) and the log-likelihood of the null model LL(0) to calculate the goodness of fit. Since the LL (β) must be estimated separately for each choice, the software will be used to calculate the log-likelihood calculations of the estimated model(s). For this purpose, Nlogit will be used to determine the LL (β) of the MNL and LCM. The LL(0) can be calculated manually using the equation.

$$LL\ (0) = \sum_{n=1}^{N} \sum_{i} \ln 1/3 \quad \textbf{(6)}$$

LL(0) = The log-likelihood of the null model with the estimated parameters of β=0
N = Total Sample Size used in the model
P_{ni} = The probability that individual (n) chooses alternative (i) (Pni =1/3)

To compare different models of the smart features with each other, the adjusted Rho-squared Test can be conducted (McFadden, 1974).

$$\rho^2 Adj = 1 - \frac{(1-\rho^2)*(n-1)}{n-k-1} \quad \textbf{(7)}$$

ρ^2 = Sample Rho-squared
n = Total sample size
k = Number of respondents

Chapter 4. Data description

This chapter gives an overview of the data collected with the survey. It provides information about the data collection, data preparation, and descriptive statistics. The sample is compared with CBS data to verify whether the sample is representative.

4.1 Survey administration

A total of 245 respondents had started the survey. These respondents were reached by recruiting knowledge workers from the internship companies and via an open call for participation through various social media channels. Of these respondents, 153 finished the survey. It took an average of 14 minutes to finish the survey. This is within the expected timeframe of 15 minutes.

4.2 Data preparation

The data preparation section describes the steps to clean the raw survey data for the data analysis phase. The dataset consists of two main types of variables: independent variables and dependent variables. The independent variables are the demographic-, work-, attitude-, personality-, and experience-related variables that are identified in chapter 2. The dependent variables are the smart feature attributes described in chapter 3. For analyzing the dependent and independent variables, three software programs are used. Microsoft Excel is used for recoding and data cleansing. Descriptive statistics of independent and dependent variables are conducted using SPSS Statistics. Furthermore, NLogit is used for the estimation of MNL and LCM.

4.2.1 Noise reduction

To increase the quality of the survey, the data is screened to spot inconsistencies or errors based on the protocols established in chapter 3. First, the data is checked on missing data. Of the 245 surveys, 94 respondents started the survey but did not finish it. Lime Survey can automatically filter out the unfinished surveys. Further, all cases are manually checked for research outliers. For example, five surveys have been removed since there were completed in less than 5 minutes. Also, nine surveys were removed because the surveys consisted of "straight-line" data. After the noise reduction, 137 full surveys are considered representative.

4.2.2 Recoding variables

Two variables were recoded for analysis. First, the categories of variable *Education* are recoded. Two respondents used the *Other* option to set their education level to PhD, and only a handful of respondents answered the *Academic education - Bachelor* option. Therefore, these two categories were merged with *Academic education – Master* and recoded as *Academic education and higher.* Also, the variable *Work hours per week* is recoded. As respondents answered their work hours as a number, these answers were recoded into five categories. This simplifies the comparative analysis (see Table 16).

Table 16: Recorded variables

Education	Work hours per week
Primary	<12h
Secondary education	12h-19h
Vocational education	20h-27h
Applied university	28h-34h
Academic education and higher	≥35h

4.2.3 Recoding for using Nlogit

The software NLogit has restrictions on the data format to perform statistical tests. The choice sets have to be transformed from the experimental design to a readable format by NLogit. This means that the alternatives must be recoded. Hence, each respondent's data should be divided into nine blocks that refer to a choice set. One block contains three rows corresponding to an alternative within that choice set (one choice set includes two alternatives and an alternative that states 'no preference'). In total, 3699 (= 137 respondents * 9 choice sets * 3 (2 alternatives and one no choice option)) data rows are created for analysis in Nlogit. To indicate one of the choice sets, see Appendix V.

Moreover, the choices also had to be recoded. Since all alternatives are recoded into blocks, it should still be clear which alternative is chosen. Therefore, the chosen alternative is recoded with 1 and the others with 0. Again, this was done for 3699 data rows to make the choices visible in the data file. After that, the excel file with the choice sets has been saved as a CSV UTF-8 (comma separated) to make the data file readable in Nlogit.

Subsequently, the data file is imported into Nlogit and analyzed. The MNL and LCM, log-likelihood, coefficient (utility score), standard error and probability are determined for both models. This process is performed for all smart features. The output of discrete choice models from Nlogit is presented in Appendix VI.

4.2.4 Calculating part-worth utility

In Nlogit, the utility parameters are estimated for the MNL and LCM. However, this is not the case for all values. If the attribute consists of two attribute levels, the program estimates only the first value. If the attribute consists of three attribute levels, the program estimates only the first two values. The unestimated values are calculated manually using the formula 'Derived part-worth utility' (see Table 17). In this way, all values are determined for the MNL and LCM.

Table 17: Derived part-worth utility (based on effect schema)

No.	Levels	Derived part-worth utility
2	Level 1	β1
	Level 2	β1∗ -1
3	Level 1	β1
	Level 2	β2
	Level 3	β1 ∗-1 +β2 ∗ -1

4.3 Descriptive statistics

This section examines the extent to which the sample is representative of office employees in the Netherlands. To get an insight, the differences in distributions between variables is conducted by chi-square test. This section also discusses the results of the descriptive statistics.

4.3.1 Representatives of the sample

It is desirable to indicate whether the sample represents office employees for this study. This was elaborated by comparing sample data with CBS data. The CBS dataset is based on a study to find characteristics of the average Dutch working population divided per profession (CBS, 2021). Therefore, the data is filtered on professions that typically work in offices. The comparison was based on the following variables: gender, education level and work hours per week. The outcomes of the distributions are shown in Table 18 and visualized in figure 8 and 9.

Table 18: Overview of the sample vs CBS

Variables	Level	Sample (N=137)	Sample (%)	Office employee the Netherlands (N)	Office employee the Netherlands (%)
Gender	Male	88	64.2	83	60.4
Chi-square: 1.030	Female	49	35.8	54	39.6
p: 0.3102	Other	-	-	-	-
Age	15-24	11	8.2	22	15.8
Chi-square:15.580	25-34	46	33.6	30	21.9
p:0.0036	35-44	26	19.2	27	19.9
	45-54	34	24.7	32	23.3
	55+	20	14.4	26	19.2
Education	Primary education	0	0	1	0.7
Chi-square:49.051	Secondary education	4	2.7	14	10.3
p:0.0001	Vocational education	9	6.8	35	25.3
	Applied university	50	36.3	43	31.5
	Academic education	74	54.1	44	32.2
Work hours per week	<12h	7	4.8	15	11.0
Chi-square: 12.840	12h-19h	4	2.7	9	6.8
p:0.0121	20h-27h	13	9.6	19	13.7
	28h-34h	29	21.2	25	17.8
	≥35h	84	61.6	69	50.7

As can be seen in Table 18, 88 male (64,2%) and 49 female (35.8%) respondents have completed the survey. Comparing the gender distribution with the CBS, the outcomes of the Chi-square show a p-value of 0.3102. This result suggests no significant difference between the sample and CBS data concerning gender. This confirms that the sample is representative of the office employees.

Also, the distribution of age is compared. The biggest share of respondents belongs to the age group of 25-34 years old (33.4%), and the smallest is the age group younger than 24 years old (8.2%). Comparing the age groups with the CBS data, the outcomes of the Chi-square show a p-value of 0.0036. This indicates that the age categories in the survey are not fully as equally distributed as the Dutch averages. There is a significant difference between the age groups. Mainly age groups 15-24, 25-34 and 55+ differ from the CBS data. However, age groups 35-44 years and 45-54 years largely correspond to the CBS data. This means these groups are represented well by the sample.

Respondents with an academic education (54,1%) are overrepresented in this survey compared to the average Dutch office worker (32,2%). On the other hand, the respondents with vocational education or lower (9,5%) are underrepresented than the Dutch average office worker (36,3%). The p-value of 0.0001 indicates that the level of education in the sample is not fully representative.

Further, most respondents (61.6%) work 35-hours per week or more. Considering the part-timers, the largest group (21.2%) works between 28h-34h. This is comparable to the total working population in the Netherlands, according to the statistics of the CBS. However, the p-value is 0.0121 and indicates a significant difference. The sample contains more full-timers than the Dutch average.

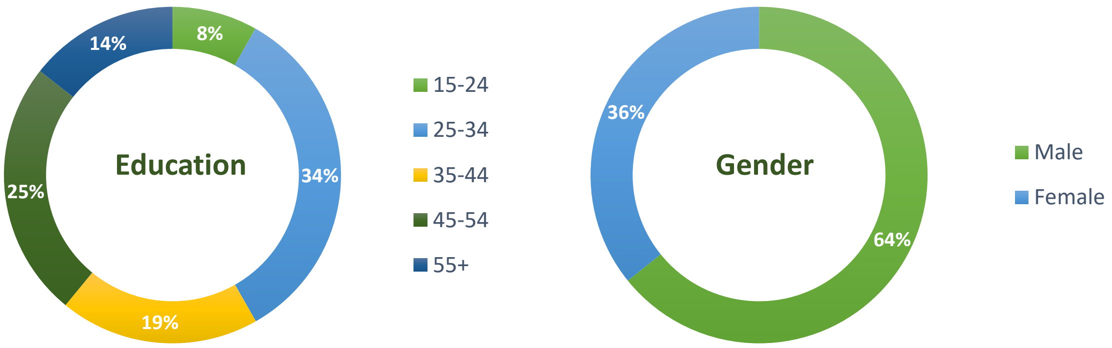


Figure 8: Distributions of Gender (Left) and Age (Right)

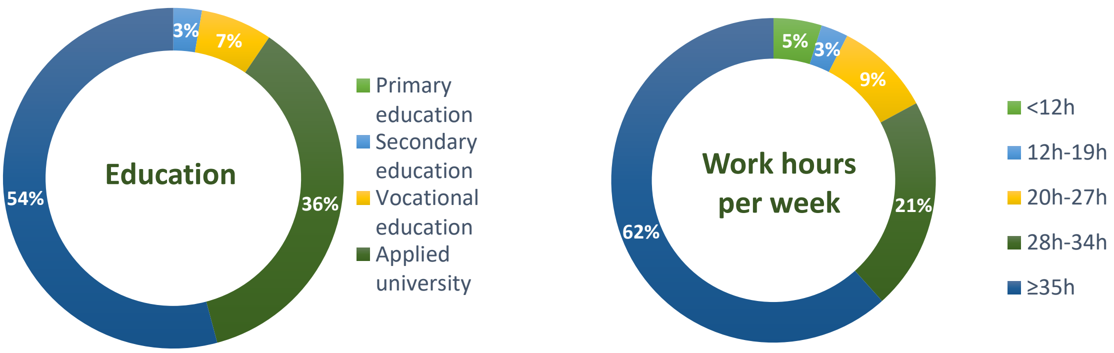


Figure 9: Distributions of Education (Left) and Work hours per week (Right)

4.3.2 Description of work activities per week -related characteristic

To gain more understanding about smart feature preferences, the work activities of the respondents were elaborated. Respondents were asked to indicate how much of the time per week they spent on work activities where the total percentage of the four work activities was 100%.

The results (see Figure 10) show that most work hours are spent on concentrated individual work (e.g., individual focused work such as writing and reading). This is followed by formal communication (e.g., collaboration, scheduled appointments). Closely behind time is spent on informal communication work-related activities (e.g., relaxing, taking a break). In general, less time was spent on other work activities.

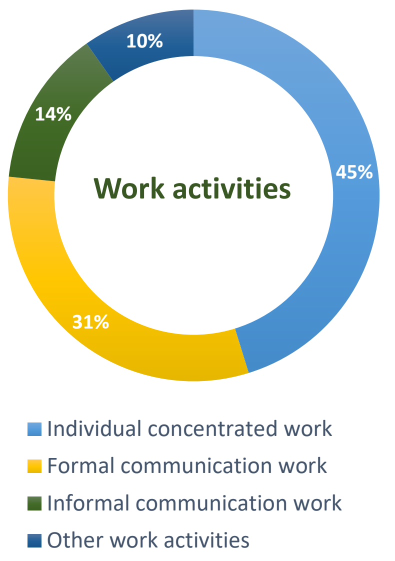


Figure 10: Distribution of work activities

4.3.4 Description of experience-related characteristic

The experience of respondents with the smart features is presented in Figure 11. Approximately, over 70% of the respondents per smart feature responded that they have heard about this smart feature. However, 50% of the respondents have never used smart parking, smart workspace, smart indoor air quality control and smart lighting control. This is not the case for smart meeting rooms. A total of 57% of respondents are familiar with this smart feature.

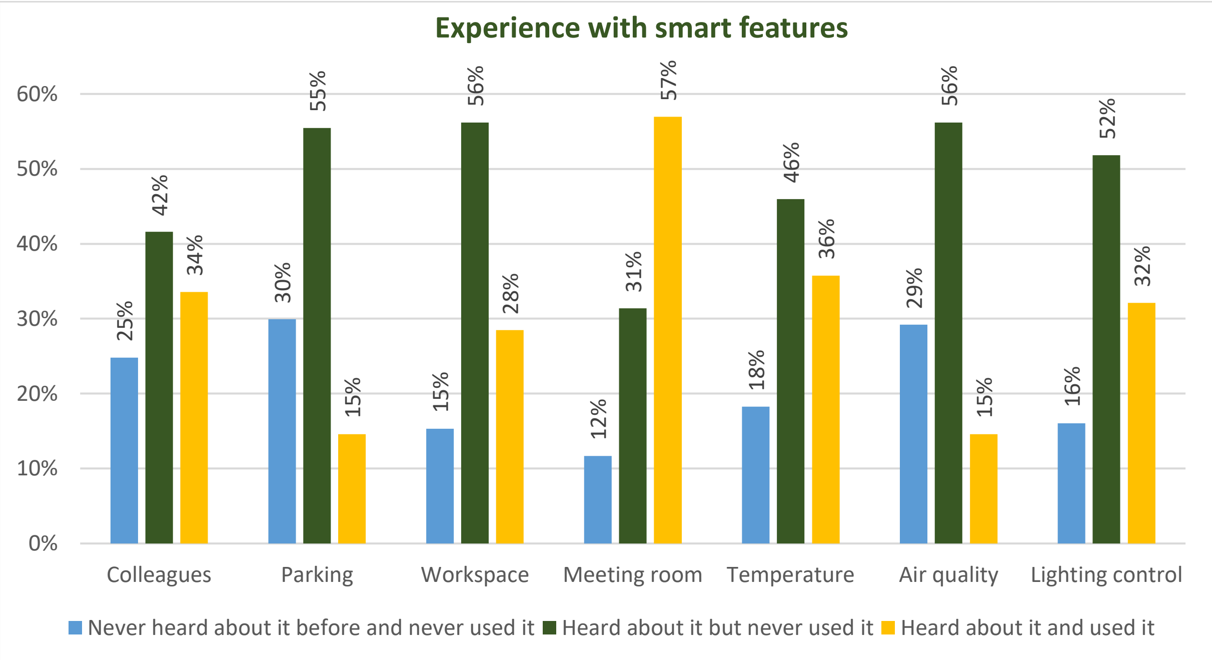


Figure 11: Distribution of smart feature experience

4.3.3 Description of personality-related characteristic

With the use of the Big Five instrument, respondents' personality is being measured to explain the smart feature preferences. The respondents were asked to indicate to what extent they agreed or disagreed (1= strongly agree to 5= strongly disagree) with the 15 personality statements based on the five personality traits "extraversion", "agreeableness", "conscientiousness", "neuroticism", and "openness". In Figure 12, the distribution per personality is presented. A major part of the sample scores high for agreeableness and relatively high for having an extraversion personality.

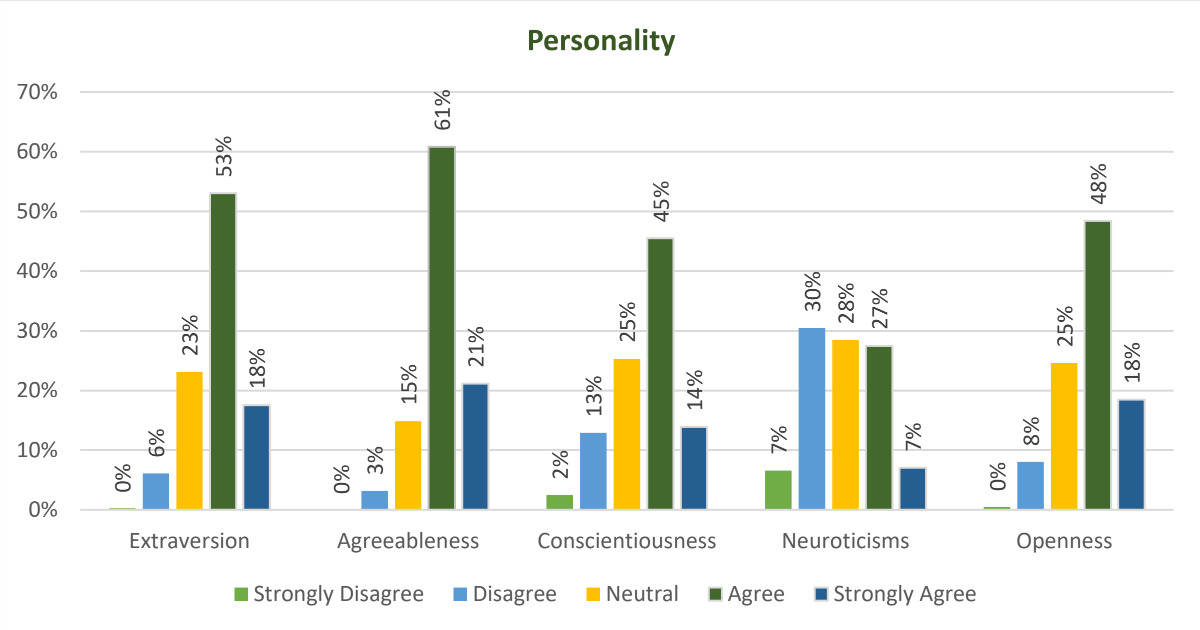


Figure 12: Distribution of personality traits

Within the BFI, only three statements per personality were included. A reliability analysis is performed to check whether the three statements are eligible to sum. Based on the Cronbach's Alpha (α), it can be indicated if the conducted scale fits the purpose of the research (Revicki, 2014). Overall, there are still a lot of misunderstandings regarding the accepted value of Cronbach's Alpha. In a study by Taber (2017), several studies were examined. Here it appears that some researchers find the following labels satisfactory; satisfactory (0.58–0.97), acceptable (0.45–0.98), sufficient (0.45–0.96).

The outcome of the reliability analysis is presented in Table 19. Based on the results, only extraversion, conscientiousness and neuroticism meet the minimum value of 0.45. Extraversion and openness are below this value and are not further included in the analysis (see Appendix VII).

Table 19: Distribution personality traits with Cronbach's Alpha

Personality traits	Mean	Variance	Std. Dev.	N of items	Cronbach's Alpha
Extraversion	11.45	3.249	1.802	3	0.656
Agreeableness	12.00	1.956	1.399	3	0.397
Conscientiousness	10.66	4.710	2.170	3	0.637
Neuroticism	8.94	6.158	2.482	3	0.681
Openness	11.29	2.488	1.577	3	0.297

4.3.4 Description of attitude-related characteristic

The attitude towards the smart features was investigated using three statements; the impact of smart features on productivity, the improvement of quality due to smart features and the contribution of smart features on making respondents more efficient in their occupation. First, to check whether the statements are reliable, a Cronbach's Alpha (α) test was performed. A Cronbach alpha tests the consistency of self-made scales, such as the Likert scale, with a recommended reliability level of 0.70 (Tavakol et al., 2011). A Cronbach's Alpha (α) of 0.83 is found (see Appendix VIII). This is higher than the recommended reliability level of 0.70. The results conclude that there is a relatively high inter-correlation between the statements. Therefore, all statements will be used for further analysis.

Figure 13 shows the extent to which respondents agree with attitude related statements. For example, the first statement is whether smart features will make respondents productive. It can be seen that 56% agree that the smart feature will contribute to their productivity. Also, over 37% of respondents are neutral. This indicates that respondents are not sure whether a smart feature will contribute to their productivity. Further, only a small percentage (strongly) disagree with the statement. The same pattern can be recognized in statement 2, about the impact of smart features on improving the quality. Again, 55% of the respondents agree with the statement, 37% are neutral, and 7% disagree. This is also the case for statement 3. However, statement 3 has a relatively larger group; over 63% of respondents agree that smart features will make them more efficient in their occupation. Overall, it can be seen that almost 55% of the respondents agree that smart features will contribute to productivity, improve the quality of work, and make them more efficient in their occupation.

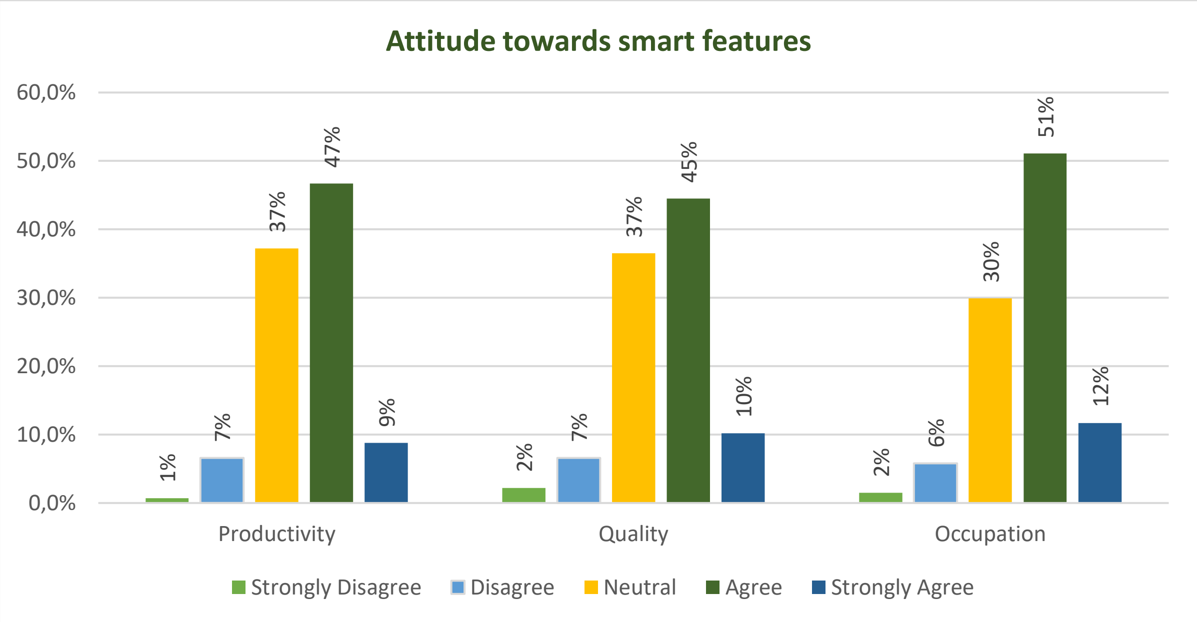


Figure 13: Distribution of attribute

4.4 Conclusion

This chapter discussed the data description of variables to overview the sample. The sample includes data from 137 respondents. Before analysis, the data were examined for research outliers. After the data preparation, a comparison was conducted based on four variables. The variables *age*, *gender*, *education,* and *work hours per week* of the sample were compared with the average Dutch office worker to check if the sample was representative (CBS, 2021). The results showed, in general, that the sample provided a representation of the office employee in the Netherlands. However, some categories are not well presented by the sample.

Based on the data of 137 respondents, the following insights have been obtained:

- A smart meeting room is the only smart feature most respondents use (57%).
- Approximately, over 70% of the respondents per smart feature responded that they have heard about this smart feature.
- Respondents overall agree that smart features will make them more productive (56%).
- Respondents also agreed that smart features would improve the quality of their work (55%).
- Most respondents agree that smart features will make them more efficient in their occupation (63%).

Chapter 5. Results

This chapter includes analyzing the data collected from the stated choice experiment. Using the software program Nlogit, parameters are estimated to determine the user expectations and preferences regarding the smart features. Therefore, an MNL is performed to understand which respondents prefer attributes and attribute levels. Further, also, an LCM is used for the analysis. With the LCM, individuals are distributed heterogeneously with a discrete distribution within a specified population (Hensher et al., 2015). In contrast with the MNL model, the LCM aims to find classes of individuals with similar patterns of parameters. Similar parameters represent similar preferences for smart feature characteristics. In this way, heterogeneity between groups of respondents can be made visible. Those models are conducted for all the smart features. The results of the MNL and LCM will be shown.

5.1 Multinomial Logit models

To provide a general insight into office employees' preferences regarding attributes of smart features, MNL has been conducted for all smart features. Before analyzing the MNL results, the models' statistics are checked to indicate the goodness of fit. This is determined by McFadden's Rho-squared (ρ^2). As is explained in Chapter 3, the Rho-squared is calculated by the Log-likelihood of the estimated parameters and the Log-likelihood of the zero models.

Table 20 shows the model performance of the MNL. In general, it can be seen that all the models have a Rho-squared value between 0.014 and 0.192. This value is slightly less than the excellent value of 0.2 and means that the model does not accurately reflect the observed choices (McFadden, 1974). The low value is caused by the differences in the respondents' preferences, also known as heterogeneity. Nevertheless, the fit is acceptable (Kemperman et al., 2008).

Table 20: McFadden's Rho-squared of smart features

Smart features	ρ^2
Smart indoor location tracking of colleagues	0.105
Smart parking	0.014
Smart workspace booking	0.133
Smart meeting room booking	0.161
Smart indoor climate control- Temperature	0.192
Smart indoor climate control- Air quality	0.165
Smart lighting	0.101
Aggregated smart feature	0.084

One of the most critical utility (β) values is the constant. This value indicates whether the respondents prefer choosing an alternative over the ‘no preference’ option. A positive constant value indicates that the respondents prefer one of the alternatives instead of the ‘no preference’ option. Further, for each attribute level, a β-value is determined. A positive β-value represents preference, while a negative β-value reflects disliking. Moreover, note that if a utility value is insignificant, it is difficult to explain that the estimated utility value is not based on coincidence.

The following sections will discuss the utility scores of each attribute based on MNL estimations. Furthermore, the relative importance is determined to gain insight into which attributes are most important to the users. The difference between the highest and the last utility value was first determined for each attribute to calculate the relative importance. Next, by calculating the range of an attribute and dividing it by the total sum of all ranges, insight is gained into the relative importance. A higher percentage means that an attribute has a stronger effect on the total utility. The following attributes are being considered:

- A1| Control
- A2| Information sharing
- A3| Communication
- A4| Knowledge acquisition
- A5| Personal information for resource efficiency

The estimation of MNL is conducted for all the smart features. For more information about the output, Appendix IX shows a detailed overview of MNL, including the part-worth utility score, standard error, and significance level.

5.1.1 Smart indoor location tracking of colleagues

According to Figure 14 and Figure 15, control is the only attribute for which the respondent does not have a specific preference. Instead, respondents indicate that they are prepared to share information with the system if it does not contain sensitive information. Respondents also want to receive information from the smart feature that displays locations of their colleagues on a map (advanced communication) as long as the system is not going to use the data to analyze individual usages patterns and store sensitive information.

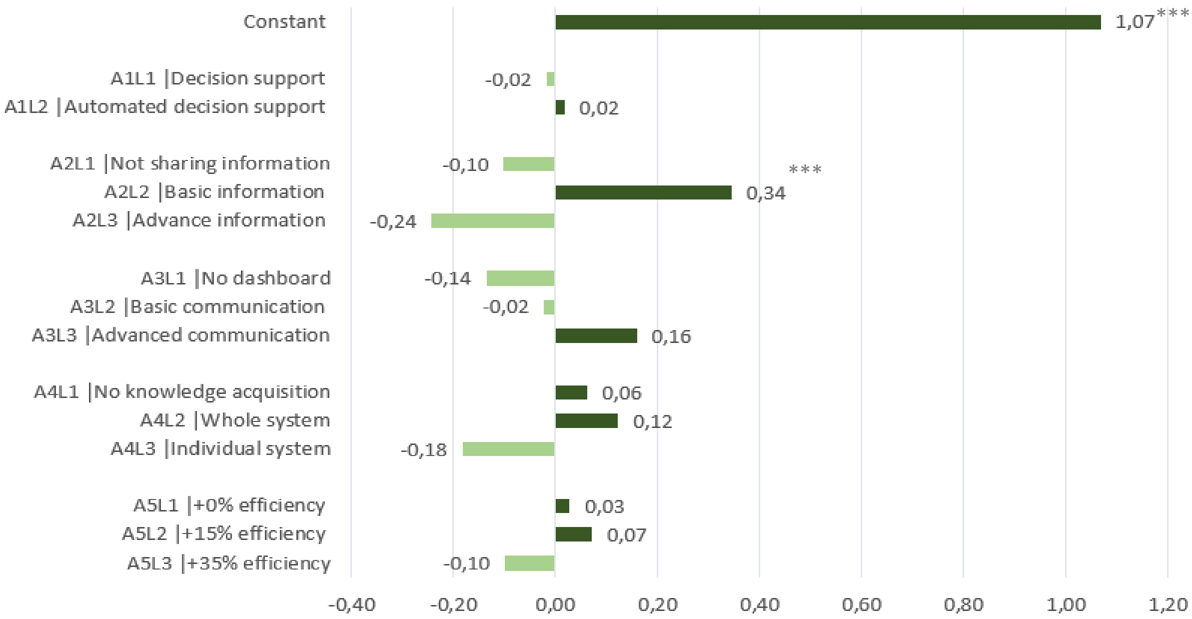


*Figure 14: Utility Scores of the Multinomial Logit Model- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

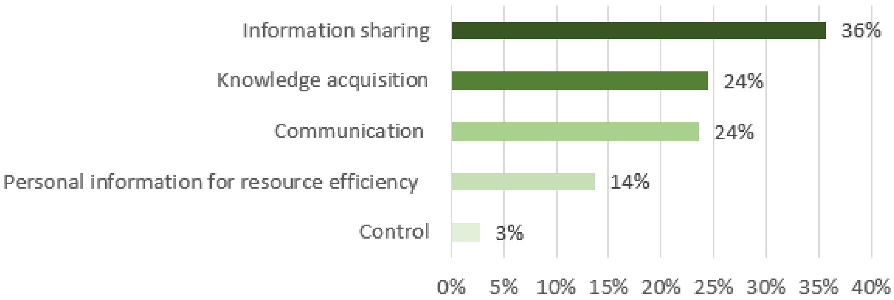


Figure 15: Relative importance of smart feature attributes

5.1.2 Smart parking

In contrast to smart indoor location tracking of colleagues, Figure 16 and Figure 17 show that respondents want to influence a smart feature (decision-support). Respondents are also willing to share information with the smart feature, such as their agenda and car type. In addition, respondents indicated that they would also like to share their personal preferences. They would like to have basic communication about available parking spots displayed on a list. Further, respondents do not want their data to be used for knowledge acquisition. Moreover, respondents can share personal data with the system if searching for a parking spot becomes more efficient.

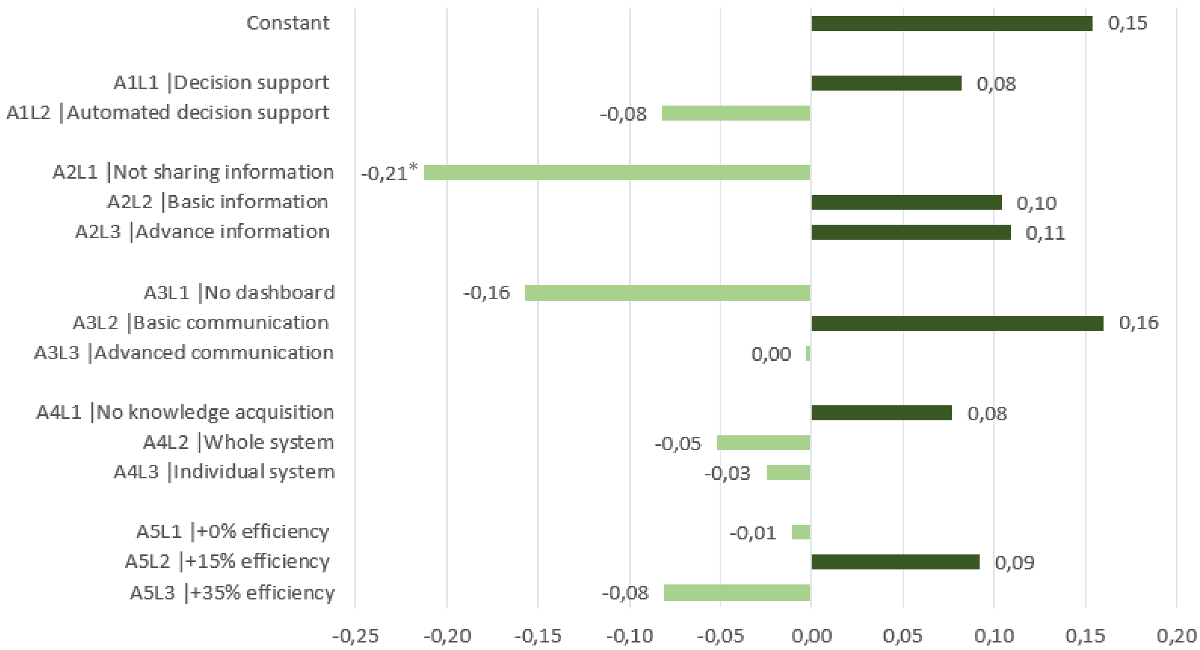


*Figure 16: Utility Scores of the Multinomial Logit Model- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

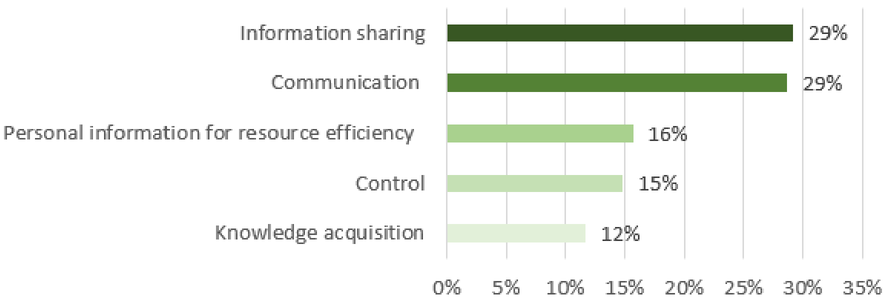


Figure 17: Relative importance of smart feature attributes

5.1.3 Smart workspace booking

Figure 18 and Figure 19 shows that the respondents would like to control the smart workspace booking system. Therefore, they are prepared to share information such as their agenda and personal preference. The results indicated that respondents prefer to have an advanced communication system. The respondents want to receive information about the availability of workspaces on an overview. Also, the respondents are willing to share their data for knowledge acquisition of the whole system. Further, respondents are also willing to share personal data if they receive a more suitable workspace based on their personal preference.

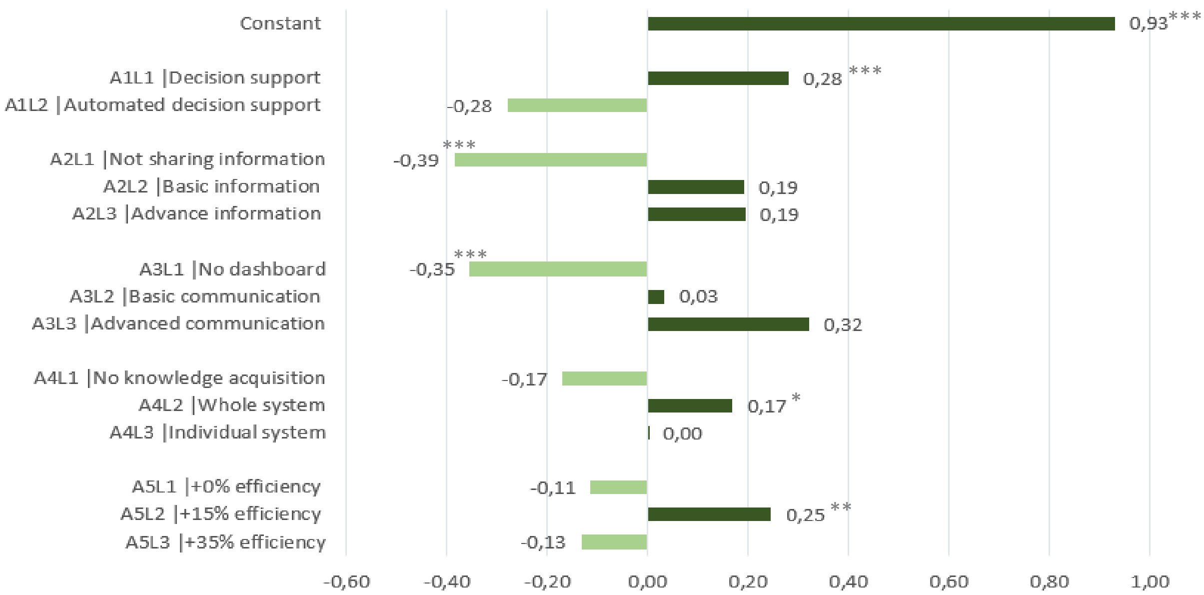


*Figure 18:Utility Scores of the Multinomial Logit Model- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

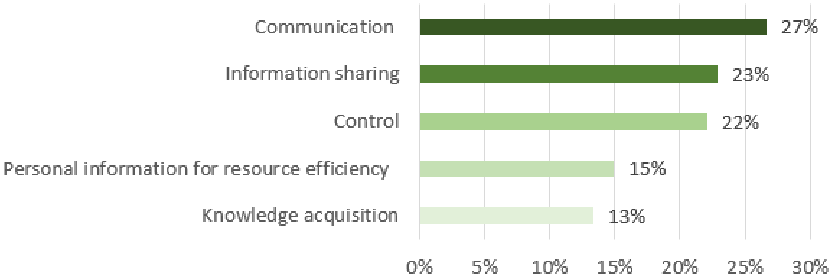


Figure 19: Relative importance of smart feature attributes

5.1.4 Smart meeting room booking

The same pattern from smart workspace booking can also be seen in smart meeting room booking. Figure 20 and Figure 21 shows that respondents would like to control the booking system. The respondents are more prepared to share basic information such as their agenda. Also, respondents indicate they would like to have an advanced communication system. Further, they want to share their data for knowledge acquisition of the whole system. Moreover, respondents are open to sharing personal data if they receive a more suitable meeting room based on their personal preference.

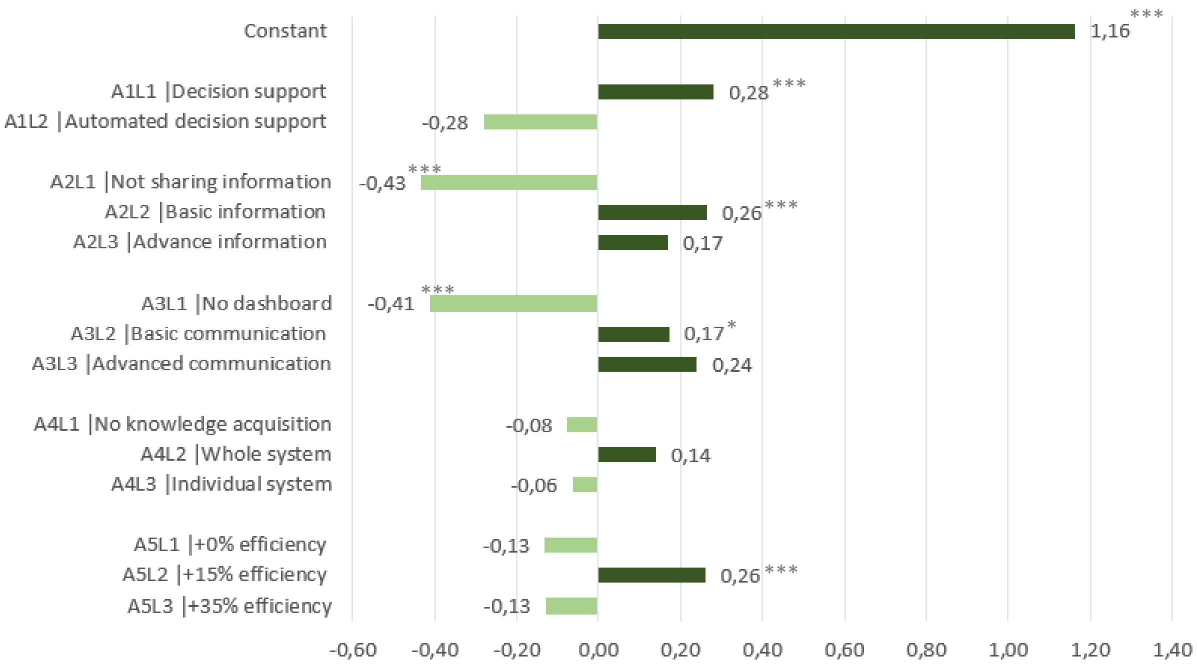


*Figure 20: Utility Scores of the Multinomial Logit Model- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

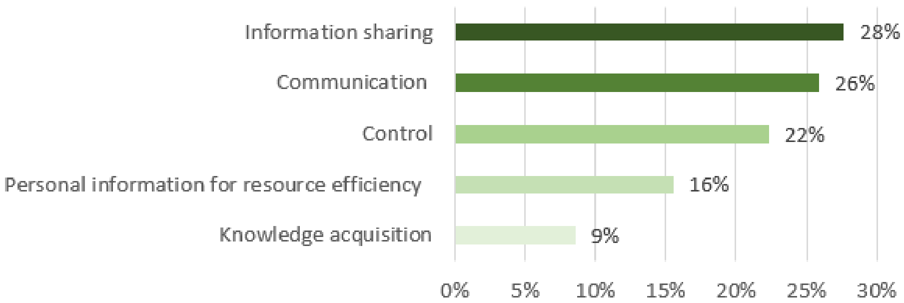


Figure 21: Relative importance of smart feature attributes

5.1.5 Smart indoor climate control – Temperature

In Figure 22, it can be noticed that smart indoor temperature control has a high constant value compared to the previous smart features. Therefore, the respondents highly prefer implementing this smart feature in an office.

Based on Figure 22Figure 23, the respondents indicate that they prefer to make their own choices and control the smart feature. It can also be notable that they want to receive feedback via a dashboard about the temperature in the office. However, respondents do not want to share sensitive personal information with the system, only basic information. Furthermore, respondents indicate that the system can use its user pattern to improve the service.

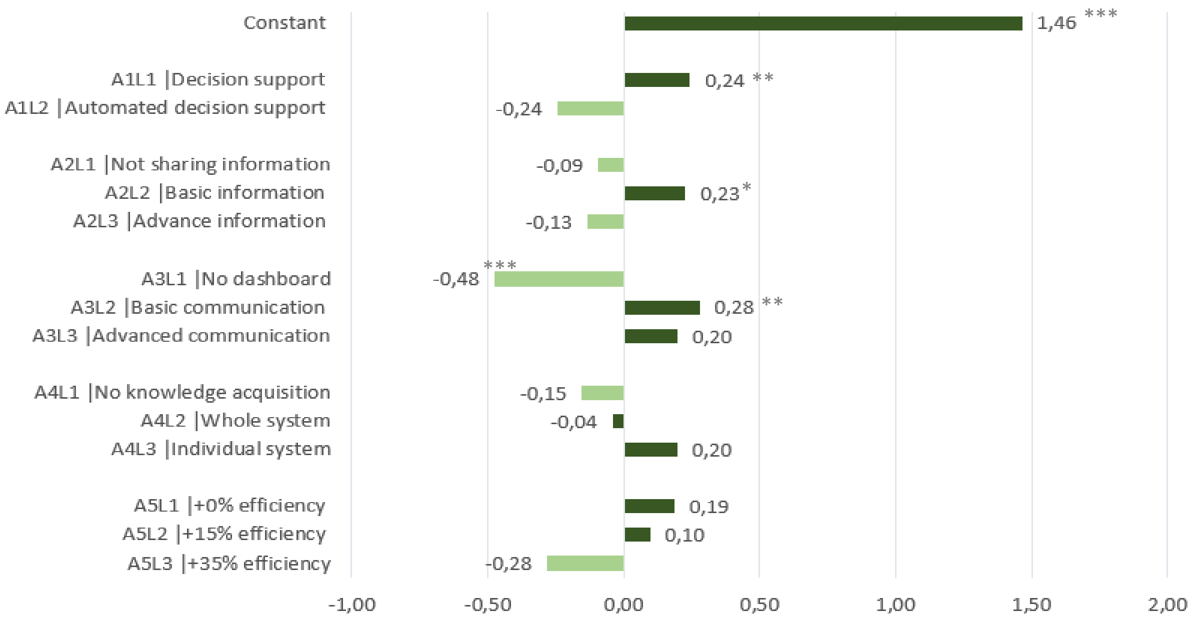


*Figure 22:Utility Scores of the Multinomial Logit Model- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

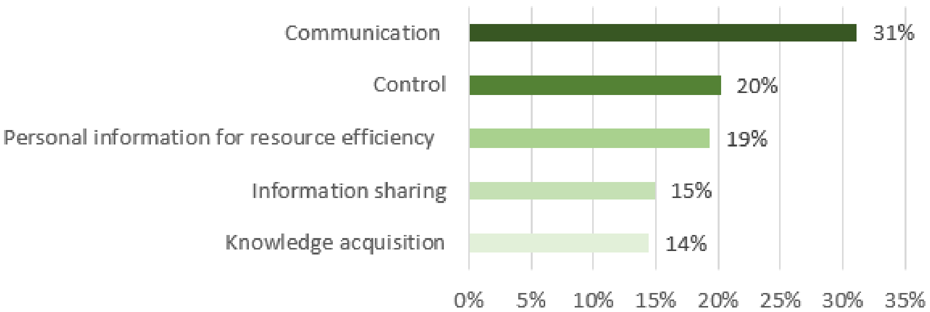


Figure 23: Relative importance of smart feature attributes

5.1.6 Smart indoor climate control – Air quality

Figure 24 and Figure 25 show that respondents are unwilling to share sensitive personal information with the system. The results indicated that respondents have no idea if they are willing to share any information with the system. This also applies to control. It can be seen that respondents have no preference for having control. However, respondents consider having a dashboard on which they receive information from the system as important.

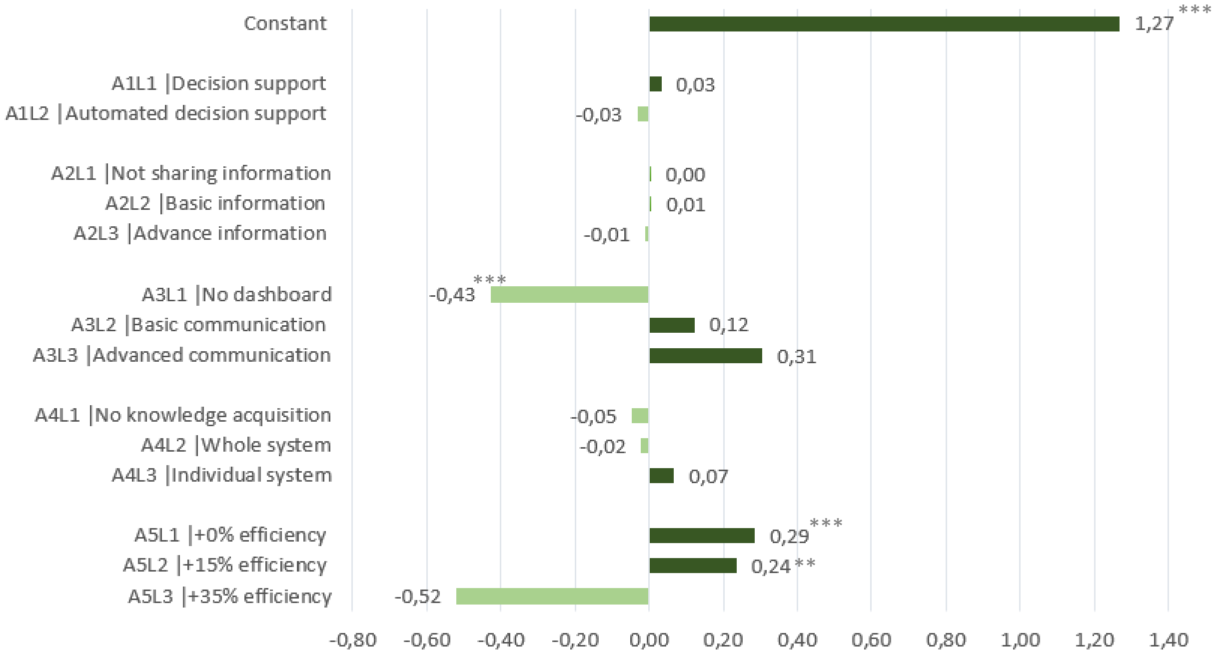


*Figure 24:Utility Scores of the Multinomial Logit Model- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

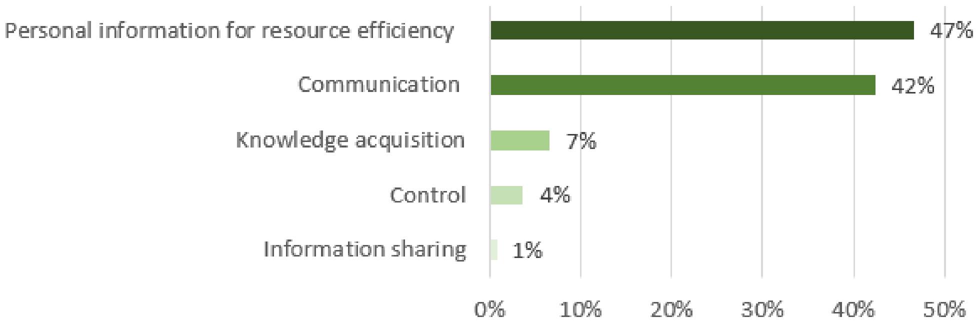


Figure 25: Relative importance of smart feature attributes

5.1.7 Smart lighting control

As with smart indoor climate control for air quality, Figure 26 and Figure 27, indicates that respondents are not willing to share sensitive personal information with the smart feature. Notably, the respondents are not sure about sharing any information with the system. On the other hand, the respondents are open if their data is used for individual knowledge acquisition. Furthermore, respondents want to control the smart feature (decision support) and have a strong preference for communicative systems that provide them with information.

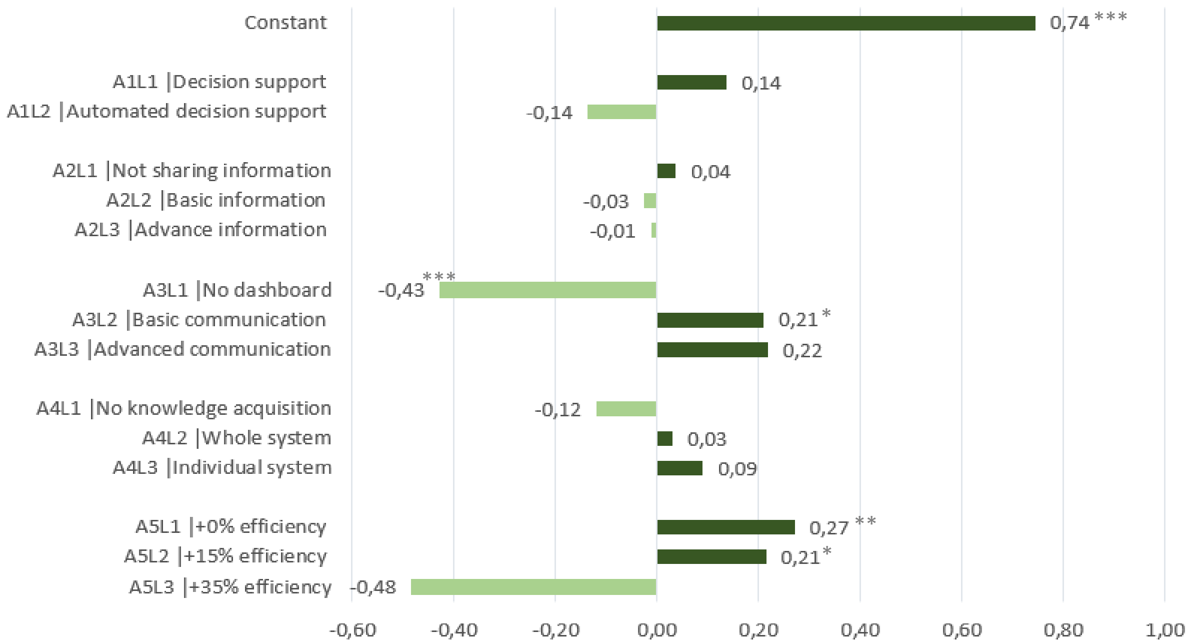


*Figure 26:Utility Scores of the Multinomial Logit Model- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

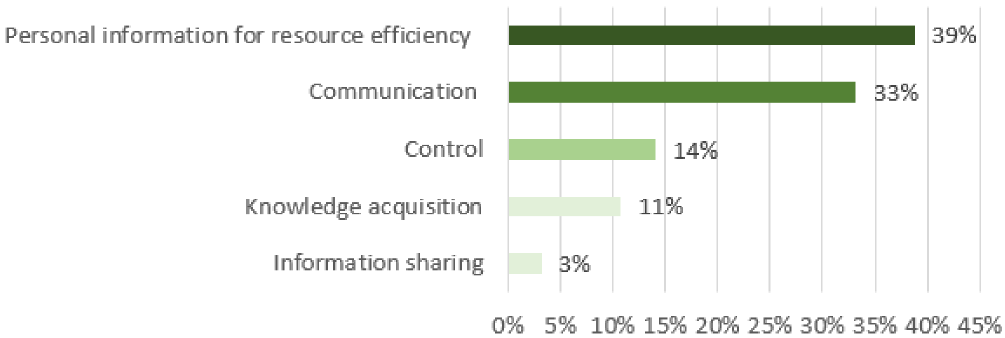


Figure 27: Relative importance of smart feature attributes

5.1.8 Aggregated smart feature

To better understand user preferences and expectations, an analysis was also conducted with all the results of the choices in one overview. The output of the analysis is presented in Figure 28 and Figure 29. The figure shows that respondents want to control the smart feature (decision-support). Further, respondents are willing to share information with the smart feature, as long as the information is not too sensitive. On the other hand, respondents strongly prefer communicative systems, such as a dashboard. Moreover, respondents are not affected by what happens next with the data (knowledge acquisition).

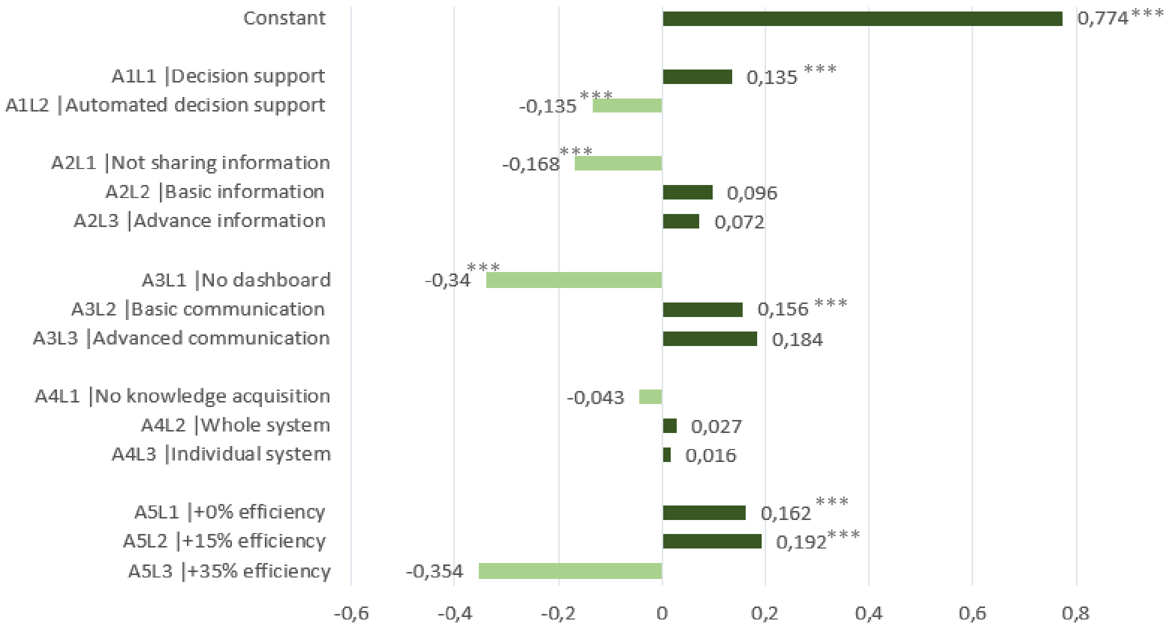


*Figure 28:Utility Scores of the Multinomial Logit Model - Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

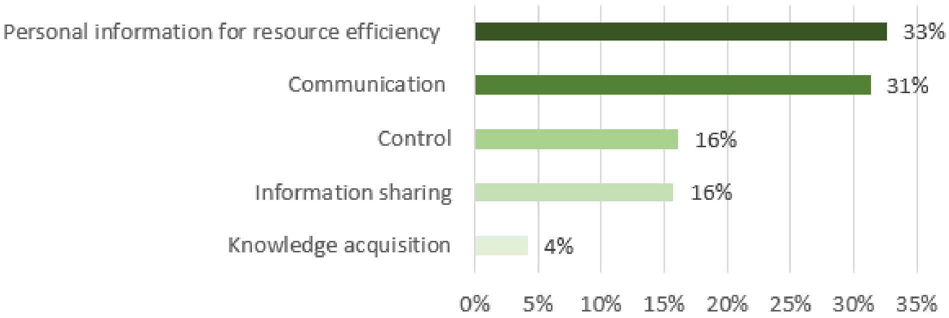


Figure 29: Relative importance of smart feature attributes

5.2 Latent Class Model

The LCM is used to identify classes of respondents. The classes can be grouped based on the differences in attribute preferences. The availability of panel data is necessary to identify groups of respondents; for example, unobservable respondent-specific parameters can be integrated to find correlations between the observations that a respondent has in common (Hensher et al., 2015). Those individual-specific parameters allow identifying similarities within classes.

The LCM also apply that a Rho-squared higher than 0.200 is an excellent fit. Table 21: McFadden's Rho-squared of smart features shows that all LCM of the smart features has a Rho-squared value higher than 0.200. In this case, the models are excellent. The models represent the observed choices well. Therefore, this means that the respondents' preferences within classes do not differ much, indicating homogeneity.

Table 21: McFadden's Rho-squared of smart features

Smart features	ρ^2
Smart indoor location tracking of colleagues	0.231
Smart parking	0.258
Smart workspace booking	0.245
Smart meeting room booking	0.267
Smart indoor climate control- Temperature	0.270
Smart indoor climate control- Air quality	0.310
Smart lighting	0.244
Aggregated smart feature	0.229

The next sections will present utility scores relative importance of each attribute between the classes based on the LCM estimations. Detailed information about the output of the LCM is shown in Appendix X. The estimate of the LCM is conducted for all the smart features. The LCM is distinguished into two classes with similar smart feature preferences. The constant value identifies the main difference between the classes. However, Chi-square tests and independent sample t-tests are conducted to investigate whether these preferences could be related to personal, socio demographic, work, attitude, or experience-related characteristics. The Chi-square tests and independent sample t-test outcomes are presented in appendix XI. To conduct those tests, the categories of the characteristics had to be recategorized into larger groups. Otherwise, it is impossible to perform the tests because there are not enough respondents per category. The following characteristics are recategorized: age, education, and work hours per week (See Appendix XII: Recoding variables for analyzing LCM).

5.2.1 Smart indoor location tracking of colleagues

In Table 22, the main difference between the two classes is the parameter of the constant. When looking at the parameter values from class 1 (β_0=2.787) and class 2 (β_0=-0.811), it can be concluded that class 1 has an overall preference for choosing a smart feature alternative instead of the no preference alternative. On the other hand, the constant of class 2 is negative, meaning that those respondents often chose the no preference alternative. Therefore, class 1 is from now on indicated as "Adapters" and class 2 as "Rejecters". In addition, the table shows that Adapters will be encouraged by basic information and discouraged by 0% efficiency. Rejecters are reluctant to share (sensitive) information.

*Table 22: Results of the LCM analysis- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

Attribute	ID Level	LC1 β)	LC2 (β)
Constant	-	2.787***	-0.811***
Control	A1L1 |Decision support	-0.034	-0.095
	A1L2 |Automated decision support	0.034	0.095
Information sharing	A2L1 |Not sharing information	-0.190	0.190
	A2L2 |Basic information	0.441**	0.479
	A2L3 |Advance information	-0.251	-0.669
Communication	A3L1 |No dashboard	-0.074	-0.389
	A3L2 |Basic communication	0.008	0.022
	A3L3 |Advanced communication	0.066	0.367
Knowledge acquisition	A4L1 |No knowledge acquisition	0.143	0.016
	A4L2 |Whole system	0.120	0.444
	A4L3 |Individual system	0.263	-0.460
Personal information for resource efficiency	A5L1 |+0% efficiency	-0.346***	1.428***
	A5L2 |+15% efficiency	0.169	0.180
	A5L3 |+35% efficiency	0.177	-1.608
Estimated Latent class probabilities		0.698***	0.302***

Most respondents are part of the Adapter class (69.80%). According to Figure 30, the Adapters find information sharing (38%) an important attribute. In particular, the attribute level 'basic information' about sharing. Adapters are also willing to share personal and even sensitive information if the system can more efficiently help to find colleagues. Other preferred attribute levels are advanced communication and individual knowledge acquisition. However, those attribute levels are insignificant.

The class of Rejecters includes fewer respondents (24.50%). The Rejecters strongly do not prefer to share sensitive personal data. They do not know if there are even willing to share any information with a smart feature. Further, they also do not want their data to be used for individual knowledge acquisition.

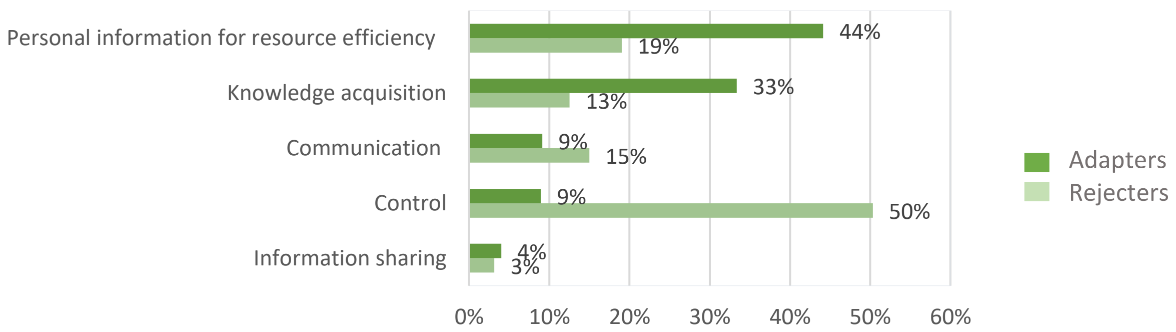


Figure 30: Relative importance of smart feature attributes

Further, to understand whether the class distribution has a relationship with personal-, demographic-, work-, experience- and attitude-related variables, Chi-square tests and independent sample t-tests are conducted. In Table 23, only the significant variables are shown.

Work hours per week are checked to indicate differences between classes. Significant differences were found between the two classes ($\chi 2 = 5.303$, $p=0.021$). 40% of the part-timers fit in LC1, while 80% of the full-timers fit in this category, indicating that mainly full-timers prefer to have a smart feature to find colleagues. The need for this is lower with the part-timers.

Also, it was checked whether there were differences between respondents familiar with the smart indoor location tracking of colleagues. Unfortunately, the values are not significant. This means that no difference was found between respondents familiar with the smart feature and those who are not.

Table 23: Results Chi-square test for differences between the two classes

Characteristic	**LC 1 (N)**	**LC1 (%)**	**LC2 (N)**	**LC2 (%)**	**Chi-square test X^2**	**Sig.**
Total	24	68.6	11	31.4		
Work hours per week					5.303	0.021
Part-time (35<)	4	40.0	6	60.0		
Full time (35>)	20	80.0	5	20.0		

5.2.2 Smart parking

Within smart parking, two classes are being distinguished. In Table 24, it can be seen that the constant values from class 1 $\beta_0=2.252$ and class 2 $\beta_0=-2.259$. There is a clear distinction between the classes: class 1 consists of "Adapters" and class 2 "Rejecters".

*Table 24: Results of the LCM analysis- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

Attribute	**ID Level**	**LC1 (β)**	**LC2 (β)**
Constant	-	2.252***	-2.259***
Control	A1L1 |Decision support	0.304**	0.267
	A1L2 |Automated decision support	-0.304	-0.267
Information sharing	A2L1 |Not sharing information	-0.384***	0.347
	A2L2 |Basic information	0.451***	-0.811
	A2L3 |Advance information	-0.067	0.464
Communication	A3L1 |No dashboard	-0.083	-0.483
	A3L2 |Basic communication	0.230*	0.382
	A3L3 |Advanced communication	-0.147	0.101
Knowledge acquisition	A4L1 |No knowledge acquisition	0.166	-0.061
	A4L2 |Whole system	-0.078	0.048
	A4L3 |Individual system	-0.088	0.013
Personal information for resource efficiency	A5L1 |+0% efficiency	-0.345**	1.466***
	A5L2 |+15% efficiency	0.237*	-0.434
	A5L3 |+35% efficiency	-0.108	-1.032
Estimated Latent class probabilities		0.634***	0.366***

The Adapter class contains the most respondents (63.40%). Figure 31 shows that sharing (basic) information with the smart feature the key driver is for the Adapters. The respondents are also willing to share personal information if the system can more efficiently recommend a parking spot. However, they do not want their data to be used for knowledge acquisition. Further, the Adapter would like to control the smart feature and receive basic communication.

Fewer respondents are in the Rejecter class (36.60%). Rejecters do not want this smart feature if they have to share personal data. However, it is notable that the respondents do not mind if their data will be used for knowledge acquisition. They are also willing to give their agenda, type of car, and personal preference if it does not contain personal data. As long as the respondent is not asked for personal data, the Rejecters might be willing to use the smart feature.

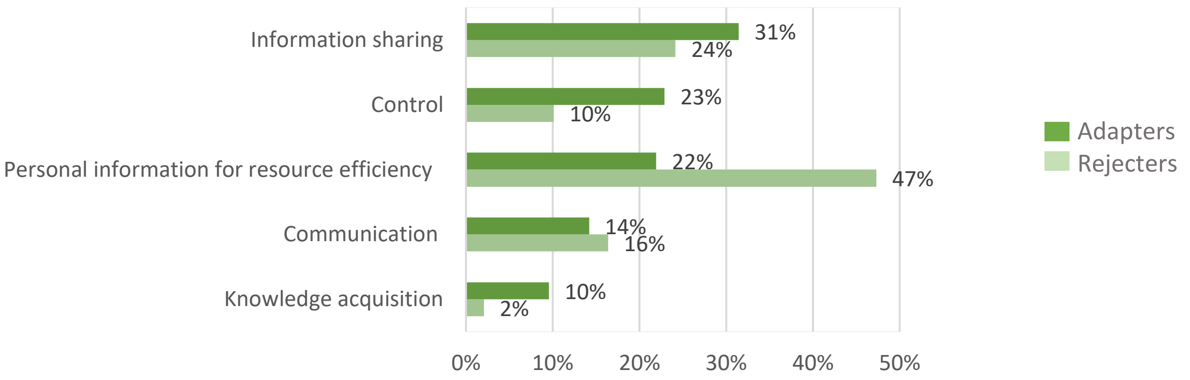


Figure 31: Relative importance of smart feature attributes

To understand whether the class distribution has a relationship with personal-, demographic-, work-, experience- and attitude-related variables, Chi-square tests and independent sample t-tests are conducted. However, no significant values are found.

5.2.3 Smart workspace booking

Similar to the previous two sub-chapters, the LC model of smart workspace booking results returned two groups: Adapters (β_0=2.639) and Rejecters (β_0=-1.110). The output of the utility values is presented in Table 25 and Figure 32.

*Table 25: Results of the LCM analysis- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

Attribute	ID Level	LC1 (β)	LC2 (β)
Constant	-	2.639***	-1.110***
Control	A1L1 | Decision support	0.130**	0.728*
	A1L2 | Automated decision support	-0.130	-0.728
Information sharing	A2L1 | Not sharing information	-0.395***	-0.310
	A2L2 | Basic information	0.079	0.278
	A2L3 | Advance information	-0.316	0.032
Communication	A3L1 | No dashboard	-0.399***	-0.310
	A3L2 | Basic communication	-0.060	0.297
	A3L3 | Advanced communication	0.459	-0.013
Knowledge acquisition	A4L1 | No knowledge acquisition	-0.225*	-0.028
	A4L2 | Whole system	0.231	-0.024
	A4L3 | Individual system	-0.006	0.052
Personal information for resource efficiency	A5L1 | +0% efficiency	0.074	0.513
	A5L2 | +15% efficiency	0.293**	0.136
	A5L3 | +35% efficiency	-0.367	-0.649
Estimated Latent class probabilities		0.757***	0.243***

The Adapters (75,7%) are again in the majority. The group is bigger than the previous two smart features, indicating that smart workspace booking is popular among a larger group of respondents. The Adapters of smart workspace booking show the same pattern as those of smart parking. Only these Adapters strongly prefer communication systems that provide them with advanced information. However, the Adapters are unwilling to share personal information with the smart feature.

Unlike the previous two smart features, the Rejecters find to control the most important attribute. Not being able to make individual decisions regarding workspace booking negatively affects their opinion on smart workspace booking systems.

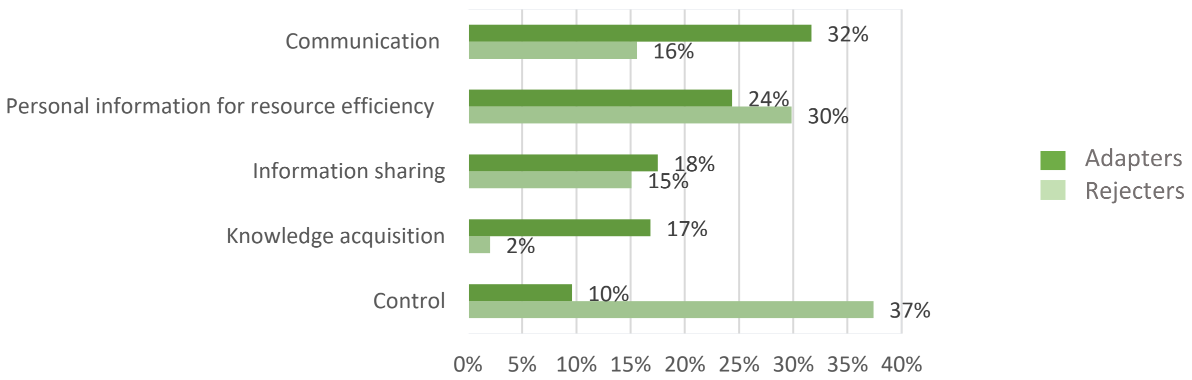


Figure 32: Relative importance of smart feature attributes

To gain insight into the respondents of the classifications, the relationship was examined to personal-, demographic-, work-, experience- and attitude-related variables. As seen in Table 26, only two significant values divide the classes. Furthermore, personality was examined through the independent sample t-test. The results showed that there is one significant characteristic: Conscientiousness. Those are respondents with a high level of self-discipline and prefer to plan. Respondents with such a personality are mainly in class 1.

Table 26: Results independent sample t-test for differences between the two classes

Characteristic	LC1 (N)	LC1 (Mean)	LC2 (N)	LC2 (Mean)	T-value	Sig.
Personality					3.176	0.003
Conscientiousness	31	11.52	10	10.10		

5.2.4 Smart meeting room booking

In contrast to previously smart features, both class 1 (β_0=3.693) and class 2 (β_0=0.726) consist of adapters (see Table 27). From the utility scores, it can be seen that class 1 is generally more reluctant about the smart feature than class 2. This class is somewhat certain about the smart feature. Therefore, class 1 is from now on indicated as the "Reluctant Adapters" and class 2 as the "Confident Adapters".

*Table 27: Results of the LCM analysis- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

Attribute	ID Level	LC1 (β)	LC2 (β)
Constant	-	3.693***	0.726***
Control	A1L1 | Decision support	-0.778	0.429***
	A1L2 | Automated decision support	0.778	-0.429
Information sharing	A2L1 | Not sharing information	-0.863	-0.582***
	A2L2 | Basic information	-0.371	0.455***
	A2L3 | Advance information	1.234	0.127
Communication	A3L1 | No dashboard	-1.840	-0.283**
	A3L2 | Basic communication	0.012	0.138
	A3L3 | Advanced communication	1.828	0.145
Knowledge acquisition	A4L1 | No knowledge acquisition	-0.131	0.150
	A4L2 | Whole system	-0.245	0.200
	A4L3 | Individual system	0.376	-0.350
Personal information for resource efficiency	A5L1 | +0% efficiency	2.484*	-0.528***
	A5L2 | +15% efficiency	0.103	0.392***
	A5L3 | +35% efficiency	-2.381	0.136
Estimated Latent class probabilities		0.340***	0.660***

The Reluctant Adapter class consists of fewer respondents (34%). The Reluctant Adapter does not prefer to share personal information with the smart feature (Figure 23). On the other hand, as long as they do not have to share personal data, they are open to sharing information about their agenda and preferences. They also do not mind if their data is used for individual knowledge acquisition. Further, the Reluctant Adapter prefers to have a dashboard that offers them advanced information and a booking system that makes automated decisions.

In contracts with the Reluctant Adapters, the Confident Adapter class consists of more respondents (66%). The utility values show that the Confident Adapters strongly prefer to share information with the smart feature. The Confident Adapters are also willing to share personal and even sensitive information. However, they do not want their data to be used for knowledge acquisition. Further, this class prefers to have control over the feature which the Reluctant Adapters do not want.

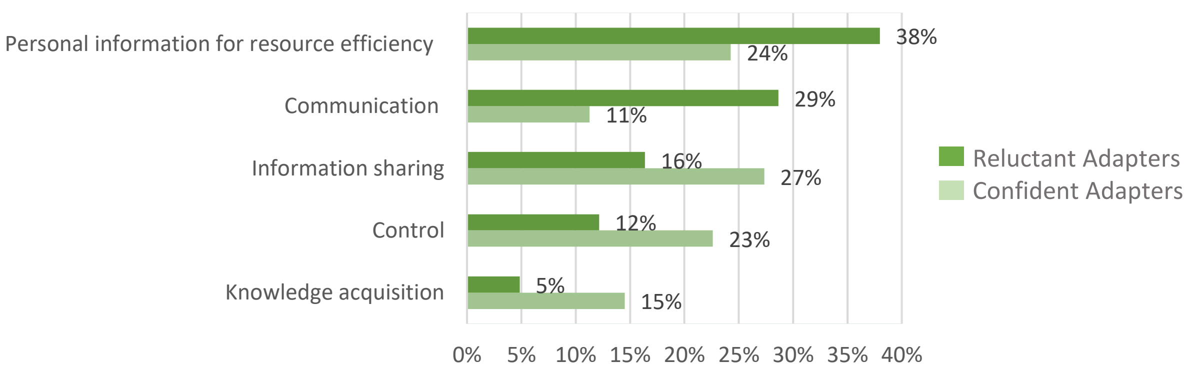


Figure 33: Relative importance of smart feature attributes

he classifications of the respondents are checked based on personal-, demographic-, work-, experience- and attitude-related variables. In Table 28, two significant values show a difference between the classes, namely personality and attitude. The insights were obtained by examining the independent sample t-tests.

The five different personalities were examined using statements to get insight into how personality differs between the respondents. The results indicated that conscientiousness provides a significant difference. Respondents with such a personality are disciplined and like to plan. Those Adapters take part mainly in the Reluctant Adapter class.

Besides, attitude towards smart features is also significant. This shows that the "smart feature makes me more productive at work" distinguishes the classes. It can be observed that respondents who stated that smart features contribute to their productivity at work mainly belong to the Reluctant Adapter class.

Table 28: Results independent-sample t-test for differences between the two classes

Characteristic	LC 1	Mean	LC2	Mean	T-value	Sig.
Personality: Conscientiousness	14	11.79	27	10.85	2.184	0.035
Attitude: Smart features make me more productive at work	14	4.07	27	3.37	2.758	0.009

5.2.5 Smart indoor climate control – Temperature

Similar to smart meeting room booking, class 1 (β0=2.171) and class 2 (β0=1.014) are positive. Also, in this case: class 1 consists of "Reluctant Adapters" and class 2 "Confident Adapters". The results are presented in Table 29 and Figure 34.

*Table 29: Results of the LCM analysis- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

Attribute	ID Level	LC1 (β)	LC2 (β)
Constant	-	2.171***	1.014***
Control	A1L1 |Decision support	-0.114	0.297*
	A1L2 |Automated decision support	0.114	-0.297
Information sharing	A2L1 |Not sharing information	0.694	-0.412**
	A2L2 |Basic information	-0.124	0.497**
	A2L3 |Advance information	-0.570	-0.085
Communication	A3L1 |No dashboard	-0.778	-0.679***
	A3L2 |Basic communication	0.210	0.384**
	A3L3 |Advanced communication	0.568	0.295
Knowledge acquisition	A4L1 |No knowledge acquisition	-0.476*	0.044
	A4L2 |Whole system	-0.332	-0.111
	A4L3 |Individual system	0.808	0.067
Personal information for resource efficiency	A5L1 |+0% efficiency	1.061***	-0.395**
	A5L2 |+15% efficiency	0.719	-0.017
	A5L3 |+35% efficiency	-1.780	0.412
Estimated Latent class probabilities		0.433***	0.567***

The Reluctant Adapter class includes fewer respondents (43.30%). The Reluctant Adapter does not prefer to share (personal) information with the smart feature. Also, they are not interested in having control over the system. However, this class want to receive information about the temperature from the smart feature.

This class has more respondents (56.7%). The Confident Adapters are willing to share information about their work activity. They are even open to sharing sensitive personal information if the system can easily meet their thermal comfort. Further, the Confident Adapters strongly prefer to receive basic information about the temperature on a dashboard and to have control over the smart feature.

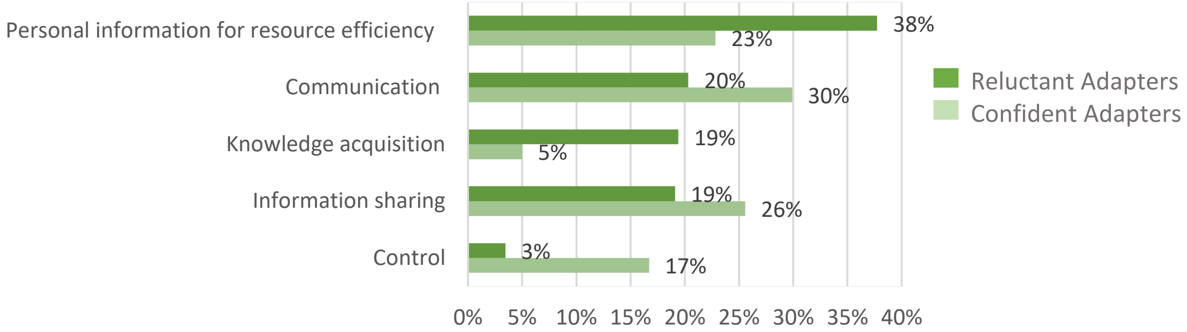


Figure 34: Relative importance of smart feature attributes

To check whether the class distribution is related to personal, demographic, work, experience and attitude related variables, Chi-square tests and independent t-tests are conducted. However, no significant values are found.

5.2.6 Smart indoor climate control – Air quality

Based on the constant parameters in Table 30, class 1 have a positive value (β=7.324), and class 2 have a negative value (β=-0.165). This shows that class 1 has an overall preference for choosing a smart feature alternative rather than the 'no preference' alternative. Therefore, class 1 will be labelled as "Adapters" and class 2 as "Rejecters". Furthermore, the table shows that Adapters will be encouraged by 0% efficiency, but the Rejecters can be unstimulated by 0% efficiency.

*Table 30: Results of the LCM analysis- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

Attribute	ID Level	LC1 (β)	LC2 (β)
Constant	-	7.324	-0.165
Control	A1L1 |Decision support	3.537	-0.301
	A1L2 |Automated decision support	-3.537	0.301
Information sharing	A2L1 |Not sharing information	-1.477	-0.027
	A2L2 |Basic information	1.112	0.099
	A2L3 |Advance information	0.365	-0.072
Communication	A3L1 |No dashboard	-3.022	-0.283
	A3L2 |Basic communication	2.895	-0.146
	A3L3 |Advanced communication	0.127	0.429
Knowledge acquisition	A4L1 |No knowledge acquisition	-1.403	0.305
	A4L2 |Whole system	1.684	0.131
	A4L3 |Individual system	-0.281	-0.436
Personal information for resource efficiency	A5L1 |+0% efficiency	0.837***	-0.542**
	A5L2 |+15% efficiency	1.494	0.134
	A5L3 |+35% efficiency	-2.331	-0.408
Estimated Latent class probabilities		0.661***	0.339***

Most respondents (66.10%) are part of the Adapter class. This class is mainly driven by having the possibility to control the smart feature (see Figure 35: Relative importance of smart feature attributes. They also want to have communications systems such as a dashboard. Further, the Adapters are also open to sharing information if it is not sensitive. Also, they are open to sharing their data for knowledge acquisition.

The Rejecters (33.90%) find knowledge acquisition the most important attribute. The Rejecters do not want their data to be used for individual knowledge acquisition. Also, they do not want to share sensitive information or their personal preference for light control. Thus, it is important that no sensitive information is requested or data is used to analyze individual usage patterns.

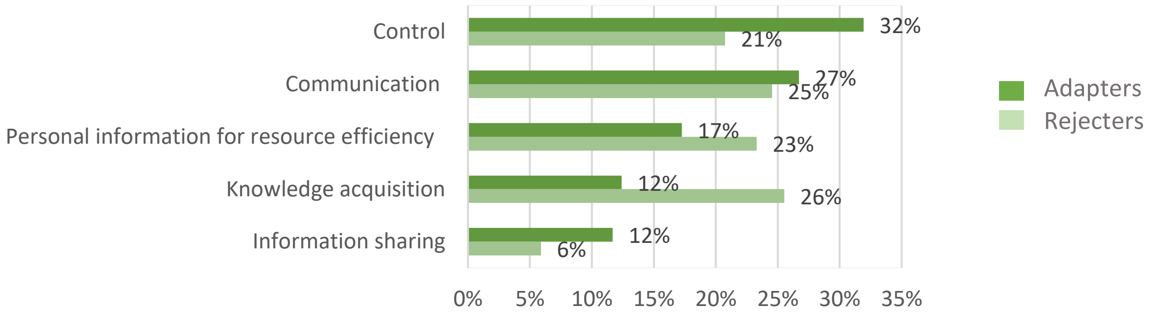


Figure 35: Relative importance of smart feature attributes

To obtain insight into the correlation between the class distribution and personal, demographic, work, experience and attitude related variables, Chi-square tests and independent t-tests are conducted. Only the significant variables are shown in Table 31 and Table 32. It can be seen that gender, hours of work per week, and personality affect the classification.

According to the results presented in Table 31 and Table 32, it can be noticed that gender plays a role within the distribution of classes (χ2 = 4.344, p=0.037). Especial, it is noticeable that men are mainly part of the Adapter class. Almost 4/5 of the men are in that class. As for women, there is a bit more woman in the Rejecter class, but the distribution is slightly more evenly. All in all, men make the biggest difference between the classes.

The work-related variable, work hours per week, indicated differences between classes (χ2 = 12.129, p=0.000). Also, it can be seen that almost 75% of the part-timers are among the Rejecters. This shows that most part-timers do not find it that important to have smart indoor climate control for climate control. However, almost 90% of the full-timers are part of the Adapter class. In short, this means that mainly full-timers would like to apply the smart feature.

Furthermore, personality was examined (χ2 = -3.525, p=0.001). The results showed that there is one significant characteristic: Conscientiousness. Those respondents with conscientiousness personalities are more part of the class Rejecters than the Adapters.

Table 31: Results Chi-square test for differences between the two classes

Characteristic	**LC 1 (N)**	**LC1 (%)**	**LC2 (N)**	**LC2 (%)**	**Chi-square test X^2**	**Sig.**

Total	20	66.7	10	33.6		
Gender					4.344	0.037
Male	14	82.4	3	17.6		
Female	6	46.2	7	53.8		
Work hours per week					12.129	0.000
Part-time (35<)	3	27.3	8	72.7		
Full time (35>)	17	89.5	2	10.5		

Table 32: Results independent sample t-test for differences between the two classes

Characteristic	LC1 (N)	LC1 (Mean)	LC2 (N)	LC2 (Mean)	T-value	Sig.
Personality					-3.525	0.001
Conscientiousness	20	7.35	10	9.80		

5.2.7 Smart lighting control

Within smart lighting control, the two classes include only adapters. Class 1 (β0=1.261) are the Reluctant Adapters and class (β0=0.375) Confident Adapters. The results are presented in Table 33 and Figure 36.

*Table 33: Results of the LCM analysis- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

Attribute	ID Level	LC1 (β)	LC2 (β)
Constant	-	1.261**	0.375**
Control	A1L1 |Decision support	0.147	0.127
	A1L2 |Automated decision support	-0.147	-0.127
Information sharing	A2L1 |Not sharing information	4.259	0.038
	A2L2 |Basic information	-9.309	0.091
	A2L3 |Advance information	5.050	-0.129
Communication	A3L1 |No dashboard	-5.332	-0.468***
	A3L2 |Basic communication	9.692	0.144
	A3L3 |Advanced communication	-4.360	0.324
Knowledge acquisition	A4L1 |No knowledge acquisition	-9.797	0.084
	A4L2 |Whole system	5.209	-0.009
	A4L3 |Individual system	4.588	-0.075
Personal information for resource efficiency	A5L1 |+0% efficiency	10.697	-0.245*
	A5L2 |+15% efficiency	-3.513	0.186
	A5L3 |+35% efficiency	-7.184	-0.059
Estimated Latent class probabilities		0.349***	0.651***

The Reluctant Adapter class consist of respondents (34.90%) who strongly do not prefer to share personal information with the system for resource efficiency. However, those Adapters are willing to share their work activities and personal preferences to the smart feature. Further, it is remarkable that the Reluctant Adapters do not prefer having control over the smart feature.

The Confident Adapter class has more respondents (65.10%) related to the Reluctant Adapters. Figure 36 show that the Confident Adapters mostly prefer receiving information, warnings and tips from the communication systems (43%). In addition, those Adapters are also willing to share personal information with the smart feature if they can perceive better service. However, they do not want their data to be used for knowledge acquisition.

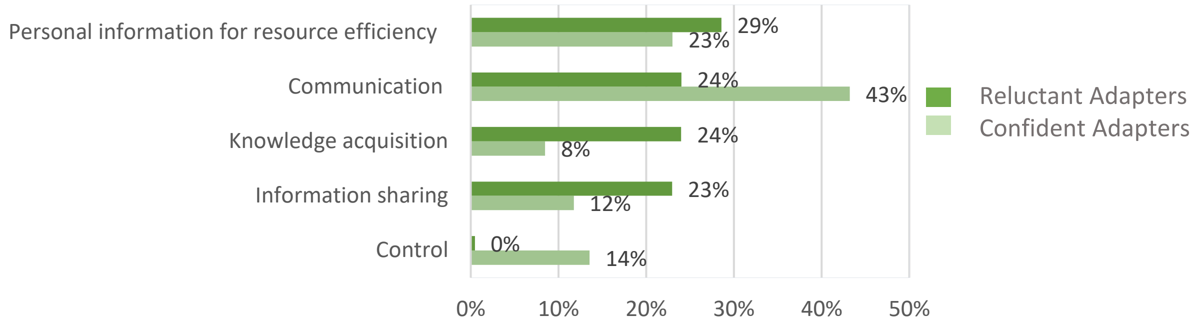


Figure 36: Relative importance of smart feature attributes

To determine whether the class distribution is related to personal, demographic, work, experience and attitude-related variables, Chi-square tests and independent t-tests are carried out. Unfortunately, no significant values are discovered.

5.2.8 Aggregated smart feature

Also, for LCM, all the results of the choices from the smart feature are included in one overview. The output of the analysis is presented in Table 34 and Figure 37. According to the constant values, class 1 ($\beta0$=2.654) consist of Adapters and in class 2 ($\beta0$=-1.532), of Rejecters. Also, the table shows that Adapters will be encouraged by sharing personal information for resource efficiency and discouraged by no dashboard. On the other hand, Rejecters can be stimulated by not sharing personal information and unstimulated by no dashboard.

*Table 34: Results of the LCM analysis- Significance codes: (0.001 = '***') (0.01 = '**') (0.05 = '*')*

Attribute	ID Level	LC1 (β)	LC2 (β)
Constant	-	2.654***	-1.532***
Control	A1L1 |Decision support	0.194***	0.166
	A1L2 |Automated decision support	-0.194	-0.166
Information sharing	A2L1 |Not sharing information	-0.209***	0.000
	A2L2 |Basic information	0.142*	0.020
	A2L3 |Advance information	0.067	-0.020
Communication	A3L1 |No dashboard	-0.326***	-0.599***
	A3L2 |Basic communication	0.168***	0.361**
	A3L3 |Advanced communication	0.158	0.238
Knowledge acquisition	A4L1 |No knowledge acquisition	-0.061	0.158
	A4L2 |Whole system	0.038	-0.004
	A4L3 |Individual system	0.023	-0.154
Personal information for resource efficiency	A5L1 |+0% efficiency	0.082	0.793***
	A5L2 |+15% efficiency	0.205***	0.214
	A5L3 |+35% efficiency	-0.287	-1.007
Estimated Latent class probabilities		0.755***	0.245***

Most respondents are part of the Adapter class (75.50%). Those respondents mainly prefer having a communication system. The adapters are also open to sharing information with the smart features as long as it is not sensitive. Further, they do not mind if the collected data is used for knowledge acquisition. Moreover, the adapters prefer to have control over the smart feature.

The Rejecter class consists of fewer respondents (24.50%). Rejecters do not want a smart feature if they have to share any data. They are reluctant to share their information with the system (information sharing and resource efficiency) and the use of their data (knowledge acquisition). Together, these three attributes account for 62% of choice and have the highest negative B-values. To meet the rejecters', it is important not to ask for personal information.

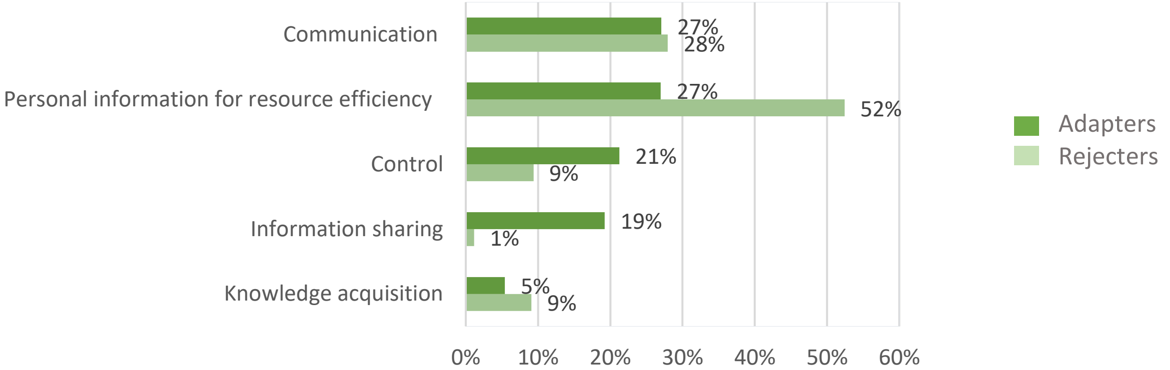


Figure 37: Relative importance of smart feature attributes

To provide a deeper understanding of the relationship between the class distributions and personal, demographic, work, experience, and attitude-related variables, Chi-square tests and independent t-tests are conducted. In Table 35 and Table 36, only the significant variables are shown. This results in the fact that there is a relationship between age, work hours, experience, work activities and attitude.

According to Table 35, age causes a significant difference between the classes ($\chi 2 = 8.071$, $p=0.021$). Respondents younger than 35 years are mainly in the Adapter class. A small group of respondents younger than 35 are part of the Rejecters. Also, respondents older than 35 years are mostly in the Adapter class. However, almost 35% of the +35 years of respondents were in the class of Rejecters.

Work hours per week were also checked to determine any differences between classes. Significant differences were found between classes ($\chi 2 = 4.779$, $p=0.029$). The Table 36 shows that almost 65% of part-time workers are in the Adapter class. Furthermore, 35% of part-timers are in the Rejecter class. However, it can be seen that a larger group of full-timers are part of the Adapters. Approximately 81% of the respondents are in the Adapter class and 19% in the Rejecter class. This means that especially full-timers would like to apply the smart feature. Among part-timers, the need for this is less.

It was also checked whether there were differences between respondents familiar with the smart features. Smart workspace booking showed a significant difference ($\chi 2=7.797$, $p=0.020$). In general, it can be seen that respondents who never heard about the smart feature are mostly in the Adapter class (90.5%). A small group (9.5%) is part of the reject class. Similarly, respondents who have heard about the smart feature but never used it are 66.2% in the Adapter class and 33.8% in the Rejecter class. This also applies to respondents who have heard of the smart feature and use it; 85% are in the Adapter class and no less than 15% in the Rejecter class.

Significant differences between classes were found only for concentrated individual work regarding the distribution of different work activities. In general, respondents that concentrated individual work are mainly part of the Adapter class.

Attitudes toward smart features are also significant. This shows that the statement "smart feature makes me more productive at work" distinguishes the classes from each other. It could be observed that respondents who state that smart features contribute to their productivity at work mainly belong to the class of Adapters.

Table 35: Results Chi-square test for differences between the two classes

Characteristic	**LC1 (N)**	**LC1 (%)**	**LC2 (N)**	**LC2 (%)**	**Chi-square test X^2**	**Sig.**
Total	103	75.2	34	24.8		
Age					8.071	0.004
15-34	53	86.9	8	13.1		
35+	50	65.8	26	34.2		
Work hours per week					4.779	0.029
Part-time (35<)	33	64.7	18	35.3		
Full time (35>)	70	81.4	16	18.6		
Experience: Smart workspace booking					7.797	0.020
Never heard about it before and never used it	19	90.5	2	9.5		
Heard about it but never used it	51	66.2	26	33.8		
Heard about it and used it	33	84.6	6	15.4		

Table 36: Results independent sample t-test for differences between the two classes

Characteristic	**LC1 (N)**	**LC1 (Mean)**	**LC2 (N)**	**LC2 (Mean)**	**T-value**	**Sig.**
Work activities					1.994	0.048
Individual concentrated work	103	47.09	34	39.56		
Attitude					2.095	0.038
Smart features make me more productive at work	103	3.64	34	3.32		

5.3 Conclusion

This section presents the output obtained by summarizing the conclusions that can be drawn from analyzing the data of the stated choice experiment. The objective was to determine which attributes of smart features are preferred by office users. Also, it was important to get insight into the relationship between personal-, demographic-, work-, experience- and attitude-related variables, and the preferences that the respondents choose. By analyzing the data, answers were found for sub-question 3 and 4.

With MNL models, general insight into users' preferences for the different attributes of smart features was gained. The results of the MNL models can be seen as the average response of the respondents. This answers sub-question 3: *"Which preferences do users have for the different attributes of smart features?"* Furthermore, the constant shows that all smart features have a positive value. This indicates that the respondents chose an alternative (package A or B) than the 'no preference' option from the choice sets. This makes it possible to understand the users' preferences regarding the different attributes.

Table 37 shows which attribute respondents prefer for each smart feature. To get a general insight into how respondents look at smart features, we combined all data from the stated choice experiment into one interview, namely aggregated smart features. The aggregated smart feature gives insight into the respondents' preferences towards the attributes. This shows that respondents generally prefer decision support, sharing basic information, advanced communication, knowledge acquisition for the whole system and +15% resource efficiency.

Table 37: Overview attribute levels of all smart features

	Control	Information sharing	Communication	Knowledge acquisition	Resource efficiency
Smart indoor location	Automated decision support	Basic information	Advanced communication	Whole system	+15% efficiency
Smart parking	Decision support	Advanced information	Basic communication	No knowledge acquisition	+15% efficiency
Smart workspace	Decision support	Advanced information	Advanced communication	Whole system	+15% efficiency
Smart meeting room	Decision support	Basic information	Advanced communication	Whole system	+15% efficiency
Smart temperature	Automated decision support	Basic information	Basic communication	Individual system	+0% efficiency
Smart air quality	Decision support	Basic information	Advanced communication	Individual system	+0% efficiency
Smart lighting	Decision support	Not sharing information	Advanced communication	Individual system	+0% efficiency
Aggregated smart feature	Decision support	Basic information	Advanced communication	Whole system	+15% efficiency

With the LCM, respondents were classified according to similar preferences for a related smart feature. LCM distinguished 137 respondents over two latent classes with similar preferences. By using the constant value, it could be seen that smart indoor location tracking of colleagues, smart parking, smart workspace booking, smart air quality, and the aggregated smart feature can be divided into two groups, namely Adapters and Rejecters.

Furthermore, it was noticed that smart meeting room booking, smart indoor climate control of temperature and smart lighting have positive constant values for both LC groups. The difference between the classes is that one class consists of Reluctant Adapters, which are open to using the smart feature but are reluctant to share (personal) information. In contrast, the other class is bit more open to share (personal) information with the smart feature. Therefore, the classes are labelled as Reluctant and Confident Adapters. The Confident Adapters do consist of more respondents than the Reluctant class.

In addition, all classes prefer two attributes the most; communication and sharing personal information for resource efficiency. As can be seen, *no dashboard* has a negative value in all classes. This indicates that the respondents generally prefer a dashboard to receive information and gain insight from the smart feature. Also, at +35% resource efficiency, there is relatively often a negative utility value among the smart features. This means that respondents are unwilling to share sensitive personal information with the system for resource efficiency. The attribute that respondents have the least strong opinion about is knowledge acquisition.

It is found that several variables have a significant effect on the distributions of the classes. This information could answer sub-question 4: *'How do personal-, socio demographic-, work-, attitude-, experience-related characteristics influence the users' preferences for a particular smart feature?'*. Different statistical tests (Chi-square tests and Independent Sample T-tests) were used to find significant differences between classes. However, smart parking, smart lighting control and smart indoor climate control of temperature showed no significant difference. Other smart features do have significant differences between classes. Table 38 shows the important relative differences in characteristics per class (not in order of most important to least important).

Table 38: Differences between classes

Smart indoor location tracking of colleagues	Adapters	Rejecters
Work hours per week	▪ More full-timers	▪ More part-timers
Smart workspace	**Adapters**	**Rejecters**
Personality: Conscientiousness	▪ More respondents with this type of personality	
Smart meeting room booking	**Reluctant Adapters**	**Confident Adapters**
Personality: Conscientiousness	▪ More respondents with this type of personality	
Attitude: Smart feature makes me productive	▪ More respondents that agree smart features will make them productive	
Smart indoor climate control – Air quality	**Adapters**	**Rejecters**
Gender	▪ More males	▪ More females
Work hours per week	▪ More full-timers	▪ More part-timers
Personality: Conscientiousness		▪ More respondents with this type of personality
Aggregated smart feature	**Adapters**	**Rejecters**
Work activities: Individual concentrated work	▪ More respondents with this type of work activity	
Attitude: Smart feature makes me productive	▪ More respondents that agree smart features will make them productive	

Chapter 6. Discussion

This thesis aimed to provide insight into the smart features that meet user expectations and preferences regarding smart office concept. The research outcomes also contributed to a better understanding of attributes within smart features. Through this research, it was possible to gain knowledge on the relationship between smart features and user perspectives. Although the research is a valuable contribution to gain more specific insight into which smart features meet the user's perspectives, a few noticeable results and limitations apply and will be discussed in this section.

6.1 Interpretation of the results

To gain insight into user expectations and preferences, all seven smart features were analyzed using MNL and LCM. Using the constant values, it can be seen that the utility scores are the highest for the three smart features. Both analysis methods showed that smart meeting room, smart indoor climate control of temperature and smart indoor climate control of air quality were the most chosen smart features by the respondents. Another study also indicated that those smart features are important to the users (Brugmans, 2017). In Brugmans' survey, respondents indicated to what extent they think smart features can contribute to their satisfaction, productivity and flexibility. Our survey extends these insights by revealing what users currently expect from a smart feature in order to meet their needs.

Furthermore, the results show that smart workspace booking and smart meeting room booking have similar respondents. This also applies to smart indoor climate control of temperature and smart indoor climate control of air quality. However, compared to the aggregated smart feature, all seven smart features differ. This indicates that users have different preferences for each smart feature. This is not surprising because each smart feature contributes to another daily activity or user's needs (Tuzcuoglu et al., 2021). Therefore, each smart needs to be approached separately.

Another matter to realize is that the literature has shown that individuals are very concerned about their privacy. However, it has also been revealed that if the benefits outweigh the risk, individuals are willing to "give up" their privacy, the so-called privacy paradox. (Kokolakis, 2017; Williams et al., 2018). This phenomenon has not been previously explored within a smart office concept. Therefore, the attribute 'Personal information for resource efficiency' investigated whether respondents would be willing to share personal information if the smart feature would serve them better and be more efficient. The survey showed that respondents are unwilling to share sensitive data (such as health data). However, it is notable that respondents are willing to share personal data for smart indoor location tracking of colleagues, smart parking, smart workspace booking and smart meeting room booking, because it directly benefits them with their daily activity or task (Tuzcuoglu et al., 2021; Kokolakis, 2017). However, this does not apply to smart indoor climate control of temperature, smart indoor climate control of air quality and smart lighting control. In these cases, respondents prefer not to share personal data. The survey performed in this study confirms the privacy paradox, people are willing to share personal data depending on the benefit.

6.2 Limitations of the research

The survey was primarily conducted within companies. These Knowledge-Based Organizations (KBO) includes high educated, young adult full-timers. This is also reflected in the dataset. It can be seen that this group mainly represent the sample data. Compared to the Dutch office population, CBS data has a bit more of a spread within the data set.

In addition, the respondents only gained access to two smart features at a time. As the survey was separated in order to increase the ease of user input, it might result in a skewed frame of reference, not taking into account the other smart features in contrast to those with which they were represented. So it could be that if the same respondents had a survey about other smart features, the respondent, in that case, would have chosen a completely different composition. Therefore, it is important to mention that the aggregated smart feature gives an overall indication of what respondents prefer. In this way it helps to compare the results of the smart features with this general overview as an average baseline.

Moreover, to explore the relationship between preferences and the personal-, demographic-, work-, attitude-, or experience-related characteristics, Chi-square tests and independent-sample t-tests were conducted. Yet, it became clear that the sample size was too small, because some categories had too few respondents, which made the analysis indicate that some characteristics are insignificant. However, according to Rose et al., (2013), it is important that an SCE is completed by a minimum of 30 respondents. For this reason, it was ensured that for each smart feature at least 30 respondents completed the survey. Unfortunately, in some cases it was not possible to determine the characteristics.

Chapter 7. Conclusion and recommendations

This chapter provides the overall conclusions of this research. The main research question will be answered. Also, the scientific and societal relevance will be described. Moreover, recommendations for further research will be discussed.

7.1 Conclusion

This research focuses on investigating smart features that meet the user expectations and preferences that can be implemented in a smart office environment. The interest in the smart office concept has been increased since technologies can be used to measure and improve the environment of the user. Due to the increased adoption of the smart office concept, the users' preferences and expectations of office environments have changed. A better understanding of users' preferences and expectations is necessary to meet the users' needs and improve the user experience, user satisfaction, and work performance (Haapakangas et al., 2018). However, the literature on smart office concepts primarily focuses on developing technology, and it is unclear what users prefer and expect from smart office environments (Tuzcuoglu et al., 2021). A research gap has been found in the user perspectives of smart office features. Having knowledge on which smart features meet user perspectives have a positive influence on the effectiveness of smart office and their users (Haapakangas et al., 2018; Tuzcuoglu et al., 2021). Therefore, the study aimed to get insight user expectations and preferences regarding smart features. In addition, this study also tried to understand how the attributes of the smart features should be designed to contribute to the users' needs. In this research, the following main research question has been answered.

> *'What kind of smart features in smart offices meet user expectations and preferences?'*

A literature review was conducted to gain knowledge about the smart features that meet the user expectations. As a result, seven smart features emerged that contribute to the user's daily activities and take the user's needs into account, namely: smart indoor location tracking of colleagues, smart parking, smart workspace booking, smart meeting room booking, smart indoor climate control of temperature, smart indoor climate control of air quality and smart lighting control. Furthermore, control, information sharing, communication, knowledge acquisition and sharing of personal data for resource efficiency are five attributes of smart features that can contribute to understanding user expectations and preferences.

Based on the results of SCE, it is found that 75.50% of knowledge workers (Adapters) prefer to have a smart feature. Generally, knowledge workers prefer a smart feature that can influence the smart feature (decision-support). Furthermore, respondents are willing to share information with the smart feature, as long as the information is not sensitive data (basic information such as agenda and work activities). Moreover, they are open to sharing personal data if they receive more services (+15% resource efficiency). Further, in the respondents are not always affected by what happens next with their data (knowledge acquisition). Also, respondents strongly prefer communicative systems, such as an overview on a dashboard (advanced communication).

Furthermore, 24.50% of the knowledge workers (Rejecters) do not want a smart feature if they have to share any personal data. Also, they do not want the collected data to be used for knowledge acquisition. This has major consequences for the implementation of smart features in offices: caution with personal information is more important to the Rejecters than the design of the smart feature itself. Nevertheless, it is an important precondition.

In addition, it was analyzed whether personal-, demographic-, work-, attitude-, experience-related characteristics influence the users' expectations and preferences regarding smart features. The analysis showed significant differences between Adapters and Rejecters. It shows that mainly knowledge workers who perform individual concentrated work and having trust in the contribution of smart features to their productivity are part of the Adapters.

This research also revealed that the knowledge workers mainly prefer certain smart features. Within the smart office concept, knowledge workers want to be provided with a smart meeting room booking, smart indoor climate control of temperature and smart indoor climate control of air quality. However, it is important to note that within these smart features, respondents prefer not to share personal data. Furthermore, smart parking is the least preferred smart feature among this group of respondents.

7.2 Scientific relevance

Previous studies about smart offices mainly focus on developing technology or collecting user behaviour through sensors to understand user preferences (Noceraet al., 2015; Dong et al., 2019; Tehseen et al., 2018; Mohamed et al., 2019; Shinde et al., 2020). However, a deeper understanding of user perspectives about smart features is rare (Tuzcuoglu et al., 2021). As a result, there is a big gap between technology development and end-users Tuzcuoglu et al., 2021; Yang et al., Unpublished). This study contributed to a better understanding of the users' preferences and expectations regarding smart features in a smart office environment.

Moreover, knowledge was added to the existing literature about which smart features and related attributes are preferred among knowledge workers. However, the most important discovery in this research is that it is crucial to include the user perspective in developing a smart feature. Without the user approach, it is impossible to develop a suitable smart feature that meets the user. As can be seen from the results, the smart features are very different from each other and deviate from the aggregated smart feature. This means that there is no optimal smart feature without the approach from the user perspective. Therefore, it is important that each smart feature is approached separately and that it contributes to the daily activity of the user and their needs.

7.3 Societal relevance

More companies want to implement the concept of smart offices with the profound use of technology in providing efficient and effective workplaces for their users (Tuzcuoglu et al., 2021). However, until now, there has been no understanding of how smart features can contribute to the daily work activities of the users and their needs due to the shortcoming in the approach of the user perspective regarding the development of smart features. This research has shown which smart features and corresponding attribute levels mainly contribute to users. Therefore, the research output will support organizations in making considered strategic choices to serve their users better. This will create a pleasant working environment in which the user experience, user satisfaction, and work performance are met.

7.4 Recommendations for further research

Since there was no research about the smart features in a smart office environment that meet the perspective of knowledge workers, this study is explorative research using a stated choice experiment. While the results of this research are valuable, there are certain aspects interesting for further investigation. Therefore, this subsection provides some interesting recommendations for further research.

As addressed earlier, the number of respondents in this research is small (N=30 per smart feature). Therefore, it is interesting to conduct a similar questionnaire with a large sample size. This will provide more insight into the results. In addition, a further understanding can also be gained about the influence of personal-, demographic-, work-, attitude-, and experience-related characteristics on users' expectations and preferences across classes.

Also, the results showed that smart meeting room booking, smart indoor climate control of temperature and smart indoor climate control of air quality, are the most preferred smart features. Within this research it is only focused on five attributes, it is recommended to research these three smart features deeper. This will help to create a smart feature that is even more effective based on the users' needs.

Additionally, this research has limited itself to seven smart features. This concludes that some other smart features may have been excluded. The used methodology can be applied to research other smart features that contribute to the knowledge workers, such as smart lockers and smart coffee machines. It is therefore recommended that this research be carried out for other smart features as well.

Furthermore, it is advisable to conduct a qualitative study to gain more insight into how knowledge workers think about the smart features and attribute levels. Understanding can be obtained into the considerations of respondents and the decisive choices. Qualitative research can be used to understand the considerations of the respondent.

Finally, smart features collect all kinds of information about their environment and the user. However, this may conflict with privacy legislation. Companies that plan to implement smart features have to consider several aspects when it comes to the use of smart features and the collection and processing of personal data (Dutch Data Protection Authority, 2021). Therefore, it is recommended to do further research on how the collected data should be handled in line with the privacy law.

Bibliography

Ahmed, S., Abbas, S. M., & Zia, H. (Eds.). (2020). Smart Cities--Opportunities and Challenges: Select Proceedings of ICSC 2019. Springer Singapore, Imprint: Springer.

Akpakwu, G. A., Silva, B. J., Hancke, G. P., & Abu-Mahfouz, A. M. (2017). A survey on 5G networks for the Internet of Things: Communication technologies and challenges. IEEE access, 6, 3619-3647.

Alter, S. (2014). Theory of workarounds. Retrieved from: Communications of the Association of Information Systems, 34(55), 1041–1066.

Alter, S. (2019). Making sense of smartness in the context of smart devices and smart systems. Information Systems Frontiers, 22(2), 381-393.

Alker, R. J., Malanca, M., & Pottage, C. (2015). Productivity in Offices The next chapter for green building. World Green building Council, 46.

Alraja, M. N., Farooque, M. M. J., & Khashab, B. (2019). The effect of security, privacy, familiarity, and trust on users' attitudes toward the use of the IoT-based healthcare: the mediation role of risk perception. IEEE Access, 7, 111341-111354.

Al-Sarawi, S., Anbar, M., Alieyan, K., & Alzubaidi, M. (2017, May). Internet of Things (IoT) communication protocols. In 2017 8th International conference on information technology (ICIT) (pp. 685-690). IEEE.

Appel-Meulenbroek, R., Groenen, P., & Janssen, I. (2011). An end-user's perspective on activity-based office concepts. Journal of Corporate Real Estate.

Appel-Meulenbroek, R., Kemperman, A. D. A. M., van Susante, P., & Hoendervanger, J. G. (2015). Differences in employee satisfaction in new versus traditional work environments. EuroFM Research Papers Advancing knowledge in FM. People Make Facilities Management, 202-209.

Ashibani, Y., & Mahmoud, Q. H. (2018, October). A behavior profiling model for user authentication in IoT networks based on app usage patterns. In IECON 2018-44th Annual Conference of the IEEE Industrial Electronics Society (pp. 2841-2846). IEEE.

Ashworth, S., Tucker, M., & Druhmann, C. K. (2019). Critical success factors for facility management employer's information requirements (EIR) for BIM. Facilities.

Autoriteitpersoonsgegevens. (2019). Privacybeleid Autoriteit Persoonsgegevens. Retrieved from:
https://autoriteitpersoonsgegevens.nl/sites/default/files/atoms/files/privacybeleid_ap_okt_2019.pdf

Barišić, A., Amaral, V., & Challenger, M. (2020). Enhancing Occupants Comfort and Well-being through a Smart Office setup. In 2020 43rd International Convention on Information, Communication and Electronic Technology (MIPRO) (pp. 1825-1830). IEEE.

Barth, S., & De Jong, M. D. (2017). The privacy paradox–Investigating discrepancies between expressed privacy concerns and actual online behavior–A systematic literature review. Telematics and informatics, 34(7), 1038-1058.

Batov, E. I. (2015). The distinctive features of "smart" buildings. Procedia Engineering, 111, 103-107.

Bo, W., Zhang, Y., Hong, X., Sun, H., & Huang, X. (2014, December). Usable security mechanisms in smart building. In 2014 IEEE 17th International Conference on Computational Science and Engineering (pp. 748-753). IEEE.

De Been, I., & Beijer, M. (2014). The influence of office type on satisfaction and perceived productivity support. Journal of Facilities Management.

Bhandari, P. (2021). Data Cleansing | A Guide with Examples & Steps. Retrieved from: https://www.scribbr.com/methodology/data-cleansing/

Brugmans, L., Appel-Meulenbroek, R., Kemperman, A., & Dinnissen, L. (2017). The strategic value of smart work environment applications. The Leader, 28-29.

Buckman, A. H., Mayfield, M., & Beck, S. B. (2014). What is a smart building? Smart and Sustainable Built Environment.

Budie, B., Appel-Meulenbroek, R., Kemperman, A., & Weijs-Perrée, M. (2019). Employee satisfaction with the physical work environment: the importance of a need-based approach. International Journal of Strategic Property Management Vol. 23 (1), 36-49.

Bodin, L. (2009). Difference in satisfaction with office environment among employees in different office types, Journal of Architectural and Planning Research. 26 241–257.

Brill, M., & Weideman, S. (2001). Disproving widespread myths about workplace design. Jasper, IN: Kimball International.

CBS. (2021). Beroepsbevolking. Retieved from: https://www.cbs.nl/nl-nl/visualisaties/dashboard-beroepsbevolking/beroepsbevolking

Danielsson, C. B., & Bodin, L. (2008). Office type in relation to health, well-being, and job satisfaction among employees. Environment and behavior, 40(5), 636-668.

Dembski, F., Wössner, U., Letzgus, M., Ruddat, M., & Yamu, C. (2020). Urban digital twins for smart cities and citizens: The case study of Herrenberg, Germany. Sustainability, 12(6), 2307.

Dong, B., Prakash, V., Feng, F., & O'Neill, Z. (2019). A review of smart building sensing system for better indoor environment control. Energy and Buildings, 199, 29-46.

Domencich, T. A., & McFadden, D. (1975). Urban travel demand-a behavioral analysis (No. Monograph).

Ireland, S. (2019). The Most Important Features For Your Smart Office In 2019. CEOWORLD Magazine. Retrieved from: https://ceoworld.biz/2019/07/26/the-most-important-features-for-your-smart-office-in-2019/

Flowscape. (n.d.) Solutions. Retrieved from: https://flowscapesolutions.com/solutions

Furdik, K., Lukac, G., Sabol, T., & Kostelnik, P. (2013). The network architecture designed for an adaptable IoT-based smart office solution. International Journal of Computer Networks and Communications Security, 1(6), 216-224.

Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital twin: Enabling technologies, challenges and open research. IEEE access, 8, 108952-108971.

Gal, C. (2005). Smart offices. Smart environments: Technology, protocols, and applications (pp. 323-343) Retrieved from: https://ebookcentral.proquest.com/lib/uunl/reader.action

Gal, C. L., Martin, J., & Durand, G. (2000). Smart office: an intelligent and interactive environment. In Managing interactions in smart environments (pp. 104-113). Springer, London.

GIRA. (n.d.). Lighting control. Retrieved from: https://www.gira.com/en/en/products/lighting-control#footer-contact

Ghaffarianhoseini, A., Berardi, U., AlWaer, H., Chang, S., Halawa, E., Ghaffarianhoseini, A., & Clements-Croome, D. (2016). What is an intelligent building? Analysis of recent interpretations from an international perspective. Architectural Science Review, 59(5), 338-357.

Haapakangas, A., Hallman, D. M., Mathiassen, S. E., & Jahncke, H. (2018). Self-rated productivity and employee well-being in activity-based offices: The role of environmental perceptions and workspace use. Building and Environment, 145, 115-124.

Haegeli, P., Haider, W., Longland, M., & Beardmore, B. (2010). Amateur decision-making in avalanche terrain with and without a decision aid: a stated choice survey. Natural Hazards, 52(1), 185-209.

Hartog, L., Weijs-Perrée, M., & Appel-Meulenbroek, R. (2018). The influence of personality on user satisfaction: multi-tenant offices. Building Research & Information, 46(4), 402-416.

Haynes, B., Suckley, L., & Nunnington, N. (2017). Workplace productivity and office type. Journal of Corporate Real Estate, 19(2), 111-138. doi:10.1108/JCRE-11-2016-0037

Heerwagen, J. H., Kampschroer, K., Powell, K., & Loftness, V. (2004). Collaborative knowledge work environments. Building Research & Information, 32:6, pp. 510-528.

Hensher, D. A., Rose, J. M., Greene, W. H. (2015). Experimental design and choice experiments. In Applied Choice Analysis. Retrieved from: https://doi.org/10.1017/cbo9781316136232.008

Hermann, M., Pentek, T., & Otto, B. (2016, January). Design principles for industrie 4.0 scenarios. In 2016 49th Hawaii international conference on system sciences (HICSS) (pp. 3928-3937). IEEE.

Himanen, M. (2017). The Significance of User Involvement in Smart Buildings Within Smart Cities. In Designing, Developing, and Facilitating Smart Cities (pp. 265-314). Springer, Cham.

Hongisto, V., Haapakangas, A., Varjo, J., Helenius, R., & Koskela, H. (2016). Refurbishment of an open-plan office–environmental and job satisfaction. Journal of environmental psychology, 45, 176-191.

JLL. (2016). A surprising way to cut real estate costs. Retrieved from: https://www.us.jll.com/en/trends-and-insights/workplace/a-surprising-way-to-cut-real-estate-costs

Kašpárková, L., Vaculík, M., Procházka, J., & Schaufeli, W. B. (2018). Why resilient workers perform better: The roles of job satisfaction and work engagement. Journal of Workplace Behavioral Health, 33(1), 43-62.

Kemperman, A. D. A. M. (2000). Temporal aspects of theme park choice behavior: modeling variety seeking, seasonality and diversification to support theme park planning Eindhoven. Retrieved from: https://doi.org/10.6100/IR542240

Kemperman, A. D., & Timmermans, H. J. (2008). Influence of socio-demographics and residential environment on leisure activity participation. Leisure sciences, 30(4), 306-324.

Kim, D., Park, K., Park, Y., & Ahn, J. H. (2019). Willingness to provide personal information: Perspective of privacy calculus in IoT services. Computers in Human Behavior, 92, 273-281.

Kokolakis, S. (2017). Privacy attitudes and privacy behaviour: A review of current research on the privacy paradox phenomenon. Computers & security, 64, 122-134.

Komiak, S. Y., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. MIS quarterly, 941-960.

Kwon, M., Remøy, H., & Van Den Dobbelsteen, A. (2019). User-focused office renovation: a review into user satisfaction and the potential for improvement. Property Management.

Nocera, J. A., Barricelli, B. R., Lopes, A., Campos, P., & Clemmensen, T. (2015). *Human Work Interaction Design: Work Analysis and Interaction Design Methods for Pervasive and Smart Workplaces*.

Lecomte, P. (2019). What is smart? A real estate introduction to cities and buildings in the digital era. Journal of General Management, 44(3), 128-137.

Lee, S. Y., & Brand, J. L. (2005). Effects of control over office workspace on perceptions of the work environment and work outcomes. Journal of environmental psychology, 25(3), 323-333.

Li, H. (2014). A novel design for a comprehensive smart automation system for the office environment. In Proceedings of the 2014 IEEE Emerging Technology and Factory Automation (ETFA) (pp. 1-4). IEEE.

Limesurvey. (n.d.). Turn questions into answers. Retrieved from: https://www.limesurvey.org/

Liu, X., & Baiocchi, O. (2016). A comparison of the definitions for smart sensors, smart objects and Things in IoT. In 2016 IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON) (pp. 1-4). IEEE.

Louviere, J., & Timmermans, H. (1990). Stated preference and choice models applied to recreation research: a review. Leisure Sciences, 12(1), 9-32.

Louviere, J. J., Flynn, T. N., & Carson, R. T. (2010). Discrete choice experiments are not conjoint analysis. Journal of choice modelling, 3(3), 57-72.

Maarleveld, M., Volker, L., & Van Der Voordt, T. J. (2009). Measuring employee satisfaction in new offices–the WODI toolkit. Journal of Facilities Management.

MAPIQ. (n.d.). Solutions. Retrieved from: https://www.mapiq.com/

McKinsey. (2015). The internet of things the value of digitizing the physical world Retrieved from: https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/the-internet-of-things-the-value-of-digitizing-the-physical-world

Medina-Borja, A. (2015). Editorial column—smart things as service providers: a call for convergence of disciplines to build a research agenda for the service systems of the future. Service Science, 7(1), ii-v.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In Frontiers in Econometrics.

Memoori. (2019). Navigating the complex smart building landscape. Retrieved from: memoori.com

Metrikus. (n.d). Back to basics: what does a smart office actually look like? Retrieved from: https://www.metrikus.io/blog/what-does-a-smart-office-look-like

Mikulecky, P. (2012, March). User adaptivity in smart workplaces. In Asian Conference on Intelligent Information and Database Systems (pp. 401-410). Springer, Berlin, Heidelberg.

Madakam, S., Lake, V., Lake, V., & Lake, V. (2015). Internet of Things (IoT): A literature review. Journal of Computer and Communications, 3(05), 164.

Minerva, R., Lee, G. M., & Crespi, N. (2020). Digital twin in the IoT context: a survey on technical features, scenarios, and architectural models. Proceedings of the IEEE, 108(10), 1785-1824.

Mohamed, N., Al-Jaroodi, J., & Lazarova-Molnar, S. (2019). Leveraging the capabilities of industry 4.0 for improving energy efficiency in smart factories. Ieee Access, 7, 18008-18020.

Munoz, S., Araque, O., Sánchez-Rada, J. F., & Iglesias, C. A. (2018). An emotion aware task automation architecture based on semantic technologies for smart offices. Sensors, 18(5), 1499.

Papagiannidis, S., & Marikyan, D. (2020). Smart offices: A productivity and well-being perspective. International Journal of Information Management, 51, 102027.

Pašek, J., & Sojková, V. (2018). Facility management of smart buildings. International Review of Applied Sciences and Engineering, 9(2), 181-187.

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. Journal of service research, 18(1), 59-74.

Pathak, A. (2021). 7 Solid Features Of A Smart Office You Can't Ignore. Retrieved from: https://blog.vantagecircle.com/features-of-smart-office/

Pearmain, Swanson, Kroes, and Bradley (1991): Stated Preference Technique – A Guide to Practice (2nd Ed.), Steer Davies Gleave and Hague Consulting Group

Piedmont, R. (2014). Inter-item Correlations. Retrieved from: https://link.springer.com/content/pdf/10.1007%2F978-94-007-0753-5_1493.pdf

Potoglou, D., Dunkerley, F., Patil, S., & Robinson, N. (2017). Public preferences for internet surveillance, data retention and privacy enhancing services: Evidence from a pan-European study. Computers in Human Behavior, 75, 811-825.

Proctor, R., Van Zandt, T.(2018). Human Factors in Simple and Complex Systems, 3rd ed. Boca Raton, FL, USA: CRC Press, 2018.

Remes, L., Dooley, K., Ketomäki, J., & Ihasalo, H. (2021). Smart workplace solutions–can they deliver the offices that employees have been waiting for?. Facilities.

Revicki, D. (2014). Internal Consistency Reliability. Retrieved from: https://link.springer.com/content/pdf/10.1007%2F978-94-007-0753-5_1493.pdf

Romero, M., Guédria, W., Panetto, H., & Barafort, B. (2020). Towards a characterisation of smart systems: A systematic literature review. Computers in industry, 120, 103224.

Rose, J., & Bliemer, M. (2013). Sample optimality in the design of stated choice experiments. Retrieved from: https://citeseerx.ist.psu.edu/viewdoc/download

Rothe, P., Lindholm, A. L., Hyvönen, A., & Nenonen, S. (2011). User preferences of office occupiers: investigating the differences. Journal of Corporate Real Estate.

Rothe, P., Lindholm, A. L., Hyvönen, A., & Nenonen, S. (2012). Work environment preferences–does age make a difference?. Facilities.

Rönka, E. (2019), Rethinking smart buildings: real estate as an active contributor to business success. Corporate Real Estate Journal, Vol. 9 No. 2, pp. 111-120.

Salosin, A., Gamayunova, O., & Mottaeva, A. (2020, August). The effectiveness of the Smart Office system. In Journal of Physics: Conference Series (Vol. 1614, No. 1, p. 012028). IOP Publishing.

Sanko, N. (2001). Guidelines for stated preference experiment design. Master of Business Adminstration diss., Ecole Nationale des Ponts et Chaussées.

SAS, (n.d.). Innovation starts with education. Retrieved from: https://www.sas.com/nl_nl/home.html

Schwab, K (2016). The fourth industrial revolution. Retrieved from: https://luminariaz.files.wordpress.com/2017/11/the-fourth-industrial-revolution-2016-21.pdf

Schleich, J., Faure, C., & Klobasa, M. (2017). Persistence of the effects of providing feedback alongside smart metering devices on household electricity demand. Energy Policy, 107, 225-233.

Shin, H., Lee, H. S., Park, M., & Lee, J. G. (2018). Facility management process of an office building. Journal of Infrastructure Systems, 24(3), 04018017.

Shinde, R., Deval, N., Kadam, S. (2020). Smart office. Retrieved from: www.jespublication.com

Silverio-Fernández, M., Renukappa, S., & Suresh, S. (2018). What is a smart device?-a conceptualisation within the paradigm of the internet of things. Visualization in Engineering, 6(1), 1-10.

Singh, D., Psychoula, I., Kropf, J., Hanke, S., & Holzinger, A. (2018, July). Users' perceptions and attitudes towards smart home technologies. In International Conference on Smart Homes and Health Telematics (pp. 203-214). Springer, Cham.

Smart Industry. (2021). Smart Elevators: Giving IoT a Lift. Retrieved from: https://www.smart-industry.net/smart-elevators-giving-iot-a-lift/

Smid, E. (2016). Adviesrapport Domesta. Groningen: Hanzehogeschool Groningen. Kenniscentrum NoorderRuimte

Smith, J., & Garriety, S. (2020). The art of flexibility: bridging five generations in the workforce. Strategic HR Review.

Survey Monkey (n.d). Survey data cleaning: 7 things to check before yfDomeou start your analysis. Retrieved from: https://www.surveymonkey.com/curiosity/survey-data-cleaning-7-things-to-check-before-you-start-your-analysis/

Taber, K. (2017). The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. Retrieved from: https://link.springer.com/article/10.1007/s11165-016-9602-2

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. International journal of medical education, 2, 53.

Tehseen, M., Javed, H., Mehmood, A., Amin, M., Hussain, I., & Jan, B. (2019). Multi modal aptitude detection system for smart office. IEEE Access, 7, 24559-24570.

TU/e. (2018). Scientific Integrity. Retrieved from: https://assets.tue.nl/fileadmin/content/universiteit/Over_de_universiteit/integriteit/Netherlands%20Code%20of%20Conduct%20for%20Research%20Integrity%202018.pdf

Tuzcuoglu, D., Yang, D., de Vries, B., & Sungur, A. (2020, November). Social interaction in an office environment: A qualitative study after relocation to a smart office. In Transdisciplinary Workplace Research Conference 2020 (pp. 355-364).

Tuzcuoğlu, D., Yang, D., de Vries, B., Sungur, A., & Appel-Meulenbroek, R. (2021). The phases of user experience during relocation to a smart office building: A qualitative case study. Journal of Environmental Psychology, 74, 101578.

Tyrberg, A. (n.d.). What is a Smart Office? Senion | Smart Office Solution. Retrieved from: https://senion.com/WHAT-IS-A-SMART-OFFICE/

Van Susante, P. (2014) Differences in employee satisfaction in new versus traditional work environments (master thesis) Eindhoven, The Netherlands: Eindhoven University of Technology

Verbeke, S., Aerto, D., Reynders, G., Ma, Y., Waide, P. (2020). Final report on the technical support to the development of a smart readiness indicator for buildings. Retrieved from: https://op.europa.eu/en/publication-detail/-/publication/bed75757-fbb4-11ea-b44f-01aa75ed71a1/language-en

Vischer, J. C. (2007). The effects of the physical environment on job performance: towards a theoretical model of workspace stress. Stress and health: Journal of the International Society for the Investigation of Stress, 23(3), 175-184.

Van Der Voordt, T. J. (2004). Productivity and employee satisfaction in flexible workplaces. Journal of Corporate Real Estate.

Vos, P., & Van der Voordt, T. (2001). Tomorrow's offices through today's eyes: Effects of innovation in the working environment. Journal of Corpoorate Real Estate Vol. 4. Nr. 1, 48-65.

Waren, K. W. F. (2010). Marketing research methods in SAS experimental design, choice, conjoint, and graphical techniques. Graphical Techniques. Cary, NC, SAS-Institute TS-722.

Williams, M., Nurse, J. R., & Creese, S. (2016, August). The perfect storm: The privacy paradox and the Internet-of-Things. In 2016 11th International Conference on Availability, Reliability and Security (ARES) (pp. 644-652). IEEE.

Wohlers, C., Hartner-Tiefenthaler, M., & Hertel, G. (2019). The relation between activity-based work environments and office workers' job attitudes and vitality. Environment and Behavior, 51(2), 167-198.

Worldgbc. (2014). Health, Wellbeing & Productivity in Offices. Retrieved from: https://www.worldgbc.org/sites/default/files/compressed_WorldGBC_Health_Wellbeing__Productivity_Full_Report_Dbl_Med_Res_Feb_2015.pdf

Yang et al. (Unpublished). An investigation of user preferences and expectations for smart office environments.

Zang, M., Xing, Z., & Tan, Y. (2019). IoT-based personal thermal comfort control for livable environment. International journal of distributed sensor networks, 15(7), 1550147719865506.

Zhang, X., Zheng, P., Peng, T., He, Q., Lee, C. K. M., & Tang, R. (2022). Promoting employee health in smart office: A survey. Advanced Engineering Informatics, 51, 101518.

Zhao, Q. (2017). Research opportunities arising from control and optimization of smart buildings. Control Theory and Technology, 15(1), 78-80.

Zhou, Q., Xing, J., & Yang, Q. (2020). Device-free occupant activity recognition in smart offices using intrinsic Wi-Fi components. Building and Environment, 172, 106737.

APPENDIX I: Matrix smart features – Attributes and Levels

General I	Attribute I Control	Attribute II Information sharing	Attribute III Communication	Attribute IV Knowledge acquisition (purpose of data use)	Attribute V Personal information for resource efficiency
Level 1	Decision support	Not sharing information	No dashboard	Knowledge acquisitions – No	+0% efficiency (none)
Level 2	Automated decision support	Basic information	Basic communication	Knowledge acquisitions – Whole system	+15% efficiency (personal information)
Level 3		Basic information + Personal preference	Advanced communication	Knowledge acquisitions – Individual system	+35% efficiency (sensitive information)
1. Smart indoor location tracking of colleagues					Time to find a colleague
Level 1	• System presents an overview of who occupied a workspace.	• None	• No dashboard (No communication at all)	• No knowledge acquisitions	• None
Level 2	• Automatically present location of colleagues based on aggregated information.	• Status busy / free	• Colleague location list in outlook	• Use aggregated data to create office usage patterns	• +15% efficiency, by sharing personal information
Level 3		• Agenda + Live location + personal preference	• Map with locations of colleagues	• Use data to create individual user office users' patterns	• +35% efficiency, by sharing sensitive personal information
2. Smart parking					Time to find a suitable parking spot
Level 1	• User can park based on aggregated information.	• None	• No dashboard	• No knowledge acquisitions	• None
Level 2	• Automatically guides based on aggregated information.	• Agenda + Vehicle type	• Basic information in a list	• Use aggregated data to create office usage patterns	• +15% efficiency, by sharing personal information
Level 3		• Agenda + Vehicle type + personal preference	• Advanced information in a map	• Use data to create individual user patterns	• +35% efficiency, by sharing sensitive personal information
3. Smart workspace booking					Workspace availability
Level 1	• User can book based on aggregated information.	• None	• No dashboard	• No knowledge acquisitions	• None
Level 2	• Automatically booked based on aggregated information.	• Agenda	• Basic information in a list	• Use aggregated data to create office usage patterns	• +15% efficiency, by sharing personal information
Level 3		• Agenda + personal preference	• Advanced information in a map	• Use data to create individual user patterns	• +35% efficiency, by sharing sensitive personal information
4. Smart meeting room booking					Meeting room availability
Level 1	• User can book based on aggregated information.	• None	• No dashboard	• No knowledge acquisitions	• None
Level 2	• Automatically booked based on aggregated information.	• Agenda	• Basic information in a list	• Use aggregated data to create office usage patterns	• +15% efficiency, by sharing personal information
Level 3		• Agenda + personal preference	• Advanced information in a map	• Use data to create individual user patterns	• +35% efficiency, by sharing sensitive personal information
5. Smart indoor climate control – Temperature					Thermal comfort
Level 1	• User can control temperature based on aggregated information.	• None	• None	No knowledge acquisitions	• None
Level 2	• Temperature is automatically controlled based on aggregated information.	• Work activity	• Dashboard with indoor temperature	• Use aggregated data to create office usage patterns	• +15% efficiency, by sharing personal information
Level 3		• Work activity + personal preference	• Dashboard with indoor temperature + warnings + tips	• Use data to create individual user patterns	• +35% efficiency, by sharing sensitive personal information
6. Smart indoor climate control – Air quality					Air quality improvements
Level 1	• User can control air quality based on aggregated information.	• None	• None	No knowledge acquisitions	• None
Level 2	• Air quality is automatically controlled based on aggregated information.	• Work activity	• Dashboard with indoor air quality	Use aggregated data to create office usage patterns	• +15% efficiency, by sharing personal information
Level 3		• Work activity + personal preference	• Dashboard with indoor air quality + warnings + tips	Use data to create individual user patterns	• +35% efficiency, by sharing sensitive personal information
7. Smart lighting control					Visual comfort
Level 1	• User can control light based on aggregated information.	• None	• None	• No knowledge acquisitions	• None
Level 2	• Light is automatically controlled based on aggregated information.	• Work activity	• Dashboard with lighting control	• Use aggregated data to create office usage patterns	• +15% efficiency, by sharing personal information
Level 3		• Work activity + personal preference	• Dashboard with lighting control + warnings + tips	• Use data to create individual user patterns	• +35% efficiency, by sharing sensitive personal information

APPENDIX II: Input SAS

```
title Evaluate Generic Candidate Designs;
%mktruns (2 3 3 3 3);

title Create Candidate Design;
%mktex(2 3 3 3 3, n=18, seed=123);

title Add Alternatives;
%mktlab(data=design, int=f1-f2);
Proc print; run;

title Find Efficient Choice Design;
%choiceff(data=final, model=class (x1-x5 / sta), nsets=9, maxiter=60, flags=f1-f2, seed=123,
options=relative, beta=zero);

title Variance-Covariance Matrix;
proc print data=bestcov;
        id __label;
        label __label = '00'x ;
        format _numeric_ zer5.2;
        var x:;
        run;

title Choice sets;
proc print; run;

title Choice sets by code;
proc print;
        by set;
        id set;
        var x:; run;

title Choice sets including Statistics;
proc print;
        by set;
        id set; run;

title Choice sets including Attributes and Levels description;
proc print label;
        label x1 = 'Control'
                x2 = 'Information sharing'
                x3 = 'Communication'
                x4 = 'Knowledge acquisition'
                x5 = 'Resource effiency'
                x6 = 'Other';

format x1 x1f. x2 x2f. x3 x3f. x4 x4f. x5 x5f. x6 x6f.;
```

```
    by set;
    id set;
    var x:; run;

proc format;
    value x1f    1='Decision support'
                     2='Automated decision support';

    value x2f    1='Not sharing information'
                     2='Basic information'
                     3='Basic information + Personal preference';

    value x3f    1='No dashboard'
                     2='Basic communication'
                     3='Advanced communication';

    value x4f    1='Knowledge acquisitions – No'
                     2='Knowledge acquisitions – Whole system'
                     3='Knowledge acquisitions – Individual system';

    value x5f    1='+0% efficiency'
                     2='+15% efficiency'
                     3='+35% efficiency';
```

APPENDIX III: Output SAS

Evaluate Generic Candidate Designs

```
              Design Summary
         Number of
         Levels          Frequency
              2              1
              3              4
```

Evaluate Generic Candidate Designs

```
            Saturated      = 10
            Full Factorial = 162
            Some Reasonable                  Cannot Be
               Design Sizes       Violations    Divided By
                         18 *              0
                         36 *              0
                         27                5    2 6
                         12                6    9
                         24                6    9
                         30                6    9
                         15               11    2 6 9
                         21               11    2 6 9
                         33               11    2 6 9
                         10 S             14    3 6 9
      * - 100% Efficient design can be made with the MktEx macro.
      S - Saturated Design - The smallest design that can be made.
          Note that the saturated design is not one of the
          recommended designs for this problem.  It is shown
          to provide some context for the recommended sizes.
```

Evaluate Generic Candidate Designs

n	Design	Reference
18	2 ** 1 3 ** 7	Orthogonal Array
36	2 ** 16 3 ** 4	Orthogonal Array
36	2 ** 11 3 ** 12	Orthogonal Array
36	2 ** 10 3 ** 8 6 ** 1	Orthogonal Array
36	2 ** 9 3 ** 4 6 ** 2	Orthogonal Array
36	2 ** 4 3 ** 13	Orthogonal Array
36	2 ** 3 3 ** 9 6 ** 1	Orthogonal Array
36	2 ** 2 3 ** 12 6 ** 1	Orthogonal Array
36	2 ** 2 3 ** 5 6 ** 2	Orthogonal Array
36	2 ** 1 3 ** 8 6 ** 2	Orthogonal Array

Create Candidate Design

Algorithm Search History

```
                            Current           Best
Design     Row,Col    D-Efficiency   D-Efficiency   Notes
----------------------------------------------------------
     1       Start        100.0000       100.0000   Tab
     1         End        100.0000
```

Create Candidate Design

```
     The OPTEX Procedure
   Class Level Information
    Class   Levels   Values
    x1           2   1 2
    x2           3   1 2 3
    x3           3   1 2 3
    x4           3   1 2 3
    x5           3   1 2 3
```

Create Candidate Design

Design Number	D-Efficiency	A-Efficiency	G-Efficiency	Average Prediction Standard Error
1	100.0000	100.0000	100.0000	0.7454

Add Alternatives

Obs	f1	f2	x1	x2	x3	x4	x5
1	1	1	1	1	1	1	1
2	1	1	1	1	2	1	3
3	1	1	1	1	3	2	3
4	1	1	1	2	1	3	1
5	1	1	1	2	2	2	2
6	1	1	1	2	3	2	1
7	1	1	1	3	1	3	2
8	1	1	1	3	2	1	2
9	1	1	1	3	3	3	3
10	1	1	2	1	1	2	2
11	1	1	2	1	2	3	1
12	1	1	2	1	3	3	2
13	1	1	2	2	1	1	3
14	1	1	2	2	2	3	3
15	1	1	2	2	3	1	2
16	1	1	2	3	1	2	3
17	1	1	2	3	2	2	1
18	1	1	2	3	3	1	1

Find Efficient Choice Design

n	Name	Beta	Label
1	x11	0	x1 1
2	x21	0	x2 1
3	x22	0	x2 2
4	x31	0	x3 1
5	x32	0	x3 2
6	x41	0	x4 1
7	x42	0	x4 2
8	x51	0	x5 1
9	x52	0	x5 2

Find Efficient Choice Design

```
Design   Iteration  D-Efficiency        D-Error
-----------------------------------------------
     1         0          1.71707 *     0.58239
               1          4.64404 *     0.21533
               2          4.95686 *     0.20174
               3          5.22834 *     0.19127
               4          5.22834       0.19127


Design   Iteration  D-Efficiency        D-Error
-----------------------------------------------
     2         0                0             .
               1          4.76719       0.20977
               2          5.05601       0.19778
               3          5.05601       0.19778


Design   Iteration  D-Efficiency        D-Error
-----------------------------------------------
     3         0                0             .
               1          4.23313       0.23623
               2          4.89971       0.20409
               3          5.04728       0.19813
```

	4	5.04728	0.19813

Design	Iteration	D-Efficiency	D-Error
4	0	0	.
	1	4.75645	0.21024
	2	5.27411 *	0.18961
	3	5.30387 *	0.18854
	4	5.30387	0.18854

Design	Iteration	D-Efficiency	D-Error
5	0	1.71707	0.58239
	1	4.58406	0.21815
	2	4.81968	0.20748
	3	4.81968	0.20748

Find Efficient Choice Design

Design	Iteration	D-Efficiency	D-Error
6	0	0	.
	1	5.05601	0.19778
	2	5.10735	0.19580
	3	5.10735	0.19580

Design	Iteration	D-Efficiency	D-Error
7	0	0	.
	1	4.35644	0.22955
	2	4.97541	0.20099
	3	5.27411	0.18961
	4	5.27411	0.18961

Design	Iteration	D-Efficiency	D-Error
8	0	0	.
	1	4.66729	0.21426
	2	5.14880	0.19422
	3	5.22834	0.19127
	4	5.22834	0.19127

Design	Iteration	D-Efficiency	D-Error
9	0	0	.
	1	4.73471	0.21121
	2	5.08191	0.19678
	3	5.11574	0.19548
	4	5.27411	0.18961
	5	5.27411	0.18961

Design	Iteration	D-Efficiency	D-Error
10	0	1.71707	0.58239
	1	4.80934	0.20793
	2	5.11574	0.19548
	3	5.24376	0.19070
	4	5.30387	0.18854
	5	5.30387	0.18854

Find Efficient Choice Design

Design	Iteration	D-Efficiency	D-Error
11	0	0	.
	1	4.45513	0.22446
	2	4.45513	0.22446

Design	Iteration	D-Efficiency	D-Error
12	0	2.19187	0.45623
	1	5.02965	0.19882
	2	5.30387 *	0.18854
	3	5.30387	0.18854

Design	Iteration	D-Efficiency	D-Error
13	0	0	.
	1	5.09892	0.19612
	2	5.09892	0.19612

Design	Iteration	D-Efficiency	D-Error
14	0	2.00301	0.49925
	1	5.20492	0.19213
	2	5.20492	0.19213

Design	Iteration	D-Efficiency	D-Error
15	0	0	.
	1	5.01179	0.19953
	2	5.24376	0.19070
	3	5.24376	0.19070

Design	Iteration	D-Efficiency	D-Error
16	0	0	.
	1	5.30387	0.18854
	2	5.30387	0.18854

Find Efficient Choice Design

Design	Iteration	D-Efficiency	D-Error
17	0	2.33657	0.42798
	1	4.52120	0.22118
	2	5.08191	0.19678
	3	5.20492	0.19213
	4	5.27411	0.18961
	5	5.27411	0.18961

Design	Iteration	D-Efficiency	D-Error
18	0	0	.
	1	4.74562	0.21072
	2	5.18113	0.19301
	3	5.27411	0.18961
	4	5.27411	0.18961

Design	Iteration	D-Efficiency	D-Error
19	0	0	.
	1	4.41377	0.22656
	2	5.04728	0.19813
	3	5.30387	0.18854
	4	5.30387	0.18854

Design	Iteration	D-Efficiency	D-Error
20	0	0	.
	1	4.55928	0.21933
	2	4.97541	0.20099
	3	5.02965	0.19882
	4	5.02965	0.19882

Design	Iteration	D-Efficiency	D-Error
21	0	0	.
	1	4.86027	0.20575
	2	4.86027	0.20575

Find Efficient Choice Design

Design	Iteration	D-Efficiency	D-Error
22	0	0	.
	1	4.91902	0.20329
	2	4.91902	0.20329

Design	Iteration	D-Efficiency	D-Error
23	0	0	.
	1	4.62037	0.21643
	2	5.27411	0.18961
	3	5.27411	0.18961

Design	Iteration	D-Efficiency	D-Error
24	0	2.00301	0.49925
	1	4.99372	0.20025
	2	4.99372	0.20025

Design	Iteration	D-Efficiency	D-Error
25	0	2.19187	0.45623
	1	4.49518	0.22246
	2	5.17311	0.19331
	3	5.19704	0.19242

Design	Iteration	D-Efficiency	D-Error
26	0	0	.
	1	4.38543	0.22803
	2	4.99372	0.20025
	3	5.27411	0.18961
	4	5.27411	0.18961

Design	Iteration	D-Efficiency	D-Error
27	0	0	.
	1	5.09892	0.19612
	2	5.30387	0.18854
	3	5.30387	0.18854

Find Efficient Choice Design

Design	Iteration	D-Efficiency	D-Error
28	0	1.71707	0.58239
	1	4.52120	0.22118
	2	5.09044	0.19645
	3	5.27411	0.18961
	4	5.27411	0.18961

Design	Iteration	D-Efficiency	D-Error
29	0	0	.
	1	5.27411	0.18961
	2	5.30387	0.18854
	3	5.30387	0.18854

Design	Iteration	D-Efficiency	D-Error
30	0	2.00301	0.49925
	1	4.81968	0.20748
	2	5.09892	0.19612
	3	5.11574	0.19548

Design	Iteration	D-Efficiency	D-Error

31	0	0	.
	1	5.30387	0.18854
	2	5.30387	0.18854

Design	Iteration	D-Efficiency	D-Error
32	0	0	.
	1	5.04728	0.19813
	2	5.27411	0.18961
	3	5.27411	0.18961

Design	Iteration	D-Efficiency	D-Error
33	0	2.00301	0.49925
	1	5.11574	0.19548
	2	5.11574	0.19548

Find Efficient Choice Design

Design	Iteration	D-Efficiency	D-Error
34	0	0	.
	1	5.21277	0.19184
	2	5.24376	0.19070
	3	5.24376	0.19070

Design	Iteration	D-Efficiency	D-Error
35	0	0	.
	1	4.87023	0.20533
	2	4.96616	0.20136
	3	5.11574	0.19548
	4	5.11574	0.19548

Design	Iteration	D-Efficiency	D-Error
36	0	1.71707	0.58239
	1	4.62037	0.21643
	2	4.89971	0.20409
	3	5.27411	0.18961
	4	5.27411	0.18961

Design	Iteration	D-Efficiency	D-Error
37	0	2.64599	0.37793
	1	5.02965	0.19882
	2	5.02965	0.19882

Design	Iteration	D-Efficiency	D-Error
38	0	0	.
	1	5.18113	0.19301
	2	5.27411	0.18961
	3	5.27411	0.18961

Find Efficient Choice Design

Design	Iteration	D-Efficiency	D-Error
39	0	2.00301	0.49925
	1	5.01179	0.19953
	2	5.15695	0.19391
	3	5.15695	0.19391

Design	Iteration	D-Efficiency	D-Error
40	0	1.71707	0.58239
	1	4.77785	0.20930
	2	5.30387	0.18854
	3	5.30387	0.18854

Design	Iteration	D-Efficiency	D-Error
41	0	2.55688	0.39110
	1	4.55928	0.21933
	2	5.27411	0.18961
	3	5.30387	0.18854
	4	5.30387	0.18854

Design	Iteration	D-Efficiency	D-Error
42	0	0	.
	1	4.44149	0.22515
	2	5.17311	0.19331
	3	5.17311	0.19331

Design	Iteration	D-Efficiency	D-Error
43	0	0	.
	1	4.97541	0.20099
	2	5.27411	0.18961
	3	5.27411	0.18961

Find Efficient Choice Design

Design	Iteration	D-Efficiency	D-Error
44	0	0	.
	1	5.18113	0.19301
	2	5.27411	0.18961
	3	5.27411	0.18961

Design	Iteration	D-Efficiency	D-Error
45	0	0	.
	1	4.92857	0.20290
	2	5.22058	0.19155
	3	5.22058	0.19155

Design	Iteration	D-Efficiency	D-Error
46	0	0	.
	1	4.82994	0.20704
	2	5.06470	0.19745
	3	5.18910	0.19271
	4	5.18910	0.19271

Design	Iteration	D-Efficiency	D-Error
47	0	2.00301	0.49925
	1	4.94749	0.20212
	2	5.30387	0.18854
	3	5.30387	0.18854

Design	Iteration	D-Efficiency	D-Error
48	0	2.00301	0.49925
	1	4.57173	0.21874
	2	5.08191	0.19678
	3	5.18113	0.19301
	4	5.27411	0.18961
	5	5.27411	0.18961

Find Efficient Choice Design

Design	Iteration	D-Efficiency	D-Error
49	0	0	.
	1	4.87023	0.20533

	2	5.19704	0.19242
	3	5.22834	0.19127
	4	5.22834	0.19127

Design	Iteration	D-Efficiency	D-Error
50	0	0	.
	1	5.30387	0.18854
	2	5.30387	0.18854

Design	Iteration	D-Efficiency	D-Error
51	0	1.71707	0.58239
	1	4.58406	0.21815
	2	5.02965	0.19882
	3	5.02965	0.19882

Design	Iteration	D-Efficiency	D-Error
52	0	2.33657	0.42798
	1	4.71261	0.21220
	2	4.77785	0.20930
	3	4.97541	0.20099
	4	4.97541	0.20099

Design	Iteration	D-Efficiency	D-Error
53	0	0	.
	1	5.05601	0.19778
	2	5.05601	0.19778

Design	Iteration	D-Efficiency	D-Error
54	0	0	.
	1	4.95686	0.20174
	2	5.27411	0.18961
	3	5.27411	0.18961

Find Efficient Choice Design

Design	Iteration	D-Efficiency	D-Error
55	0	0	.
	1	4.97541	0.20099
	2	5.30387	0.18854
	3	5.30387	0.18854

Design	Iteration	D-Efficiency	D-Error
56	0	0	.
	1	4.73471	0.21121
	2	5.02965	0.19882
	3	5.02965	0.19882

Design	Iteration	D-Efficiency	D-Error
57	0	2.45536	0.40727
	1	4.42771	0.22585
	2	4.89971	0.20409
	3	4.97541	0.20099
	4	5.04728	0.19813
	5	5.04728	0.19813

Design	Iteration	D-Efficiency	D-Error
58	0	0	.
	1	5.14880	0.19422
	2	5.27411	0.18961
	3	5.27411	0.18961

Design	Iteration	D-Efficiency	D-Error

```
      59        0                0            .
                1          5.30387      0.18854
                2          5.30387      0.18854
```

Find Efficient Choice Design

```
  Design   Iteration  D-Efficiency       D-Error
  ----------------------------------------------
      60        0                0            .
                1          4.84012      0.20661
                2          5.01179      0.19953
                3          5.24376      0.19070
                4          5.24376      0.19070
```

Find Efficient Choice Design

```
        Final Results
  Design                   12
  Choice Sets               9
  Alternatives              2
  Parameters                9
  Maximum Parameters        9
  D-Efficiency         5.3039
  Relative D-Eff      58.9319
  D-Error              0.1885
  1 / Choice Sets      0.1111
```

Find Efficient Choice Design

n	Variable Name	Label	Variance	DF	Standard Error
1	x11	x1 1	0.48000	1	0.69282
2	x21	x2 1	0.19979	1	0.44698
3	x22	x2 2	0.32993	1	0.57440
4	x31	x3 1	0.18313	1	0.42793
5	x32	x3 2	0.18826	1	0.43389
6	x41	x4 1	0.17313	1	0.41608
7	x42	x4 2	0.16493	1	0.40612
8	x51	x5 1	0.16479	1	0.40595
9	x52	x5 2	0.16493	1	0.40612
				9	

Variance-Covariance Matrix

__label	x11	x21	x22	x31	x32	x41	x42	x51	x52
x1 1	0.48	-0.01	0.16	0.07	0.11	0.02	-0.02	-0.06	-0.07
x2 1	-0.01	0.20	0.07	0.05	-0.00	0.02	-0.04	-0.01	0.00
x2 2	0.16	0.07	0.33	0.07	0.09	0.07	-0.03	-0.02	-0.01
x3 1	0.07	0.05	0.07	0.18	0.03	0.02	-0.03	-0.05	-0.01
x3 2	0.11	-0.00	0.09	0.03	0.19	0.03	-0.03	-0.01	-0.01
x4 1	0.02	0.02	0.07	0.02	0.03	0.17	-0.01	0.01	0.03
x4 2	-0.02	-0.04	-0.03	-0.03	-0.03	-0.01	0.16	0.01	0.00
x5 1	-0.06	-0.01	-0.02	-0.05	-0.01	0.01	0.01	0.16	0.01
x5 2	-0.07	0.00	-0.01	-0.01	-0.01	0.03	0.00	0.01	0.16

Choice sets

Obs	Design	Efficiency	Index	Set	Prob	n	f1	f2	x1	x2	x3	x4	x5
1	12	5.30387	15	1	0.5	199	1	1	2	2	3	1	2
2	12	5.30387	11	1	0.5	200	1	1	2	1	2	3	1
3	12	5.30387	9	2	0.5	201	1	1	1	3	3	3	3

Obs	Design	Efficiency	Index	Set	Prob	n	f1	f2	x1	x2	x3	x4	x5
4	12	5.30387	17	2	0.5	202	1	1	2	3	2	2	1
5	12	5.30387	16	3	0.5	203	1	1	2	3	1	2	3
6	12	5.30387	12	3	0.5	204	1	1	2	1	3	3	2
7	12	5.30387	10	4	0.5	205	1	1	2	1	1	2	2
8	12	5.30387	18	4	0.5	206	1	1	2	3	3	1	1
9	12	5.30387	8	5	0.5	207	1	1	1	3	2	1	2
10	12	5.30387	6	5	0.5	208	1	1	1	2	3	2	1
11	12	5.30387	1	6	0.5	209	1	1	1	1	1	1	1
12	12	5.30387	14	6	0.5	210	1	1	2	2	2	3	3
13	12	5.30387	13	7	0.5	211	1	1	2	2	1	1	3
14	12	5.30387	5	7	0.5	212	1	1	1	2	2	2	2
15	12	5.30387	2	8	0.5	213	1	1	1	1	2	1	3
16	12	5.30387	7	8	0.5	214	1	1	1	3	1	3	2
17	12	5.30387	4	9	0.5	215	1	1	1	2	1	3	1
18	12	5.30387	3	9	0.5	216	1	1	1	1	3	2	3

Choice sets by code

Set	x1	x2	x3	x4	x5
1	2	2	3	1	2
	2	1	2	3	1

Set	x1	x2	x3	x4	x5
2	1	3	3	3	3
	2	3	2	2	1

Set	x1	x2	x3	x4	x5
3	2	3	1	2	3
	2	1	3	3	2

Set	x1	x2	x3	x4	x5
4	2	1	1	2	2
	2	3	3	1	1

Set	x1	x2	x3	x4	x5
5	1	3	2	1	2
	1	2	3	2	1

Set	x1	x2	x3	x4	x5
6	1	1	1	1	1
	2	2	2	3	3

Set	x1	x2	x3	x4	x5
7	2	2	1	1	3
	1	2	2	2	2

Set	x1	x2	x3	x4	x5
8	1	1	2	1	3
	1	3	1	3	2

Set	x1	x2	x3	x4	x5
9	1	2	1	3	1
	1	1	3	2	3

Choice sets including Statistics

Set	Design	Efficiency	Index	Prob	n	f1	f2	x1	x2	x3	x4	x5
1	12	5.30387	15	0.5	199	1	1	2	2	3	1	2
	12	5.30387	11	0.5	200	1	1	2	1	2	3	1

Set	Design	Efficiency	Index	Prob	n	f1	f2	x1	x2	x3	x4	x5
2	12	5.30387	9	0.5	201	1	1	1	3	3	3	3
	12	5.30387	17	0.5	202	1	1	2	3	2	2	1

Set	Design	Efficiency	Index	Prob	n	f1	f2	x1	x2	x3	x4	x5
3	12	5.30387	16	0.5	203	1	1	2	3	1	2	3
	12	5.30387	12	0.5	204	1	1	2	1	3	3	2

Set	Design	Efficiency	Index	Prob	n	f1	f2	x1	x2	x3	x4	x5
4	12	5.30387	10	0.5	205	1	1	2	1	1	2	2
	12	5.30387	18	0.5	206	1	1	2	3	3	1	1

Set	Design	Efficiency	Index	Prob	n	f1	f2	x1	x2	x3	x4	x5
5	12	5.30387	8	0.5	207	1	1	1	3	2	1	2
	12	5.30387	6	0.5	208	1	1	1	2	3	2	1

Set	Design	Efficiency	Index	Prob	n	f1	f2	x1	x2	x3	x4	x5
6	12	5.30387	1	0.5	209	1	1	1	1	1	1	1
	12	5.30387	14	0.5	210	1	1	2	2	2	3	3

Set	Design	Efficiency	Index	Prob	n	f1	f2	x1	x2	x3	x4	x5
7	12	5.30387	13	0.5	211	1	1	2	2	1	1	3
	12	5.30387	5	0.5	212	1	1	1	2	2	2	2

Set	Design	Efficiency	Index	Prob	n	f1	f2	x1	x2	x3	x4	x5
8	12	5.30387	2	0.5	213	1	1	1	1	2	1	3
	12	5.30387	7	0.5	214	1	1	1	3	1	3	2

Set	Design	Efficiency	Index	Prob	n	f1	f2	x1	x2	x3	x4	x5
9	12	5.30387	4	0.5	215	1	1	1	2	1	3	1
	12	5.30387	3	0.5	216	1	1	1	1	3	2	3

Choice sets including Attributes and Levels description

Set	Control	Information sharing	Communication	Knowledge acquisition	Resource effiency
1	Automated decision support	Basic information	Advanced communication	Knowledge acquisitions – No	+15% efficiency
	Automated decision support	Not sharing information	Basic communication	Knowledge acquisitions – Individual system	+0% efficiency

Set	Control	Information sharing	Communication	Knowledge acquisition	Resource effiency
2	Decision support	Basic information + Personal preference	Advanced communication	Knowledge acquisitions – Individual system	+35% efficiency
	Automated decision support	Basic information + Personal preference	Basic communication	Knowledge acquisitions – Whole system	+0% efficiency

Set	Control	Information sharing	Communication	Knowledge acquisition	Resource effiency
3	Automated decision support	Basic information + Personal preference	No dashboard	Knowledge acquisitions – Whole system	+35% efficiency
	Automated decision support	Not sharing information	Advanced communication	Knowledge acquisitions – Individual system	+15% efficiency

Set	Control	Information sharing	Communication	Knowledge acquisition	Resource effiency
4	Automated decision support	Not sharing information	No dashboard	Knowledge acquisitions – Whole system	+15% efficiency
	Automated decision support	Basic information + Personal preference	Advanced communication	Knowledge acquisitions – No	+0% efficiency

Set	Control	Information sharing	Communication	Knowledge acquisition	Resource effiency

Set	Control	Information sharing	Communication	Knowledge acquisition	Resource effiency
5	Decision support	Basic information + Personal preference	Basic communication	Knowledge acquisitions – No	+15% efficiency
	Decision support	Basic information	Advanced communication	Knowledge acquisitions – Whole system	+0% efficiency

Set	Control	Information sharing	Communication	Knowledge acquisition	Resource effiency
6	Decision support	Not sharing information	No dashboard	Knowledge acquisitions – No	+0% efficiency
	Automated decision support	Basic information	Basic communication	Knowledge acquisitions – Individual system	+35% efficiency

Set	Control	Information sharing	Communication	Knowledge acquisition	Resource effiency
7	Automated decision support	Basic information	No dashboard	Knowledge acquisitions – No	+35% efficiency
	Decision support	Basic information	Basic communication	Knowledge acquisitions – Whole system	+15% efficiency

Set	Control	Information sharing	Communication	Knowledge acquisition	Resource effiency
8	Decision support	Not sharing information	Basic communication	Knowledge acquisitions – No	+35% efficiency
	Decision support	Basic information + Personal preference	No dashboard	Knowledge acquisitions – Individual system	+15% efficiency

Set	Control	Information sharing	Communication	Knowledge acquisition	Resource effiency
9	Decision support	Basic information	No dashboard	Knowledge acquisitions – Individual system	+0% efficiency
	Decision support	Not sharing information	Advanced communication	Knowledge acquisitions – Whole system	+35% efficiency

APPENDIX IV: LimeSurvey

User expectation and preferences in a smart office
Welcome
To start, I would like to **thank you** for participating in this study. My name is Sara Guendouz and this survey is part of my master's graduation in the study Construction Management & Engineering (CME) at Eindhoven University of Technology (TU/e). The subject of my research is user expectations and preferences in smart office environments. The goal of this experiment is to get insight into the relationship between smart features and user perspectives.

This questionnaire consists of three parts:
1. Respondent information
2. Experience
3. Choice Experiment (part I and part II)

The questionnaire will take circa **15 minutes** of your time.
Your answers will be saved **anonymously** and the information will not be made public.

If you are interested in the results of my research or have any questions, please contact me at S.guendouz@student.tue.nl

Once again, thank you for your willingness to participate in my research!

Sincerely,
Sara Guendouz
There are 81 questions in this survey.

Consent to save answers
"I declare that I am participating voluntarily in this research and that I am aware that at any point in time I have the right to quit the survey or withdraw my data without the need of any motivation. The purpose and aim of the study are made clear to me. My retrieved data will be aggregated to group level, evaluated and published for scientific purposes, such as research papers and a graduation thesis. When the research process is completed, my individual records will be deleted by the research team. All data on group level will be kept on secure and encrypted university storage. No third party will have access to my data and only the principal researcher and his team have the right to look into the data. If the data will be made public in any way, all personal information will be completely anonymized. For any additional information I can contact the principal researcher Sara Guendouz (s.guendouz@student.tue.nl) or her supervisors dr.ir. Dujuan Yang (d.yang@tue.nl), and Alex Donkers (a.j.a.donkers@tue.nl) of Eindhoven University of Technology."
 * I agree to these conditions to participate in the study

Please choose **only one** of the following:
- Yes
- No

General introduction- Have you ever heard of Smart Offices?
A smart office is a workplace equipped with technologies to help employees work more productively and efficiently. These technologies collect information about the office environment and the user. With the collected information, smart offices use analytics to gain insight and provide effective and efficient workplaces that are more responsive to work dynamics and user needs.

SEVERAL BENEFITS OF SMART OFFICE

- Productivity boost
- Improves communication
- Provide connectivity
- Enhanced comfort and health

2. Respondent information
2.1 Demographic related questions

Question 1 of 15: What is your gender?
- o Male
- o Female
- o Other

Question 2 of 15: What is your age? *
- o 15–24
- o 25–34
- o 35–44
- o 45–54
- o 55+

Question 3 of 15: What is your highest finished education? *
- o Primary education
- o Secondary education (VMBO, HAVO, VWO)
- o Vocational education (MBO)
- o Applied university (HBO)
- o Academic education - University Bachelor's (Undergrad)
- o Academic education - University Masters (Postgrad)
- o Other

If you are unfamiliar with the Dutch Education System, please fill in 'Other' including a description.

2. Respondent information

2.2 Personality related statements

Question 6 of 15: How would you describe yourself, using the statements below describing your personality traits?

Please fill into what extent you agree with this statement.

Please choose the appropriate response for each item:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I like to be around other people	○	○	○	○	○
I am helpful, not selfish, with others	○	○	○	○	○
I make plans and stick to them	○	○	○	○	○
I get nervous easily	○	○	○	○	○
I am curious about many different things	○	○	○	○	○
I am energetic	○	○	○	○	○
I like to cooperate with others	○	○	○	○	○
I am a hard worker	○	○	○	○	○
I can be tense; not always easy going	○	○	○	○	○
I tend to overthink	○	○	○	○	○
I am talkative	○	○	○	○	○
I am considerate with others	○	○	○	○	○
I tend to do things quickly	○	○	○	○	○
I tend to worry	○	○	○	○	○
I am creative and inventive	○	○	○	○	○

3. Experience

Question 7 of 15: How familiar are you with smart indoor location tracking of colleagues? *
- o Never heard about it before and never used it
- o Heard about it but never used it
- o Heard about it and used it

Smart indoor location tracking of colleagues focuses on finding colleagues in an office.

Question 8 of 15: How familiar are you with smart parking? *
- o Never heard about it before and never used it
- o Heard about it but never used it
- o Heard about it and used it

Smart parking helps users to find suitable parking spots.

Question 9 of 15: How familiar are you with smart workspace booking?
- o Never heard about it before and never used it
- o Heard about it but never used it
- o Heard about it and used it

Smart booking helps users to find and reserve suitable (individual) workspaces.

Question 10 of 15: How familiar are you with smart meeting room booking? *
- o Never heard about it before and never used it
- o Heard about it but never used it
- o Heard about it and used it

Smart booking helps users to find and reserve suitable meeting rooms.

Question 11 of 15: How familiar are you with smart indoor climate control for temperature?
- o Never heard about it before and never used it
- o Heard about it but never used it
- o Heard about it and used it

Smart indoor climate control - temperature helps users to 'take control' and adapt to their preferred environment. (e.g. this can be controlled by an app)

Question 12 of 15: How familiar are you with smart indoor climate control for air quality?
- o Never heard about it before and never used it
- o Heard about it but never used it
- o Heard about it and used it

Smart indoor climate control helps users to 'take control' and adapt to their preferred environment. (e.g. this can be controlled by an app - possibility to refresh the air in a room)

Question 13 of 15: How familiar are you with smart lighting control ? *****
- o Never heard about it before and never used it
- o Heard about it but never used it
- o Heard about it and used it

Smart lighting control helps users to 'take control' and adapt to their preferred environment. (e.g. this can be controlled by an app - possibility to change light intensity and color temperature)

4. Attitude related statements

Question 14 of 15: What are your feelings about smart features?

Please fill in to what extent you agree with this statement.
Please choose the appropriate response for each item:

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
Smart features (will) make me more productive at work.	○	○	○	○	○
Smart features (will) contribute to a better quality of my work.	○	○	○	○	○
Smart features (will) make me more efficient in my occupation	○	○	○	○	○

Examples of smart features: smart indoor location tracking of colleagues, smart parking, smart booking, smart indoor climate control and smart lighting control

5. Choice experiment – Explanation

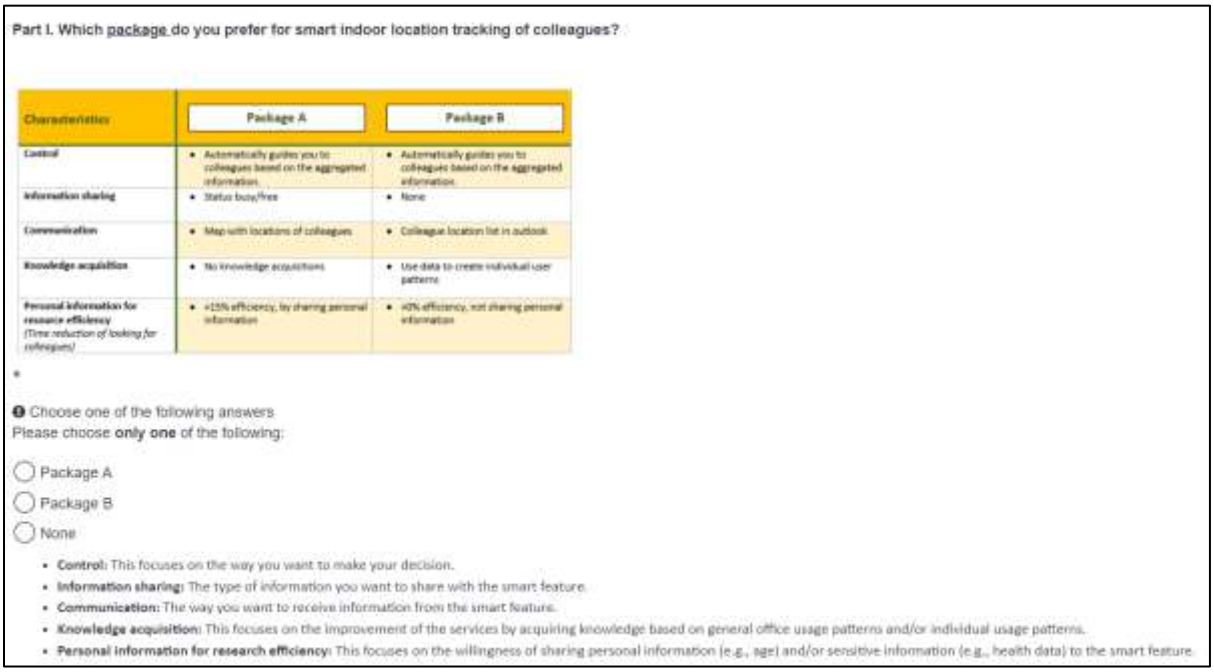
Question 15 of 15: Choice experiment - Which package do you prefer?

In this last part of the survey, I would like you to compare **two packages of a smart feature**. Take a look at the characteristics and decide which package suits you best. If the packages are equal to you, or if you don't prefer both choices, please select the 'None' option.

The choice experiment consists of **PART I** and **PART II.** In each part, 9 packages of a smart feature are presented.

This means you will have the same table shown 9 times, but with different combinations - Please read carefully!

Example of overview in Lime survey:



Part I. Which package do you prefer for smart indoor location tracking of colleagues?

Characteristics	Package A	Package B
Control	• Automatically guides you to colleagues based on the aggregated information	• Automatically guides you to colleagues based on the aggregated information
Information sharing	• Status busy/free	• None
Communication	• Map with locations of colleagues	• Colleague location list in outlook
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Time reduction of looking for colleagues)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

*

Choose one of the following answers
Please choose **only one** of the following:

- Package A
- Package B
- None

- **Control:** This focuses on the way you want to make your decision.
- **Information sharing:** The type of information you want to share with the smart feature.
- **Communication:** The way you want to receive information from the smart feature.
- **Knowledge acquisition:** This focuses on the improvement of the services by acquiring knowledge based on general office usage patterns and/or individual usage patterns.
- **Personal information for research efficiency:** This focuses on the willingness of sharing personal information (e.g., age) and/or sensitive information (e.g., health data) to the smart feature.

Choice experiment 1: **Smart indoor location tracking of colleagues**

Choice set 1 **Characteristics**	**Package A**	**Package B**
Control	• Automatically guides you to colleagues based on the aggregated information.	• Automatically guides you to colleagues based on the aggregated information.
Information sharing	• Status busy/free	• None
Communication	• Map with locations of colleagues	• Colleague location list in outlook
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Time reduction of looking for colleagues)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 2 **Characteristics**	**Package A**	**Package B**
Control	• You can find the location of colleagues based on the aggregated information.	• Automatically guides you to colleagues based on the aggregated information.
Information sharing	• Agenda + live location + personal preference	• Agenda + live location + personal preference
Communication	• Map with locations of colleagues	• Colleague location list in outlook
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Time reduction of looking for colleagues)*	• +35% efficiency, by sharing sensitive personal information	• +0% efficiency, not sharing personal information

Choice set 3 **Characteristics**	**Package A**	**Package B**
Control	• Automatically guides you to colleagues based on the aggregated information.	• Automatically guides you to colleagues based on the aggregated information.
Information sharing	• Agenda + live location + personal preference	• None
Communication	• No dashboard	• Map with locations of colleagues
Knowledge acquisition	• Use aggregated data to create office usage patterns	• Use data to create individual user patterns
Personal information for resource efficiency *(Time reduction of looking for colleagues)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 4 **Characteristics**	**Package A**	**Package B**
Control	• Automatically guides you to colleagues based on the aggregated information.	• Automatically guides you to colleagues based on the aggregated information.
Information sharing	• None	• Agenda + live location + personal preference
Communication	• No dashboard	• Map with locations of colleagues
Knowledge acquisition	• Use aggregated data to create office usage patterns	• No knowledge acquisitions
Personal information for resource efficiency *(Time reduction of looking for colleagues)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 5 **Characteristics**	**Package A**	**Package B**
Control	• You can find the location of colleagues based on aggregated information.	• You can find the location of colleagues based on aggregated information.
Information sharing	• Agenda + live location + personal preference	• Status busy / free
Communication	• Colleague location list in outlook	• Map with locations of colleagues
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Time reduction of looking for colleagues)*	• +35% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 6 **Characteristics**	**Package A**	**Package B**
Control	• User can find the location of colleagues based on aggregated information.	• Automatically guides you to colleagues based on the aggregated information.
Information sharing	• None	• Status busy / free
Communication	• No dashboard	• Colleague location list in outlook
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Time reduction of looking for colleagues)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice set 7 **Characteristics**	**Package A**	**Package B**
Control	• Automatically guides you to colleagues based on the aggregated information.	• You can find the location of colleagues based on aggregated information.
Information sharing	• Status busy / free	• Status busy / free
Communication	• No dashboard	• Colleague location list in outlook
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Time reduction of looking for colleagues)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 8 **Characteristics**	**Package A**	**Package B**
Control	• User can find the location of colleagues based on aggregated information.	• User can find the location of colleagues based on aggregated information.
Information sharing	• None	• Agenda + live location + personal preference
Communication	• Colleagues location list in outlook	• No dashboard
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Time reduction of looking for colleagues)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 9

Characteristics	**Package A**	**Package B**
Control	• User can find the location of colleagues based on aggregated information.	• User can find the location of colleagues based on aggregated information.
Information sharing	• Status busy / free	• None
Communication	• No dashboard	• Map with locations of colleagues
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Time reduction of looking for colleagues)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice experiment 2: **Smart parking**

Choice set 1 **Characteristics**	**Package A**	**Package B**
Control	• Automatically guides based on aggregated information.	• Automatically guides based on aggregated information.
Information sharing	• Agenda + Vehicle type	• None
Communication	• Advanced information in a map	• Basic information in a list
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Time reduction of looking for parking spot)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 2 **Characteristics**	**Package A**	**Package B**
Control	• User can park based on aggregated information.	• Automatically guides based on aggregated information.
Information sharing	• Agenda + vehicle type + personal preference	• Agenda + vehicle type + personal preference
Communication	• Advanced information in a map	• Basic information in a list
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Time reduction of looking for parking spot)*	• +35% efficiency, by sharing sensitive personal information	• +0% efficiency, not sharing personal information

Choice set 3 **Characteristics**	**Package A**	**Package B**
Control	• Automatically guides based on aggregated information.	• Automatically guides based on aggregated information.
Information sharing	• Agenda + Vehicle type + personal preference	• None
Communication	• No dashboard	• Advanced information in a map
Knowledge acquisition	• Use aggregated data to create office usage patterns	• Use data to create individual user patterns
Personal information for resource efficiency *(Time reduction of looking for parking spot)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 4 **Characteristics**	**Package A**	**Package B**
Control	• Automatically guides based on aggregated information.	• Automatically guides based on aggregated information.
Information sharing	• None	• Agenda + vehicle type + personal preference
Communication	• No dashboard	• Advanced information in a map
Knowledge acquisition	• Use aggregated data to create office usage patterns	• No knowledge acquisitions
Personal information for resource efficiency *(Time reduction of looking for parking spot)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 5 **Characteristics**	**Package A**	**Package B**
Control	• User can park based on aggregated information.	• User can park based on aggregated information.
Information sharing	• Agenda + vehicle type + personal preference	• Agenda + vehicle type
Communication	• Basic information in a list	• Advanced information in a map
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Time reduction of looking for parking spot)*	• +35% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 6 **Characteristics**	**Package A**	**Package B**
Control	• User can park based on aggregated information.	• Automatically guides based on aggregated information.
Information sharing	• None	• Agenda + vehicle type
Communication	• No dashboard	• Basic information in a list
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Time reduction of looking for parking spot)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice set 7 **Characteristics**	**Package A**	**Package B**
Control	• Automatically guides based on aggregated information.	• User can park based on aggregated information.
Information sharing	• Agenda + vehicle type	• Agenda + vehicle type
Communication	• No dashboard	• Basic information in a list
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Time reduction of looking for parking spot)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 8 **Characteristics**	**Package A**	**Package B**
Control	• User can park based on aggregated information.	• User can park based on aggregated information.
Information sharing	• None	• Agenda + vehicle type + personal preference
Communication	• Basic information in a list	• No dashboard
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Time reduction of looking for parking spot)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 9 **Characteristics**	**Package A**	**Package B**
Control	• User can park based on aggregated information.	• User can park based on aggregated information.
Information sharing	• Agenda + Vehicle type	• None
Communication	• No dashboard	• Advanced information in a map
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Time reduction of looking for parking spot)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice experiment 3: **Smart workspace booking**

Choice set 1

Characteristics	Package A	Package B
Control	• Automatically booked based on aggregated information.	• Automatically booked based on aggregated information.
Information sharing	• Agenda	• None
Communication	• Advanced information in a map	• Basic information in a list
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Suitable workspace)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 2

Characteristics	Package A	Package B
Control	• User can book based on aggregated information.	• Automatically booked based on aggregated information.
Information sharing	• Agenda + personal preference	• Agenda + personal preference
Communication	• Advanced information in a map	• Basic information in a list
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Suitable workspace)*	• +35% efficiency, by sharing sensitive personal information	• +0% efficiency, not sharing personal information

Choice set 3 **Characteristics**	**Package A**	**Package B**
Control	• Automatically booked based on aggregated information.	• Automatically booked based on aggregated information.
Information sharing	• Agenda + personal preference	• None
Communication	• No dashboard	• Advanced information in a map
Knowledge acquisition	• Use aggregated data to create office usage patterns	• Use data to create individual user patterns
Personal information for resource efficiency *(Suitable workspace)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 4 **Characteristics**	**Package A**	**Package B**
Control	• Automatically booked based on aggregated information.	• Automatically booked based on aggregated information.
Information sharing	• None	• Agenda + personal preference
Communication	• No dashboard	Advanced information in a map
Knowledge acquisition	• Use aggregated data to create office usage patterns	• No knowledge acquisitions
Personal information for resource efficiency *(Suitable workspace)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 5 **Characteristics**	**Package A**	**Package B**
Control	• User can book based on aggregated information.	• User can book based on aggregated information.
Information sharing	• Agenda + personal preference	• Agenda
Communication	• Basic information in a list	• Advanced information in a map
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Suitable workspace)*	• +35% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 6 **Characteristics**	**Package A**	**Package B**
Control	• User can book based on aggregated information.	• Automatically booked based on aggregated information.
Information sharing	• None	• Agenda
Communication	• No dashboard	• Basic information in a list
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Suitable workspace)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice set 7 **Characteristics**	**Package A**	**Package B**
Control	• Automatically booked based on aggregated information.	• User can book based on aggregated information.
Information sharing	• Agenda	• Agenda
Communication	• No dashboard	• Basic information in a list
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Suitable workspace)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 8 **Characteristics**	**Package A**	**Package B**
Control	• User can book based on aggregated information.	• User can book based on aggregated information.
Information sharing	• None	• Agenda + personal preference
Communication	• Basic information in a list	• No dashboard
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Suitable workspace)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 9 **Characteristics**	**Package A**	**Package B**
Control	• User can book based on aggregated information.	• User can book based on aggregated information.
Information sharing	• Agenda	• None
Communication	• No dashboard	• Advanced information in a map
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Suitable workspace)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice experiment 4: **Smart meeting room booking**

Choice set 1 **Characteristics**	**Package A**	**Package B**
Control	• Automatically booked based on aggregated information.	• Automatically booked based on aggregated information.
Information sharing	• Agenda	• None
Communication	• Advanced information in a map	• Basic information in a list
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Suitable meeting room)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 2 **Characteristics**	**Package A**	**Package B**
Control	• User can book based on aggregated information.	• Automatically booked based on aggregated information.
Information sharing	• Agenda + personal preference	• Agenda + personal preference
Communication	• Advanced information in a map	• Basic information in a list
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Suitable meeting room)*	• +35% efficiency, by sharing sensitive personal information	• +0% efficiency, not sharing personal information

Choice set 3 **Characteristics**	**Package A**	**Package B**
Control	• Automatically booked based on aggregated information.	• Automatically booked based on aggregated information.
Information sharing	• Agenda + personal preference	• None
Communication	• No dashboard	• Advanced information in a map
Knowledge acquisition	• Use aggregated data to create office usage patterns	• Use data to create individual user patterns
Personal information for resource efficiency *(Suitable meeting room)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 4 **Characteristics**	**Package A**	**Package B**
Control	• Automatically booked based on aggregated information.	• Automatically booked based on aggregated information.
Information sharing	• None	• Agenda + personal preference
Communication	• No dashboard	• Advanced information in a map
Knowledge acquisition	• Use aggregated data to create office usage patterns	• No knowledge acquisitions
Personal information for resource efficiency *(Suitable meeting room)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 5 **Characteristics**	**Package A**	**Package B**
Control	• User can book based on aggregated information.	• User can book based on aggregated information.
Information sharing	• Agenda + personal preference	• Agenda
Communication	• Basic information in a list	• Advanced information in a map
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Suitable meeting room)*	• +35% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 6 **Characteristics**	**Package A**	**Package B**
Control	• User can book based on aggregated information.	• Automatically booked based on aggregated information.
Information sharing	• None	• Agenda
Communication	• No dashboard	• Basic information in a list
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Suitable meeting room)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice set 7 **Characteristics**	**Package A**	**Package B**
Control	• Automatically booked based on aggregated information.	• User can book based on aggregated information.
Information sharing	• Agenda	• Agenda
Communication	• No dashboard	• Basic information in a list
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Suitable meeting room)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 8 **Characteristics**	**Package A**	**Package B**
Control	• User can book based on aggregated information.	• User can book based on aggregated information.
Information sharing	• None	• Agenda + personal preference
Communication	• Basic information in a list	• No dashboard
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Suitable meeting room)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 9 **Characteristics**	**Package A**	**Package B**
Control	• User can book based on aggregated information.	• User can book based on aggregated information.
Information sharing	• Agenda	• None
Communication	• No dashboard	• Advanced information in a map
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Suitable meeting room)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice experiment 5: **Smart indoor climate control - Temperature**

Choice set 1 **Characteristics**	**Package A**	**Package B**
Control	• Temperature is automatically controlled based on aggregated information.	• Temperature is automatically controlled based on aggregated information.
Information sharing	• Work activity	• None
Communication	• Dashboard with indoor temperature + warnings + tips	• Dashboard with indoor temperature
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Thermal comfort)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 2 **Characteristics**	**Package A**	**Package B**
Control	• User can control temperature based on aggregated information.	• Temperature is automatically controlled based on aggregated information.
Information sharing	• Work activity + personal preference	• Work activity + personal preference
Communication	• Dashboard with indoor temperature + warnings + tips	• Dashboard with indoor temperature
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Thermal comfort)*	• +35% efficiency, by sharing sensitive personal information	• +0% efficiency, not sharing personal information

Choice set 3 **Characteristics**	**Package A**	**Package B**
Control	• Temperature is automatically controlled based on aggregated information.	• Temperature is automatically controlled based on aggregated information.
Information sharing	• Work activity + personal preference	• None
Communication	• No dashboard	• Dashboard with indoor temperature + warnings + tips
Knowledge acquisition	• Use aggregated data to create office usage patterns	• Use data to create individual user patterns
Personal information for resource efficiency *(Thermal comfort)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 4 **Characteristics**	**Package A**	**Package B**
Control	• Temperature is automatically controlled based on aggregated information.	• Temperature is automatically controlled based on aggregated information.
Information sharing	• None	• Work activity + personal preference
Communication	• No dashboard	• Dashboard with indoor temperature + warnings + tips
Knowledge acquisition	• Use aggregated data to create office usage patterns	• No knowledge acquisitions
Personal information for resource efficiency *(Thermal comfort)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 5 **Characteristics**	**Package A**	**Package B**
Control	• User can control temperature based on aggregated information.	• User can control temperature based on aggregated information.
Information sharing	• Work activity + personal preference	• Work activity
Communication	• Dashboard with indoor temperature	• Dashboard with indoor temperature + warnings + tips
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Thermal comfort)*	• +35% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 6 **Characteristics**	**Package A**	**Package B**
Control	• User can control temperature based on aggregated information.	• Temperature is automatically controlled based on aggregated information.
Information sharing	• None	• Work activity
Communication	• No dashboard	• Dashboard with indoor temperature
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Thermal comfort)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice set 7 **Characteristics**	**Package A**	**Package B**
Control	• Temperature is automatically controlled based on aggregated information.	• User can control temperature based on aggregated information.
Information sharing	• Work activity	• Work activity
Communication	• No dashboard	• Dashboard with indoor temperature
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Thermal comfort)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 8 **Characteristics**	**Package A**	**Package B**
Control	• User can control temperature based on aggregated information.	• User can control temperature based on aggregated information.
Information sharing	• None	• Work activity + personal preference
Communication	• Dashboard with indoor temperature	• No dashboard
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Thermal comfort)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 9 **Characteristics**	**Package A**	**Package B**
Control	• User can control temperature based on aggregated information.	• User can control temperature based on aggregated information.
Information sharing	• Work activity	• None
Communication	• No dashboard	• Dashboard with indoor temperature + warnings + tips
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Thermal comfort)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice experiment 6: **Smart indoor climate control – Air quality**

Choice set 1 **Characteristics**	**Package A**	**Package B**
Control	• Air quality is automatically controlled based on aggregated information.	• Air quality is automatically controlled based on aggregated information.
Information sharing	• Work activity	• None
Communication	• Dashboard with indoor air quality + warnings + tips	• Dashboard with indoor air quality
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Air quality improvements)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 2 **Characteristics**	**Package A**	**Package B**
Control	• User can control Air quality based on aggregated information.	• Air quality is automatically controlled based on aggregated information.
Information sharing	• Work activity + personal preference	• Work activity + personal preference
Communication	• Dashboard with indoor Air quality + warnings + tips	• Dashboard with indoor Air quality
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Air quality improvements)*	• +35% efficiency, by sharing sensitive personal information	• +0% efficiency, not sharing personal information

Choice set 3 **Characteristics**	**Package A**	**Package B**
Control	• Air quality is automatically controlled based on aggregated information.	• Air quality is automatically controlled based on aggregated information.
Information sharing	• Work activity + personal preference	• None
Communication	• No dashboard	• Dashboard with indoor Air quality + warnings + tips
Knowledge acquisition	• Use aggregated data to create office usage patterns	• Use data to create individual user patterns
Personal information for resource efficiency *(Air quality improvements)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 4 **Characteristics**	**Package A**	**Package B**
Control	• Air quality is automatically controlled based on aggregated information.	• Air quality is automatically controlled based on aggregated information.
Information sharing	• None	• Work activity + personal preference
Communication	• No dashboard	• Dashboard with indoor Air quality + warnings + tips
Knowledge acquisition	• Use aggregated data to create office usage patterns	• No knowledge acquisitions
Personal information for resource efficiency *(Air quality improvements)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 5 **Characteristics**	**Package A**	**Package B**
Control	• User can control Air quality based on aggregated information.	• User can control Air quality based on aggregated information.
Information sharing	• Work activity + personal preference	• Work activity
Communication	• Dashboard with indoor Air quality	• Dashboard with indoor Air quality + warnings + tips
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Air quality improvements)*	• +35% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 6 **Characteristics**	**Package A**	**Package B**
Control	• User can control Air quality based on aggregated information.	• Air quality is automatically controlled based on aggregated information.
Information sharing	• None	• Work activity
Communication	• No dashboard	• Dashboard with indoor Air quality
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Air quality improvements)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice set 7 **Characteristics**	**Package A**	**Package B**
Control	• Air quality is automatically controlled based on aggregated information.	• User can control Air quality based on aggregated information.
Information sharing	• Work activity	• Work activity
Communication	• No dashboard	• Dashboard with indoor Air quality
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Air quality improvements)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 8 **Characteristics**	**Package A**	**Package B**
Control	• User can control Air quality based on aggregated information.	• User can control Air quality based on aggregated information.
Information sharing	• None	• Work activity + personal preference
Communication	• Dashboard with indoor Air quality	• No dashboard
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Air quality improvements)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 9 **Characteristics**	**Package A**	**Package B**
Control	• User can control Air quality based on aggregated information.	• User can control Air quality based on aggregated information.
Information sharing	• Work activity	• None
Communication	• No dashboard	• Dashboard with indoor Air quality + warnings + tips
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Air quality improvements)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice experiment 7: **Smart lighting control**

Choice set 1 **Characteristics**	**Package A**	**Package B**
Control	• Light is automatically controlled based on aggregated information.	• Light is automatically controlled based on aggregated information.
Information sharing	• Work activity	• None
Communication	• Dashboard with lighting control + warnings + tips	• Dashboard with lighting control
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Visual comfort)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 2 **Characteristics**	**Package A**	**Package B**
Control	• User can control light based on aggregated information.	• Light is automatically controlled based on aggregated information.
Information sharing	• Work activity + personal preference	• Work activity + personal preference
Communication	• Dashboard with lighting control + warnings + tips	• Dashboard with lighting control
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Visual comfort)*	• +35% efficiency, by sharing sensitive personal information	• +0% efficiency, not sharing personal information

Choice set 3 **Characteristics**	**Package A**	**Package B**
Control	• Light is automatically controlled based on aggregated information	• Light is automatically controlled based on aggregated information
Information sharing	• Work activity + personal preference	• None
Communication	• No dashboard	• Dashboard with lighting control + warnings + tips
Knowledge acquisition	• Use aggregated data to create office usage patterns	• Use data to create individual user patterns
Personal information for resource efficiency *(Visual comfort)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 4 **Characteristics**	**Package A**	**Package B**
Control	• Light is automatically controlled based on aggregated information	• Light is automatically controlled based on aggregated information
Information sharing	• None	• Work activity + personal preference
Communication	• No dashboard	• Dashboard with lighting control + warnings + tips
Knowledge acquisition	• Use aggregated data to create office usage patterns	• No knowledge acquisitions
Personal information for resource efficiency *(Visual comfort)*	• +15% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 5 **Characteristics**	**Package A**	**Package B**
Control	• User can control light based on aggregated information.	• User can control light based on aggregated information.
Information sharing	• Work activity + personal preference	• Work activity
Communication	• Dashboard with lighting control	• Dashboard with lighting control + warnings + tips
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Visual comfort)*	• +35% efficiency, by sharing personal information	• +0% efficiency, not sharing personal information

Choice set 6 **Characteristics**	**Package A**	**Package B**
Control	• User can control light based on aggregated information.	• Light is automatically controlled based on aggregated information
Information sharing	• None	• Work activity
Communication	• No dashboard	• Dashboard with lighting control
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Visual comfort)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

Choice set 7 **Characteristics**	**Package A**	**Package B**
Control	• Light is automatically controlled based on aggregated information	• User can control light based on aggregated information.
Information sharing	• Work activity	• Work activity
Communication	• No dashboard	• Dashboard with lighting control
Knowledge acquisition	• No knowledge acquisitions	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Visual comfort)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 8 **Characteristics**	**Package A**	**Package B**
Control	• User can control light based on aggregated information.	• User can control light based on aggregated information.
Information sharing	• None	• Work activity + personal preference
Communication	• Dashboard with lighting control	• No dashboard
Knowledge acquisition	• No knowledge acquisitions	• Use data to create individual user patterns
Personal information for resource efficiency *(Visual comfort)*	• +35% efficiency, by sharing sensitive personal information	• +15% efficiency, by sharing personal information

Choice set 9 **Characteristics**	**Package A**	**Package B**
Control	• User can control light based on aggregated information.	• User can control light based on aggregated information.
Information sharing	• Work activity	• None
Communication	• No dashboard	• Dashboard with lighting control + warnings + tips
Knowledge acquisition	• Use data to create individual user patterns	• Use aggregated data to create office usage patterns
Personal information for resource efficiency *(Visual comfort)*	• +0% efficiency, not sharing personal information	• +35% efficiency, by sharing sensitive personal information

APPENDIX V: Example recoding of choice set

Idresp	Set	Prof	Alt	Chosen	Const	Control1	Info1	Info2	Com1	Com2	Know1	Know2	Res1	Res2
19	1	15	1	0	1	-1	0	1	-1	-1	1	0	0	1
19	1	11	2	1	1	-1	1	0	0	1	-1	-1	1	0
19	1	0	3	0	0	0	0	0	0	0	0	0	0	0
19	2	9	1	0	1	1	-1	-1	-1	-1	-1	-1	-1	-1
19	2	17	2	1	1	-1	-1	-1	0	1	0	1	1	0
19	2	0	3	0	0	0	0	0	0	0	0	0	0	0
19	3	16	1	0	1	-1	-1	-1	1	0	0	1	-1	-1
19	3	12	2	1	1	-1	1	0	-1	-1	-1	-1	0	1
19	3	0	3	0	0	0	0	0	0	0	0	0	0	0
19	4	10	1	0	1	-1	1	0	1	0	0	1	0	1
19	4	18	2	1	1	-1	-1	-1	-1	-1	1	0	1	0
19	4	0	3	0	0	0	0	0	0	0	0	0	0	0
19	5	8	1	0	1	1	-1	-1	0	1	1	0	0	1
19	5	6	2	1	1	1	0	1	-1	-1	0	1	1	0
19	5	0	3	0	0	0	0	0	0	0	0	0	0	0
19	6	1	1	1	1	1	1	0	1	0	1	0	1	0
19	6	14	2	0	1	-1	0	1	0	1	-1	-1	-1	-1
19	6	0	3	0	0	0	0	0	0	0	0	0	0	0
19	7	13	1	0	1	-1	0	1	1	0	1	0	-1	-1
19	7	5	2	1	1	1	0	1	0	1	0	1	0	1
19	7	0	3	0	0	0	0	0	0	0	0	0	0	0
19	8	2	1	0	1	1	1	0	0	1	1	0	-1	-1
19	8	7	2	1	1	1	-1	-1	1	0	-1	-1	0	1
19	8	0	3	0	0	0	0	0	0	0	0	0	0	0
19	9	4	1	1	1	1	0	1	1	0	-1	-1	1	0
19	9	3	2	0	1	1	1	0	-1	-1	0	1	-1	-1
19	9	0	3	0	0	0	0	0	0	0	0	0	0	0

APPENDIX VI: Nlogit

Smart feature 1: Smart indoor location tracking of colleagues

```
|-> Reset $
|-> Read; file = C:\Users\meyer\Desktop\Part IV Data Analyse\Data preparation for Nlogit (def)\Recode analysis design (SF1)N.csv $
Last observation read from data file was      945
|-> CREATE ; p1 = 0 ; p2 = 0$
|-> NAMELIST ; cp = p1,p2$
|-> Nlogit ; Choice = 1,2,3
    ; Pds     = 9
    ; Lhs     = CHOSEN
    ; Rhs     = CONST,CONTROL1,INFO1,INFO2,COM1,COM2,KNOW1,KNOW2,RES1,RES2
    ; parameters
    ; lcm
          ; classp = cp
    ; Pts     = 2$
Iterative procedure has converged
Normal exit:   5 iterations. Status=0, F=     .3096585D+03

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -309.65845
Estimation based on N =    315, K =  10
Inf.Cr.AIC  =    639.3 AIC/N =    2.030
---------------------------------------
            Log likelihood R-sqrd R2Adj
Constants only   -317.3756  .0243-.0093
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of obs.=   315, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient       Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------------
 CONST|1|    1.06728***     .16024     6.66  .0000      .75320   1.38135
CONTRO|1|    -.01672        .10072     -.17  .8682    -.21412    .18069
 INFO1|1|    -.10128        .10440     -.97  .3320    -.30590    .10334
 INFO2|1|     .34353***     .12744     2.70  .0070     .09376    .59330
  COM1|1|    -.13556        .10115    -1.34  .1802    -.33380    .06268
  COM2|1|    -.02177        .10500     -.21  .8358    -.22756    .18403
 KNOW1|1|     .06122        .10576      .58  .5627    -.14607    .26850
 KNOW2|1|     .12237        .10127     1.21  .2269    -.07611    .32085
  RES1|1|     .02804        .10094      .28  .7812    -.16980    .22587
  RES2|1|     .07143        .10288      .69  .4875    -.13020    .27306
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 03:52:06 PM
-----------------------------------------------------------------------------


-----------------------------------------------------------------------------

Iterative procedure has converged
Normal exit:  27 iterations. Status=0, F=     .2661716D+03

-----------------------------------------------------------------------------
Latent Class Logit Model
Dependent variable               CHOSEN
Log likelihood function      -266.17161
Restricted log likelihood    -346.06287
Chi squared [ 21](P= .000)    159.78251
Significance level               .00000
McFadden Pseudo R-squared      .2308576
Estimation based on N =    315, K =  21
Inf.Cr.AIC  =    574.3 AIC/N =    1.823
---------------------------------------
            Log likelihood R-sqrd R2Adj
No coefficients  -346.0629  .2309 .2043
Constants only   -317.3756  .1613 .1324
At start values  -309.6555  .1404 .1108
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of latent classes =            2
Average Class Probabilities
     .698  .302
LCM model with panel has      35 groups
Fixed number of obsrvs./group=        9
Number of obs.=   315, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient       Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------------
        |Random utility parameters in latent class -->> 1
 CONST|1|    2.78731***     .41354     6.74  .0000     1.97680   3.59783
CONTRO|1|     .03374        .13706      .25  .8056    -.23489    .30237
 INFO1|1|    -.18965        .13149    -1.44  .1492    -.44738    .06807
 INFO2|1|     .44095**      .17564     2.51  .0121     .09670    .78520
  COM1|1|    -.07387        .11976     -.62  .5374    -.30860    .16086
  COM2|1|     .00883        .12838      .07  .9452    -.24279    .26044
 KNOW1|1|     .14344        .13342     1.08  .2823    -.11805    .40493
 KNOW2|1|     .12044        .11882     1.01  .3108    -.11245    .35333
  RES1|1|    -.34562***     .12835    -2.69  .0071    -.59719   -.09405
  RES2|1|     .16057        .12981     1.30  .1941    -.08585    .42299
        |Random utility parameters in latent class -->> 2
 CONST|2|    -.81110***     .30605    -2.65  .0080   -1.41094   -.21125
CONTRO|2|    -.09509        .24788     -.38  .7013    -.58092    .39074
 INFO1|2|     .18966        .27801      .68  .4951    -.35524    .73456
 INFO2|2|     .47890        .29905     1.60  .1093    -.10723   1.06504
  COM1|2|    -.38941        .30492    -1.28  .2016    -.98704    .20822
  COM2|2|     .02219        .30000      .07  .9410    -.56580    .61018
 KNOW1|2|     .01575        .29053      .05  .9568    -.55368    .58519
 KNOW2|2|     .04443        .29577      .15  .8806    -.53526    .62412
  RES1|2|    1.42841***     .28010     5.10  .0000     .87942   1.97740
  RES2|2|     .17988        .31709      .57  .5705    -.44161    .80136
        |Estimated latent class probabilities
 PrbCls1|     .69762***     .08222     8.48  .0000     .53647    .85877
 PrbCls2|     .30238***     .08222     3.68  .0002     .14123    .46353
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 03:52:07 PM
-----------------------------------------------------------------------------
```

Smart feature 2: Smart parking

```
|-> Reset $
|-> Read; file = C:\Users\aeyer\Desktop\Part IV Data Analyse\Data preparation for Nlogit (def)\Recode analysis design (SF2).csv $
Last observation read from data file was      945
|-> CREATE ; p1 = 0 ; p2 = 0$
|-> NAMELIST ; cp = p1,p2$
|-> Nlogit ; Choice = 1,2,3
     ; Pds    = 9
     ; Lhs    = CHOSEN
     ; Rhs    = CONST,CONTROL1,INFO1,INFO2,COM1,COM2,KNOW1,KNOW2,RES1,RES2
     ; parameters
     ; lcm
           ; classp = cp
     ; Pts    = 2$
Iterative procedure has converged
Normal exit:   4 iterations. Status=0, F=     .3413037D+03

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -341.30370
Estimation based on N =    315, K =  10
Inf.Cr.AIC  =    702.6 AIC/N =    2.230
---------------------------------------
            Log likelihood R-sqrd R2Adj
Constants only   -344.9989  .0107-.0234
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of obs.=   315, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
  CONST|1|     .15391       .12371     1.24  .2135     -.08856     .39638
 CONTRO|1|     .08197       .09538      .86  .3901     -.10496     .26891
  INFO1|1|   -.21281*       .11134    -1.91  .0560     -.43103     .00541
  INFO2|1|     .10428       .12333      .85  .3978     -.13744     .34600
   COM1|1|   -.15685        .11022    -1.42  .1547     -.37287     .05917
   COM2|1|     .16019       .10639     1.51  .1321     -.04833     .36870
  KNOW1|1|     .07707       .10830      .71  .4766     -.13518     .28933
  KNOW2|1|   -.05169        .10856     -.48  .6340     -.26446     .16109
   RES1|1|   -.01058        .10685     -.10  .9211     -.22000     .19885
   RES2|1|     .09230       .10684      .86  .3876     -.11710     .30170
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 03:56:44 PM
-----------------------------------------------------------------------------
```

```
-----------------------------------------------------------------------------

Iterative procedure has converged
Normal exit:  27 iterations. Status=0, F=     .2568716D+03

-----------------------------------------------------------------------------
Latent Class Logit Model
Dependent variable               CHOSEN
Log likelihood function      -256.87165
Restricted log likelihood    -346.06287
Chi squared [ 21](P= .000)    178.38245
Significance level               .00000
McFadden Pseudo R-squared      .2577313
Estimation based on N =    315, K =  21
Inf.Cr.AIC  =    555.7 AIC/N =    1.764
---------------------------------------
            Log likelihood R-sqrd R2Adj
No coefficients  -346.0629  .2577 .2321
Constants only   -344.9989  .2554 .2298
At start values  -341.3036  .2474 .2214
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of latent classes =            2
Average Class Probabilities
      .634  .366
LCM model with panel has      35 groups
Fixed number of obsrvs./group=        9
Number of obs.=   315, skipped    0 obs
--------+--------------------------------------------------------------------
        |                  Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient       Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
        |Random utility parameters in latent class -->> 1
  CONST|1|    2.25192***    .33668     6.69  .0000     1.59204    2.91179
 CONTRO|1|     .30381**     .14188     2.14  .0322      .02574     .58189
  INFO1|1|   -.38368***     .13447    -2.85  .0043     -.64723    -.12013
  INFO2|1|     .45085***    .17470     2.58  .0099      .10844     .79327
   COM1|1|   -.08326        .12759     -.65  .5140     -.33332     .16681
   COM2|1|     .22962*      .13333     1.72  .0850     -.03170     .49095
  KNOW1|1|     .16641       .13561     1.23  .2198     -.09938     .43220
  KNOW2|1|   -.07796        .12827     -.61  .5434     -.32936     .17345
   RES1|1|   -.34474**      .14049    -2.45  .0141     -.62010    -.06938
   RES2|1|     .23692*      .13318     1.78  .0752     -.02411     .49794
        |Random utility parameters in latent class -->> 2
  CONST|2|   -2.25896***    .36161    -6.25  .0000    -2.96770   -1.55022
 CONTRO|2|     .27666       .32058      .86  .3881     -.35166     .90499
  INFO1|2|     .34744       .34505     1.01  .3140     -.32885    1.02374
  INFO2|2|   -.81135        .50205    -1.62  .1061    -1.79535     .17266
   COM1|2|   -.48285        .38646    -1.25  .2115    -1.24030     .27460
   COM2|2|     .38197       .32118     1.19  .2343     -.24753    1.01147
  KNOW1|2|   -.06060        .34765     -.17  .8616     -.74198     .62078
  KNOW2|2|     .04762       .32659      .15  .8841     -.59249     .68772
   RES1|2|    1.46647***    .35490     4.13  .0000      .77107    2.16187
   RES2|2|   -.43837        .40065    -1.09  .2739    -1.22363     .34689
        |Estimated latent class probabilities
 PrbCls1|     .63352***     .08305     7.63  .0000      .47074     .79629
 PrbCls2|     .36648***     .08305     4.41  .0000      .20371     .52926
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 03:56:45 PM
-----------------------------------------------------------------------------
```

Smart feature 3: Smart workspace booking

```
|-> Reset $
|-> Read; file = C:\Users\meyer\Desktop\Part IV Data Analyse\Data preparation for Nlogit (def)\Recode analysis design (SF3).csv $
Last observation read from data file was    1107
|-> CREATE ; p1 = 0 ; p2 = 0$
|-> NAMELIST ; cp = p1,p2$
|-> Nlogit ; Choice = 1,2,3
      ; Pds     = 9
      ; Lhs     = CHOSEN
      ; Rhs     = CONST,CONTROL1,INFO1,INFO2,COM1,COM2,KNOW1,KNOW2,RES1,RES2
      ; parameters
      ; lcm
             ; classp = cp
      ; Pts     = 2$
Iterative procedure has converged
Normal exit:   5 iterations. Status=0, F=     .3516154D+03

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -351.61544
Estimation based on N =    369, K =  10
Inf.Cr.AIC  =    723.2 AIC/N =    1.960
---------------------------------------
            Log likelihood R-sqrd R2Adj
Constants only   -371.2042  .0528  .0250
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of obs.=    369, skipped    0 obs
--------+--------------------------------------------------------------------
        |                 Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient      Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
 CONST|1|     .93045***    .14431     6.45  .0000      .64760   1.21329
CONTRO|1|     .27983***    .09927     2.82  .0048      .08527    .47439
 INFO1|1|   -.38638***    .10173    -3.80  .0001    -.58577   -.18699
 INFO2|1|     .19155       .11661     1.64  .1005    -.03700    .42010
  COM1|1|   -.35433***    .10664    -3.32  .0009    -.56335   -.14532
  COM2|1|     .03270       .10396      .31  .7531    -.17105    .23645
 KNOW1|1|   -.17007        .10389    -1.64  .1016    -.37369    .03354
 KNOW2|1|     .16901*      .09960     1.70  .0900    -.02637    .36439
  RES1|1|     .11317       .09488     1.19  .2330    -.07280    .29913
  RES2|1|     .24580**     .09901     2.48  .0130     .05174    .43985
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 03:59:41 PM
-----------------------------------------------------------------------------


-----------------------------------------------------------------------------

Iterative procedure has converged
Normal exit:  30 iterations. Status=0, F=     .3061473D+03

-----------------------------------------------------------------------------
Latent Class Logit Model
Dependent variable               CHOSEN
Log likelihood function      -306.14734
Restricted log likelihood    -405.38793
Chi squared [ 21](P= .000)    198.48119
Significance level               .00000
McFadden Pseudo R-squared      .2448040
Estimation based on N =    369, K =  21
Inf.Cr.AIC  =    654.3 AIC/N =    1.773
---------------------------------------
            Log likelihood R-sqrd R2Adj
No coefficients  -405.3879  .2448  .2227
Constants only   -371.2042  .1753  .1511
At start values  -351.6113  .1293  .1038
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of latent classes =            2
Average Class Probabilities
      .757  .243
LCM model with panel has      41 groups
Fixed number of obsrvs./group=        9
Number of obs.=    369, skipped    0 obs
--------+--------------------------------------------------------------------
        |                 Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient      Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
        |Random utility parameters in latent class -->> 1
 CONST|1|    2.63859***    .49785     5.30  .0000     1.66282   3.61435
CONTRO|1|     .13048       .14350      .91  .3632    -.15078    .41173
 INFO1|1|   -.39462***    .11710    -3.37  .0008    -.62412   -.16511
 INFO2|1|     .07938       .15267      .52  .6031    -.21986    .37861
  COM1|1|   -.39865***    .12116    -3.29  .0010    -.63612   -.16117
  COM2|1|   -.06000        .13012     -.46  .6447    -.31504    .19504
 KNOW1|1|   -.22515*       .12203    -1.84  .0650    -.46433    .01403
 KNOW2|1|     .23118**     .11282     2.05  .0405     .01006    .45231
  RES1|1|     .07370       .10936      .67  .5004    -.14065    .28804
  RES2|1|     .29259**     .11419     2.56  .0104     .06878    .51639
        |Random utility parameters in latent class -->> 2
 CONST|2|   -1.10958***    .36189    -3.07  .0022    -1.81887   -.40029
CONTRO|2|     .72794*      .37329     1.95  .0512    -.00369   1.45958
 INFO1|2|   -.31039        .29990    -1.03  .3007    -.89820    .27741
 INFO2|2|     .27789       .31493      .88  .3776    -.33936    .89514
  COM1|2|   -.30952        .41120     -.75  .4516   -1.11546    .49641
  COM2|2|     .29663       .31607      .94  .3480    -.32286    .91613
 KNOW1|2|   -.02814        .27891     -.10  .9196    -.57480    .51852
 KNOW2|2|   -.02351        .30642     -.08  .9389    -.62407    .57706
  RES1|2|     .51277       .40892     1.25  .2099    -.28870   1.31424
  RES2|2|     .13585       .28230      .48  .6304    -.41745    .68916
        |Estimated latent class probabilities
 PrbCls1|     .75680***    .07282    10.39  .0000      .61407    .89953
 PrbCls2|     .24320***    .07282     3.34  .0008      .10047    .38593
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 03:59:43 PM
-----------------------------------------------------------------------------
```

Smart feature 4: Smart meeting room booking

```
|-> Reset $
|-> Read; file = C:\Users\meyer\Desktop\Part IV Data Analyse\Data preparation for Nlogit (def)\Recode analysis design (SF4).csv $
Last observation read from data file was    1107
|-> CREATE ; p1 = 0 ; p2 = 0$
|-> NAMELIST ; cp = p1,p2$
|-> Nlogit ; Choice = 1,2,3
    ; Pds     = 9
    ; Lhs     = CHOSEN
    ; Rhs     = CONST,CONTROL1,INFO1,INFO2,COM1,COM2,KNOW1,KNOW2,RES1,RES2
    ; parameters
    ; lcm
          ; classp = cp
    ; Pts     = 2$
Iterative procedure has converged
Normal exit:   5 iterations. Status=0, F=     .3401549D+03

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -340.15493
Estimation based on N =    369, K =  10
Inf.Cr.AIC  =    700.3 AIC/N =    1.898
---------------------------------------
           Log likelihood R-sqrd R2Adj
Constants only   -361.7510  .0597 .0322
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of obs.=   369, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient     Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
 CONST|1|    1.16344***    .15592     7.46  .0000      .85783   1.46904
CONTRO|1|     .28073***    .10261     2.74  .0062      .07962    .48183
 INFO1|1|    -.43340***    .10196    -4.25  .0000     -.63325   -.23356
 INFO2|1|     .26417**     .11806     2.24  .0253      .03277    .49557
  COM1|1|    -.41225***    .10761    -3.83  .0001     -.62317   -.20134
  COM2|1|     .17233*      .10346     1.67  .0958     -.03045    .37512
 KNOW1|1|    -.07614       .10238     -.74  .4571     -.27680    .12453
 KNOW2|1|     .13988       .10004     1.40  .1620     -.05619    .33595
  RES1|1|     .13138       .09416     1.40  .1629     -.05317    .31594
  RES2|1|     .26033***    .09867     2.64  .0083      .06694    .45372
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 04:01:27 PM
-----------------------------------------------------------------------------


---------------------------------------------------------------------------

Iterative procedure has converged
Normal exit:  32 iterations. Status=0, F=     .2971671D+03

---------------------------------------------------------------------------
Latent Class Logit Model
Dependent variable               CHOSEN
Log likelihood function      -297.16707
Restricted log likelihood    -405.38793
Chi squared [ 21](P= .000)    216.44173
Significance level               .00000
McFadden Pseudo R-squared      .2669563
Estimation based on N =    369, K =  21
Inf.Cr.AIC  =    636.3 AIC/N =    1.724
---------------------------------------
           Log likelihood R-sqrd R2Adj
No coefficients  -405.3879  .2670 .2455
Constants only   -361.7510  .1785 .1545
At start values  -340.1493  .1264 .1008
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of latent classes =            2
Average Class Probabilities
     .340  .660
LCM model with panel has      41 groups
Fixed number of obsrvs./group=        9
Number of obs.=   369, skipped    0 obs
--------+------------------------------------------------------------------
        |                Standard            Prob.      95% Confidence
  CHOSEN|  Coefficient     Error       z    |z|>Z*        Interval
--------+------------------------------------------------------------------
        |Random utility parameters in latent class -->> 1
 CONST|1|    3.69294***   1.28772     2.87  .0041     1.16906   6.21682
CONTRO|1|    -.77773       .57290    -1.36  .1746    -1.90060    .34514
 INFO1|1|    -.86310      1.30175     -.66  .5073    -3.41448   1.68828
 INFO2|1|    -.37077       .59771     -.62  .5351    -1.54226    .80073
  COM1|1|   -1.83999      1.58778    -1.16  .2465    -4.95199   1.27200
  COM2|1|     .01214       .46309      .03  .9791     -.89549    .91977
 KNOW1|1|    -.13055       .66916     -.20  .8453    -1.44207   1.18097
 KNOW2|1|    -.24527       .66666     -.37  .7129    -1.55189   1.06136
  RES1|1|    2.48365*     1.37134     1.81  .0701     -.20413   5.17144
  RES2|1|     .10252      1.07415      .10  .9240    -2.00278   2.20781
        |Random utility parameters in latent class -->> 2
 CONST|2|     .72611***    .17102     4.25  .0000      .39092   1.06131
CONTRO|2|     .42877***    .12262     3.50  .0005      .18843    .66911
 INFO1|2|    -.58221***    .14364    -4.05  .0001     -.86375   -.30068
 INFO2|2|     .45484***    .16370     2.78  .0055      .13399    .77570
  COM1|2|    -.28268**     .13031    -2.17  .0301     -.53809   -.02727
  COM2|2|     .13797       .12892     1.07  .2845     -.11470    .39065
 KNOW1|2|     .14980       .13430     1.12  .2647     -.11343    .41303
 KNOW2|2|     .19662       .12539     1.57  .1169     -.04913    .44237
  RES1|2|    -.52831***    .13669    -3.87  .0001     -.79621   -.26041
  RES2|2|     .39170***    .13074     3.00  .0027      .13545    .64795
        |Estimated latent class probabilities
 PrbCls1|     .33970***    .07431     4.57  .0000      .19406    .48533
 PrbCls2|     .66030***    .07431     8.89  .0000      .51467    .80594
--------+------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 04:01:28 PM
---------------------------------------------------------------------------
```

Smart feature 5: Smart indoor climate control - Temperature

```
|-> Reset $
|-> Read; file = C:\Users\amyer\Desktop\Part IV Data Analyse\Data preparation for Nlogit (def)\Recode analysis design (SF5).csv $
Last observation read from data file was      810
|-> CREATE ; p1 = 0 ; p2 = 0$
|-> NAMELIST ; cp = p1,p2$
|-> Nlogit ; Choice = 1,2,3
     ; Pds    = 9
     ; Lhs    = CHOSEN
     ; Rhs    = CONST,CONTROL1,INFO1,INFO2,COM1,COM2,KNOW1,KNOW2,RES1,RES2
     ; parameters
     ; lcm
          ; classp = cp
     ; Pts    = 2$
Iterative procedure has converged
Normal exit:   6 iterations. Status=0, F=     .2397600D+03

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -239.76002
Estimation based on N =    270, K =  10
Inf.Cr.AIC  =    499.5 AIC/N =    1.850
---------------------------------------
           Log likelihood R-sqrd R2Adj
Constants only   -249.9286  .0407  .0019
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of obs.=   270, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient     Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------------
 CONST|1|    1.46371***    .20557     7.12  .0000     1.06081   1.86661
CONTRO|1|     .24394**     .11964     2.04  .0415      .00945    .47844
 INFO1|1|    -.09444       .11613     -.81  .4161     -.32205    .13318
 INFO2|1|     .22731*      .13645     1.67  .0957     -.04013    .49475
  COM1|1|    -.47491***    .12337    -3.85  .0001     -.71671   -.23311
  COM2|1|     .27773**     .11691     2.38  .0175      .04858    .50687
 KNOW1|1|    -.15382       .11577    -1.33  .1840     -.38072    .07308
 KNOW2|1|    -.04224       .11777     -.36  .7198     -.27306    .18858
  RES1|1|     .18643*      .10722     1.74  .0821     -.02373    .39658
  RES2|1|     .09589       .11426      .84  .4014     -.12806    .31984
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 04:03:13 PM
-----------------------------------------------------------------------------

-----------------------------------------------------------------------------

Iterative procedure has converged
Normal exit:  27 iterations. Status=0, F=     .2165642D+03

-----------------------------------------------------------------------------
Latent Class Logit Model
Dependent variable               CHOSEN
Log likelihood function      -216.56422
Restricted log likelihood    -296.62532
Chi squared [ 21](P= .000)    160.12219
Significance level               .00000
McFadden Pseudo R-squared      .2699065
Estimation based on N =    270, K =  21
Inf.Cr.AIC  =    475.1 AIC/N =    1.760
---------------------------------------
           Log likelihood R-sqrd R2Adj
No coefficients  -296.6253  .2699  .2404
Constants only   -249.9286  .1335  .0984
At start values  -239.7587  .0967  .0602
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of latent classes =            2
Average Class Probabilities
     .433  .567
LCM model with panel has      30 groups
Fixed number of obsrvs./group=        9
Number of obs.=   270, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient     Error       z    |z|>Z*          Interval
--------+--------------------------------------------------------------------
        |Random utility parameters in latent class -->> 1
 CONST|1|    2.17054***    .53544     4.05  .0001     1.12110   3.21997
CONTRO|1|    -.11415       .37697     -.30  .7620     -.85300    .62471
 INFO1|1|     .69408       .51556     1.35  .1782     -.31639   1.70455
 INFO2|1|    -.12449       .28986     -.43  .6676     -.69260    .44362
  COM1|1|    -.77822       .49404    -1.58  .1152    -1.74652    .19009
  COM2|1|     .21041       .27031      .78  .4363     -.31939    .74021
 KNOW1|1|    -.47627*      .25081    -1.90  .0576     -.96785    .01532
 KNOW2|1|    -.33161       .45925     -.72  .4703    -1.23173    .56851
  RES1|1|    1.06110***    .22329     4.75  .0000      .62347   1.49874
  RES2|1|     .71910       .51542     1.40  .1630     -.29111   1.72930
        |Random utility parameters in latent class -->> 2
 CONST|2|    1.01376***    .24484     4.14  .0000      .53388   1.49363
CONTRO|2|     .29686*      .16507     1.80  .0721     -.02666    .62038
 INFO1|2|    -.41207**     .17818    -2.31  .0207     -.76130   -.06284
 INFO2|2|     .49719**     .19783     2.51  .0120      .10944    .88493
  COM1|2|    -.67931***    .18140    -3.74  .0002    -1.03485   -.32377
  COM2|2|     .38443**     .16659     2.31  .0210      .05792    .71094
 KNOW1|2|     .04393       .17033      .26  .7965     -.28991    .37778
 KNOW2|2|    -.11136       .15919     -.70  .4842     -.42336    .20065
  RES1|2|    -.39522**     .17159    -2.30  .0213     -.73154   -.05890
  RES2|2|    -.01693       .15817     -.11  .9148     -.32693    .29308
        |Estimated latent class probabilities
 PrbCls1|     .43317***    .09269     4.67  .0000      .25151    .61483
 PrbCls2|     .56683***    .09269     6.12  .0000      .38517    .74849
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 04:03:14 PM
-----------------------------------------------------------------------------
```

Smart feature 6: Smart indoor climate control – Air quality

```
|-> Reset $
|-> Read; file = C:\Users\meyer\Desktop\Part IV Data Analyse\Data preparation for Nlogit (def)\Recode analys
Last observation read from data file was      810
|-> CREATE ; p1 = 0 ; p2 = 0$
|-> NAMELIST ; cp = p1,p2$
|-> Nlogit ; Choice = 1,2,3
    ; Pds     = 9
    ; Lhs     = CHOSEN
    ; Rhs     = CONST,CONTROL1,INFO1,INFO2,COM1,COM2,KNOW1,KNOW2,RES1,RES2
    ; parameters
    ; lcm
          ; classp = cp
    ; Pts     = 2$
Iterative procedure has converged
Normal exit:   5 iterations. Status=0, F=     .2477575D+03

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -247.75754
Estimation based on N =    270, K =  10
Inf.Cr.AIC  =    515.5 AIC/N =    1.909
---------------------------------------
           Log likelihood R-sqrd R2Adj
Constants only   -256.1001  .0326-.0066
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of obs.=   270, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient     Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
  CONST|1|   1.26758***     .19025     6.66  .0000       .89469   1.64047
 CONTRO|1|    .03158        .11769      .27  .7885      -.19908    .26224
  INFO1|1|    .00388        .11671      .03  .9735      -.22486    .23262
  INFO2|1|    .00619        .13558      .05  .9636      -.25954    .27192
   COM1|1|   -.42685***     .12119    -3.52  .0004      -.66438   -.18932
   COM2|1|    .12214        .11604     1.05  .2925      -.10529    .34958
  KNOW1|1|   -.04635        .11491     -.40  .6867      -.27157    .17886
  KNOW2|1|   -.02086        .11780     -.18  .8595      -.25174    .21003
   RES1|1|    .28536***     .10699     2.67  .0077       .07566    .49507
   RES2|1|    .23534**      .11425     2.06  .0394       .01142    .45926
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 08:05:21 PM
-----------------------------------------------------------------------------
```

```
-----------------------------------------------------------------------------
Iterative procedure has converged
Normal exit:  32 iterations. Status=0, F=     .2047393D+03
-----------------------------------------------------------------------------
Latent Class Logit Model
Dependent variable               CHOSEN
Log likelihood function      -204.73930
Restricted log likelihood    -296.62532
Chi squared [ 21](P= .000)    183.77204
Significance level               .00000
McFadden Pseudo R-squared      .3097713
Estimation based on N =    270, K =  21
Inf.Cr.AIC  =    451.5 AIC/N =    1.672
---------------------------------------
           Log likelihood R-sqrd R2Adj
No coefficients  -296.6253  .3098 .2818
Constants only   -256.1001  .2005 .1682
At start values  -247.7477  .1736 .1402
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of latent classes =            2
Average Class Probabilities
     .661  .339
LCM model with panel has      30 groups
Fixed number of obsrvs./group=        9
Number of obs.=   270, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient     Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
        |Random utility parameters in latent class -->> 1....................
  CONST|1|   7.32420       5.48810     1.33  .1820     -3.43228  18.08069
 CONTRO|1|   3.53698       4.19045      .84  .3986     -4.67615  11.75011
  INFO1|1|  -1.47684       1.91796     -.77  .4413     -5.23598   2.28229
  INFO2|1|   1.11177       1.48848      .75  .4551     -1.80559   4.02914
   COM1|1|  -3.02233       2.82688    -1.07  .2850     -8.56292   2.51826
   COM2|1|   2.89462       3.23732      .89  .3712     -3.45042   9.23966
  KNOW1|1|  -1.40343       1.50152     -.93  .3500     -4.34635   1.53950
  KNOW2|1|   1.68444       2.18863      .77  .4415     -2.60519   5.97406
   RES1|1|    .83713***     .29890     2.80  .0051       .25130   1.42297
   RES2|1|   1.49434       1.35054     1.11  .2685     -1.15267   4.14135
        |Random utility parameters in latent class -->> 2....................
  CONST|2|   -.16522        .24314     -.68  .4968      -.64176    .31132
 CONTRO|2|   -.30101        .19659    -1.53  .1257      -.68633    .08431
  INFO1|2|   -.02658        .23209     -.11  .9088      -.40147    .42831
  INFO2|2|    .09869        .26878      .37  .7135      -.42810    .62548
   COM1|2|   -.28348        .23929    -1.18  .2362      -.75249    .18553
   COM2|2|   -.14559        .23325     -.62  .5325      -.60276    .31158
  KNOW1|2|    .30520        .21980     1.39  .1649      -.12553    .73608
  KNOW2|2|    .13128        .21735      .60  .5458      -.29471    .55727
   RES1|2|   -.54209**      .24287    -2.23  .0256     -1.01811   -.06607
   RES2|2|    .13415        .21929      .61  .5407      -.29564    .56395
        |Estimated latent class probabilities................................
 PrbCls1|    .66123***      .08772     7.54  .0000       .48929    .83316
 PrbCls2|    .33877***      .08772     3.86  .0001       .16684    .51071
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 08:05:22 PM
-----------------------------------------------------------------------------
```

Smart feature 7: Smart lighting control

```
|-> Reset $
|-> Read; file = C:\Users\meyer\Desktop\Part IV Data Analyse\Data preparation for Nlogit (def)\Recode analysis design (SF7).csv $
Last observation read from data file was      837
|-> CREATE ; p1 = 0 ; p2 = 0$
|-> NAMELIST ; cp = p1,p2$
|-> Nlogit ; Choice = 1,2,3
     ; Pds     = 9
     ; Lhs     = CHOSEN
     ; Rhs     = CONST,CONTROL1,INFO1,INFO2,COM1,COM2,KNOW1,KNOW2,RES1,RES2
     ; parameters
     ; lcm
          ; classp = cp
     ; Pts     = 2$
Iterative procedure has converged
Normal exit:   5 iterations. Status=0, F=     .2755772D+03
-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function      -275.57718
Estimation based on N =     279, K =  10
Inf.Cr.AIC  =    571.2 AIC/N =    2.047
---------------------------------------
           Log likelihood R-sqrd R2Adj
Constants only   -283.7837  .0289-.0091
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of obs.=    279, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient      Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
 CONST|1|     .74445***     .15727     4.73  .0000      .43620   1.05270
CONTRO|1|     .13731        .11129     1.23  .2173     -.08082    .35543
 INFO1|1|     .03715        .11371      .33  .7439     -.18571    .26001
 INFO2|1|    -.02515        .13120     -.19  .8480     -.28229    .23199
  COM1|1|    -.42849***     .12392    -3.46  .0005     -.67137   -.18561
  COM2|1|     .20898*       .11527     1.81  .0698     -.01695    .43491
 KNOW1|1|    -.12032        .11621    -1.04  .3005     -.34808    .10745
 KNOW2|1|     .03021        .11705      .26  .7964     -.19921    .25962
  RES1|1|     .26971**      .10719     2.52  .0119      .05963    .47980
  RES2|1|     .21416*       .11390     1.88  .0601     -.00908    .43741
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 04:05:20 PM
-----------------------------------------------------------------------------

-----------------------------------------------------------------------------

Iterative procedure has converged
Normal exit:  51 iterations. Status=0, F=     .2466337D+03
-----------------------------------------------------------------------------
Latent Class Logit Model
Dependent variable               CHOSEN
Log likelihood function      -246.63375
Restricted log likelihood    -306.51283
Chi squared [ 21](P= .000)    119.75817
Significance level               .00000
McFadden Pseudo R-squared      .1953559
Estimation based on N =     279, K =  21
Inf.Cr.AIC  =    535.3 AIC/N =    1.919
---------------------------------------
           Log likelihood R-sqrd R2Adj
No coefficients  -306.5128   .1954 .1639
Constants only   -283.7837   .1309 .0969
At start values  -275.5742   .1050 .0700
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of latent classes =            2
Average Class Probabilities
    .349  .651
LCM model with panel has      31 groups
Fixed number of obsrvs./group=        9
Number of obs.=    279, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient      Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
        |Random utility parameters in latent class -->> 1
 CONST|1|    1.26050**      .55610     2.27  .0234      .17057   2.35043
CONTRO|1|     .14653        .54880      .27  .7895     -.92910   1.22215
 INFO1|1|    4.25886      177653.6      .00 1.0000 ***********  ***********
 INFO2|1|   -9.30863      355307.2      .00 1.0000 ***********  ***********
  COM1|1|   -5.33241      177653.6      .00 1.0000 ***********  ***********
  COM2|1|    9.69236      355307.2      .00 1.0000 ***********  ***********
 KNOW1|1|   -9.79684      355307.2      .00 1.0000 ***********  ***********
 KNOW2|1|    5.20942      177653.6      .00 1.0000 ***********  ***********
  RES1|1|   10.6972       355307.2      .00 1.0000 ***********  696399.9727
  RES2|1|   -3.51326      177653.6      .00 1.0000 ***********  ***********
        |Random utility parameters in latent class -->> 2
 CONST|2|     .37480**      .17733     2.11  .0346      .02723    .72237
CONTRO|2|     .12711        .13044      .97  .3298     -.12855    .38278
 INFO1|2|     .03792        .14682      .26  .7962     -.24985    .32569
 INFO2|2|     .09070        .16959      .53  .5928     -.24168    .42308
  COM1|2|    -.46761***     .15278    -3.06  .0022     -.76705   -.16818
  COM2|2|     .14390        .14112     1.02  .3079     -.13270    .42049
 KNOW1|2|     .08421        .14403      .58  .5588     -.19809    .36651
 KNOW2|2|    -.00897        .14678     -.06  .9513     -.29664    .27871
  RES1|2|    -.24492*       .14809    -1.65  .0982     -.53517    .04533
  RES2|2|     .18593        .14037     1.32  .1853     -.08919    .46104
        |Estimated latent class probabilities
PrbCls1|      .34853***     .08692     4.01  .0001      .17817    .51890
PrbCls2|      .65147***     .08692     7.49  .0000      .48110    .82183
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Jan 25, 2022 at 04:05:21 PM
-----------------------------------------------------------------------------
```

Smart feature 8: Aggregated smart feature

```
|-> Reset $
|-> Read ; file = C:\Users\meyer\Desktop\Part IV Data Analyse\Data preparation for Nlogit (def)\Recode analysis design for nlogit (all2SF).csv$
Last observation read from data file was    3699
|-> CREATE ; p1 = 0 ; p2 = 0$
|-> NAMELIST ; cp = p1,p2$
|-> Nlogit ; Choice = 1,2,3
    ; Pds    = 9
    ; Lhs    = CHOSEN
    ; Rhs    = CONST,CONTROL1,INFO1,INFO2,COM1,COM2,KNOW1,KNOW2,RES1,RES2
    ; parameters
    ; lcm
              ; classp = cp
    ; Pts    = 2$
Iterative procedure has converged
Normal exit:   5 iterations. Status=0, F=     .1240608D+04

-----------------------------------------------------------------------------
Discrete choice (multinomial logit) model
Dependent variable               Choice
Log likelihood function     -1240.60815
Estimation based on N =   1233, K =  10
Inf.Cr.AIC  =   2501.2 AIC/N =    2.029
---------------------------------------
            Log likelihood R-sqrd R2Adj
Constants only  -1272.7334  .0252  .0169
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of obs.=  1233, skipped   0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient     Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
 CONST|1|     .77429***    .07423    10.43  .0000      .62880     .91978
CONTRO|1|     .13471***    .05136     2.62  .0087      .03404     .23538
 INFO1|1|    -.16757***    .05383    -3.11  .0019     -.27307    -.06207
 INFO2|1|     .09619       .06212     1.55  .1215     -.02556     .21793
  COM1|1|    -.34028***    .05620    -6.05  .0000     -.45044    -.23013
  COM2|1|     .15634***    .05369     2.91  .0036      .05111     .26157
 KNOW1|1|    -.04253       .05423     -.78  .4330     -.14882     .06377
 KNOW2|1|     .02743       .05388      .51  .6107     -.07817     .13303
  RES1|1|     .16162***    .05099     3.17  .0015      .06169     .26155
  RES2|1|     .19170***    .05252     3.65  .0003      .08877     .29463
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Feb 05, 2022 at 11:11:30 PM
-----------------------------------------------------------------------------
```

```
-----------------------------------------------------------------------------

Iterative procedure has converged
Normal exit:  34 iterations. Status=0, F=     .1044396D+04

-----------------------------------------------------------------------------
Latent Class Logit Model
Dependent variable               CHOSEN
Log likelihood function     -1044.39572
Restricted log likelihood   -1354.58895
Chi squared [ 21](P= .000)    620.38646
Significance level               .00000
McFadden Pseudo R-squared      .2289944
Estimation based on N =   1233, K =  21
Inf.Cr.AIC  =   2130.8 AIC/N =    1.728
---------------------------------------
            Log likelihood R-sqrd R2Adj
No coefficients -1354.5890  .2290  .2224
Constants only  -1272.7334  .1794  .1724
At start values -1240.5896  .1581  .1509
Note: R-sqrd = 1 - logL/Logl(constants)
Warning:  Model does not contain a full
set of ASCs. R-sqrd is problematic. Use
model setup with ;RHS=one to get LogL0.
---------------------------------------
Response data are given as ind. choices
Number of latent classes =            2
Average Class Probabilities
    .755  .245
LCM model with panel has     137 groups
Fixed number of obsrvs./group=        9
Number of obs.=  1233, skipped    0 obs
--------+--------------------------------------------------------------------
        |                Standard            Prob.       95% Confidence
  CHOSEN|  Coefficient     Error       z    |z|>Z*         Interval
--------+--------------------------------------------------------------------
        |Random utility parameters in latent class -->> 1......................
 CONST|1|    2.65437***    .21304    12.46  .0000     2.23683    3.07191
CONTRO|1|     .19398***    .07076     2.74  .0061      .05520     .33267
 INFO1|1|    -.20902***    .06132    -3.41  .0007     -.32920    -.08885
 INFO2|1|     .14209*      .07877     1.80  .0713     -.01230     .29648
  COM1|1|    -.32610***    .06186    -5.27  .0000     -.44735    -.20485
  COM2|1|     .16794***    .06393     2.63  .0086      .04264     .29325
 KNOW1|1|    -.06092       .06093    -1.00  .3174     -.18034     .05851
 KNOW2|1|     .03846       .06011      .64  .5222     -.07934     .15627
  RES1|1|     .08193       .05707     1.44  .1511     -.02992     .19377
  RES2|1|     .20497***    .05920     3.46  .0005      .08894     .32100
        |Random utility parameters in latent class -->> 2......................
 CONST|2|   -1.53190***    .17678    -8.67  .0000    -1.87839   -1.18541
CONTRO|2|     .16647       .13693     1.22  .2241     -.10192     .43485
 INFO1|2|     .00047       .16933      .00  .9978     -.33140     .33234
 INFO2|2|     .01972       .17925      .11  .9124     -.33161     .37104
  COM1|2|    -.59890***    .20055    -2.99  .0028     -.99197    -.20583
  COM2|2|     .36142**     .15869     2.28  .0228      .05038     .67245
 KNOW1|2|     .15846       .15993      .99  .3218     -.15499     .47191
 KNOW2|2|    -.00401       .16586     -.02  .9807     -.32910     .32108
  RES1|2|     .79286***    .17628     4.50  .0000      .44736    1.13837
  RES2|2|     .21433       .17848     1.20  .2298     -.13547     .56414
        |Estimated latent class probabilities..................................
 PrbCls1|     .75467***    .03826    19.73  .0000      .67969     .82965
 PrbCls2|     .24533***    .03826     6.41  .0000      .17035     .32031
--------+--------------------------------------------------------------------
***, **, * ==>  Significance at 1%, 5%, 10% level.
Model was estimated on Feb 05, 2022 at 11:11:32 PM
-----------------------------------------------------------------------------
```

APPENDIX VII: Validation personality related statements

Personality trait 1: Extraversion

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	137	100.0
	Excluded[a]	0	.0
	Total	137	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.656	.660	3

Item Statistics

	Mean	Std. Deviation	N
e1	4.00	.707	137
e2	3.88	.762	137
e3	3.57	.864	137

Inter-Item Correlation Matrix

	e1	e2	e3
e1	1.000	.396	.373
e2	.396	1.000	.410
e3	.373	.410	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
e1	7.45	1.866	.457	.210	.578
e2	7.57	1.703	.486	.237	.535
e3	7.88	1.507	.469	.221	.566

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
11.45	3.249	1.802	3

Personality trait 2: Agreeableness

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	137	100.0
	Excluded[a]	0	.0
	Total	137	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.397	.396	3

Item Statistics

	Mean	Std. Deviation	N
a1	4.07	.699	137
a2	4.08	.687	137
a3	3.85	.692	137

Inter-Item Correlation Matrix

	a1	a2	a3
a1	1.000	.096	.309
a2	.096	1.000	.133
a3	.309	.133	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
a1	7.93	1.077	.270	.099	.235
a2	7.92	1.266	.142	.021	.472
a3	8.15	1.052	.300	.106	.175

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
12.00	1.956	1.399	3

Personality trait 3: Conscientiousness

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	137	100.0
	Excluded[a]	0	.0
	Total	137	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.637	.637	3

Item Statistics

	Mean	Std. Deviation	N
c1	3.37	.955	137
c2	3.80	.986	137
c3	3.50	.908	137

Inter-Item Correlation Matrix

	c1	c2	c3
c1	1.000	.433	.430
c2	.433	1.000	.245
c3	.430	.245	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
c1	7.29	2.238	.546	.299	.393
c2	6.87	2.483	.404	.192	.600
c3	7.17	2.700	.397	.189	.604

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
10.66	4.710	2.170	3

Personality trait 4: Neuroticism

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	137	100.0
	Excluded[a]	0	.0
	Total	137	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.681	.678	3

Item Statistics

	Mean	Std. Deviation	N
n1	2.85	1.179	137
n2	2.97	.947	137
n3	3.12	1.037	137

Inter-Item Correlation Matrix

	n1	n2	n3
n1	1.000	.312	.586
n2	.312	1.000	.341
n3	.586	.341	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
n1	6.09	2.639	.556	.357	.507
n2	5.97	3.896	.365	.135	.735
n3	5.82	2.984	.586	.370	.467

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
8.94	6.158	2.482	3

Personality trait 5: Openness

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	137	100.0
	Excluded[a]	0	.0
	Total	137	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.297	.305	3

Item Statistics

	Mean	Std. Deviation	N
o1	4.13	.716	137
o2	3.45	.915	137
o3	3.72	.804	137

Inter-Item Correlation Matrix

	o1	o2	o3
o1	1.000	.101	.168
o2	.101	1.000	.114
o3	.168	.114	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
o1	7.16	1.650	.177	.035	.203
o2	7.85	1.351	.141	.020	.286
o3	7.58	1.481	.184	.038	.178

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
11.29	2.488	1.577	3

APPENDIX VIII: Validation attitude related statements

Case Processing Summary

		N	%
Cases	Valid	137	100.0
	Excluded[a]	0	.0
	Total	137	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.829	.830	3

Item Statistics

	Mean	Std. Deviation	N
ATTProd	3.56	.775	137
ATTQual	3.54	.849	137
ATTOcc	3.66	.817	137

Inter-Item Correlation Matrix

	ATTProd	ATTQual	ATTOcc
ATTProd	1.000	.597	.631
ATTQual	.597	1.000	.629
ATTOcc	.631	.629	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ATTProd	7.20	2.262	.680	.465	.772
ATTQual	7.22	2.069	.679	.462	.773
ATTOcc	7.10	2.107	.705	.498	.745

Scale Statistics

Mean	Variance	Std. Deviation	N of Items
10.76	4.449	2.109	3

APPENDIX IX: Multinominal Logit Models

Smart feature 1: Smart indoor location tracking of colleagues

Statistics Multinomial Logit Model	
Number of observations	315
Number of parameters	10
Log-likelihood of the zero model (LL (0))	-346.063
Log-likelihood of the estimated parameters (LL(β))	-309.658
McFadden Rho-squared (p^2)	0.105
Adjusted Rho-squared (p^2_{adj})	0.076

Attribute	**ID Level**	**Utility (β)**	**Std.Error**	**Z (t-value)**	**Pr(>| t)**
Constant	-	1.067***	0.160	6.66	0.000
Control	A1L1 |Decision support	-0.017	0.101	-0.17	0.868
	A1L2 |Automated decision support	0.017	-	-	-
Information sharing	A2L1 |Not sharing information	-0.101	0.104	-0.97	0.332
	A2L2 |Basic information	0.344***	0.127	2.70	0.007
	A2L3 |Advance information	-0.243	-	-	-
Communication	A3L1 |No dashboard	-0.136	0.101	-1.34	0.180
	A3L2 |Basic communication	-0.022	0.105	-0.21	0.836
	A3L3 |Advanced communication	0.158	-	-	-
Knowledge acquisition	A4L1 |No knowledge acquisition	0.061	0.106	0.58	0.563
	A4L2 |Whole system	0.122	0.101	1.21	0.227
	A4L3 |Individual system	-0.183	-	-	-
Personal information for resource efficiency	A5L1 |+0% efficiency	0.028	0.101	0.28	0.781
	A5L2 |+15% efficiency	0.071	0.103	0.69	0.488
	A5L3 |+35% efficiency	-0.099	-	-	-

*Significance (p= < 0.10, * p < 0.05, **p < 0.01***)

Smart feature 2: Smart parking

Statistics Multinomial Logit Model	
Number of observations	315
Number of parameters	10
Log-likelihood of the zero model (LL (0))	-346.063
Log-likelihood of the estimated parameters (LL(B))	-341.304
McFadden Rho-squared (p2)	0.014
Adjusted Rho-squared ($p2_{adj}$)	-0.019

Attribute	ID Level	Utility (β)	Std.Error	Z (t-value)	Pr(>|t)
Constant	-	0.154	0.124	1.24	0.216
Control	A1L1 |Decision support	0.082	0.095	0.86	0.390
	A1L2 |Automated decision support	-0.082	-	-	-
Information sharing	A2L1 |Not sharing information	-0.213*	0.111	-1.91	0.056
	A2L2 |Basic information	0.104	0.123	0.85	0.398
	A2L3 |Advance information	0.109	-	-	-
Communication	A3L1 |No dashboard	-0.157	0.110	-1.42	0.155
	A3L2 |Basic communication	0.160	0.106	1.51	0.132
	A3L3 |Advanced communication	-0.003	-	-	-
Knowledge acquisition	A4L1 |No knowledge acquisition	0.077	0.108	0.71	0.477
	A4L2 |Whole system	-0.052	0.109	-0.48	0.634
	A4L3 |Individual system	-0.025	-	-	-
Personal information for resource efficiency	A5L1 |+0% efficiency	-0.011	0.107	-0.10	0.921
	A5L2 |+15% efficiency	0.092	0.107	0.86	0.388
	A5L3 |+35% efficiency	-0.081	-	-	-

*Significance (p= < 0.10, * p < 0.05, **p < 0.01***)

Smart feature 3: Smart workspace booking

Statistics Multinomial Logit Model	
Number of observations	369
Number of parameters	10
Log-likelihood of the zero model (LL (0))	-405.388
Log-likelihood of the estimated parameters (LL(B))	-351.615
McFadden Rho-squared (p2)	0.133
Adjusted Rho-squared ($p2_{adj}$)	0.108

Attribute	**ID Level**	**Utility (β)**	**Std.Error**	**Z (t-value)**	**Pr(>|t)**
Constant	-	0.930***	0.144	6.45	0.000
Control	A1L1 |Decision support	0.280***	0.099	2.82	0.005
	A1L2 |Automated decision support	-0.280	-	-	-
Information sharing	A2L1 |Not sharing information	-0.386***	0.102	-3.80	0.000
	A2L2 |Basic information	0.192	0.117	1.64	0.101
	A2L3 |Advance information	0.194	-	-	-
Communication	A3L1 |No dashboard	-0.354***	0.107	-3.32	0.001
	A3L2 |Basic communication	0.033	0.104	0.31	0.753
	A3L3 |Advanced communication	0.321	-	-	-
Knowledge acquisition	A4L1 |No knowledge acquisition	-0.170	0.104	-1.64	0.102
	A4L2 |Whole system	0.169*	0.100	1.70	0.090
	A4L3 |Individual system	0.001	-	-	-
Personal information for resource efficiency	A5L1 |+0% efficiency	-0.113	0.095	1.19	0.233
	A5L2 |+15% efficiency	0.246**	0.099	2.48	0.013
	A5L3 |+35% efficiency	-0.133	-	-	-

*Significance (p= < 0.10, * p < 0.05, **p < 0.01***)

Smart feature 4: Smart meeting room booking

Statistics Multinomial Logit Model	
Number of observations	369
Number of parameters	10
Log-likelihood of the zero model (LL (0))	-405.388
Log-likelihood of the estimated parameters (LL(B))	-340.155
McFadden Rho-squared (p2)	0.161
Adjusted Rho-squared ($p2_{adj}$)	0.137

Attribute	ID Level	Utility (β)	Std.Error	Z (t-value)	Pr(>|t)
Constant	-	1.163***	0.156	7.46	0.000
Control	A1L1 |Decision support	0.281***	0.103	2.74	0.006
	A1L2 |Automated decision support	-0.281	-	-	-
Information sharing	A2L1 |Not sharing information	-0.433***	0.102	-4.25	0.000
	A2L2 |Basic information	0.264**	0.118	2.24	0.025
	A2L3 |Advance information	0.169	-	-	-
Communication	A3L1 |No dashboard	-0.412***	0.108	-3.83	0.000
	A3L2 |Basic communication	0.172*	0.103	1.67	0.096
	A3L3 |Advanced communication	0.240	-	-	-
Knowledge acquisition	A4L1 |No knowledge acquisition	-0.076	0.102	-0.74	0.457
	A4L2 |Whole system	0.140	0.100	1.40	0.162
	A4L3 |Individual system	-0.064	-	-	-
Personal information for resource efficiency	A5L1 |+0% efficiency	-0.131	0.094	1.40	0.163
	A5L2 |+15% efficiency	0.260***	0.099	2.64	0.008
	A5L3 |+35% efficiency	-0.129	-	-	-

*Significance (p= < 0.10, * p < 0.05, **p < 0.01***)

Smart feature 5: Smart indoor climate control – Temperature

Statistics Multinomial Logit Model	
Number of observations	270
Number of parameters	10
Log-likelihood of the zero model (LL (0))	-296.625
Log-likelihood of the estimated parameters (LL(B))	-239.760
McFadden Rho-squared (p2)	0.192
Adjusted Rho-squared ($p2_{adj}$)	0.160

Attribute	ID Level	Utility (β)	Std.Error	Z (t-value)	Pr(>|t)
Constant	-	1.464***	0.206	7.12	0.000
Control	A1L1 |Decision support	0.244**	0.120	2.04	0.042
	A1L2 |Automated decision support	-0.244	-	-	-
Information sharing	A2L1 |Not sharing information	-0.094	0.116	-0.81	0.416
	A2L2 |Basic information	0.227*	0.136	1.67	0.096
	A2L3 |Advance information	-0.133	-	-	-
Communication	A3L1 |No dashboard	-0.475***	0.123	-3.85	0.000
	A3L2 |Basic communication	0.278**	0.117	2.38	0.018
	A3L3 |Advanced communication	0.197	-	-	-
Knowledge acquisition	A4L1 |No knowledge acquisition	-0.154	0.116	-1.33	0.184
	A4L2 |Whole system	-0.042	0.118	-0.36	0.720
	A4L3 |Individual system	0.196	-	-	-
Personal information for resource efficiency	A5L1 |+0% efficiency	0.186	0.107	1.74	0.082
	A5L2 |+15% efficiency	0.096	0.114	0.84	0.401
	A5L3 |+35% efficiency	-0.282	-	-	-

*Significance (p= < 0.10, * p < 0.05, **p < 0.01***)

Smart feature 6: Smart indoor climate control – Air quality

Statistics Multinomial Logit Model	
Number of observations	369
Number of parameters	10
Log-likelihood of the zero model (LL (0))	-296.625
Log-likelihood of the estimated parameters (LL(B))	-247.758
McFadden Rho-squared (p2)	0.165
Adjusted Rho-squared ($p2_{adj}$)	0.132

Attribute	**ID Level**	**Utility (β)**	**Std.Error**	**Z (t-value)**	**Pr(>|t)**
Constant	-	1.268***	0.190	6.66	0.000
Control	A1L1 |Decision support	0.032	0.118	0.27	0.789
	A1L2 |Automated decision support	-0.032	-	-	-
Information sharing	A2L1 |Not sharing information	0.004	0.117	0.03	0.973
	A2L2 |Basic information	0.006	0.136	0.05	0.964
	A2L3 |Advance information	-0.01	-	-	-
0Communication	A3L1 |No dashboard	-0.427***	0.121	-3.52	0.000
	A3L2 |Basic communication	0.122	0.116	1.05	0.293
	A3L3 |Advanced communication	0.305	-	-	-
Knowledge acquisition	A4L1 |No knowledge acquisition	-0.046	0.115	-0.40	0.687
	A4L2 |Whole system	-0.021	0.118	-0.18	0.860
	A4L3 |Individual system	0.067	-	-	-
Personal information for resource efficiency	A5L1 |+0% efficiency	0.285***	0.107	2.67	0.008
	A5L2 |+15% efficiency	0.235**	0.114	2.06	0.039
	A5L3 |+35% efficiency	-0.520	-	-	-

*Significance (p= < 0.10, * p < 0.05, **p < 0.01***)

Smart feature 7: Smart lighting control

Statistics Multinomial Logit Model	
Number of observations	279
Number of parameters	10
Log-likelihood of the zero model (LL (0))	-306.513
Log-likelihood of the estimated parameters (LL(B))	-275.577
McFadden Rho-squared (p2)	0.101
Adjusted Rho-squared ($p2_{adj}$)	0.067

Attribute	ID Level	Utility (β)	Std.Error	Z (t-value)	Pr(>|t)
Constant	-	0.744***	0.157	4.73	0.000
Control	A1L1 |Decision support	0.137	0.111	1.23	0.217
	A1L2 |Automated decision support	-0.137	-	-	-
Information sharing	A2L1 |Not sharing information	0.037	0.114	0.33	0.744
	A2L2 |Basic information	-0.025	0.131	-0.19	0.848
	A2L3 |Advance information	-0.012	-	-	-
Communication	A3L1 |No dashboard	-0.428***	0.124	-3.46	0.001
	A3L2 |Basic communication	0.210*	0.115	1.81	0.070
	A3L3 |Advanced communication	0.218	-	-	-
Knowledge acquisition	A4L1 |No knowledge acquisition	-0.120	0.116	-1.04	0.301
	A4L2 |Whole system	0.030	0.117	0.26	0.796
	A4L3 |Individual system	0.090	-	-	-
Personal information for resource efficiency	A5L1 |+0% efficiency	0.270**	0.107	2.52	0.012
	A5L2 |+15% efficiency	0.214*	0.114	1.88	0.060
	A5L3 |+35% efficiency	-0.484	-	-	-

*Significance (p= < 0.10, * p < 0.05, **p < 0.01***)

Smart feature 8: Aggregated smart feature

Statistics Multinomial Logit Model	
Number of observations	1233
Number of parameters	10
Log-likelihood of the zero model (LL (0))	-1354.589
Log-likelihood of the estimated parameters (LL(B))	-1240.608
McFadden Rho-squared (p2)	0.084
Adjusted Rho-squared ($p2_{adj}$)	0.077

Attribute	ID Level	Utility (β)	Std.Error	Z (t-value)	Pr(>|t)
Constant	-	0.774***	0.074	10.43	0.000
Control	A1L1 |Decision support	0.135***	0.051	5.62	0.009
	A1L2 |Automated decision support	-0.135***	-	-	-
Information sharing	A2L1 |Not sharing information	-0.168***	0.054	-3.11	0.002
	A2L2 |Basic information	0.096	0.062	1.55	0.122
	A2L3 |Advance information	0.072	-	-	-
Communication	A3L1 |No dashboard	-0.340***	0.056	-6.05	0.000
	A3L2 |Basic communication	0.156***	0.053	2.91	0.004
	A3L3 |Advanced communication	0.184	-	-	-
Knowledge acquisition	A4L1 |No knowledge acquisition	-0.043	0.054	-0.78	0.433
	A4L2 |Whole system	0.027	0.054	0.51	0.611
	A4L3 |Individual system	0.016	-	-	-
Personal information for resource efficiency	A5L1 |+0% efficiency	0.162***	0.051	3.17	0.002
	A5L2 |+15% efficiency	0.192***	0.053	3.65	0.000
	A5L3 |+35% efficiency	-0.354	-	-	-

*Significance (p= < 0.10, * p < 0.05, **p < 0.01***)

APPENDIX X: Recoding variables for Chi-Square analyzing

Variables (Before)	Variables (After)
Age	**Age (Recoded)**
15-24 25-34	Age ≤34
35-44 45-54 55+	Age ≥35
Education	**Education (Recoded)**
Primary education Secondary education Vocational education	Low education
Applied university	Medium education
Academic education	High education
Work hours per week	**Work hours per week (Recoded)**
<12h 12h-19h 20h-27h 28h-34h	Work hours ≤34h (Part-time)
≥35h	Work hours ≥35h (Full-time)

APPENDIX XI: Latent Class Models

Smart feature 1: Smart indoor location tracking of colleagues

Statistics	
Number of observations	315
Number of parameters	21
Log-likelihood of the zero model (LL (0))	-346.063
Log-likelihood of the estimated parameters (LL(B))	-266.171
McFadden Rho-squared (p2)	0.231
Adjusted Rho-squared ($p2_{adj}$)	0.176

Attribute	ID Level	LC1 Utility (β)	LC2 Utility (β)
Constant	-	2.787***	-0.811***
Control	A1L1 |Decision support	-0.034	-0.095
	A1L2 |Automated decision support	0.034	0.095
Information sharing	A2L1 |Not sharing information	-0.190	0.190
	A2L2 |Basic information	0.441**	0.479
	A2L3 |Advance information	-0.251	-0.669
Communication	A3L1 |No dashboard	-0.074	-0.389
	A3L2 |Basic communication	0.008	0.022
	A3L3 |Advanced communication	0.066	0.367
Knowledge acquisition	A4L1 |No knowledge acquisition	0.143	0.016
	A4L2 |Whole system	0.120	0.444
	A4L3 |Individual system	0.263	-0.460
Personal information for resource efficiency	A5L1 |+0% efficiency	-0.346***	1.428***
	A5L2 |+15% efficiency	0.169	0.180
	A5L3 |+35% efficiency	0.177	-1.608
Estimated Latent class probabilities		Class 1: 0.698***	Class 2: 0.302***

Smart feature 2: Smart parking

Statistics	
Number of observations	315
Number of parameters	21
Log-likelihood of the zero model (LL (0))	-346.063
Log-likelihood of the estimated parameters (LL(B))	-256.872
McFadden Rho-squared (p2)	0.258
Adjusted Rho-squared ($p2_{adj}$)	0.205

Attribute	**ID Level**	**LC1 Utility (β)**	**LC2 Utility (β)**
Constant	-	2.252***	-2.259***
Control	A1L1 |Decision support	0.304**	0.267
	A1L2 |Automated decision support	-0.304	-0.267
Information sharing	A2L1 |Not sharing information	-0.384***	0.347
	A2L2 |Basic information	0.451***	-0.811
	A2L3 |Advance information	-0.067	0.464
Communication	A3L1 |No dashboard	-0.083	-0.483
	A3L2 |Basic communication	0.230*	0.382
	A3L3 |Advanced communication	-0.147	0.101
Knowledge acquisition	A4L1 |No knowledge acquisition	0.166	-0.061
	A4L2 |Whole system	-0.078	0.048
	A4L3 |Individual system	-0.088	0.013
Personal information for resource efficiency	A5L1 |+0% efficiency	-0.345**	1.466***
	A5L2 |+15% efficiency	0.237*	-0.434
	A5L3 |+35% efficiency	-0.108	-1.032
Estimated Latent class probabilities		Class 1: 0.634***	Class 2: 0.366***

Smart feature 3: Smart workspace booking

Statistics	
Number of observations	369
Number of parameters	21
Log-likelihood of the zero model (LL (0))	-405.388
Log-likelihood of the estimated parameters (LL(B))	-306.147
McFadden Rho-squared (p2)	0.245
Adjusted Rho-squared ($p2_{adj}$)	0.199

Attribute	**ID Level**	**LC1 Utility (β)**	**LC2 Utility (β)**
Constant	-	2.639***	-1.110***
Control	A1L1 |Decision support	0.130**	0.728*
	A1L2 |Automated decision support	-0.130	-0.728
Information sharing	A2L1 |Not sharing information	-0.395***	-0.310
	A2L2 |Basic information	0.079	0.278
	A2L3 |Advance information	-0.316	0.032
Communication	A3L1 |No dashboard	-0.399***	-0.310
	A3L2 |Basic communication	-0.060	0.297
	A3L3 |Advanced communication	0.459	-0.013
Knowledge acquisition	A4L1 |No knowledge acquisition	-0.225*	-0.028
	A4L2 |Whole system	0.231	-0.024
	A4L3 |Individual system	-0.006	0.052
Personal information for resource efficiency	A5L1 |+0% efficiency	0.074	0.513
	A5L2 |+15% efficiency	0.293**	0.136
	A5L3 |+35% efficiency	-0.367	-0.649
Estimated Latent class probabilities		Class 1: 0.757***	Class 2: 0.243***

Smart feature 4: Smart meeting room booking

Statistics	
Number of observations	369
Number of parameters	21
Log-likelihood of the zero model (LL (0))	-405.388
Log-likelihood of the estimated parameters (LL(B))	-297.167
McFadden Rho-squared (p2)	0.267
Adjusted Rho-squared ($p2_{adj}$)	0.223

Attribute	**ID Level**	**LC1 Utility (β)**	**LC2 Utility (β)**
Constant	-	3.693***	0.726***
Control	A1L1 |Decision support	-0.778	0.429***
	A1L2 |Automated decision support	0.778	-0.429
Information sharing	A2L1 |Not sharing information	-0.863	-0.582***
	A2L2 |Basic information	-0.371	0.455***
	A2L3 |Advance information	1.234	0.127
Communication	A3L1 |No dashboard	-1.840	-0.283**
	A3L2 |Basic communication	0.012	0.138
	A3L3 |Advanced communication	1.828	0.145
Knowledge acquisition	A4L1 |No knowledge acquisition	-0.131	0.150
	A4L2 |Whole system	-0.245	0.200
	A4L3 |Individual system	0.376	-0.350
Personal information for resource efficiency	A5L1 |+0% efficiency	2.484*	-0.528***
	A5L2 |+15% efficiency	0.103	0.392***
	A5L3 |+35% efficiency	-2.381	0.136
Estimated Latent class probabilities		Class 1: 0.340***	Class 2: 0.660***

Smart feature 5: Smart indoor climate control – Temperature

Statistics	
Number of observations	270
Number of parameters	21
Log-likelihood of the zero model (LL (0))	-296.625
Log-likelihood of the estimated parameters (LL(B))	-216.564
McFadden Rho-squared (p2)	0.270
Adjusted Rho-squared ($p2_{adj}$)	0.208

Attribute	ID Level	LC1 Utility (β)	LC2 Utility (β)
Constant	-	2.171***	1.014***
Control	A1L1 |Decision support	-0.114	0.297*
	A1L2 |Automated decision support	0.114	-0.297
Information sharing	A2L1 |Not sharing information	0.694	-0.412**
	A2L2 |Basic information	-0.124	0.497**
	A2L3 |Advance information	-0.570	-0.085
Communication	A3L1 |No dashboard	-0.778	-0.679***
	A3L2 |Basic communication	0.210	0.384**
	A3L3 |Advanced communication	0.568	0.295
Knowledge acquisition	A4L1 |No knowledge acquisition	-0.476*	0.044
	A4L2 |Whole system	-0.332	-0.111
	A4L3 |Individual system	0.808	0.067
Personal information for resource efficiency	A5L1 |+0% efficiency	1.061***	-0.395**
	A5L2 |+15% efficiency	0.719	-0.017
	A5L3 |+35% efficiency	1.780	0.412
Estimated Latent class probabilities		Class 1: 0.433***	Class 2: 0.567***

Smart feature 6: Smart indoor climate control – Air quality

Statistics	
Number of observations	270
Number of parameters	21
Log-likelihood of the zero model (LL (0))	-296.625
Log-likelihood of the estimated parameters (LL(B))	-204.739
McFadden Rho-squared (p2)	0.310
Adjusted Rho-squared ($p2_{adj}$)	0.251

Attribute	**ID Level**	**LC1 Utility (β)**	**LC2 Utility (β)**
Constant	-	7.324	-0.165
Control	A1L1 |Decision support	3.537	-0.301
	A1L2 |Automated decision support	-3.537	0.301
Information sharing	A2L1 |Not sharing information	-1.477	-0.027
	A2L2 |Basic information	1.112	0.099
	A2L3 |Advance information	0.365	-0.072
Communication	A3L1 |No dashboard	-3.022	-0.283
	A3L2 |Basic communication	2.895	-0.146
	A3L3 |Advanced communication	0.127	0.429
Knowledge acquisition	A4L1 |No knowledge acquisition	-1.403	0.305
	A4L2 |Whole system	1.684	0.131
	A4L3 |Individual system	-0.281	-0.436
Personal information for resource efficiency	A5L1 |+0% efficiency	0.837***	-0.542**
	A5L2 |+15% efficiency	1.494	0.134
	A5L3 |+35% efficiency	-2.331	-0.408
Estimated Latent class probabilities		Class 1: 0.661***	Class 2: 0.339***

Smart feature 7: Smart lighting control

Statistics Multinomial Logit Model	
Number of observations	297
Number of parameters	21
Log-likelihood of the zero model (LL (0))	-326.288
Log-likelihood of the estimated parameters (LL(B))	-246.634
McFadden Rho-squared (p2)	0.244
Adjusted Rho-squared ($p2_{adj}$)	0.186

Attribute	ID Level	LC1 Utility (β)	LC2 Utility (β)
Constant	-	1.261**	0.375**
Control	A1L1 |Decision support	0.147	0.127
	A1L2 |Automated decision support	-0.147	-0.127
Information sharing	A2L1 |Not sharing information	4.259	0.038
	A2L2 |Basic information	-9.309	0.091
	A2L3 |Advance information	5.050	-0.129
Communication	A3L1 |No dashboard	-5.332	-0.468***
	A3L2 |Basic communication	9.692	0.144
	A3L3 |Advanced communication	-4.360	0.324
Knowledge acquisition	A4L1 |No knowledge acquisition	-9.797	0.084
	A4L2 |Whole system	5.209	-0.009
	A4L3 |Individual system	4.588	-0.075
Personal information for resource efficiency	A5L1 |+0% efficiency	10.697	-0.245*
	A5L2 |+15% efficiency	-3.513	0.186
	A5L3 |+35% efficiency	-7.184	-0.059
Estimated Latent class probabilities		Class 1: 0.349***	Class 2: 0.651***

Smart feature 8: Aggregated smart feature

Statistics Multinomial Logit Model	
Number of observations	1233
Number of parameters	21
Log-likelihood of the zero model (LL (0))	-1354.589
Log-likelihood of the estimated parameters (LL(B))	-1044.396
McFadden Rho-squared (p2)	0.229
Adjusted Rho-squared ($p2_{adj}$)	0.216

Attribute	**ID Level**	**LC1 Utility (β)**	**LC2 Utility (β)**
Constant	-	2.654***	-1.532***
Control	A1L1 |Decision support	0.194***	0.166
	A1L2 |Automated decision support	-0.194	-0.166
Information sharing	A2L1 |Not sharing information	-0.209***	0.000
	A2L2 |Basic information	0.142*	0.020
	A2L3 |Advance information	0.067	-0.020
Communication	A3L1 |No dashboard	-0.326***	-0.599***
	A3L2 |Basic communication	0.168***	0.361**
	A3L3 |Advanced communication	0.158	0.238
Knowledge acquisition	A4L1 |No knowledge acquisition	-0.061	0.158
	A4L2 |Whole system	0.038	-0.004
	A4L3 |Individual system	0.023	-0.154
Personal information for resource efficiency	A5L1 |+0% efficiency	0.082	0.793***
	A5L2 |+15% efficiency	0.205***	0.214
	A5L3 |+35% efficiency	-0.287	-1.007
Estimated Latent class probabilities		Class 1: 0.755***	Class 2: 0.245***

APPENDIX XII: Defining the Latent Classes

Smart feature 1: Smart indoor location tracking of colleagues

Characteristic	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X^2	Sig.
Total	24	68.6	11	31.4		
Gender					0.129	0.720
Male	16	66.7	8	33.3		
Female	8	72.7	3	27.3		
Age					0.129	0.720
15-34	8	72.2	3	27.3		
35+	16	66.7	8	33.3		
Education					0.962	0.618
Low	3	75.0	1	25.0		
Medium	10	76.9	3	23.1		
High	11	61.1	7	38.1		
Work hours per week					5.303	0.021
Part time (35<)	4	40.0	6	60.0		
Full time (35>)	20	80.0	5	20.0		

Significance (p= < 0.10, * p < 0.05, **p < 0.01*)*

Characteristic- ***Experience***	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X^2	Sig.
Total	24	68.6	11	31.4		
Smart indoor tracking location of colleagues					0.637	0.727
Never heard about it before and never used it	7	77.8	2	22.2		
Heard about it and used it	7	70.0	3	30.0		
Heard about it but never used it	10	62.5	6	37.5		
Smart parking					1.094	0.579
Never heard about it before and never used it	7	77.8	2	22.2		
Heard about it and used it	5	55.6	4	44.4		
Heard about it but never used it	12	70.6	5	29.4		
Smart workspace booking					3.863	0.145
Never heard about it before and never used it	7	87.5	1	12.5		
Heard about it and used it	8	80.0	2	20.0		
Heard about it but never used it	9	52.9	8	47.1		
Smart meeting room booking					1.823	0.402
Never heard about it before and never used it	2	50.0	2	50.0		
Heard about it but never used it	12	80.0	3	20.0		
Heard about it and used it	10	62.5	6	37.5		
Smart indoor climate control – Temperature					7.955	0.019
Never heard about it before and never used it	6	100	0	0		
Heard about it but never used it	6	42.9	8	57.1		
Heard about it and used it	12	80.0	3	20.0		
Smart indoor climate control – Air quality					10.201	0.006
Never heard about it before and never used it	9	90.0	1	10.0		
Heard about it but never used it	8	44.4	10	55.6		
Heard about it and used it	7	100.0	0	0.0		
Smart lighting					2.636	0.268
Never heard about it before and never used it	4	100.0	0	0.0		
Heard about it but never used it	10	58.8	7	41.2		
Heard about it and used it	10	71.4	4	28.6		

Characteristic	LC 1 Mean	LC2 Mean	t- test t-value	Sig.
Total	24	11		
Personality				
Extraversion	11.08	11.36	-0.425	0.674
Agreeableness	11.91	13.00	-2.247	0.031
Conscientiousness	11.29	11.73	-0.640	0.526
Neuroticisms	8.92	7.55	1.893	0.067
Openness	11.29	11.18	0.195	0.846
Work activities				
Individual concentrated work	49.17	42.27	0.884	0.383
Formal communication work	28.33	35.00	-1.053	0.300
Informal communication work	12.92	16.36	-0.933	0.358
Other work activities	9.58	6.36	1.026	0.312
Attitude				
Smart features make me more productive at work	3.79	3.36	1.662	0.106
Smart features contribute to a better quality of my work	3.71	3.64	0.234	0.816
Smart features make me more efficient in my occupation	3.88	3.82	0.175	0.862

Smart feature 2: Smart parking

Characteristic	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X²	Sig.
Total	22	62.9	13	37.1		
Gender					0.004	0.948
Male	15	62.5	9	37.5		
Female	7	37.5	4	36.4		
Age					0.048	0.948
15-34	7	63.6	4	36.4		
35+	15	62.5	9	37.5		
Education					2.629	0.269
Low	3	75.0	1	25.0		
Medium	10	76.9	3	23.1		
High	9	50.0	9	50.0		
Work hours per week					3.133	0.077
Part time (35<)	4	40.0	6	60.0		
Full time (35>)	18	72.0	7	28.0		

Significance (p= < 0.10, * p < 0.05, **p < 0.01*)*

Characteristic- *Experience*	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X²	Sig.
Total						
Smart indoor tracking location of colleagues					1.567	0.457
Never heard about it before and never used it	7	77.8	2	22.2		
Heard about it and used it	5	50.0	5	50.0		
Heard about it but never used it	10	62.5	6	37.5		
Smart parking					0.230	0.891
Never heard about it before and never used it	6	66.7	3	33.3		
Heard about it and used it	6	66.7	3	33.3		
Heard about it but never used it	10	58.8	7	41.2		
Smart workspace booking					6.762	0.064
Never heard about it before and never used it	7	87.5	1	12.5		
Heard about it and used it	8	80.0	2	20.0		
Heard about it but never used it	7	41.2	10	58.8		
Smart meeting room booking					0.645	0.724
Never heard about it before and never used it	3	75.0	1	25.0		
Heard about it but never used it	10	66.7	5	33.3		
Heard about it and used it	9	56.3	7	43.8		
Smart indoor climate control – Temperature					1.734	0.420
Never heard about it before and never used it	4	66.7	2	33.3		
Heard about it but never used it	7	50.0	7	50.0		
Heard about it and used it	11	73.3	4	26.7		
Smart indoor climate control – Air quality					0.850	0.654
Never heard about it before and never used it	7	70.0	3	30.0		
Heard about it but never used it	10	55.6	8	44.4		
Heard about it and used it	5	71.4	2	28.6		
Smart lighting					0.842	0.656
Never heard about it before and never used it	2	50.0	2	50.0		
Heard about it but never used it	10	58.8	7	41.2		
Heard about it and used it	10	71.4	4	28.6		

Characteristic	LC 1 Mean	LC2 Mean	t- test t-value	Sig.
Total				
Personality				
Extraversion	10.91	11.62	-1.132	0.266
Agreeableness	11.95	12.77	-1.709	0.097
Conscientiousness	11.41	11.46	-0.080	0.937
Neuroticisms	8.59	8.31	0.387	0.701
Openness	11.14	11.46	-0.605	0.549
Work activities				
Individual concentrated work	49.77	42.31	0.999	0.325
Formal communication work	27.50	35.38	-1.307	0.200
Informal communication work	14.77	12.69	0.581	0.565
Other work activities	7.95	9.62	-0.545	0.590
Attitude				
Smart features make me more productive at work	3.64	3.69	-0.217	0.829
Smart features contribute to a better quality of my work	3.77	3.54	0.801	0.429
Smart features make me more efficient in my occupation	3.86	3.85	0.056	0.956

Smart feature 3: Smart workspace booking

Characteristic	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X^2	Sig.
Total	31	75.6	10	24.4		
Gender					0.837	0.360
Male	20	71.4	8	28.6		
Female	11	84.6	2	15.4		
Age					3.691	0.055
15-34	17	89.5	2	10.5		
35+	14	63.6	8	36.4		
Education					2.409	0.300
Low	5	83.3	1	16.7		
Medium	13	65.0	7	35.0		
High	13	86.7	2	13.3		
Work hours per week					0.200	0.655
Part time (35<)	13	72.2	5	27.8		
Full time (35>)	18	78.3	5	21.7		

Significance (p= < 0.10, * p < 0.05, **p < 0.01*)*

Characteristic- ***Experience***	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X^2	Sig.
Total						
Smart indoor tracking location of colleagues					6.404	0.041
Never heard about it before and never used it	6	85.7	1	14.3		
Heard about it and used it	8	53.3	7	46.7		
Heard about it but never used it	17	89.5	2	10.5		
Smart parking					0.692	0.707
Never heard about it before and never used it	11	73.3	4	26.7		
Heard about it and used it	2	100.0	0	0.0		
Heard about it but never used it	18	75.0	6	25.0		
Smart workspace booking					1.804	0.406
Never heard about it before and never used it	7	77.8	2	22.2		
Heard about it and used it	9	90.0	1	10.0		
Heard about it but never used it	15	68.2	7	31.8		
Smart meeting room booking					0.247	0.884
Never heard about it before and never used it	4	80.0	1	20.0		
Heard about it but never used it	7	70.0	3	30.0		
Heard about it and used it	20	76.9	6	23.1		
Smart indoor climate control – Temperature					6.786	0.034
Never heard about it before and never used it	5	50.0	5	50.0		
Heard about it but never used it	16	76.2	5	23.8		
Heard about it and used it	10	100.0	6	0		
Smart indoor climate control – Air quality					1.702	0.427
Never heard about it before and never used it	11	68.8	5	31.3		
Heard about it but never used it	16	76.2	5	23.8		
Heard about it and used it	4	100.0	0	0.0		
Smart lighting					4.849	0.089
Never heard about it before and never used it	6	66.7	33.3	9		
Heard about it but never used it	14	66.7	33.3	21		
Heard about it and used it	11	100.0	0.0	11		

Characteristic	**LC 1 Mean**	**LC2 Mean**	**t- test t-value**	**Sig.**
Total				
Personality				
Extraversion	11.16	10.70	0.761	0.451
Agreeableness	11.97	11.40	1.206	0.235
Conscientiousness	11.52	10.10	3.176	0.003
Neuroticisms	8.10	8.40	-0.335	0.739
Openness	10.83	11.80	-1.521	0.136
Work activities				
Individual concentrated work	49.52	52.00	-0.394	0.696
Formal communication work	30.16	26.00	0.733	0.468
Informal communication work	12.39	13.50	-0.368	0.715
Other work activities	7.94	8.50	-0.230	0.819
Attitude				
Smart features make me more productive at work	3.68	3.40	0.914	0.366
Smart features contribute to a better quality of my work	3.65	3.50	0.430	0.670
Smart features make me more efficient in my occupation	3.65	3.50	0.475	0.638

Smart feature 4: Smart meeting room booking

Characteristic	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X^2	Sig.
Total	14	34.1	27	65.9		
Gender					0.097	0.756
Male	10	35.7	18	64.3		
Female	4	30.8	9	69.2		
Age					0.997	0.318
15-34	8	42.1	11	57.9		
35+	6	27.3	16	72.7		
Education					2.236	0.327
Low	1	16.7	5	83.3		
Medium	9	45.0	11	55.0		
High	4	26.7	11	73.3		
Work hours per week					0.321	0.571
Part time (35<)	7	38.9	61.1	18		
Full time (35>)	7	30.4	69.6	23		

Significance (p= < 0.10, * p < 0.05, **p < 0.01*)*

Characteristic- *Experience*	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X^2	Sig.
Total						
Smart indoor tracking location of colleagues					3.043	0.218
Never heard about it before and never used it	4	57.1	3	42.9		
Heard about it and used it	3	20.0	12	80.0		
Heard about it but never used it	7	36.8	12	63.2		
Smart parking					4.386	0.112
Never heard about it before and never used it	8	53.3	7	46.7		
Heard about it and used it	0	0.0	2	100.0		
Heard about it but never used it	6	25.0	18	75.0		
Smart workspace booking					1.039	0.595
Never heard about it before and never used it	4	44.4	5	55.6		
Heard about it and used it	4	40.0	6	60.0		
Heard about it but never used it	6	27.3	16	72.7		
Smart meeting room booking					1.797	0.407
Never heard about it before and never used it	2	40.0	3	60.0		
Heard about it but never used it	5	50.0	5	50.0		
Heard about it and used it	7	26.9	19	73.1		
Smart indoor climate control – Temperature					2.268	0.322
Never heard about it before and never used it	4	40.0	6	60.0		
Heard about it but never used it	5	23.8	16	76.2		
Heard about it and used it	5	50.0	5	50.0		
Smart indoor climate control – Air quality					4.364	0.113
Never heard about it before and never used it	8	50.0	8	50.0		
Heard about it but never used it	4	19.0	17	81.0		
Heard about it and used it	2	50.0	2	50.0		
Smart lighting					5.462	0.065
Never heard about it before and never used it	6	66.7	3	33.3		
Heard about it but never used it	5	23.8	16	76.2		
Heard about it and used it	3	27.3	8	72.7		

Characteristic	LC 1 Mean	LC2 Mean	t- test t-value	Sig.
Total				
Personality				
Extraversion	10.57	11.30	-1.341	0.188
Agreeableness	11.79	11.85	-0.152	0.880
Conscientiousness	11.79	10.85	2.184	0.035
Neuroticisms	8.29	8.11	0.213	0.832
Openness	10.64	11.30	-1.127	0.267
Work activities				
Individual concentrated work	53.57	48.33	0.925	0.360
Formal communication work	25.36	31.11	-1.129	0.266
Informal communication work	12.86	12.56	0.110	0.913
Other work activities	8.21	8.00	0.096	0.924
Attitude				
Smart features make me more productive at work	4.07	3.37	2.758	0.009
Smart features contribute to a better quality of my work	3.93	3.44	1.633	0.110
Smart features make me more efficient in my occupation	3.86	3.48	1.385	0.174

Smart feature 5: Smart indoor climate control – Temperature

Characteristic	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X^2	Sig.
Total	13	43.3	17	56.7		
Gender					1.033	0.310
Male	6	35.3	11	64.7		
Female	7	53.8	6	46.2		
Age					0.136	0.713
15-34	7	46.7	8	53.3		
35+	6	40.0	9	60.0		
Education					1.697	0.428
Low	1	100.0	0	0.0		
Medium	3	33.3	6	66.7		
High	9	45.0	11	55.0		
Work hours per week					1.824	0.177
Part time (35<)	3	27.3	8	72.7		
Full time (35>)	10	52.6	9	47.4		

Significance (p= < 0.10, * p < 0.05, **p < 0.01*)*

Characteristic- *Experience*	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X^2	Sig.
Total						
Smart indoor tracking location of colleagues					1.715	0.424
Never heard about it before and never used it	3	33.3	6	66.7		
Heard about it and used it	4	36.4	7	63.6		
Heard about it but never used it	6	60.0	4	40.0		
Smart parking					1.382	0.501
Never heard about it before and never used it	5	45.5	6	54.5		
Heard about it and used it	1	20.0	4	80.0		
Heard about it but never used it	7	50.0	7	50.0		
Smart workspace booking					2.386	0.303
Never heard about it before and never used it	0	0.0	100.0	2		
Heard about it and used it	4	36.4	63.6	11		
Heard about it but never used it	9	52.9	47.1	17		
Smart meeting room booking					0.529	0.768
Never heard about it before and never used it	1	50.0	1	50.0		
Heard about it but never used it	3	33.3	6	66.7		
Heard about it and used it	9	47.4	10	52.6		
Smart indoor climate control – Temperature					0.044	0.978
Never heard about it before and never used it	2	40.0	3	60.0		
Heard about it but never used it	6	42.9	8	57.1		
Heard about it and used it	5	45.5	6	54.5		
Smart indoor climate control – Air quality					0.788	0.674
Never heard about it before and never used it	3	37.5	5	62.5		
Heard about it but never used it	8	42.1	11	57.9		
Heard about it and used it	2	66.7	1	33.3		
Smart lighting					0.984	0.611
Never heard about it before and never used it	1	25.0	3	75.0		
Heard about it but never used it	9	50.0	9	50.0		
Heard about it and used it	3	37.5	5	62.5		

Characteristic	LC 1 Mean	LC2 Mean	t- test t-value	Sig.
Total				
Personality				
Extraversion	12.92	12.47	0.875	0.389
Agreeableness	11.77	11.47	0.551	0.586
Conscientiousness	7.85	8.41	-0.719	0.478
Neuroticisms	12.08	11.47	1.392	0.175
Openness	12.46	11.29	2.506	0.018
Work activities				
Individual concentrated work	36.15	42.35	-0.906	0.373
Formal communication work	37.69	29.41	1.478	0.151
Informal communication work	15.77	12.06	1.575	0.127
Other work activities	10.38	16.18	-1.377	0.179
Attitude				
Smart features make me more productive at work	3.31	3.65	-1.370	0.181
Smart features contribute to a better quality of my work	3.31	3.35	-0.170	0.866
Smart features make me more efficient in my occupation	3.46	3.65	-0.644	0.525

Smart feature 6: Smart indoor climate control – Air quality

Characteristic	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X^2	Sig.
Total	20	66.7	10	33.6		
Gender					4.344	0.037
Male	14	82.4	3	17.6		
Female	6	46.2	7	53.8		
Age					0.600	0.439
15-34	11	73.3	4	26.7		
35+	9	60.0	6	40.0		
Education					1.100	0.577
Low	1	100.0	1	0.0		
Medium	15	55.6	9	44.4		
High	14	70.0	20	30.0		
Work hours per week					12.129	0.000
Part time (35<)	3	27.3	8	72.7		
Full time (35>)	17	89.5	2	10.5		

Significance (p= < 0.10, * p < 0.05, **p < 0.01*)*

Characteristic- *Experience*	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X^2	Sig.
Total						
Smart indoor tracking location of colleagues					1.836	0.399
Never heard about it before and never used it	5	55.6	4	44.4		
Heard about it and used it	9	81.8	2	18.2		
Heard about it but never used it	6	60.0	4	40.0		
Smart parking					2.538	0.281
Never heard about it before and never used it	7	63.6	4	36.4		
Heard about it and used it	2	40.0	3	60.0		
Heard about it but never used it	11	78.6	3	21.4		
Smart workspace booking					1.075	0.584
Never heard about it before and never used it	2	100.0	0	0.0		
Heard about it and used it	7	63.6	4	36.4		
Heard about it but never used it	11	64.7	6	35.3		
Smart meeting room booking					5.789	0.055
Never heard about it before and never used it	0	0.0	2	100.0		
Heard about it but never used it	5	55.6	4	44.4		
Heard about it and used it	15	78.9	4	21.1		
Smart indoor climate control – Temperature					0.318	0.853
Never heard about it before and never used it	3	60.0	2	40.0		
Heard about it but never used it	9	64.3	5	35.7		
Heard about it and used it	8	72.7	3	27.3		
Smart indoor climate control – Air quality					2.526	0.283
Never heard about it before and never used it	4	50.0	4	50.0		
Heard about it but never used it	13	68.4	6	31.6		
Heard about it and used it	3	100.0	0	0.0		
Smart lighting					3.625	0.163
Never heard about it before and never used it	1	25.0	3	75.0		
Heard about it but never used it	13	72.2	5	27.8		
Heard about it and used it	6	75.0	2	25.0		

Characteristic	LC 1 Mean	LC2 Mean	t- test t-value	Sig.
Total				
Personality				
Extraversion	12.65	12.70	-0.091	0.928
Agreeableness	11.45	11.90	-0.795	0.433
Conscientiousness	7.35	9.80	-3.525	0.001
Neuroticisms	11.95	11.30	1.421	0.166
Openness	12.05	11.30	1.434	0.163
Work activities				
Individual concentrated work	39.25	40.50	-0.171	0.865
Formal communication work	32.50	34.00	-0.246	0.808
Informal communication work	14.25	12.50	0.683	0.500
Other work activities	14.00	13.00	0.219	0.828
Attitude				
Smart features make me more productive at work	3.60	3.30	1.141	0.263
Smart features contribute to a better quality of my work	3.30	3.40	-0.358	0.723
Smart features make me more efficient in my occupation	3.55	3.60	-0.164	0.871

Smart feature 7: Smart lighting control

Characteristic	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X^2	Sig.
Total	11	35.5	20	64.5		
Gender					0.040	0.842
Male	7	36.8	12	63.2		
Female	4	33.3	8	66.7		
Age					0.259	0.611
15-34	5	31.3	11	68.8		
35+	6	40.0	9	60.0		
Education					5.540	0.063
Low	0	0.0	2	100.0		
Medium	8	57.1	6	42.9		
High	3	20.0	12	80.0		
Work hours per week					0.040	0.842
Part time (35<)	4	33.3	8	66.7		
Full time (35>)	7	36.8	12	63.2		

Significance (p= < 0.10, * p < 0.05, **p < 0.01*)*

Characteristic- *Experience*	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X^2	Sig.
Total						
Smart indoor tracking location of colleagues					0.981	0.612
Never heard about it before and never used it	2	22.2	7	77.8		
Heard about it and used it	4	40.0	6	60.0		
Heard about it but never used it	5	41.7	7	58.3		
Smart parking					1.619	0.445
Never heard about it before and never used it	1	16.7	5	83.3		
Heard about it and used it	1	25.0	3	75.0		
Heard about it but never used it	9	42.9	12	57.1		
Smart workspace booking					4.297	0.117
Never heard about it before and never used it	0	0.0	2	100.0		
Heard about it and used it	1	12.5	7	87.5		
Heard about it but never used it	10	47.6	11	52.4		
Smart meeting room booking					0.634	0.728
Never heard about it before and never used it	2	40.0	3	60.0		
Heard about it but never used it	4	44.4	5	55.6		
Heard about it and used it	5	29.4	12	70.6		
Smart indoor climate control – Temperature					3.603	0.165
Never heard about it before and never used it	3	75.0	1	25.0		
Heard about it but never used it	5	35.7	9	64.3		
Heard about it and used it	2	23.1	10	76.9		
Smart indoor climate control – Air quality					1.496	0.473
Never heard about it before and never used it	3	50.0	3	50.0		
Heard about it but never used it	7	36.8	12	63.2		
Heard about it and used it	1	16.7	5	83.3		
Smart lighting					0.502	0.778
Never heard about it before and never used it	2	40.0	3	60.0		
Heard about it but never used it	6	40.0	9	60.0		
Heard about it and used it	3	27.3	8	72.7		

Characteristic	LC 1 Mean	LC2 Mean	t- test t-value	Sig.
Total				
Personality				
Extraversion	10.18	11.60	-2.094	0.045
Agreeableness	12.27	12.35	-0.145	0.886
Conscientiousness	10.82	11.95	-1.961	0.060
Neuroticisms	8.00	7.65	0.501	0.620
Openness	11.09	11.15	-0.102	0.920
Work activities				
Individual concentrated work	44.09	41.00	0.422	0.676
Formal communication work	33.64	34.00	-0.058	0.954
Informal communication work	11.18	16.20	-1.660	0.108
Other work activities	11.09	8.80	0.689	0.497
Attitude				
Smart features make me more productive at work	11.09	3.50	-0.421	0.677
Smart features contribute to a better quality of my work	3.55	3.45	0.281	0.780
Smart features make me more efficient in my occupation	3.73	3.50	0.787	0.438

Smart feature 8: Aggregated smart feature

Characteristic	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X²	Sig.
Total	103	75.2	34	24.8		
Gender					0.795	0.373
Male	64	72.7	24	27.3		
Female	39	79.6	10	20.4		
Age					8.071	0.004
15-34	53	86.9	8	13.1		
35+	50	65.8	26	34.2		
Education					0.737	0.692
Low	11	84.6	2	15.4		
Medium	41	73.2	15	26.8		
High	51	75.0	17	25.0		
Work hours per week					4.779	0.029
Part time (35<)	33	64.7	18	35.3		
Full time (35>)	70	81.4	16	18.6		

Significance (p= < 0.10, * p < 0.05, **p < 0.01*)*

Characteristic- *Experience*	LC 1 (N)	LC1 (%)	LC2 (N)	LC2 (%)	Chi-square test X²	Sig.
Total						
Smart indoor tracking location of colleagues					0.775	0.679
Never heard about it before and never used it	25	73.5	9	26.5		
Heard about it and used it	33	71.7	13	28.3		
Heard about it but never used it	45	78.9	12	21.1		
Smart parking					0.344	0.842
Never heard about it before and never used it	31	75.6	10	24.4		
Heard about it and used it	14	70.0	6	30.0		
Heard about it but never used it	58	76.3	18	23.7		
Smart workspace booking					7.797	0.020
Never heard about it before and never used it	19	90.5	2	9.5		
Heard about it and used it	33	84.6	6	15.4		
Heard about it but never used it	51	66.2	26	33.8		
Smart meeting room booking					3.040	0.219
Never heard about it before and never used it	11	68.8	5	31.3		
Heard about it but never used it	29	67.4	14	32.6		
Heard about it and used it	63	80.8	15	19.2		
Smart indoor climate control – Temperature					3.024	0.220
Never heard about it before and never used it	20	80.0	5	20.0		
Heard about it but never used it	43	68.3	20	31.7		
Heard about it and used it	40	81.6	9	18.4		
Smart indoor climate control – Air quality					0.404	0.817
Never heard about it before and never used it	29	72.5	11	27.5		
Heard about it but never used it	58	75.3	19	24.7		
Heard about it and used it	16	80.0	4	20.0		
Smart lighting					2.877	0.237
Never heard about it before and never used it	15	68.2	7	31.8		
Heard about it but never used it	51	71.8	20	28.2		
Heard about it and used it	37	84.1	7	15.9		

Characteristic	LC 1 Mean	LC2 Mean	t- test t-value	Sig.
Total				
Personality				
Extraversion	11.45	11.44	0.015	0.988
Agreeableness	11.96	12.12	-0.564	0.573
Conscientiousness	10.55	11.00	-1.041	0.300
Neuroticisms	9.02	8.71	0.637	0.525
Openness	11.25	11.41	-0.509	0.611
Work activities				
Individual concentrated work	47.09	39.56	1.994	0.048
Formal communication work	29.85	36.03	-1.950	0.053
Informal communication work	13.41	12.26	-0.515	0.607
Other work activities	9.65	10.15	-0.276	0.783
Attitude				
Smart features make me more productive at work	3.64	3.32	2.095	0.038
Smart features contribute to a better quality of my work	3.61	3.32	1.728	0.086
Smart features make me more efficient in my occupation	3.72	3.47	1.541	0.126