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The use of qualitative and quantitative methods to enhance occupant behaviour research in developing countries

Florianópolis
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Certificamos que esta é a **versão original e final** do trabalho de conclusão que foi julgado adequado para obtenção do título de doutor em Engenharia Civil no Programa de Pós-Graduação em Engenharia Civil da Universidade Federal de Santa Catarina.

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Abstract

This research aims to assess occupant behaviour in offices using qualitative and quantitative approaches and propose alternatives to encourage similar evaluations in developing countries. For doing so, the method applied is divided into three main steps: literature reviews, a case study based on qualitative data collection, and a case study relying on quantitative measurements. The first literature review focused on innovative technologies to quantitatively assess the human dimension of building performance, and the following innovations were highlighted: Cyber-Physical Systems, behavioural sensing, Kinect technology, Internet of Things, human-in-the-loop, virtual reality, and immersive environments. Then, also based on advances from the literature, the challenges and opportunities of using the following social science methods to provide qualitative background for this field are presented: questionnaires, interviews, brainstorming, post-occupation evaluations, personal diaries, elicitation, ethnography, and cultural probes. The qualitative case study carried out in Florianópolis evidenced the feasibility of behavioural theories (Theory of Planned Behaviour and Social Cognitive Theory) to evaluate adaptive behaviours through structural equation modelling – a novel approach in this field. Furthermore, the analysis of subjective and comfort-related drivers for occupant behaviour confirmed the relationship between building adjustments and multi-domain comfort conditions. In other words, although environmental variables linked to different comfort domains (visual, thermal, acoustic, and air quality) impact occupant behaviour, such adjustments can also characterise new sources of discomfort. Then, the quantitative case study relied on six-year continuous monitoring carried out in offices in Perugia, Italy. Based on Information Theory concepts and deep learning algorithms, a method to determine the minimum duration of window operation monitoring that leads to reliable models was proposed. The results indicated that the colder seasons (winter and autumn) are less informative and, therefore, field monitoring with more significant influence from these seasons is more likely to result in underperforming models. The conclusions of this thesis outlined the importance of using qualitative and quantitative methods as their outcomes are complementary. By gathering occupant-related data using different approaches, building stakeholders can understand subjective and objective aspects that affect human-building interactions, as well as determine possible strategies to optimise building design and control. Indeed, this thesis provided detailed documentation of different approaches, and building stakeholders from developing countries can benefit from the highlighted opportunities and recommendations to boost occupant behaviour research in those countries.

Keywords: Behavioural theories. Deep learning algorithm. Multidisciplinary evaluation. Office buildings. Qualitative approaches. Technological innovations.

Resumo

O objetivo desta pesquisa é avaliar o comportamento de usuários em escritórios por meio de abordagens qualitativas e quantitativas, e propor diretrizes para aprimorar as práticas nessa área em países em desenvolvimento. O método aplicado é dividido em três etapas principais: revisões de literatura, um estudo de caso utilizando métodos qualitativos e um estudo de caso com avaliações quantitativas. A primeira revisão de literatura evidenciou os potenciais das seguintes inovações tecnológicas para avaliar a dimensão humana do desempenho de edificações: sistemas ciberfísicos, sensores ativos e passivos, tecnologia *Kinect*, *Internet of Things*, *human-in-the-loop*, realidade virtual e ambientes imersivos. Em seguida, também com base nos avanços da literatura, foram apresentados os desafios e oportunidades da utilização dos seguintes métodos comumente empregados em ciências sociais: questionários, entrevistas, *brainstorming*, avaliações pós-ocupação, diários pessoais, elicitação, etnografia e sondas culturais. O estudo de caso com dados subjetivos realizado em Florianópolis evidenciou a viabilidade de teorias de comportamento (Teoria do Comportamento Planejado e Teoria Social Cognitiva) para avaliar adaptações realizadas por usuários em escritórios por meio de modelagem de equações estruturais – uma abordagem inovadora nesta área. Além disso, a análise da influência de fatores subjetivos e relacionados ao conforto dos usuários confirmou a relação entre ajustes das edificações e as condições de conforto multi-domínios. Em outras palavras, se por um lado variáveis ambientais ligadas a diferentes domínios de conforto (visual, térmico, acústico e qualidade do ar) impactam o comportamento dos usuários, os ajustes em si também podem caracterizar novas fontes de desconforto. O estudo de caso com dados objetivos foi baseado em resultados de um monitoramento contínuo ao longo de seis anos realizado em escritórios localizados em Perugia, na Itália. Um método para determinar durações mínimas de monitoramento de operação de janelas que resultem em modelos confiáveis foi proposto com base em conceitos de Teoria da Informação e algoritmos de *deep learning*. Os resultados indicaram que as estações mais frias (inverno e outono) são menos informativas e, portanto, monitoramentos de campo enviesados com dados dessas estações são mais prováveis de resultar em modelos de comportamento menos representativos. As conclusões desta tese evidenciaram a viabilidade de métodos complementares em pesquisas sobre comportamento de usuários. Por meio de coletas de dados com abordagens variadas, diferentes partes interessadas podem melhorar a compreensão sobre aspectos subjetivos e objetivos que impactam nas interações entre usuários e edificações. Profissionais do setor de edificações em países em desenvolvimento podem se basear nas oportunidades e recomendações apresentadas para escolher abordagens adequadas aos problemas que precisam ser resolvidos e popularizar avaliações nesta área.

Palavras-chave: Abordagens qualitativas. Algoritmos de aprendizagem profunda. Avaliação multidisciplinar. Edificações de escritório. Inovações tecnológicas. Teorias de comportamento.

Resumo expandido

Introdução

O setor de edificações é responsável por grande parte da energia primária consumida mundialmente e, consequentemente, do total de emissões de gás-carbônico relacionado ao consumo energético. Para se obter edificações mais eficientes, é necessário entender as principais causas dos elevados consumos energéticos com o intuito de propor alternativas eficazes. Dentre os fatores mais impactantes no consumo total de energia em edificações, a literatura destaca os relacionados à dimensão humana, como operação e manutenção, comportamento do usuário e qualidade do ambiente interno. Diversos métodos (qualitativos e quantitativos) podem ser aplicados para avaliar o comportamento dos usuários em edificações, e as escolhas geralmente estão relacionadas às possibilidades de cada local e equipamentos disponíveis. Apesar do crescimento dessa área nos últimos anos e dos avanços atingidos quanto ao monitoramento e modelagem de comportamento de usuário, a maioria dos estudos foi realizada na Europa, América do Norte e China, o que evidencia a lacuna em relação às realidades de países em desenvolvimento. Portanto, é necessário documentar e apresentar a viabilidade de diferentes de estratégias para impulsionar o desenvolvimento desta área em outras regiões geográficas. Outra alternativa para resolver esse problema é a utilização das bases de dados disponíveis para propor estratégias de otimização para futuros monitoramentos. Com o aperfeiçoamento e validação de diretrizes baseadas em dados, espera-se que mais profissionais conduzam avaliações em campo e que essa área se torne mais difundida em países em desenvolvimento.

Objetivos

O objetivo desta tese é avaliar o comportamento de usuários em escritórios por meio de abordagens qualitativas e quantitativas, e propor diretrizes para aprimorar as práticas nessa área em países em desenvolvimento. Especificamente, objetiva-se:

- Determinar inovações tecnológicas viáveis para avaliar e incluir a dimensão humana relacionada ao desempenho de edificações ao longo de seu ciclo de vida;
- Apresentar os principais desafios e oportunidades relacionados ao uso de métodos das ciências sociais para avaliar a dimensão humana do consumo energético em edificações;
- Utilizar uma estrutura multidisciplinar que combina aspectos de física da edificação a teorias de comportamento para identificar efeitos subjacentes aos ajustes de aparelhos de ar-condicionado, lâmpadas, janelas e cortinas/persianas;
- Avaliar o impacto de aspectos subjetivos e diferentes domínios de conforto ambiental no comportamento de usuários em escritórios;
- Criar um método baseado em dados objetivos para propor otimizações de monitoramentos de operação de janelas em relação às durações mínimas necessárias para obtenção de modelos representativos.

Método

Diferentes abordagens foram combinadas nesta pesquisa, englobando revisão de literatura e estudos de caso utilizando dados subjetivos e dados objetivos. Com isso, cinco artigos científicos foram redigidos visando atingir os objetivos específicos desta tese.

Inicialmente, dois artigos de revisão de literatura foram publicados. O primeiro focou em inovações tecnológicas que podem ser utilizadas para avaliar e incluir a dimensão humana no desempenho de edificações ao longo de seu ciclo de vida. O segundo avaliou métodos comumente empregados nas ciências sociais para destacar os desafios e as oportunidades de sua aplicação no setor de edificações.

O terceiro e o quarto artigos desta tese foram desenvolvidos com dados subjetivos obtidos com a aplicação do questionário desenvolvido durante as atividades do Anexo 66 ("*Definition and Simulation of Occupant Behavior in Buildings*"). Este instrumento combina Teoria do Comportamento Planejado, Teoria Social Cognitiva e a estrutura DNAS (*Drivers, Needs, Actions, and Systems*). A aplicação do questionário foi aprovada pelo Comitê de Ética em Pesquisa com Seres Humanos da UFSC (parecer consubstanciado número 2.391.007). O terceiro artigo consistiu na implementação de modelagem de equações estruturais para avaliar os principais efeitos subjacentes no comportamento adaptativo dos ocupantes. Além disso, avaliou-se como aspectos subjetivos ligados a construtos de teorias de comportamento influenciam o compartilhamento e controle dos sistemas das edificações. O quarto artigo avaliou a influência de aspectos subjetivos e de diferentes domínios de conforto ambiental no comportamento de usuários em escritórios. Nesse caso, análises qualitativas e algoritmos de aprendizado de máquina (árvores de decisão) foram empregados para determinar os principais preditores em relação ao ajuste de cada um dos sistemas avaliados. Por fim, uma estrutura para sintetizar a relação bidirecional entre desconforto multi-domínio e comportamento dos usuários foi proposta.

O quinto artigo é baseado em um estudo de caso com dados objetivos de comportamento de usuários monitorados ao longo de seis anos em Perugia, na Itália. Um método que combina conceitos de Teoria da Informação com algoritmos de *deep learning* para otimizar estudos de campo sobre a operação de janelas foi proposto. A base de dados foi dividida em subconjuntos (com durações entre 1 e 72 meses) para avaliar a representatividade de monitoramentos mais curtos. Além disso, esses subconjuntos foram utilizados para treinar e testar mais de 7.000 redes neurais por meio de um processo recursivo realizado em linguagem Python. Com esse processo, determinou-se a influência da duração dos monitoramentos e do tipo de variáveis avaliadas (ambiente interno e ambiente externo) no desempenho dos modelos obtidos considerando-se as proporções de falsos e verdadeiros positivos como indicador. Os resultados obtidos foram transformados em recomendações para otimizar a coleta de dados em relação ao ajuste de janelas no futuro.

Resultados e Discussão

As revisões de literatura evidenciaram o potencial de diferentes abordagens e ferramentas. Em relação às inovações tecnológicas, os resultados do primeiro artigo ressaltam a possibilidade do uso de sistemas ciberfísicos, sensores ativos e passivos, tecnologia *Kinect*, *Internet of Things*, *human-in-the-loop*, realidade virtual e ambientes imersivos em diferentes fases do ciclo de vida das edificações. Além disso, métodos qualitativos comumente empregados em pesquisas de ciências sociais também são viáveis para avaliar a dimensão humana do desempenho de edificações. Os resultados da segunda revisão de literatura indicam a possibilidade de aplicar questionários, entrevistas, *brainstorming*, avaliações pós-ocupação, diários pessoais, elicitação, etnografia e sondas culturais com diferentes atores envolvidos nessa área.

O primeiro estudo realizado com os dados subjetivos (terceiro artigo) indicou a efetividade de teorias de comportamento nessa área. Os resultados evidenciaram que a intenção de compartilhar os sistemas e o controle percebido pelos ocupantes possuem efeitos positivos e estatisticamente significativos nos ajustes de aparelhos de ar-condicionado, janelas e cortinas/persianas. Por outro lado, os ajustes no sistema de iluminação devem ser avaliados adicionando outros fatores à estrutura atual, como indicadores de hábitos. Os resultados também evidenciaram que os usuários consideram mais difícil compartilhar o controle dos aparelhos de ar-condicionado do que o controle dos demais sistemas avaliados. Além disso, o gênero dos ocupantes também influencia nesse aspecto. Em comparação às mulheres, os homens reportaram menores intenções de compartilhar o controle do ar-condicionado e indicaram menores expectativas de seus colegas de trabalho para que o façam.

O segundo estudo com base nas avaliações subjetivas (quarto artigo) confirmou variações contrastantes em relação às principais fontes de desconforto nos ambientes de trabalho (e.g. enquanto 16% dos respondentes consideram que janelas muito próximas são uma fonte de desconforto térmico, 9% dos participantes reportaram o mesmo sobre janelas distantes). Esses resultados evidenciam a necessidade de avaliações de campo para determinar de maneira objetiva as características dos ambientes de trabalho que mais impactam os níveis de conforto e produtividade dos ocupantes. Os resultados da modelagem por meio de árvores de decisão confirmaram a influência da opinião dos ocupantes sobre a qualidade do ambiente interno e de fatores subjetivos, contextuais e pessoais no comportamento dos usuários. Por fim, um fluxograma conceitual exemplificou a relação entre ajustes das edificações e as condições de conforto multi-domínios. Ou seja, além de as variáveis ambientais ligadas a diferentes esferas de conforto (visual, térmico, acústico e qualidade do ar) influenciarem o modo como os ocupantes se comportam, os próprios comportamentos podem caracterizar novas fontes de desconforto tanto para o responsável pelo ajuste quanto para seus colegas de trabalho.

O estudo com dados objetivos de comportamento de usuários (quinto artigo) evidenciou que variáveis internas são mais prováveis de reduzir a incerteza sobre a operação de janelas em comparação a variáveis ambientais externas, utilizando valores de entropia condicional e informação mútua como referência (conceitos de Teoria da Informação). Além disso, considerando as subdivisões realizadas na base de dados completa para avaliar a representatividade de monitoramentos de campo com durações variando entre 1 e 72 meses, concluiu-se que monitoramentos mais curtos e influenciados pelo outono ou inverno são os que mais divergem em relação à base de dados completa. Essas divergências foram percebidas porque em períodos mais frios as janelas passam mais tempo fechadas. Os resultados podem ser inicialmente transferidos para outras localidades com estações definidas. Entretanto, espera-se que avaliações similares sejam realizadas com diferentes bases de dados coletadas em contextos climáticos variados para que generalizações mais robustas sejam propostas.

Essas tendências foram avaliadas com os resultados de um método recursivo para treinar e testar redes neurais profundas considerando subconjuntos com diversas durações. Confirmou-se que a inclusão de variáveis do ambiente interno melhora o desempenho dos modelos e, como consequência, monitoramentos mais curtos são viáveis. Enquanto todos os modelos de baixa performance que incluíram variáveis do ambiente interno eram baseados em subconjuntos menores de dois anos, foram necessários 4,5 anos para que todos os modelos baseados apenas em dados externos atingissem desempenhos satisfatórios. Por fim, as principais diretrizes para otimizar os estudos de campo são baseadas na influência da sazonalidade: profissionais da área podem minimizar a necessidade de monitoramentos extensos iniciando as avaliações de campo em estações mais informativas como primavera ou verão. Nesse caso, os resultados indicam alta probabilidade de modelos com bom desempenho com pelo menos nove meses de monitoramento quando variáveis internas e externas são incluídas, pelo menos um ano quando apenas variáveis internas são monitoradas e mais de dois anos quando somente variáveis externas são incluídas.

Considerações Finais

Uma abordagem multidisciplinar combinando revisões de literatura, avaliações qualitativas, teorias de comportamento, avaliações quantitativas e aprendizado de máquina foi realizada. Desta forma, apresentou-se a viabilidade de diferentes estratégias para que outros profissionais da área possam aplicar métodos condizentes com a realidade do local a ser avaliado a fim de popularizar essa prática. As conclusões respaldam tanto a replicação dos métodos apresentados quanto a proposição de novas avaliações em outras regiões brasileiras e países em desenvolvimento com base nas oportunidades apresentadas pelas revisões de literatura e pelos estudos de caso. Esses avanços são especialmente necessários considerando que a maior parte das informações disponíveis até hoje representam a realidade de países desenvolvidos. A documentação e popularização de estudos sobre a dimensão humana do desempenho de edificações em outros países em desenvolvimento pode minimizar essa lacuna e favorecer tomadas de decisão mais adequadas às realidades locais. Consequentemente, espera-se contribuir aos esforços internacionais em direção à obtenção de edificações centradas nas necessidades de seus usuários e energeticamente eficientes.

Palavras-Chave: Abordagens qualitativas. Algoritmos de aprendizagem profunda. Avaliação multidisciplinar. Edificações de escritório. Inovações tecnológicas. Teorias de comportamento.

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Acronyms

ABM	Agent-Based Modelling
AI	Artificial Intelligence
BPS	Building Performance Simulation
BD	Big Data Analytics
CPSs	Cyber-Physical Systems
CPSSs	Cyber-Physical-Social Systems
DNAS	Drivers, Needs, Actions and Systems
DTP	Double Translation Process
EHS	English Housing Survey
EPC	Energy Performance Certificate
FNR	False Negative Rate
FPR	False Positive Rate
HBI	Human-Building Interactions
HITL	Human-in-the-loop
HVAC	Heating, Ventilation and Air-Conditioning
IEA	International Energy Agency
IEQ	Indoor Environmental Quality
INMET	Brazilian National Institute of Meteorology
IoT	Internet of Things
KPIs	Key Performance Indicators
MIT	Massachusetts Institute of Technology
ML	Machine Learning
MOA	Motivation-Opportunity-Ability theory
OB	Occupant behaviour
PBC	Perceived Behavioural Control
PCS	Personal Comfort Systems
PCT	Perceptual Control Theory
PMF	Probability Mass Function
PMV	Predicted Mean Vote
POEs	Post-occupancy evaluations
ReLU	Rectified Linear Unit
ROC	Receiver Operating Characteristics
SEM	Structural Equation Modelling

SCT	Social Cognitive Theory
SRHI	Self-Reported Habit Index
TPB	Theory of Planned Behaviour
TNR	True Negative Rate
TPR	True Positive Rate
TUS	Time Use Survey
VBN	Values-Beliefs-Norms
VEs	Virtual Environments
VR	Virtual Reality

Summary

1. Introduction

Buildings are responsible for a high share of total energy use worldwide, and the International Energy Agency (IEA) conducts regular evaluations in this field. In a report published in 2019, IEA showed that although the energy use in buildings is not overgrowing like the population worldwide, this sector still accounted for 36% of global final energy use and nearly 40% of energy-related CO_2 emissions (GABC, 2019). Brazil faces a similar issue as buildings are responsible for a high share of energy use every year. The Brazilian Energy Balance from 2020 shows that the buildings sector consumed more than 40% of the domestic electricity supply (BRASIL, 2020). Therefore, the need to achieve energy-efficient strategies to mitigate this problem across the world is clear. Building stakeholders cannot focus only on physical or technical aspects, as the influence of the human dimension on energy use in buildings has been stressed in recent studies (D'OCA; HONG; LANGEVIN, 2018). Considering the total energy use in buildings, Yoshino, Hong and Nord (2017) concluded that three out of the six most influencing aspects are related to the occupants and their acts. Such human-related factors comprise operation and maintenance, occupant behaviour, and indoor environmental conditions.

Occupant behaviour research is expected to provide building stakeholders with both subjective and objective information that must be included in the loop of buildings' life cycle (WAGNER; O'BRIEN; DONG, 2017). Qualitative research gathers personal information like opinions, attitudes, perceptions or preferences to understand people in several contexts, while quantitative research gathers objective data in numbers, statistics, modelling, and so on (SOVACOOL; AXSEN; SORRELL, 2018). First, understanding occupants with qualitative research may result in subjective insights that aim to improve occupant-centric design and operation of buildings, with expected improvements on indoor environmental quality while also keeping attention to energy consumption levels. Second, objective knowledge can be translated into mathematical models, which are linked to enhancements on current building performance simulation practices as well as data-driven building control. Assessing occupant behaviour in buildings is generally context-related, as practitioners may use several methods or tools available that fit into specific contexts and issues that need to be considered. Indeed, there are no standardised methods to evaluate and model occupant behaviour, and several strategies have been applied in this field (STAZI; NASPI; D'ORAZIO, 2017).

Although the evident importance of understanding subjective aspects of human-building interactions, building scientists still have a lot to learn by transferring knowledge from social sciences (SOVACOOL, 2014). Therefore, documenting the pros and cons of methods used in social sciences that fit energy research practices may pave the way to popularise their application in building science. Besides the relevance of many methods, a recent literature review also highlighted the feasibility and importance of different behavioural theories to study occupant interactions with building systems (HEYDARIAN *et al.*, 2020). The authors identified 27 specific theories that have been applied, which come from psychology, sociology, and economics. The advances in this field also highlight the possibility of using insights and constructs from behavioural theories when applying different methods available to assess humans' perspectives. Such a combination would also play a role in a broader evaluation of the human dimension of energy use in buildings, including other stakeholders closely related to buildings' performance over their life cycles (D'OCA; HONG; LANGEVIN, 2018).

Apart from subjective assessments, sensor-based evaluations are also widespread in this field as they enable monitoring indoor conditions and occupant presence and actions. Indeed, this approach is valid to infer occupant-related conditions (e.g., inferring occupancy with measurements of CO_2 concentration indoors (CALÌ *et al.*, 2015)) or explaining some adjustments made (e.g., determine typical temperatures linked to air-conditioning adjustment (DEAR; KIM; PARKINSON, 2018)). Previous studies have highlighted the most common triggers for various human-building interactions. For instance, Wagner, O'Brien and Dong (2017) provided a comprehensive literature overview of factors found to have an influence on behaviour and those found to have no influence. They were organised according to building types (office, residential or educational) and considered individual and environmental adjustments. Literature reviews have also been published in international journals providing big pictures for occupant behaviour research in commercial and residential buildings (BALVEDI; GHISI; LAMBERTS, 2018; GUNAY; O'BRIEN; BEAUSOLEIL-MORRISON, 2013; ZHANG *et al.*, 2018). Stazi, Naspi and D'Orazio (2017) presented driving factors that influence the operation of windows, lighting, shading and blinds, air-conditioning, thermostat, fans and doors. The authors also discussed essential aspects of reliably modelling occupant behaviours. Literature reviews have also focused on specific building systems. For instance, Fabi, Andersen and Corgnati (2016) discussed the drivers for light-switching in office buildings focusing on visual comfort concerns. Fabi *et al.* (2012) assessed the main factors influencing window opening behaviours in residential and commercial buildings. O'Brien, Kapsis and Athienitis (2013) presented a critical review on the use of window shades in offices, with comprehensive details of previous experiments' results to identify the consensus reached so far.

1.1. Problem and relevance of this work

As previously stated, research regarding the human dimension of building performance has increased in the last few years. Such a trend is directly linked to the advances in the state-of-the-art related to the activities developed in the context of the International Energy Agency (IEA) Annex 66 "Definition and Simulation of Occupant Behavior in Buildings" (YAN *et al.*, 2017). The final report of this international effort was published in 2018 (YAN; HONG, 2018). Throughout the activities, frameworks related to different aspects of occupant behaviour were presented, like interdisciplinary approaches for collecting data, guidelines for modelling occupant behaviour and evaluating such models, and integrating them into Building Performance Simulation programmes. After the Annex 66 conclusion, some unanswered questions about occupant comfort and behaviour and a slight penetration of advanced occupant modelling into practice led to the follow-up IEA Annex 79 "Occupant-Centric Building Design and Operation" (O'BRIEN *et al.*, 2020). This new group is developing research in multi-domain exposure and human behaviour, as well as data-driven modelling strategies and occupant-centric building design and operation.

Such a clear path proposed during these Annexes' activities towards better understanding and representing occupant-related aspects in buildings is driving essential changes in the literature. As previously presented, several literature reviews have summarised important outcomes and reached a consensus on aspects that influence human-building interactions. Another key and emerging topic, which has been evaluated under the framework of Annex 79, comprises the multi-domain investigations of occupants' perceptions and behaviour. A recent literature review summarised what has been done on this subject, and the authors concluded that multi-domain comfort results are still somehow inconclusive and, in part, contradictory (SCHWEIKER *et al.*, 2020). As a consequence, the authors encouraged researchers to join or establish collaborative activities as future directions in this field, as well as reaching a common framework to enable further meta-analysis to align the findings with those previously presented. Considering all the available advances in this field, it is essential to highlight that such results are still biased towards developed countries and cold climates. Recent literature reviews considering qualitative researches based on behavioural theories (HEYDARIAN *et al.*, 2020), quantitative ones to establish occupant behaviour models (CARLUCCI *et al.*, 2020), and also multi-domain approaches to occupants' perception and behaviour indoor (SCHWEIKER *et al.*, 2020) shared a similar outcome: the majority of the studies in this field came from North America, Europe and China. Therefore, it is crucial to enrich the knowledge by gathering information in a more diverse geographical spectrum, considering that climate and cultural contexts are also likely to influence occupants' interactions with buildings.

Besides the geographical and cultural dimensions, it is also important to consider contextual aspects in developing countries that support the need to include knowledge from those underrepresented realities in this field. First, developing countries face high rates of new building construction due to social and economic development, and policymakers should rely on local insights instead of recommending policies based on developed countries' realities (KAMAL; AL-GHAMDI; KOÇ, 2019). Second, as developing countries are expected to have higher increases in energy use caused by urbanisation and economic development, occupants' awareness and behaviours are placed in a prominent position to achieve energy conservation (ÜRGE-VORSATZ *et al.*, 2012). Third, the literature supports that costumers from developing countries place smaller values on energy-efficient investments than those from developed ones (MATSUMOTO; OMATA, 2017). Thus, in a broad perspective, the discussions and results reached throughout this research are relevant given the context stated above. Indeed, by increasing both subjective and objective knowledge about the human dimension of building energy use, and in this case, especially occupant behaviours, practitioners in the building sectors are likely to include such knowledge in the loop of their work. Further, in a stricter perspective, by including occupants in the scope of building performance with different methods available, higher levels of awareness are also expected in the future. This achievement may also increase the value placed on energy-efficient investments and measures, with an expected consequence of higher acceptance and adoption of new technologies.

1.2. Contribution and innovation

As the use of multidisciplinary approaches is highly recommended to improve occupant-related research (HONG *et al.*, 2016; SOVACOOL, 2014), this thesis started from questions such as: What are the methods and opportunities available? From which fields can building stakeholders transfer knowledge aiming to improve their practices? How can the building industry take advantage of different technological innovations that are being increasingly created and improved? Thus, the first contribution of this work is a comprehensive documentation of technological innovations and social science methods that may be used in occupant behaviour research. This step was based on a literature review, and the outcomes provide building stakeholders with up-to-date methods and insights that may be used in their professional practices. Indeed, by providing details about different opportunities, such results contribute to practitioners choosing approaches that fit local contexts and needs. As occupant behaviour research is generally context-related and professionals may use different tools and methods, comprehensive documentation of different opportunities may encourage applying previously unknown approaches – i.e. new technology or unknown qualitative methods. Considering a developing country perspective, such documentation is also crucial to emphasise low-cost opportunities to gather occupant-related data and increase the knowledge considering local aspects.

Other contributions of this research are aligned with the importance of gathering knowledge from both qualitative and quantitative aspects during building operation. First, considering the subjective part, this thesis relies on the results of the multidisciplinary framework proposed during the Annex 66 activities (D'OCA *et al.*, 2017). This framework aimed to synthesise building physics with social psychology by including insights from the Theory of Planned Behaviour (TPB) and the Social Cognitive Theory (SCT) to explain the social dynamics of occupant behaviour in offices. Indeed, considering a case study using this framework, it was possible to assess subjective aspects linked to occupants' interactions with different building systems (HVAC, lighting, windows, and blinds/shades) and capture relations between observed and latent variables that influence occupant behaviour in offices. The method is also innovative in this field since it is based on a well-established statistical approach (Structural Equation Modelling) to capture such relations. In a recent literature review, Schweiker *et al.* (2020) recommended the use of this method for further work on indoor environmental perceptual and behavioural studies as it may capture interactions and their complexity. Thus, innovative knowledge about subjective effects linked to adaptive behaviours in offices is presented to building stakeholders.

Additionally, the outcomes from this framework were used to synthesise the observed interrelation between multi-domain comfort and human-building interaction in the evaluated offices. This contribution evidenced the importance of assessing both the short and long-term influence of occupants' actions, especially in shared spaces, considering such actions a possible new source of discomfort either for the occupant who performed the adjustment or for co-workers in shared spaces. In a broader perspective, this study also brings innovation to the field by using machine learning algorithms (in this case, classification decision trees) to determine the most impactful aspects associated with the adjustments of HVAC, lighting, windows, and blinds/shades. This strategy fits current needs on modelling occupant behaviour and is based on data collected through qualitative approaches. Therefore, it enables the evaluation of IEQ-beliefs, subjective, contextual and personal factors on human-building interactions, which is generally missed with sensor-based evaluations. Although it does not replace objective-based modelling that is key to improving building performance simulation practices, it is an appealing and low-cost strategy for modelling behaviours that can help determine qualitative aspects that should be improved to provide occupants with more opportunities for adaptations at work.

Finally, from the quantitative analysis, this research provides an innovative approach that combines insights from Information Theory with a modelling strategy based on deep learning to provide guidelines for optimising window monitoring in offices. The proposition of this method is an innovation in data-driven occupant behaviour research and is aligned with developments in Engineering and Technology Schools. As most of the previous research came from developed countries, the method proposed herein established a formalism to use such data for providing guidelines to optimise future field studies. Therefore, building stakeholders from other locations may use such recommendations to balance the needs for big data and the likelihood of achieving reliable models. Additionally, other pieces of research may replicate the method with new databases to enhance the knowledge transferability and propose strong generalisations towards standardising occupant behaviour research approaches. The results reached so far may already be used as initial guidelines for window monitoring in developing countries, which is also an original contribution of this thesis.

1.3. Objectives

1.3.1. General objective

The general objective of this thesis is to assess occupant behaviour in offices using both qualitative and quantitative approaches and propose alternatives to encourage similar evaluations in developing countries.

1.3.2. Specific objectives

The general objective was divided into five specific objectives, and each of them represents one article that composes this thesis, as follows:

- Determine technological innovations that play a role to assess and include the human dimension in the building performance-loop;
- Present the main challenges and opportunities regarding the use of social science methods to assess the human dimension of energy use in buildings;
- Use an interdisciplinary framework that combines building-related and behavioural theories to identify underlying effects on occupants' adaptive behaviours related to the adjustments in HVAC, lighting, windows and shades/blinds;

- Evaluate the effect of multi-domain triggers, including subjective and comfort-related aspects, on the occupant behaviour in offices;
- Establish a data-driven method to optimise window operation monitoring by proposing minimum experiment durations that still result in reliable models.

1.4. Structure of the thesis

The structure of this thesis is based on the requirements of Resolution 03/PPGEC/2020. Therefore, this work combines three contextual chapters regarding the Introduction, Discussions and Conclusions with five articles reporting different tasks performed during the Doctorate – each article is presented in a chapter. Importantly, all the co-authors provided a shared authorship agreement, as shown in Appendix A. Although the articles were transcribed to this document, adjustments in the style were made to meet the ABNT (Brazilian Association of Technical Standards) requirements. Also, all the references were presented at the end of this document for conciseness. An overview of all the chapters is presented in this section.

The first chapter introduces the research topic. Thus, it synthesises the problem and relevance of this work, its contributions and innovations, as well as the general and specific objectives. It emphasises the importance of using qualitative and quantitative approaches in occupant-related research and highlights an issue evidenced by the literature: although a consistent increase on this subject was observed in the last few years, occupant behaviour research is still lacking in developing countries. It discusses the prominence of using different approaches to collect complementary information and encourage stakeholders to conduct similar research in other locations.

As previous works highlighted the importance of using objective data (achieved by means of quantitative methods like sensor-based evaluations), the initial step of this thesis comprised a comprehensive overview of different ways to gather such data from buildings. Therefore, the second chapter presents a literature review about technological innovations that may be used to assess and include the human dimensions in the building performance loop, which was published in the *Energy and Buildings* journal in 2019. Recently documented technologies (from 2015 up to 2019) were evaluated based on Scopus results. The review presents challenges and opportunities related to Cyber-Physical Systems, behavioural sensing, Kinect technology, Internet of Things (IoT), human-in-the-loop approaches, virtual reality and immersive environments. Documenting such innovations is also essential in developing countries, as various possibilities are presented to stakeholders who can determine the best fit for the current needs and resources available.

Although innovative technologies are important, those devices fail to collect subjective information like social norms and cultural settings that are likely to affect the way occupants interact with buildings. Therefore, previous works highly recommended using multidisciplinary approaches to assess occupant behaviour in buildings and collect complementary information. Moving forward with the knowledge gathered about technological innovations, a new literature review was performed to have an overview of methods commonly used in social sciences that can also be used in the building sector to evaluate human-related aspects. This follow-up review, published in the *Energy and Buildings* journal in 2020, is presented in the third chapter. The outcomes support the use of questionnaires, interviews, brainstorming, post-occupancy evaluations, personal diaries, elicitation, ethnographic studies, and cultural probe. The pros and cons of each method were discussed to provide building stakeholders with evidence to support their choices about appropriated approaches.

Given the usefulness of qualitative information in this field, the fourth and fifth chapters present and discuss the results obtained through a case study at the Federal University of Santa Catarina. Such a case study was based on an interdisciplinary framework that synthesises building physics insights with social psychology constructs, developed during the Annex 66 activities. The instrument combines the DNAS (*Drivers, Needs, Actions and Systems*) framework with the Theory of Planned Behaviour and the Social Cognitive Theory. The case study comprised an online survey of employees at the University, and two analyses were carried out using the data gathered.

The first analysis is presented in the fourth chapter. It aimed to assess underlying effects on adaptive behaviours of office occupants. This study was published in the *Building and Environment* journal in 2020, and it is based on the influence of behavioural theories' constructs on adaptive behaviours. Additionally, it enabled contextualising the most impactful underlying effects related to each system evaluated (HVAC, windows, lights, and shades/blinds). Conclusions present theory-based outcomes to understand the subjectiveness of adaptive behaviours and also to intervene when necessary. The successful evaluation is an initial proof that low-cost qualitative methods may provide building managers with valuable information that can be translated into actions or improvements to boost occupants' adaptations at work. However, as this first analysis was social-theory-based, broader evaluations would still play a role to better explain the dynamics in such offices.

A follow-up analysis presented in the fifth chapter assesses subjective and comfort-related triggers in occupant behaviour. Such a study was published in the *Energy Research and Social Science* journal in 2021, and it discusses the inseparable relation between multi-domain comfort and occupant behaviour in buildings. For doing so, an overview of the primary sources of discomfort perceived by the occupants (regarding thermal, visual, air quality, and acoustic domains), as well as the main reasons for adjusting building systems (HVAC, windows, lights, and shades/blinds) are presented. Finally, an in-depth analysis of the main reasons for adjusting building systems enabled machine learning algorithms to determine which aspects (IEQ-beliefs, subjective, contextual and personal factors) are more likely to impact human-building interactions throughout the year. The results highlight the importance of using qualitative data collection in this field and the advances that can be reached by including machine learning to capture complex relations among the variables.

Although there are positive outcomes of qualitative data, the importance of objective information should not be neglected in this field. Therefore, the sixth chapter comprises a final case study that takes into account quantitative measurements in offices. As previously discussed, most of the occupant-related databases and evaluations come from developed countries, and such knowledge could be translated into optimisation strategies beyond purely context-related models. Thus, data from a long-term monitoring campaign in Perugia-Italy was used to propose guidelines for future studies related to window operation. It involves developing a method that combines core concepts of Information Theory with a comprehensive modelling strategy based on deep learning to test the results. This work was carried out in 2021, during the exchange period at the Environmental Applied Physics Laboratory at the University of Perugia. It was submitted to the *Applied Energy* journal and it is now under review.

The seventh chapter presents the final discussions regarding how occupant behaviour research can be improved in developing countries. The discussions are based on the main outcomes reached from each study conducted throughout the Doctorate. It also highlights the opportunities provided by the growth in the number of connected devices in the last years to create low-cost occupant-centric tools to monitor human-building interactions in buildings. Finally, the eighth chapter presents the main conclusions. It emphasises the importance of complementary research approaches, i.e. qualitative and quantitative-based approaches, to assess occupant behaviour and encourage similar evaluations in developing countries. Additionally, the chapter highlights the limitations of this research and recommendations for potential future developments in this area.

2. Literature review on technological innovations

This chapter is the transcription of the following paper:

> **Technological innovations to assess and include the human dimension in the building-performance loop: A review.**
>
> Authored by: Mateus Vinícius Bavaresco, Simona D'Oca, Enedir Ghisi, and Roberto Lamberts.
>
> Published in Energy and Buildings (ISSN: 0378-7788), volume 202, in 2019, and catalogued through the DOI: doi.org/10.1016/j.enbuild.2019.109365.

Abstract

The human dimension plays an essential role in the energy performance of buildings and is considered as significant as technological advances. Several studies highlighted the negative influence of occupant behaviour in underperforming buildings, while some support that technological innovations may reduce human-related uncertainties. Thus, one may consider that fully automated smart buildings are essential to achieve energy efficiency. However, if technology excludes people from decision-making processes, low acceptance and comfort/welfare levels may be reported from users. Therefore, the right combination of humans and technologies are expected to solve these problems. Buildings are emerging as complex Cyber-Physical Systems, including the Social dimension, and this provides an excellent opportunity to achieve high-performance outcomes, considering both technical and social aspects. Thus, the right choice among available up-to-date behavioural sensing – comprising active and passive sensors, as well as Kinect technology – are important in the Internet-of-Things (IoT) era. IoT-driven buildings can use real-time monitoring data to inform users and drive behavioural-based consumption change, which is an important aspect to achieve high-performance buildings and deliver user-centred services. An essential feature in this regard is to allow for human-in-the-loop approaches enabled by human-centric computing and smart devices, which has grown fast in the last few years. This literature review summarises applications and main challenges related to the combination of the human dimension and technological innovations in the building sector. This combination is expected to increase user welfare and reduce the energy consumption in buildings, as human and machine components of intelligence may complement each other regarding building performance.

1. Introduction

The building sector is very important in the role of the clean energy transition as it is responsible for about 36% of final energy use worldwide (GABC, 2019). Considering the actual energy use in buildings, Yoshino, Hong and Nord (2017) have shown that half of the most influential factors (three out of six) are human-influenced. Therefore, it is very important to evaluate and understand the human dimension of energy consumption in buildings, which is presented as equally important as technological innovations (D'OCA; HONG; LANGEVIN, 2018). Much has been done to understand occupant behaviour (D'OCA *et al.*, 2017; D'OCA; HONG, 2014; FENG *et al.*, 2016; HONG *et al.*, 2016; YAN *et al.*, 2017) and translate it into models to enable computer simulation (GAETANI; HOES; HENSEN, 2016; HONG *et al.*, 2018; O'BRIEN *et al.*, 2017a, 2017b; SUN; HONG, 2017). Nonetheless, it is a challenging practice due to the stochastic nature of human behaviour (HONG *et al.*, 2017), which should be represented in dynamic rather than static way (NGUYEN; AIELLO, 2013). Additionally, some inappropriate human-building interactions may result in high energy use even in buildings designed as Net Zero Energy ones (JIA; SRINIVASAN; RAHEEM, 2017); and those incongruous controls are considered as the "dark side" of human behaviour in buildings (MASOSO; GROBLER, 2010). Even if occupant-related uncertainties would be solved for a hypothetical situation, building use may change during its life cycle as well as users' preferences (KIM *et al.*, 2018a), which creates the need of continually evaluating occupant responses for given indoor conditions.

Considering the challenges related to the human dimension of building performances, one may reason that a great way to increase energy efficiency is by fully automating buildings so that their performance would not rely on human-related uncertainties. However, occupant-proof smart buildings are hardly achieved because systems which exclude user preferences are poorly accepted (SADEGHI *et al.*, 2016); and perceived control over building systems had been related to higher comfort levels (GUO; MEGGERS, 2015; LANGEVIN; WEN; GURIAN, 2012), productivity (BOERSTRA; LOOMANS; HENSEN, 2014), and energy savings (COLE; BROWN, 2009). Therefore, to obtain more efficient buildings, both technical and behavioural aspects should be integrated (MOEZZI; JANDA, 2014). Optimal operation of building systems is a key to reduce energy consumption and increase efficiency; therefore it is necessary to incorporate knowledge about human preferences in building maintenance (PARK; NAGY, 2018). Intelligent and autonomous control systems can consider human preferences during decision-making processes because new technologies can connect people to those systems

(KUMAR *et al.*, 2016). This connection could bridge the gap between expected and delivered indoor conditions as actual user preferences may be included in the loop of building control.

Along these lines, automation systems have improved in terms of sophistication lately, and intercommunication between various devices is allowed by Internet-of-Things (IoT) approaches (ALAA *et al.*, 2017). There is evident potential in this field, as the number of online-capable devices is expected to increase exponentially soon, reaching about 30 billion objects by 2020 (REKA; DRAGICEVIC, 2018). IoT-based systems may benefit from all those devices and gather information to improve performance of such system considering human knowledge, needs and preferences. Additionally, IoT devices enable informative communication between objects and humans with sensing, actuation, and control (RAY, 2018), which is important to deliver high-performance buildings to society. However, the implications of each sensing technology depend on many factors as granularity, accuracy, price, availability, ease of deployment and communications so that best-suited feature can be chosen among all the available ones (AHMAD *et al.*, 2016). Moreover, technology alone does not guarantee low consumption (HONG *et al.*, 2015a), so “smart buildings” are even impossible to reach without “smart users” (WURTZ; DELINCHANT, 2017). Consequently, it is very important to determine the right combination of human awareness and technology to benefit from the twofold relation that exists between them: one may use data/insights from the other to keep improving the building performance during its life cycle.

Therefore, relying on the fact that buildings are emerging as Cyber-Physical-Social Systems, we reason that reaching high levels of energy efficiency depends on the integration of humans and technologies. First, as humans interact with buildings and cannot be excluded from the control of systems, even fully automated buildings can increase their performances if human knowledge and preferences are considered. Current technologies can improve both design and operation practices in commercial and residential buildings; however, it is necessary to find the best options available and to what extent some innovation may contribute in the role of achieving high Indoor Environmental Quality (IEQ) levels and energy-efficient buildings. In this paper, different behavioural sensing technologies, networks, human-in-the-loop control, and virtual/immersive realities are shown as promising innovations to deliver high-performance buildings and lead to the decarbonisation of future buildings by comprehending and including the human dimension in the loop of building performance.

2. A literature review

One organised the literature review according to the main technological innovations found to be related to the human dimension of building performance. Figure 2.1 shows that both occupant behaviour and technology-related research (in this case, IoT and behavioural sensing) have increased from 2015 up to now. Therefore, this was the timeframe chosen to assess the literature to find suitable papers. Figure 2.1 shows the number of papers found in Scopus (one of the leading organisations on citation index) considering the topics related to technology and human dimension of building performance. Those papers were the basis for the analysis of the literature, and, after refining the database, more technologies were found and individually searched as well. Therefore, the following sections summarise outcomes regarding those new technologies found in the literature: 1. Cyber-Physical Systems; 2. Behavioural sensing (both active and passive technologies); 3. Kinect technology; 4. Internet of Things; 5. Human-in-the-Loop; 6. Virtual reality and immersive environments. Although reviewing many articles published in journals highly involved in occupant behaviour research (e.g., Energy and Buildings, Building and Environment, Renewable and Sustainable Energy Reviews, etc.), the final database comprises a more significant number of papers from IEEE (Institute of Electrical and Electronics Engineers). As this organisation is highly involved with technologies, many of the findings were available in their database. In light of this concern, papers from conferences were also included in the review, considering that many innovative technologies are presented in those events. The main applications and hindrances were identified, as well as ways to combine different technologies to improve building performance regarding both energy consumption and indoor quality.

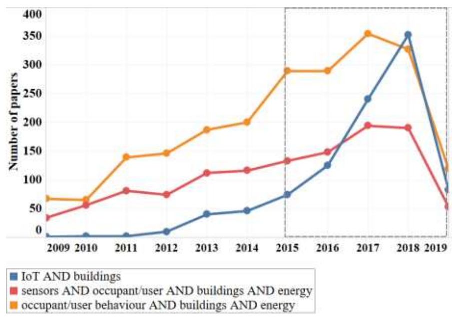

Figure 2.1. Number of papers in the Scopus database according to the terms used (2009 – May 2019).

2.1. Cyber-Physical Systems

Cyber-Physical Systems (CPSs) are those in which both cyber and physical worlds are combined, and information from each world can be exchanged with the other one. Some may consider a whole city as a CPS (power grid, connected vehicles, wearable devices, etc.) and buildings are part of this interaction with their surroundings – building-to-building and building-to-grid integrations (MANIC *et al.*, 2016). However, smart buildings themselves are CPSs, and they need to contemplate both the physical environment and human behaviours to improve energy performance and deliver user-driven or user-centred services (CHEN *et al.*, 2017). Even the building envelope itself can be part of a CPS in the future: Cheng *et al.* (2016) proposed little fragments for envelopes that are cyber controlled and adapt themselves according to both indoor and outdoor conditions to improve comfort, experiences and spatial experiences for users. The adaptation of the building envelope according to the desired indoor condition is still in its infancy stage; however, on the topic of building systems, real-world information from user preferences and behaviours have been used to adjust systems like heating (DU *et al.*, 2018), HVAC (ARJUNAN *et al.*, 2015; JIA *et al.*, 2017; KORKAS; BALDI; KOSMATOPOULOS, 2017) and lighting (LEE; LEE; LEE, 2018; SOL *et al.*, 2018), which is important to deliver high-quality indoor environments for users. Although there are many benefits, constraints as lack of privacy (JIA *et al.*, 2017; SU *et al.*, 2018) and presence of uncertainties (ROCHER *et al.*, 2018) are still related to the use of CPSs in buildings. About privacy concerns, Jia *et al.* (2017) presented the concept of "free-lunch privacy", which is related to the absence of data collection during unnecessary moments – e.g., when outside temperature is moderate there is no need to obtain occupancy for HVAC control because there will be no use of cooling/heating. In this regard, it is important to identify the critical data that should be provided to deliver optimal service and minimise the risks for occupants' privacy. Moreover, multi-criteria decision making is a suitable approach to reduce uncertainties related to user satisfaction in such environments and provide a high-quality service as well (ROCHER *et al.*, 2018).

Additionally, delivering an effective Energy Management System is hard due to the impact of occupant behaviour on building performance; thus CPSs play an important role to manage the energy consumption of buildings, and they can lead to the sustainable operation of smart cities and buildings. Neighbouring buildings tend to behave similarly due to the existence of micro-communities in human society; therefore, such clusters are opportunities to improve energy management of a smart city offered by micro-grids as the whole groups are open CPSs (LI; WEN, 2017). Regarding buildings alone, CPSs play a significant role to forecast load with both machine learning (RODRIGUES *et al.*, 2017) and information from different data sources (like meteorological and human congestion) (HORI *et al.*, 2016). Similarly, they are adequate to manage energy consumption according to occupancy using Wi-Fi to detect people presence (WANG *et al.*, 2018), algorithms for self-error correction of occupancy counting (LEE; LEE;

LEE, 2018) or machine learning to predict the need of comfort level and priority of energy consumption in different rooms (REENA; MATHEW; JACOB, 2015). In this regard, as CPSs rely on sensed data from the real world, they are useful to understand power usage in homes and cognitively understand user behaviours (CHEN *et al.*, 2017) or recognise users intention to provide the desired service (RAFFERTY *et al.*, 2017). Real-time monitoring is supportive for Cyber-Physical-System performance (FUJITA *et al.*, 2015) because it allows the integration of locations, activities, sensations, and intentions of users; which enable to predict users' demand and provide user-centred building management. Such a system could lead to a reduction in energy consumption in buildings and intensification of users' welfare.

In this way, a brand-new concept to provide high-quality indoor environments for users is the integration of the Social Dimension to the already known Cyber-Physical Systems. The role of Cyber-Physical-Social Systems (CPSSs, as shown in Figure 2.2) is strongly related to user behaviour, as informed and motivated users can cooperate with smart-building systems and reduce energy consumption (CAMBEIRO *et al.*, 2018). Social Systems are integrated into Cyber-Physical Systems mainly due to the human-centric computing evolution (ZENG *et al.*, 2016). It is the fusion about humans, computers and things to combine human and machine bits of intelligence to transform abstractions into daily concrete applications (TANG *et al.*, 2018) and provide better services for users (ZENG *et al.*, 2016), such as adaptive and context-aware CPSs (LU, 2018). By including the Social dimension in those systems, gamification and human-in-the-loop approaches (CAMBEIRO *et al.*, 2018) can promote energy-efficient behaviour due to the competitive aspect of the social game to encourage responsible energy use (KONSTANTAKOPOULOS *et al.*, 2019). The Social dimension can be achieved directly from users through their smartphones (AGRAWAL *et al.*, 2015; SMIRNOV; KASHEVNIK; PONOMAREV, 2015; SU *et al.*, 2018) and other smart products (MATEI *et al.*, 2016) that allow understanding not only demographics but also contexts of daily activities; or even from their online social networks that enable recognizing people and understanding their social behaviour (SULTANA; PAUL; GAVRILOVA, 2017) or location (FUJITA *et al.*, 2015) to provide the best service for each one. Integrating this contextual knowledge in automation systems may change the interactions with both physical and virtual worlds.

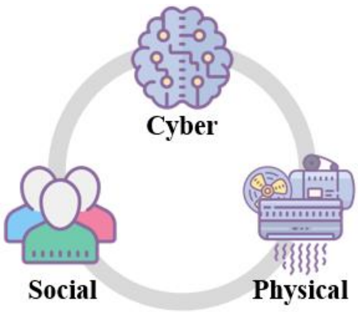

Figure 2.2. Illustration of dimensions considered in a Cyber-Physical-Social System.

Although many advantages provided by CPSs and CPSSs regarding the consideration of the human dimension in building control and operation, the challenge of user acceptance is still an issue (QUINTAS; MENEZES; DIAS, 2017). As data gathered by these systems are both from and about users, it is essential to consider the way this information is handled and presented to users (WOLFF *et al.*, 2018). In the following sections, in-deep considerations are made regarding different dimensions of CPSs and CPSSs, as the role of gathering information through sensors and up-to-date technology are shown as possible problem solvers throughout the building life cycle.

2.2. Behavioural sensing

As data from buildings are strategic to understand how their performance can be enhanced, there is a need to consider the correct approach depending on the situation. Regarding human activity recognition, for instance, various sensors may be used: body-worn sensors (describe body movements), object sensors (infer activity through object movements), ambient sensors (understand activity through ambient variations) or hybrid sensors (combine different sensors to provide more accuracy) (WANG *et al.*, 2017). Following this trend, this section summarises the main dissimilarities between passive and active sensors, and how stakeholders can use them to improve building performance.

2.2.1. Passive sensors

Tracking localisations, movements or behaviours of occupants is a prerequisite to understanding the influence of the human dimension in building performance. In this regard, passive sensors are widely used because they are cheaper and consume less energy than active ones (SAHOO; PATI, 2017). The low energy consumption is related to the sensor operation: as they do not emit any energy to probe the space, they are known as “passive” solutions (HAQ *et al.*, 2014). Therefore, Passive Infrared (PIR) sensors are presented as a solution for occupancy evaluation in buildings. However, PIR sensors fail in detecting stationary objects (LIU *et al.*, 2017; LUPPE; SHABANI, 2017; SAAD; ABAS; PEBRIANTI, 2016); and this leads to reliability issues in monitoring and improperly control of buildings. As they depend on others' body energy to sense the space, "false-off" may occur frequently in systems' control as sensors fail in detecting a stationary body (HAQ *et al.*, 2014). Therefore, different passive sensors and/or combination of sensors have been presented to solve this problem: capacitive and ultrasonic motion sensors (LINDAHL *et al.*, 2016), infrared array sensor (Grid-EYE) (BERRY; PARK, 2017), passive sources like webcam-based motion detection (NEWSHAM *et al.*, 2017), and combination of passive infrared with active sensors like Hall Effect (SKOCIR *et al.*, 2016), and with plug-load meters (SHETTY *et al.*, 2018). Although an indirect solution, occupancy can also be measured according to human position or direction of their walk inside buildings. Passive solutions are recommended, and researchers have used:

- Passive sensors from smartphones – microphone, magnetometer, and light sensor – (GALVÁN-TEJADA *et al.*, 2015);
- Passive seismic sensors (TANG; HUANG; MANDAL, 2017) and passive sparse sensors (PAN *et al.*, 2016) to detect ambient structural vibration caused by human walking; passive electric field sensing to detect variations in the ambient electric field generated by human movement (FU *et al.*, 2018);
- Passive infrared sensor coupled with a wearable piezoresistive accelerometer to estimate people's behavioural state as well (LI; LIU; SHENG, 2015); and
- Passive infrared sensors combined with a magnetic switch to detect door opening/closing and a transducer to estimate weight from steps on the floor, which has been presented as a way to detect intrusion (DARAMAS *et al.*, 2016), but it is also valid to recognise people's arrival/departure and infer occupancy.

Besides occupancy, passive sensors are helpful to study occupant behaviour in buildings in simple and non-intrusive ways (URWYLER *et al.*, 2015), which can provide personalised control of systems and improve both energy efficiency and human experiences in indoor environments. Passive Infrared Sensors can be used to infer specific activities in particular parts of a home – in front of the refrigerator, in the shower, etc. – (SKUBIC; GUEVARA; RANTZ, 2015), which is useful to infer specific behaviours, or can be combined with accelerometers and RGB-D cameras to recognise human activities (NGUYEN *et al.*, 2017). Passive Radio-Frequency Identification can be coupled with passive accelerometers to study real-time bed-egress recognition (WICKRAMASINGHE *et al.*, 2017), and with passive tags and antennas to track position and activities of the daily life of occupants (ALSINGLAWI *et al.*, 2016). Passive Doppler radar (LI; TAN; PIECHOCKI, 2018) and passive wireless sensor with Doppler (TAN *et al.*, 2015) can capture human movements, recognise physical activities and breathing movements. Wearable technology that combines passive sensors (accelerometer, gyroscope, magnetometer, and barometric pressure sensor) can measure arm movements, human posture and walk (LEUENBERGER *et al.*, 2017), which is very important to infer activity levels and deliver user-centred services. Passive sensors also help to understand people behaviour from meaningful actions. It is the case of eating behaviour detection, which is possible by evaluating activities that occur right before the eating itself: e.g., reed sensor to detect items taken from the refrigerator, and force sensor to detect food placed in the common eating location (O'BRIEN; KATKOORI; ROWE, 2015). As the applications of each sensor are numerous, each professional has to identify the best option/application to deliver the most desired service with the least constraints possible.

The usability of passive sensors also comprises automation and implementation of user-centred systems for building control. Passive Infrared Sensors with Raspberry Pi (GHOSH, 2016) and with other sensors in an Internet-of-Things device (JI *et al.*, 2017) are solutions for building automation and management systems; and can benefit context-awareness application to control and monitor real environments (NON-ALISAVATH *et al.*, 2017) or transform actual into smart objects, as the case of "smart mirror" that provides personalised information to building users when they look at the mirror (ATHIRA *et al.*, 2016). Thus, the inclusion of passive sensors in low-cost solutions that benefit user-centred systems for buildings is presented in literature and is valuable concerning the future of building performance. In this regard, stakeholders should rely on advanced models (either statistical or artificial intelligence) to obtain the most suitable knowledge to improve indoor conditions and reduce energy consumption. Therefore, the combination of PIR sensors and learning classification algorithms as Naïve Bayesian, support vector machine, and random forest (NEF *et al.*, 2015) or hidden Markov model (YIN *et al.*, 2016) can track human location or daily activities and feed control models in automated systems. Integration of passive-infrared sensors with accessibility maps (YANG; SHENG; ZENG, 2015), and with accessibility maps and A-star algorithms (YANG *et al.*, 2018) can improve the data generated as the best locations for each sensor inside the building can be determined. Finally, passive sensors from tablet devices were used to create a real-time map of noise (MATHUR *et al.*, 2015), which can result in better choice of place to work in big buildings according to the task someone will perform. We highlight that even being less intrusive compared to active technologies (e.g., cameras), the use of passive sensors may also result in privacy concerns and, consequently, low acceptability from users. Therefore, it is the responsibility of professionals involved in this role to guarantee that privacy of users will be taken into account and users will be informed about what data are being obtained and how they are being used. Throughout this review, more topics regarding privacy concern are discussed, and possible solutions are presented.

2.2.2. Active sensors

While passive sensors can be supplied with external power forces (e.g., radio frequency or infrared-emitting source), active sensors need internal power and, in some cases, they can convert energy from the sensing parameter into electricity to keep operating. Nakahata *et al.* (2017) show that there are two main kinds of active sensors: those that use self-generated signals to probe the environment; and those that use self-motion to sense the variables. Therefore, this section shows the main findings related to both categories of active sensing, including technology able to generate power and probe the environment at the same time.

Active sensor networks can monitor and control sensed data (MOSLEH; TALIB, 2017) and are essential for better managing building performance (OSIEGBU *et al.*, 2015). In this regard, electricity load monitoring – e.g., smart plugs and bidirectional triode thyristor (PETROVIC; MORIKAWA, 2017) – plays an important role allowing indirect estimation of human activity and occupancy (ROSSIER; LANG; HENNEBERT, 2017); and sensors with active radio-frequency identification can be installed in pipes to infer human behaviours related to water consumption (TSUKIYAMA, 2015). Once occupancy or activity recognition are important to improving smart-building performance (such as Active and Assisted Living environments (MACHOT *et al.*, 2017)), there are many ways for actively probing that:

- Active sensing may detect human presence by emitting beams of light with photoelectric sensors (O'BRIEN; KATKOORI; ROWE, 2015) or by estimating acoustic properties impacted by people presence with ultrasonic chirps (SHIH; ROWE, 2015);
- Solutions as pan-tilt camera coupled with laser rage sensor (SUN; SHIMOYAMA; MATSUHITA, 2018) or coupled with zoom system (SHUMAKER; LACKEY, 2015) can adapt themselves to best sense human presence;
- Infrared motion sensors coupled with servo motor change their field of view to sense a greater area (MA; HU; HAO, 2017);

- Estimote stickers and beacons enabled with Bluetooth Low Energy system are able to recognise occupancy and human motion (MOHEBBI; STROULIA; NIKOLAIDIS, 2017); and
- Ultrasonic active sensing is a high-quality solution to detect specific human movements as hand gesture (SANG; SHI; LIU, 2018), which may benefit smart buildings if human movements could control systems.

Besides active sensors that rely on external power to probe the spaces, there are these categories of active sensing (active transducers) that convert energy of one form into another: e.g., nanostructured piezoelectric transducers can convert energy from slow fluids like human breath (BICCARIO; VITTORIO; D'AMICO, 2017) and energy associated with human walking (PROTO *et al.*, 2017) to electric energy. Harvesting such biomechanical energy can enable self-powered devices for personalized monitoring. Similarly, a high number of nanogenerators can create power from human blowing and conversation (ALAM *et al.*, 2018), human motion (CHENG *et al.*, 2015; MA *et al.*, 2018; PENG *et al.*, 2016), and touches, impacts, vibrations or pressures (GARCIA *et al.*, 2018). Therefore, this kind of nanogenerators enable the creation of self-powered sensors and can be used to track humans (LIU *et al.*, 2017) or even be applied in fabrics to charge wearable devices like smart clothes (KIM *et al.*, 2015; SEUNG *et al.*, 2015), and allow motion monitoring and improve human-machine interactions (DONG *et al.*, 2018). As human-centred body sensor network presents interdisciplinary advantages (MIAO *et al.*, 2018), other kinds of wearable devices rely on active sensing technology and improve smart buildings or healthcare performances. Intelligent wristband devices that sense wrist skin temperature and heart rate can be used to control HVAC according to people's thermal sensation (LI *et al.*, 2018); BLE-enabled wearable device coupled with accelerometer detect elderly falls (SPRUTE *et al.*, 2015); and wearable active voiceprint sensor can recognise human voices, which is a great solution to control devices (LI *et al.*, 2017).

Additionally, active sensing favours the creation of intelligent devices (such as smart floor, smart shoes, smart TVs, etc.) (FRONTONI *et al.*, 2017), which can allow for improvements on building technology or advances in the field of robotics. In this regard, occupant-centred control of buildings may rely on robots to sense human needs in real-world situations. It would be helpful in healthcare centres to improve the life quality of people who need constant attention. Considering this situation, the active sensing loop used for autonomous lifelong learning in robots are helpful as it allows them to acquire new abilities over time (FRANCHI; MUTTI; GINI, 2016). Moreover, mobile robots can collect much more data in comparison with static ones as they can look for information inside the buildings (WANG;

VELOSO; SESHAN, 2016), and this is a great way to sense intended variables actively. Robots can recognise daily activities in homes when given movements similar to humans' (NAKAHATA *et al.*, 2017), understand specific actions as hands' movements (ITO *et al.*, 2016), or detect and track people by involving both humans and robots in the loop (ROSSI *et al.*, 2015). However, there are uncertainties related to robots' confusion with the surrounding environment and furniture that may affect the sensing performance (YU *et al.*, 2017). In this regard, Kinect technology (presented in Section 2.3) can be used in the role of robotics as well due to their features that provide a range of applicability. Thus, a different cognitive architecture may allow robots to sense the world similarly to humans (BENJAMIN; LYONS, 2015), and context-dependent active controller based on human sight has been provided to solve this problem (YU *et al.*, 2017). As a final remark on this subject, it is important to state that robots are a great way to sense environments actively, and their inclusion should be considered during the proposal of solutions to improve user-centred services, mainly for those with special needs.

2.3. Kinect technology

Although many sensors have already been used in the field of human-building interaction studies, innovative ways of studying human behaviours help to understand both verbal and nonverbal psychological factors that lead to a behaviour (CIPRESSO; IMMEKUS, 2017). Kinects are an example of a dependable feature to assess high-quality behavioural data, which benefit cognitive science research and sensitively address behavioural patterns (ROLLE; VOYTEK; GAZZALEY, 2015). The principle of Kinects relies on Structured Light Scanners that actively illuminate scenes to probe the environment (KALANTARI; NECHIFOR, 2017), which is also a useful strategy to control systems with occupants' data as triggers (OGAWA; MITA, 2015). Some constraints about using them have been presented: privacy and security fears about using Kinects are cited as data of individuals and their environment are exposed (JANA; NARAYANAN; SHMATIKOV, 2017); also, the sensed data is limited to the equipment field-of-view, which may reduce both quality and quantity of the gathered data (TIRKEL *et al.*, 2018). However, Kinects provide different features (Depth, Skeleton, Microphones, and RGB cameras) (TRAN *et al.*, 2017), and this allows a variety of applications to solve specific problems. Regarding privacy, solutions like installing Kinect cameras in the ceiling to track people and calculate occupancy without recognising them (PETERSEN *et al.*, 2016), and using skeleton data (MIZUMOTO *et al.*, 2018) or depth registration (DZIEDZIC; DA; NOVAKOVIC, 2018) to study human behaviours and posture are effective in reducing privacy issues by minimising the chance to recognise people. Concerning field-of-view limitation, one may include enough number of sensors to probe the whole environment or consider the inclusion of some servo motor as presented in the passive sensor subsection.

All the features of Kinect technology have been used in studies regarding the human dimension of building performance. Depth cameras can infer occupant's location (PAZHOUMAND-DAR; LAM; MASEK, 2016), detect the presence of a group of people and characterise collaborative tasks (SEVRIN *et al.*, 2016), detect activity and recognise human postures (HO *et al.*, 2016), and infer nonverbal communication as body motion in joint actions (GAZIV *et al.*, 2017). Skeleton positions in 3D coordinates can control devices using gestures (BALAJI *et al.*, 2018; FERNANDEZ *et al.*, 2015), recognise people's activities (COSTA; TRIGUEIROS; CUNHA, 2016; FONG *et al.*, 2017; MIZUMOTO *et al.*, 2018), and infer body motions (TAMEI *et al.*, 2015) and postures (FRANCO; MAGNANI; MAIO, 2017). Microphones of Kinects can be used as voice receiver (RATHNAYAKE *et al.*, 2016) and control home appliances through voice recognition (IQBAL *et al.*, 2016), or recognise activities in offices with audios (DING; LIU, 2016). RGB cameras can also be used when people (GOSSEN, 2015) or people's emotions (KITA; MITA, 2015) need to be recognised. As a general trend, for people recognition, Kinect technology is often associated with probabilistic models as presented in (DUBOIS; BRESCIANI, 2015).

Finally, following the concept that robots can act as active sensors in buildings and improve user-centred services, it is worth mentioning that Kinect technology can be included in this role as well. Besides Kinects suit sensing needs in robots (IIDA; MITA, 2017), they are also a dependable feature to improve the reliability of sensed data when combined with probabilistic approaches (LIU *et al.*, 2018). Additionally, Kinect-based control for robots can improve the quality of human-robot communications: e.g., one may consider Kinects as a way to control robots with hand gestures (WU *et al.*, 2015). Those applications could deliver user-centred services when necessary, which can increase human approval over smart systems.

2.4. Internet of Things (IoT)

By all means, evidence supports that to monitor as much as possible each part of a building helps to form knowledge about all the related aspects regarding building performance. For instance, data may confirm that some adverse outcome is user-driven, while other is a system malfunction; therefore, gathering information is an important way to find solutions for each problem. As shown before, many sensors fit the expectations related to human-building interaction monitoring or whatever different aspects stakeholders may consider appropriate. In this sense, a stronger concept is joining lots of sensors to monitor various aspects of a building, which is allowed by the application of the Internet of Things (IoT) technology. IoT-based systems rely on the interconnection of everyday objects (CHEW *et al.*, 2017), which links persons and organisations and improves management and distribution of energy in both building and city levels (HAASE *et al.*, 2017). Although promising, its cost is a negative hindrance (PARK *et al.*, 2017), as well as the fact that most IoT devices are battery-powered so may fail during operation (GALININA *et al.*, 2015), and its acceptance depends on people's trust on the system (ALHOGAIL; ALSHAHRANI, 2018). However, as this technology is still in its early stages, infeasibility due to the high cost should be overcome shortly.

Additionally, regarding the lack of power during IoT devices usage, it is necessary to expand their lifespan as long as possible and also calculate the correct number of sensors in a system to reduce the constraint of batteries dying. Regarding trust, Digital Forensic play an essential role in IoT-based environments (KEBANDE; KARIE; VENTER, 2018) as it pinpoints changes in data receipt (RADOVAN; GOLUB, 2017), and people may feel safer to adopt this technology. Since the benefits of ubiquitous computing in observing human behaviour in indoor environments (HANSEN, 2016), three main aspects enabled by IoT technology are presented in this section: real-time monitoring, behavioural-based consumption change, and user-centric Energy Management Systems.

Real-time monitoring of environmental data or comfort parameters can be linked to occupancy (SARALEGUI; ANTÓN; ORDIERES-MERÉ, 2017), or occupant behaviour (ANDREI *et al.*, 2018); as well as people's comfort levels can be inferred from their attitudes (BOURELOS *et al.*, 2018). Device-free occupancy estimation has been proposed by analysing the channel state information, and it shows the effects of the physical environment on wireless signals and enable occupancy counting through the impact of people's body on wireless propagation (YANG *et al.*, 2018). IoT-enabled wearable devices – and also devices that people carry with them during the day like cell phones – are useful for sensing both inside parameters (like electrocardiogram monitoring (SPANÒ; PASCOLI; IANNACCONE, 2016)) and outside parameters (like HVAC exposure (HAPPLE *et al.*, 2017)) related to people activities. Such approaches can provide location-aware (MORENO; SKARMETA, 2015), user-behaviour-aware (HUANG *et al.*, 2015) or occupancy-aware (CARVALHO *et al.*, 2017) services. This concept relies on information from previous sections of this review, as a variety of sensors can be used in such IoT-based environments to provide reliable real-time monitoring. All those real-time monitoring features enabled by IoT adoption in buildings provide a basis to deliver high-quality services to users. For doing so, by continually gathering data, behavioural-based interventions can be successfully achieved to reduce energy consumption and increase indoor quality levels, as people may know to what extent their interactions impact building performance.

Understanding human behaviours are critical to achieving behavioural-based consumption change. As human behaviour plays an important role in building performance, activity recognition is important to empower energy-efficient and user-satisfying services (KHAN; ROY, 2018) and also Assisted Living Environments (AL-SHAQI; MOURSHED; REZGUI, 2016) in the IoT era. In this regard, IoT-enabled buildings collect behavioural data throughout their operation as products and devices are active agents and provide data continuously (MATEI *et al.*, 2016). IoT-based solutions can give feedback regarding different aspects of building performance like indoor (CASADO-MANSILLA *et al.*, 2018) and outdoor conditions (BELLAVISTA; GIANNELLI; ZAMAGNA, 2017), water (REHMAN *et al.*, 2018) and energy consumption (MYLONAS *et al.*, 2017), or problems in the systems (DHOBI; TEVAR, 2018). Such feedbacks enable behavioural-based consumption changes and may solve the problem of sloppy end-users in automated buildings (JACOBSSON; BOLDT; CARLSSON, 2016).

Similarly, smart (or “enchanted”) objects can persuasively communicate to humans and change behaviours (HUANG, 2016) as well. However, the role of feedback has been reported as a tedious activity (LU, 2018), so rewarding or gamification approaches can reduce this problem (FERREIRA *et al.*, 2018). Interestingly, besides users having feedbacks from objects and systems, IoT technology also allows systems to get feedback from users to deliver personalised services (BANSAL; CHANA; CLARKE, 2017; DAS; MUKHERJEE, 2017; SHIREHJINI; SEMSAR, 2017). Therefore, the importance of feedbacks in IoT-based environments is twofold: users may give feedback to smart systems adapt themselves to human needs, and smart systems may give feedbacks to users adapt their behaviours to achieve higher energy efficiency levels. In this way, high-quality and low-energy buildings can be delivered to the society. Although widely related to IoT-based systems, the role of feedbacks is discussed in the human-in-the-loop subsection of this paper as well, as both cases can improve their performances through feedback inclusion.

User-centric building management provides steps to save energy and raise environmental consciousness (MORENO; ZAMORA; SKARMETA, 2015), and the steps may be provided using human interfaces devices like mobile phones, tablets, personal voice assistants (DHOBI; TEVAR, 2018; PETNIK; VANUS, 2018). Including human behaviour evaluation and feedbacks, Energy Management Systems can boost their performances. As buildings are socio-technical systems that integrate heterogeneous entities (sensors, actuators, devices, occupants, etc.) (BAKHOUYA *et al.*, 2017), IoT structures allow evaluating, redesigning and improving managerial measures (ZHU; ANAGNOSTOPOULOS; CHATZIGIANNAKIS, 2018). Using this innovative technology allow providing context-aware user-centric building management systems as IoT technology can bridge the gap between expected and delivered services as it considers real-world data to provide personalised services. Regarding smart building management, individualised approaches can use activity recognition (GARIBA; PIPALIYA, 2016), combine people and processes monitoring data (FERREIRA *et al.*, 2018), human behaviour and environmental data (SEMBROIZ *et al.*, 2019), human behaviour and trends in energy consumption (FOTOPOULOU *et al.*, 2017), or combine energy production and consumption data (BELLAGENTE *et al.*, 2015).

Henceforth, IoT-based solutions are expected to increase the performance of buildings considering both quantitative aspects (operation of systems like HVAC) and qualitative aspects (indoor environmental quality delivered to the users). For doing so, all the three main elements presented in this section seem to be integrated, as shown in Figure 2.3. With real-time monitoring of indoor conditions or building operation, behavioural-based consumption change may be achieved as users can be informed about their influence on the building performance. This combination, in turn, enables user-centric Energy Management Systems, which can choose the best solutions aiming to reduce energy use while still considering the human dimension of building performance and delivering high-quality indoor environments. In this aspect, a promising concept is to integrate as much as possible each part of the IoT-based system with one another. As smart devices can mimic human behaviour and interact with each other (KOMAROV; KONOVALOV; KAZANTSEV, 2016; XIAO; SIDHU; CHRISTIANSON, 2015), in the near future IoT networks are expected to have a certain degree of consciousness (JUNG *et al.*, 2018), and this concept is called Social Internet of Things. By integrating all the possible aspects of people in technologies like IoT, future advances are expected to focus on the insertion of the human dimension.

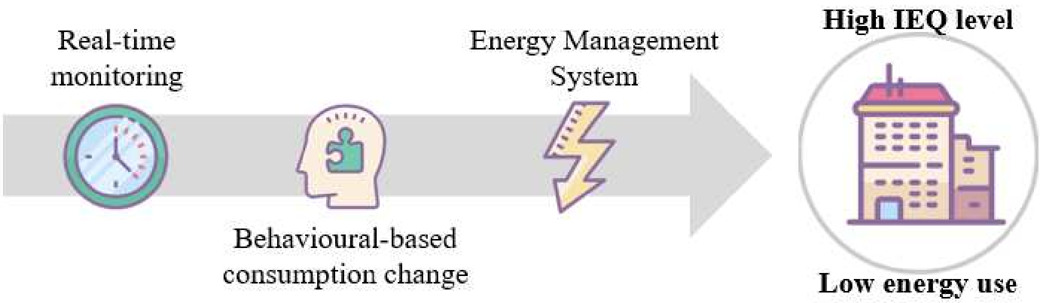

Figure 2.3. Integration of the three main aspects related to IoT-based buildings considered in this review.

2.5. Human-in-the-Loop

Including humans in decision-making processes of buildings is highly desired, as eliminating humans from the control is almost impossible (BISADI *et al.*, 2018). In this aspect, an alternative is to contemplate a human-in-the-loop (HITL) component for buildings and systems design and operation. In HITL systems, human needs are placed as the central point for energy optimisation (ZEILER; LABEODAN, 2019), and even building management does not need an explicit model of human behaviour as it indirectly receives this information according to occupant iterations (EICHLER; DARIVIANAKIS; LYGEROS, 2018). Including human knowledge/needs/preferences in the loop is very important to achieving high-performance buildings throughout the operation phase as rooms may be used for different purposes, occupants and their preferences may change, and ageing may affect building and systems' performances (KIM *et al.*, 2018a). Additionally, HITL can allow consensus-based decision instead of pre-established rules and such decentralised control may minimise conflicts as control strategies are given for each piece of equipment (SEITZ *et al.*, 2017). As buildings are emerging as complex systems, if HITL is linked to advanced sensing technologies (like IoT) and modern building management systems, a hybrid adaptive control can be used to sense, actuate and manage in dynamic ways to enhance energy efficiency (BISADI *et al.*, 2018), which can result in comfort-aware systems (JUNG; JAZIZADEH, 2019). For doing so, humans can be put in the loop in buildings' contexts using different approaches.

Although complicated and hard to predict, occupant behaviour provides valuable insights that can be converted into knowledge for systems. Thus, a highly documented approach to include humans in the loop of buildings is by giving them constant information or feedbacks. Figure 2.4 shows the twofold relation of feedbacks: both building-to-users and users-to-building feedbacks can be used to provide knowledge and improve building performance. Along these lines, building managers and occupants can interact to each other through gamification approaches: giving support for users to reduce energy consumption and rating them according to the results can stimulate competitive aspects and achieve individual motivation (KONSTANTAKOPOULOS *et al.*, 2019). Feedbacks are vastly denoted in the literature as a way to integrate social science approaches to technological solutions and reduce the energy consumption in buildings as they influence users' attitudes towards systems' control in a building (EICHLER; DARIVIANAKIS; LYGEROS, 2017).

However, if occupants are not allowed to adjust systems in smart buildings, such feedbacks will be omitted (LAZAROVA-MOLNAR; MOHAMED, 2017), and a massive amount of knowledge about control boundaries may be lost. From feedbacks, one may obtain:

real-time thermal comfort levels reported from users (GUPTA *et al.*, 2018), real-time lighting conditions combined with photographs for decision-makers to control the environment (TAN *et al.*, 2018), useful information inferred from users iterations – as locations inside buildings captured from feedbacks given through smartphones (CAMBEIRO *et al.*, 2018). Even in automated buildings, where users do not control the systems, including human dimension in systems' adjustments through feedbacks can increase the perceived control, which is related to higher satisfaction levels in offices (BOERSTRA; LOOMANS; HENSEN, 2014; GUO; MEGGERS, 2015; LANGEVIN; WEN; GURIAN, 2012). Besides high-involving approaches, sending hints for users to better control systems is a way to include humans in the loop and improve the energy performance of buildings as well; this is great because user autonomy and sense of control are maintained.

Additionally, the role of hints gives support to improve building operation as understanding if a not-accepted hint was undetected, ignored or rejected can drive important conclusions (DOMASZEWICZ *et al.*, 2016). Inferring metabolic rates from wearable sensors (measurements of heart rate, activity level, and caloric consumption) to calculate appropriate predicted mean vote (PMV) of thermal comfort is also a way to include humans in the loop of HVAC control without bothering them (HASAN; ALSALEEM; RAFAIE, 2016). Even without asking for feedbacks, humans can be put in the loop with non-intrusive sensors to infer human-building interactions and adapt automated building controls according to activity recognition (KHAN *et al.*, 2016). Thus, more than capturing information about HITL components, it is necessary to produce knowledge about understanding and modelling behaviours of humans in the loop as well (WURTZ; DELINCHANT, 2017).

Such approaches play an important role in building performance simulation, as robust models of human behaviour can be used for the design of renovations and retrofits (STAZI *et al.*, 2018) because it could determine which changes in building characteristics would impact on human practices in those models. In this regard, one may consider it as user-centred simulation-based retrofits. For doing so, a great way is to combine Agent-Based Modelling (ABM) with usual Building Performance Simulation (BPS) approaches, because sometimes BPS fails to consider occupant behaviour and ABM can capture occupants' actions but lacks reliable ways to measure the performance of building systems (PAPADOPOULOS; AZAR, 2016).

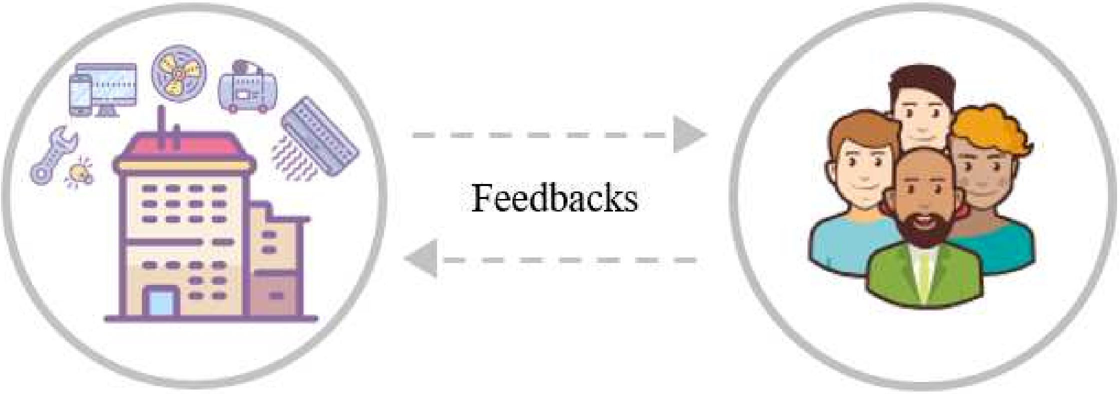

Figure 2.4. The role of feedback to improve user behaviour and system performance.

Besides the feedbacks from human-building interactions, HITL approaches may also consider the role of data gathered throughout building operation. As points of smart buildings connect cyber and physical worlds, there are vast amounts of data obtained all the time. This big data, which can be translated into metadata to interpret them and discover needs quickly (KOH *et al.*, 2018), provide significant insights to building management. Similarly, valuable insights can be found if small and big data are combined: specific information from each sensor during one day, for example, with massive datasets about the whole-year energy consumption (ZEILER; LABEODAN, 2019). In this regard, a HITL component can also be considered to improve building performance: by providing knowledge from data to users, they can start caring about their impact on the building performance (HOLMEGAARD; JOHANSEN; KJAERGAARD, 2017), which is very important because even all the efforts to achieve "smart buildings" may be insufficient without "smart users" (WURTZ; DELINCHANT, 2017). Users must be active agents in buildings rather than passive recipients (DOMASZEWICZ *et al.*, 2016), so they should interact with all those data and use them in the best way possible. Nonetheless, systems' performances are strongly linked to the way people will understand and interact with them, so data interpretation is fundamental to achieve higher performances in HITL-based systems. As different charts provoke diverse insights about the data, it is important to understand the knowledge and familiarity of users with these aspects to address the best changes. Thus, if people's insights are included in next generation of data/presentation, a HITL data generation will be achieved in preliminary stages of a HITL system, which can outperform the expectations (KANDOGAN; ENGELKE, 2018). Additionally, such a HITL data analysis approach could solve real problems that users consider significant for them in their buildings. Therefore, although poorly explored yet, this is a prominent subject, and it opens the door for the development of theories about human-data interactions (DOAN, 2018).

As a final remark on this topic, HITL components are important in the cyber world as well: cognitive and physical functions from humans and machines can be linked to consider the human dimension and improve outcomes in the physical world (BOY, 2018; GUO *et al.*, 2015). Such HITL component in artificial intelligence is useful to solve complex problems because the way humans approach problem-solving situations can be translated into knowledge for machine learning creation (KOTTKE *et al.*, 2018) or even to develop collaborative tasks between humans and robots (NEGRUT *et al.*, 2018). A problem that different stakeholders may face in the future regarding this topic is related to the extent credits should be given to the humans involved in the knowledge production (ZANZOTTO, 2019). Regarding fully automated buildings in the future with high integration of humans and machines, a great way to put humans in the loop is including them in the decision-making. In this regard, a practical HITL approach can share decision-making process between humans and machines: while humans can focus on IEQ quality, machines can be responsible for complex dynamics in HVAC system, energy storage and generation (KANE, 2018).

2.6. Virtual Reality and Immersive Environments

Psychological Science has been widely involved with research about human cognition and behaviours. For doing so, researchers usually apply well-known approaches like questionnaires or interviews. Those methods from Social Sciences play an essential role in this regard, but such self-reported outcomes may present biases (Social Desirability Response) and do not represent the actual user behaviour (WAGNER; O'BRIEN; DONG, 2017). Although people may change their behaviours when observed (issue reported in the literature as "Hawthorne effect" (WAGNER; O'BRIEN; DONG, 2017)), current technology may play a role to obtain people's actual behaviours instead of their opinions about their behaviours (CIPRESSO; IMMEKUS, 2017). An example of this is the use of Virtual Reality, which fits perfectly in Quantitative Psychology Measurements as it allows the creation of realistic situations to understand human needs and behaviours (CIPRESSO; IMMEKUS, 2017; ZHU *et al.*, 2018). Virtual Objects (KIBRIA *et al.*, 2017) and Virtual Environments (VEs) enable longitudinal studies of human preferences or behaviours in short-term experiments (SAEIDI *et al.*, 2018), as a lot of conditions can be included in an experiment. Also, expensive-real-world experiments can be replicated in VEs to reduce the study cost (SAEIDI; ZHU; CHOKWITTHAYA, 2018). Besides such a promising potential, the use of VEs to study human needs/preferences/behaviours in buildings is still in its early stage: while researchers of human behaviour generally develop predictive models, researchers of VEs are still looking for evidence that VEs are good enough to represent people's behaviour by comparing to in-situ evaluation outcomes (ZHU *et al.*, 2018). Currently there is evidence that results regarding thermal comfort and thermal sensations from both virtual and real-world scenarios are similar (OZCELIK; BECERIK-GERBER, 2018; SAEIDI *et al.*, 2017, 2018); however, there is still need to increase the knowledge about this technology.

Although there are advantages, the literature also confirms that VEs-based experiments are related to a lot of concerns regarding different aspects of their performance. Thus, we identified the main concerns presented and found possible solutions as well. Besides cheaper in some cases, short-term experiments with VEs produce a much lower amount of data compared to usual real-life approaches as sensor-based monitoring. Thus, mathematical models – such as the Hidden Markov Baum-Welch algorithm – can learn from VEs-based outcomes and estimate or generate new data for studying hypothesis (CHOKWITTHAYA *et al.*, 2018). Additionally, issues related to the use of VEs are still occurring, like participants do not feel relaxed, cosy and pleasant compared to the way they feel in a real-world experiment (SAEIDI *et al.*, 2015), or having cyber sickness (ZHU *et al.*, 2018) or motion sickness (HEYDARIAN *et al.*, 2015b) during those experiments. Thus, excluding people with those tendencies and controlling time to have quick VE-based tests are important to obtaining reliable results. To understand the extent people may feel sick using VEs, the Simulator Sickness Questionnaire (ZHU *et al.*, 2018) can be applied to participants before the experiment. Furthermore, wearable devices can affect human perception of the environment (YEOM; CHOI; ZHU, 2017), as the exact representation of real situations in virtual scenes is a limitation (HEYDARIAN *et al.*, 2016). Then, if more natural VEs are created, people have better experiences, and more positive outcomes can be achieved (WAGLER; HANUS, 2018). However, the more realistic, interactive and immersive the VE, the more expensive the experiment becomes (SAEIDI *et al.*, 2018). This opens room for discussions about "sufficient representation of reality" (CIPRESSO; IMMEKUS, 2017) – authors show that the representation must be enough to evoke similar responses compared to real environments; thus the level of details must be related to the research purpose. In this regard, critical aspects found in the literature that are likely to affect the performance of VEs include the sense of presence as users must feel like being present in the space (CIPRESSO; IMMEKUS, 2017; MATSAS; VOSNIAKOS, 2017; OZCELIK; BECERIK-GERBER, 2018), situation awareness (MATSAS; VOSNIAKOS, 2017), immersion (HEYDARIAN *et al.*, 2015a; NIU; PAN; ZHAO, 2016; ZHU *et al.*, 2018) and interactivity (NIU; PAN; ZHAO, 2016; OZCELIK; BECERIK-GERBER, 2018).

As building systems are influenced by and also influence human behaviour (UNGUREANU; HARTMANN, 2018), different stakeholders related to building design and operation can improve their practices with the advent of Virtual Reality in discovering human preferences and feelings (HEYDARIAN *et al.*, 2015b; KAN; KAUFMANN, 2018), which can be translated into design boundaries (HEYDARIAN *et al.*, 2017; HEYDARIAN; BECERIK-GERBER, 2017) or strategies for improving building performance. VEs were used to collect information about user behaviour or needs related to light preferences (HEYDARIAN *et al.*, 2015a, 2015c, 2016, 2017; NIU; PAN; ZHAO, 2016), window-blind adjustments (SAEIDI; ZHU; CHOKWITTHAYA, 2018), people's natural movements (VILAR *et al.*, 2015), body and brain outcomes using biosensors (CIPRESSO; IMMEKUS, 2017) and electroencephalogram-based measurements (ZHANG *et al.*, 2018), and crowd behaviours (DICKINSON *et al.*, 2018; JORJAFKI; SAGARIN; BUTAIL, 2018). Real-world tendencies like behavioural contagion were also observed in VEs (JORJAFKI; SAGARIN; BUTAIL, 2018), which indicate that social proof is impactful in VEs. It opens room for the need to understand the extent to which virtual characters can impact others' behaviour by social influence. In this regard, virtual characters also play an important role, as recommender systems (generally related to shopping behaviour (CHOU *et al.*, 2016)) can be used in the energy research field to give recommendations for users and pro-environmental behaviours can be assessed (KHASHE *et al.*, 2015, 2017). Regarding pro-environmental requests, Khashe *et al.* (2017) found that the person who gives the recommendation in VEs impacts the result: a request from the building manager, for example, may be better to evoke social norms of compliance in comparison with the building itself presenting a request in VEs through a text balloon. Besides the importance for estimating the human dimension of energy consumption during the operation phase, VEs also allow pre-occupancy evaluations, and if the future occupants are known both the design and the energy consumption estimations can be improved (NIU; PAN; ZHAO, 2016). Those evaluations are helpful to create models for building performance simulation that considers future-user behaviours, which could bridge the gap between estimated and measured energy consumption during operation phase (HEYDARIAN; BECERIK-GERBER, 2017).

Following the trends found for the other innovations in this literature review, Virtual Environments are also a key technology to improve robots abilities (MATSAS; VOSNIAKOS, 2017). Camera-based robots can capture images from environments while humans analyse it in VEs and mathematical models transform it into robot controls (DU; SHENG; LIU, 2016), which can benefit occupants with special needs as those in Assisted Living Environments. Additionally, gamification is an important feature for VEs as it can encourage people to perform specific behaviours, while VEs can capture this and transform it into knowledge to improve robot abilities by observing humans (KASHI; LEVY-TZEDEK, 2018; WALTHER-FRANKS *et al.*, 2015).

3. Discussion

This literature review has shown the benefits of technology adoption for different concerns related to building performance. High-IEQ-level and low-energy buildings are aimed with all those approaches. It is important and very expected as modern societies spend much time inside buildings, so buildings could contribute to both improve people's welfare and achieve targets of decarbonisation through energy efficiency. Therefore, given the extent that innovative technology may be applied in the context of building design and operation, it is important to inform different stakeholders about the suitability of various innovations. As buildings are emerging as Cyber-Physical-Social Systems, the three dimensions involved must be included in the loop of building performance. Along these lines, Figure 2.5 shows the reviewed aspects that can be added to contemplate better the human dimension of building performance. By informing all the stakeholders about what technology may fit their needs, upcoming buildings could rely on technological innovations to overcome known problems. In this regard, besides technology developers and vendors, building designers, operators, managers, and occupants must understand how the equipment work to obtain the best outcomes from them. Therefore, this section highlights the main benefits and constraints related to the technologies reviewed, aiming to inform a broad public involved in the role of building performance.

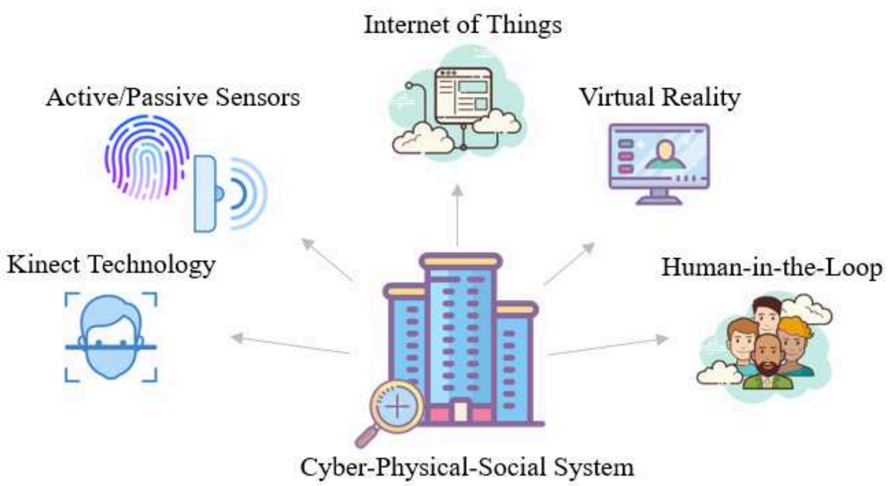

Figure 2.5. Technologies related to the role of transforming actual buildings into Cyber-Physical-Social Systems.

3.1. Worthwhile applications of technology during building design and operation

As buildings are emerging as Cyber-Physical-Social Systems (CPSSs), all the dimensions – e.g., artificial intelligence, building systems, and users – must be considered in the role of building performance. In a Cyber-Physical-Social context, a digital measure of a physical feature may be obtained with the necessary/feasible granularity. All of this can provide enough knowledge to understand to what extent the social dimension interferes on the physical one, and what are the outcomes on building performance. About monitoring, numerous applications of Passive Sensors have been shown in the literature. Generally, this feature is characterised as a low-cost option – considering both purchase and maintenance, as it does not consume much power to function. Therefore, broad applications of passive sensors were found: either considering specific attitudes as eating behaviours or regarding a whole automation system. Active Sensors can probe numerous aspects as well, including specific behaviours and entire systems function. However, a great advantage related to their usage is the possible conversion of energy from one to another form. It is the case of nanogenerators that can be used in smart clothes or things that people use. Such applications would exponentially increase the knowledge generation about the influence of people physiological aspects on their behaviours and how buildings can be designed and controlled to deliver user-centred services. Also, Kinect Technology provides a variety of features – Depth, Skeleton, Microphones, and RGB cameras – convenient in the role of the human dimension of building performance. Therefore, it is possible to use the most suitable feature (or combination of elements) according to the stakeholder need: one may use the Microphones to control building systems while others may consider the Skeleton scanner for doing so. In this specific situation, the singular needs of a user or a group of users may play a role in such a decision.

Although the benefits provided by each behavioural sensing technology presented in this study, combining different technologies is even more likely to result in a great outcome. Internet-of-Things (IoT) technology enables to associate as many sensors as possible/feasible, which is important to gather knowledge about building performance relying on the interconnection of everyday objects (CHEW *et al.*, 2017). An IoT-driven system would allow collecting a considerable amount of data, which we found to be related to a three-aspect improvement for future buildings. First, real-time monitoring – allowed by all the sources of data (sensors) included in such a system – provides essential knowledge related to building performance. Data allow understanding which of the adverse outcomes is due to system malfunction and which is user-driven. Second, if user-driven failures are identified, IoT-driven systems provide remarkable opportunities to consider behavioural-based consumption change, as users may be involved in the role of building performance through different approaches as feedbacks, gamification or pro-environmental requests. Third, the inclusion of an IoT component in buildings is also important to improve Energy Management Systems, which can solve problems of a system malfunction in smart buildings and include the users in the role of Energy Management as well. It would benefit the creation of user-centred and context-aware Energy Management Systems.

Regardless of the aspect presented as valuable for IoT-driven systems, it is evident that with a Human-in-the-Loop (HITL) component it is possible to maintain low energy consumption levels and improve the Indoor Environmental Quality according to specific human needs. Even in fully automated buildings, humans can be put in the loop of control, which is a way of sharing decision-making with them and increasing people's sense of control over the building systems. A fundamental aspect related to the inclusion of a HITL component in buildings is through feedbacks. The role of feedbacks was found to be twofold: it can come from building systems to users and from users to building systems. By providing knowledge from one to another, both human and machine bits of intelligence can be combined to achieve better outcomes. Additionally to this topic, this literature review highlighted the possible inclusion of human intelligence in the generation of feedbacks from building systems. If the human capacities are considered during the feedback generation, the most effective results can be achieved, as stakeholders can understand what kind of feedback works the best for each group of people.

Finally, Virtual Reality (VR) and Immersive Environments (IEs) were shown as strategic tools during building design. Such technologies allow understanding human behaviours and needs in short-term experiments or even to replicate expensive real-life experiments in low-cost ways. The knowledge obtained with those approaches can be translated into design boundaries as human preferences play an essential role to deliver user-centred buildings. Additionally, VR can improve building performance during its usage as well: e.g., the inclusion of a virtual component in Building Energy Management can drive substantial changes in the role of energy consumption through personalised requests.

3.2. Main challenges to apply technological innovations

Although conclusively promising, the use of technology related to the human dimension of building performance has to overcome some challenges. Firstly, as some technologies are still in their early stage, their high cost is a hindrance, as people may feel unsure about the benefits of investing that money. Secondly, privacy issues are denoted in the literature as a current problem. As the role of IoT-driven society is emerging recently, sensing each part of a building and gathering data from different behaviours may leave occupants insecure about the trust in the system. To reduce this problem, professionals involved in this role may use technologies in less-intrusive ways, i.e. gathering only data that are really necessary is a way to reduce this issue, as well as reducing people recognition opportunities when this feature is not necessary. Both high cost and privacy concerns may lead to low acceptance levels reported by people, which opens the door to assess this limitation through a multidisciplinary lens. As the combination of varied expertise can bridge the gap between technology creation and adoption, theories and models from multidisciplinary effort can drive exciting findings related to this topic and developers of building technology should rely on this knowledge to improve their products. If technology adoption is increased, both high cost and low trust in such innovations can be enhanced: as the industry would produce in large scale, the price could reduce; as more people would be in contact with them in a daily basis, trust levels could be increased.

Additionally, as presented throughout the paper, the use of technology innovations may fail in specific situations. This is the case of passive sensors, which fail to recognise stationary objects and can result in inadequate control of buildings or systems (e.g., “false-off”). Considering all the behavioural sensing presented, a well-known concept that may play a role in this field is the “Hawthorne effect”, which explains that people may change their spontaneous behaviours when being observed. This issue is even more expressive in short-term experiments, considering that in long-term ones people may forget about the monitoring over time. Therefore, future research may investigate to what extent occupant behaviours are affected by sensors deployment. Furthermore, virtual-based experiments (as those conducted in virtual/immersive environments) can result in cyber and motion sickness. These issues have to be studied in depth to obtain conclusive insights and continually improve experiment practices. Finally, this literature review also highlighted that people may not feel relaxed, cosy and pleased in virtual-based experiments compared to real-life ones.

In general, the role of technology creation and adoption is related to different stakeholders of buildings. For instance, even with a considerable effort of the technology industry on creating promising technologies to improve building performance, no application will be made without involving building designers, owners, operators, and managers. Therefore, the usage of technology related to the human dimension of building performance is partly dependent on each stakeholder involved in the building life cycle. Likewise, it is highly recommended that occupants of buildings that use such technologies should be continually informed about what kind of data are being collected and in what ways there are being used to improve building performance. This finding is congruent with evidence provided by D'Oca *et al.* (2018) regarding the need to educate key stakeholders related to their perspective on the human dimension of building performance. Likewise, critical stakeholders related to technology adoption in buildings must understand on their view to what extent they can benefit from technological innovations from now on.

4. Conclusions

This literature review aimed to highlight the broad applicability of technological innovations to understand the human dimension of building performance, as well as include it in the role of building design and operation, considering that buildings are emerging as Cyber-Physical-Social Systems. Therefore, up-to-date literature (from 2015 up to May 2019) was selected to determine the trends in this field. A general aspect of this review was the contemplation of the human dimension in all the technologies reviewed, either by considering specific human behaviours/needs/preferences or by including them in the decision-making of a fully automated system. Such a concept relied on the fact that technology alone does not guarantee energy-efficient buildings (HONG *et al.*, 2015a), because the human dimension of energy consumption is as important as the systems themselves (D'OCA; HONG; LANGEVIN, 2018). Therefore, including a social aspect in the loop of technologies is a way to achieve smart buildings enabled by "smart users" (WURTZ; DELINCHANT, 2017).

A benefit of including technological innovations in the role of building performance is the possibility to gather a considerable amount of data, which can be translated into knowledge as design boundaries or control needs/constraints. Behavioural sensing has been proved to impact the knowledge generation in this aspect positively. Therefore, stakeholders may choose the most appropriate features, and numerous technologies have and are being created in this concern: passive sensors are a low-cost solution considering both their purchase and maintenance, so a broad number of applications are enabled if constraints like failures to detect stationary objects (due to their dependency on others' body energy) are overcome; active sensors, even being more expensive, provide ample sensing opportunities and low-power energy generation as well, which can drive a change in occupant behavioural research as this technology enables smart objects to both sense and provide services to users; finally, Kinect technology provides different features (Depth, Skeleton, Microphones, and RGB cameras) and the combination of them offers excellent opportunity to deepen understanding of human behaviour/preferences according to specific needs.

A remarkable prospect found in the literature is the advances provided by IoT-driven systems, which enables the combination of as many sensors as one may consider necessary. It allows real-time monitoring and analysis that can boost building performance through behavioural-based consumption change by including occupants in the loop of building control. Such a concept fits perfectly in some user-centred Energy Management Systems as energy consumption can be reduced while high-quality indoor environments are delivered to users. A key aspect of delivering user-centred systems is the human-in-the-loop component provided by including human knowledge into building systems. It has been proposed mainly through feedbacks, both from building systems to users and from users to building systems. The combination of human and machine bits of intelligence are expected to solve different problems: mechanical-based controls may take care of technical aspects like the HVAC performance, while human-based controls may take care of indoor conditions. A final opportunity found is the inclusion of Virtual Reality and Immersive Environments in the role of building performance. Using those technologies provide insights into design boundaries and control strategies, and different stakeholders can apply up-to-date Virtual Reality and Immersive Environments to deliver user-centred services.

This new generation of smart buildings is promising to reduce energy use and enhance indoor quality levels. However, it is fundamental to determine the right amount of sensors as over installation may be expensive and pointless if unnecessary data are collected throughout the building operation. Thus, concise definitions about the right granularity and quantity of data are needed to boost technology adoption in different scenarios. Moreover, as many technologies are still in their early stage, some efforts are required to reduce their constraints. Understand the drivers of trust in those systems are important to creating and delivering systems in which users will feel safe during building operation. It opens room for multidisciplinary efforts regarding technology adoption and trust. Additionally, the vast amount of data gathered from the field should be assessed to provide valuable insights instead of pointless conclusions. Besides the technical aspects, a social dimension of data usage should be considered: as technological means are significantly impacted by their users, which can act as sensors/actuators as well (CAMBEIRO *et al.*, 2018), the accurate delivery of information can transform actual users into informed and conscious ones. It is also an opportunity for multidisciplinary effort regarding data interpretation, and it opens room for developing theories and models about human-data interaction (DOAN, 2018).

3. Literature review about qualitative methods that suit energy research

This chapter is the transcription of the following paper:

Methods used in social sciences that suit energy research: A literature review on qualitative methods to assess the human dimension of energy use in buildings

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Abstract

Different stakeholders are involved in the energy consumption in buildings: occupants, designers, managers, operators, policymakers, technology developers and vendors. Therefore, it is necessary to understand their opinions and needs to optimise the energy consumption in buildings during their lifespan. Questionnaires and interviews have been applied; however, the literature still supports that energy research lacks social science approaches to improve their outcomes. Although limitations are inherent in qualitative methods (e.g., social desirability bias), much information such as human needs, preferences and opinions cannot be obtained through quantitative methods like building monitoring. Therefore, to have a deeper understanding of human-related aspects regarding the energy consumption in buildings, this literature review synthesises opportunities and main challenges of applying methods commonly used in social sciences. We reviewed papers published over the last five years (from 2014 to 2019) and presented information about questionnaires, interviews, brainstorming, post-occupancy evaluation, personal diaries, elicitation studies, ethnographic studies, and cultural probe. Increasing use of qualitative methods is expected to support the spread of human-centred policies and design/control of buildings, with a consequent overall optimisation of energy performance of buildings as well as the comfort of occupants.

1. Introduction

Buildings are responsible for about 36% of the final energy use worldwide (GABC, 2019), which opens the room to find solutions for optimising their overall performance. Human-related aspects of energy consumption in buildings are highly denoted in the literature: among the six most influential factors for energy use in buildings – climate, building envelope, building services and energy systems, building operation and maintenance, occupant activities and behaviour, and indoor environmental quality – the latter three factors are related to humans (YOSHINO; HONG; NORD, 2017). Therefore, it is necessary to understand subjective aspects that lead to energy use in buildings: i.e., focusing on human-related aspects instead of only evaluating building physics (WOLFF *et al.*, 2017). An updated literature review concerning driving factors that influence occupant behaviour in buildings was presented (STAZI; NASPI; D'ORAZIO, 2017). Authors concluded that, despite the numerous studies and assessment methods, a standardised method to evaluate and model occupant behaviour is necessary. In this regard, the Annex 66 project represented significant advances in the role of occupant behaviour understanding and representation (YAN *et al.*, 2017), and an ontology has been proposed for the first time to improve such practices (HONG *et al.*, 2015a, 2015b). Going further, a questionnaire-based evaluation was put further to integrate the ontology with social characteristics related to the human dimension of energy use in buildings (D'OCA *et al.*, 2017). Although it is not an ordinary practice for research on this topic, the advantage of integrating qualitative methods in such studies was presented as an opportunity to understand subjective aspects related to energy use in buildings. In light of this concern, literature reviews were presented to assess the importance of using questionnaires in the energy research field (CARPINO; MORA; SIMONE, 2019; BELAFI; HONG; REITH, 2018).

Along with questionnaires, another widely used method to investigate occupant behaviour in buildings is the interview. A book about methods and challenges to explore occupant behaviour in buildings was published recently (WAGNER; O'BRIEN; DONG, 2017), and meaningful information and details are presented to researchers and other stakeholders interested in occupant behaviour research. One chapter was dedicated to exploring qualitative methods to assess occupant behaviour in buildings, and detailed information about both survey and interview-based evaluations are presented. The inclusion of such qualitative methods in this field is aligned with the fact that occupant behaviour in buildings needs multidisciplinary efforts (HONG *et al.*, 2016), and knowledge from varied domains should be included. Therefore, going further on this topic, and relying on the fact that other stakeholders (in addition to the occupants) may impact on the energy use of buildings (D'OCA; HONG; LANGEVIN, 2018), attention is needed to guarantee a broad overview of humans involved in this role. In other words, not only occupants are related to energy use in buildings but also building designers, managers, operators, policymakers, technology developers and vendors.

Considering the broad relation of different stakeholders to the energy use of buildings, other qualitative methods – especially those used in the social sciences – can provide valuable information to the field of energy research, as well as be included in standard practices during varied phases of the life cycle of buildings. This intention is aligned with the recommendation of including social science approaches in energy research to solve the problem of lacking qualitative methods in this field (SOVACOOL, 2014). Additionally to occupant behaviour studies, qualitative methods may improve other pieces of research related to the human dimension of energy use in buildings. Therefore, stakeholders of the building sector need to be informed about the opportunities and challenges of including different qualitative methods in their practices. By informing them about many suitable approaches to evaluate qualitative aspects of energy use in buildings, stakeholders may be motivated to perform some of them when possible.

Bearing in mind that approaches used in social sciences may improve energy research practices, the objective of this paper is to review the most updated literature to find suitable methods to assess qualitative aspects of the performance of buildings. Such literature review aimed to present valuable information for future research related to the human dimension of energy use in buildings. The literature of the past five years (from 2014 to 2019) was reviewed to gather information about which qualitative methods are being used in this field. Therefore, we present challenges and opportunities related to questionnaires, interviews, brainstorming sessions, post-occupancy evaluation, personal diaries, elicitation studies, ethnographic studies, and cultural probe.

2. Systematic search

A systematic search was conducted to find as many papers that have used qualitative methods to evaluate the human dimension of energy use in buildings as possible. By "human dimension", we mean different actors involved in the building sector: occupants, designers, managers, operators, policymakers, technology developers and vendors. By "buildings", we mean both commercial and residential sectors, as stakeholders from both of them may apply some qualitative methods. In this regard, known methods (questionnaire, survey, interview, diary, and post-occupancy evaluation) were used as part of the keyword search and combined with widely used terms in this field (i.e., human dimension, user preference, occupant behaviour). The literature was searched in Scopus using the following terms and Boolean operators to include several combinations:

((*questionnaire* **OR** *survey* **OR** *interview* **OR** *diar** **OR** *“post-occupancy evaluation”***)**
AND ((*human* **OR** *user* **OR** *occupant***) W/2 (***behav** **OR** *preference* **OR** *dimension***))**
AND *buildings*
AND (*energy* **OR** *comfort***))**

The Boolean operators chosen represent the following rules:

- **OR**: finds all the documents that contain any of the terms;
- **AND**: presents only the documents that contain all the terms;
- **W/2**: is a proximity operator to define a two-word interval from chosen terms (e.g., *human* <max. of two words> *needs*);
- *: replace multiple characters (e.g., behav* = behavior, behaviour, behave).

As our research purpose was to focus on the most recently published papers, a timeframe of five years was defined (from 2014 up to July 2019) to evaluate the literature. This timeframe was chosen due to the increase of pieces of research in this topic from 2014 on. The major influencing factor for this trend was the approval of the IEA-EBC Annex 66 (Definition and Simulation of Occupant Behaviour in Buildings) in 2013; therefore, in the following years, a great number of studies were released throughout the world. Even limiting the scope to recent studies, 323 documents were found in this first search, and the sample was refined to exclude work that was poorly related to the field. Therefore, the abstracts were read to refine the sample and a final database was reached. Throughout this process, other methods (i.e., focus groups, brainstorming, elicitation, ethnography, and cultural probe) were found to be suitable as they were cited in the literature; thus, individual searches were conducted as well. The final sample reviewed comprised 206 papers published from 2014 up to 2019 (Figure 3.1), in different journals (Table 3.1).

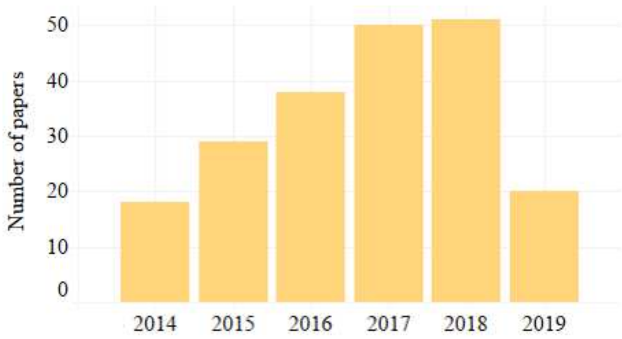

Figure 3.1. The number of papers reviewed per year of publication.

Table 3.1. International journals in which the majority of papers reviewed in this article were published.

Journal	Number of papers	Cite Score	SNIP	SJR
Energy and Buildings	42	5.360	1.826	1.934
Building and Environment	23	5.600	2.198	1.879
Energy Research and Social Science	15	5.750	1.735	2.138
Energy Procedia	10	1.300	0.582	0.468
Building Research and Information	9	3.540	1.595	1.283

Considering the final database, this review presents methods, challenges and opportunities of using qualitative methods in energy research, especially to evaluate the human dimension of energy use in buildings. Table 3.2 shows the methods included in this review and their corresponding sections throughout the manuscript. Along these sections, different insights are presented to stakeholders involved in the life cycle of buildings to inform a broad public and contribute to improving future research in this field.

Table 3.2. Methods reviewed in this paper and their corresponding sections throughout the manuscript.

Qualitative method	Section
Questionnaires or surveys	3.1
Interviews	3.2
Brainstorming	3.3
Post-occupancy evaluations	3.4
Personal diaries	3.5
Elicitation studies	3.6
Ethnographic studies	3.7
Cultural probe	3.8

3. Methods used in social sciences

3.1. Questionnaire or Survey

Questionnaires are broadly applied to study different aspects related to the human dimension of the energy performance of buildings, and literature reviews have been written regarding the use of this tool in cross-sectional surveys (BELAFI; HONG; REITH, 2018) and in residential contexts (CARPINO; MORA; SIMONE, 2019). Through this method, the literature supports findings regarding different aspects related to occupant behaviour (AMIN *et al.*, 2016; BAVARESCO; GHISI, 2018; GOLDSWORTHY, 2017; GUNAY *et al.*, 2016; GUPTA; KAPSALI; HOWARD, 2018; HU *et al.*, 2016; KALVELAGE; DORNEICH, 2016; NASPI *et al.*, 2018; PAN; PAN, 2018; RAMOS *et al.*, 2015; RHODES *et al.*, 2015; SAFAROVA, 2017; XUE; MAK; CHEUNG, 2014), occupancy (CARPINO *et al.*, 2018; LIISBERG *et al.*, 2016; RINALDI; SCHWEIKER; IANNONE, 2018), household profiles (BANDURSKI *et al.*, 2017; BEN; STEEMERS, 2018; HANSEN; GRAM-HANSSEN; KNUDSEN, 2018; SDEI *et al.*, 2015), as well as information that can improve Energy Performance Certificates (EPC) (DELGHUST *et al.*, 2015; ISMAEL; SHEALY, 2018; AZIZI; WILKINSON; FASSMAN, 2015; MONFILS; HAUGLUSTAINE, 2016; OYEWOLE; KOMOLAFE, 2018; REN; CHEN; JAMES, 2018). Additionally, as it is a subjective way of asking people about their opinions, a considerable number of theories, models and constructs from social sciences have been integrated into questionnaire-based energy research, as follow:

- Motivation-Opportunity-Ability (MOA) theory: to study intentions and attitudes on energy use (LI *et al.*, 2019);
- Theory of Planned Behaviour (TPB): to understand different constructs concerning energy-related behaviours (OBAIDELLAH *et al.*, 2019; SHI *et al.*, 2017; TETLOW *et al.*, 2015);
- TPB was also combined with Social Cognitive Theory (SCT): to improve a holistic sense of understanding occupant behaviours (BÉLAFI; REITH, 2018; D'OCA *et al.*, 2017, 2018);
- Perceptual Control Theory (PCT): to evaluate comfort-driven behaviour in buildings (LANGEVIN; GURIAN; WEN, 2015);
- Personal Construct Psychology theory: to understand representations about events or objects that humans have in their minds (DEY; LEE, 2017);
- YOU-ME-US model: to evaluate if the decisions are made according to the needs of one specific person or if it takes into consideration the group (RAW; LITTLEFORD; CLERY, 2017);
- Hofstede's Cultural Dimensions model: to compare subjects from different cultures regarding the effectiveness of eco-feedback systems to reduce the energy consumption of buildings (MA *et al.*, 2017);

- Values-Beliefs-Norms (VBN) framework: to evaluate a causal chain of variables that lead to behaviours (HEWITT *et al.*, 2016);
- Drivers-Needs-Actions-Systems (DNAS) framework: to analyse four main components related to occupants behaviour and energy use in buildings (BÉLAFI; REITH, 2018; D'OCA *et al.*, 2017, 2018; HAINES; KYRIAKOPOULOU; LAWTON, 2019);
- Values: anything that occupants consider is of worth, merit, utility, or importance; which can lead to oriented energy use improvement (AMASYALI; EL-GOHARY, 2016; HEWITT *et al.*, 2016);
- "Big Five" personality traits: commonly used in psychology studies, they can be used in energy research to understand to what extent the personality of users can affect their acceptability of different conditions or technologies (AHMADI-KARVIGH *et al.*, 2017);
- Self-Reported Habit Index (SRHI): to calculate if a given behaviour is usual for occupants (TETLOW *et al.*, 2015).

Although most of these applications do not result in actual behaviours (e.g., time-dependent or indoor-conditions-driven models), understanding constructs related to them (i.e., attitudes, social norms, and perceived control) are adequate to tailor policies and energy use interventions according to a target population.

Aiming to achieve an in-depth overview on the use of questionnaires, we divided the further parts of this theme according to different formats used in questionnaire-based research. Various methods, considering their challenges and importance, are presented to inform stakeholders related to the human dimension of the energy performance of buildings. Additionally, a final section on the main kinds of questions is presented, as well as some recommendations for future research.

3.1.1. Types of questionnaires

This review found that right-here-right-now, cross-sectional, and longitudinal questionnaires are the three main types used to assess the human dimension of energy use in buildings. Therefore, this subsection synthesises methods and opportunities of using each of them in further research.

3.1.1.1. Right-here-right-now questionnaires

Right-here-right-now questionnaires are those in which subjects respond according to their right-in-time perceptions or behaviours. In other words, respondents state their opinion or status related to the current moment of the survey participation (e.g., rating the actual IEQ or informing his/her clothing level). Differently from questionnaires in which participants respond considering a whole season or year, right-here-right-now questionnaires may reduce retrospective bias, as respondents do not need to think about past events to give their opinions. However, when this type of questionnaire is used, researchers should consider that repetitive intervention might bother respondents. Along these lines, this literature review did not find a recommended time interval to apply such questionnaires; however, a possible solution is to define a target number of responses enough to drive meaningful conclusions and then establish the time interval to reach the necessary responses.

This type of questionnaire is broadly used to evaluate opinions and perceptions of occupants about the indoor conditions of buildings. Such right-in-time surveys can rely on printed or online questionnaires; regarding the online versions, they can be either intrusive or non-intrusive, depending on the need to answer before closing the pop-up on the personal computer (WEST; WARD; WALL, 2014). Many researchers rely on ASHRAE 55 (ASHRAE, 2003) standardised method to assess thermal comfort in buildings. Therefore, right-here-right-now questionnaires were used to evaluate thermal comfort in offices (INDRAGANTI; BOUSSAA, 2017), and houses (KC *et al.*, 2018; VELLEI *et al.*, 2016) – common practices: ask about thermal sensation, acceptability and preferences of occupants. Additionally, this kind of questionnaire can ask about the status of systems (air-conditioning, windows, fans, curtains, etc.) (CHEN; HWANG; SHIH, 2014; KUMAR *et al.*, 2016), which is a great way to infer adaptive behaviours of occupants. Regarding adaptations, right-here-right-now questionnaires are also a great way to infer clothing levels and changes that users do throughout the day (GOU *et al.*, 2018; MUSTAPA *et al.*, 2016). Besides thermal conditions, this kind of questionnaire was used to understand preferences regarding lighting (KRÜGER; TAMURA; TRENTO, 2018).

In this manner, future research can benefit from this approach to infer occupants' perceptions of Indoor Environmental Quality (IEQ), e.g., thermal, visual, acoustic comfort and air quality conditions. Combined with measurements, a broad understanding of acceptable ranges of IEQ can improve design practices and standards. The main advantage of combining questionnaires with other methods like measurements is the opportunity to validate self-reported information (CEDENO LAURENT; SAMUELSON; CHEN, 2017;

KHOSROWPOUR *et al.*, 2018). Right-here-right-now questionnaires can be applied when sensors and equipment are being installed in the field (GAUTHIER, 2016); after that, to minimise privacy concerns related to the presence of researchers in the space, right-now conditions can be asked to users through smartphone-based questionnaires (PARK; CHOI, 2019). Additionally, with smartphone-based intervention, feedback systems may be proposed when sensors are combined to the experiment (i.e., besides only asking about indoor conditions to users, an app can inform them about wasting behaviours (VELLEI *et al.*, 2016)).

Finally, right-here-right-now questionnaires can be used to investigate the performance of new technologies, and it can path the way for developers to consider human preferences in future products. It is the case of thermochromic (TC) windows, which have been tested according to users' preferences considering visual comfort aspects (LIANG *et al.*, 2019), as well as the test of different materials in rammed-earth houses (BECKETT *et al.*, 2018). With similar purposes, determining user needs and preferences can benefit the creation of retrofit strategies as they can be translated into energy-saving opportunities (IRULEGI *et al.*, 2017).

3.1.1.2. Cross-sectional questionnaires

Cross-sectional questionnaires are those in which a sample of subjects are asked about their opinions at a single point in time (DE LEEUW; HOX; DILLMAN, 2008), which can be within a defined timeframe (months or seasons) or longer periods to understand tendencies. This approach is largely used in energy research to obtain information about occupant behaviour in buildings (BELAFI; HONG; REITH, 2018). Cross-sectional questionnaires can highlight trends on household habits (RECEK; KUMP; DOVJAK, 2019), including appliances that people commonly use (GOUVEIA; SEIXAS; MESTRE, 2017), pro-environmental behaviours (FABI *et al.*, 2017), or adjustments of specific building systems, e.g., window and door operation (SILVA; ALMEIDA; GHISI, 2016), air conditioner operation (FENG; YAN; WANG, 2015), occupancy (PETIDIS *et al.*, 2018), internal blind adjustments (BAVARESCO; GHISI, 2018), shower and bath habits (MORA; CARPINO; SIMONE, 2015). Specific behaviours, as well as models that try to represent the whole impact of occupants on energy use, are essential. Different complexity levels of data are useful, and professionals must define the complexity needed when evaluating occupant behaviour (CHEN *et al.*, 2015).

Obtaining data about various behaviours is important to improve occupant representation in building performance simulation gradually. Therefore, not only actual behaviours can be reported in cross-sectional questionnaires: a current trend is inferring from occupants their opinions about various constructs of behavioural theories (e.g., Beliefs/Values, Behaviour/Attitudes, and Knowledge (VOGIATZI *et al.*, 2018)). This approach is great to know drivers of behaviours and improve its understanding and representation. In this regard, Motivation-Opportunity-Ability (MOA) Model (LI *et al.*, 2019), YOU-ME-US Model (RAW; LITTLEFORD; CLERY, 2017), Hofstede's Cultural Dimensions Model (MA *et al.*, 2017), and Values-Beliefs-Norms Model (HEWITT *et al.*, 2016) were used to understand influential factors on energy use in buildings due to occupants rather than the actual energy use. Identifying most common needs and individual dynamics of users is very important to determine and create national or local policies to reduce energy use, giving that energy use can be more related to household habits rather than the dwelling itself (RAW; LITTLEFORD; CLERY, 2017). Similarly, constructs of both the Theory of Planned Behaviour and Social Cognitive Theory were synthesised with building physics aspects to create a framework to assess human-building interactions in offices (D'OCA *et al.*, 2017). The framework is being applied in different countries to compare cultural aspects of energy use in buildings. So far, results from the Hungarian (BELAFI; REITH, 2018) and Italian (D'OCA *et al.*, 2018) cases have been published, and a general article including other countries will be released soon.

A weakness of this type of questionnaire is that when occupants are asked about their behaviours at one point in time, they may be confused to define their everyday habits throughout a more significant timeframe. Therefore, there are concerns about the reliability of such self-reported data, and the social desirability bias (when people report what they think they do instead of what they truly do) are largely discussed in the literature (BELAFI; HONG; REITH, 2018; D'OCA *et al.*, 2017; WAGNER; O'BRIEN; DONG, 2017). A solution regarding this problem is to reduce the scope of the survey, i.e. if occupants are asked about their common behaviours, one may limit the timeframe to the current season instead of a whole year.

3.1.1.3. Longitudinal questionnaires

Different from cross-sectional questionnaires, longitudinal ones are those in which the opinions of people are asked more than once. Both right-here-right-now and cross-sectional questionnaires can be used to create a longitudinal survey, and parameters like cooling set-point in houses (JAFFAR *et al.*, 2018) can be found to be an important predictor of energy consumption. The literature supports that long-term longitudinal studies in energy research should be released at national levels to inform policymakers about common practices and preferences of users. Although this kind of evaluation is time-consuming, it is meaningful to obtain patterns of occupant behaviour – especially when combined with measurements in the field (SUN *et al.*, 2019), which can also improve building performance simulation (BPS) practices. Additionally, continually gathering data on IEQ conditions and systems operation provide realistic feedback from the perspective of users (SUN *et al.*, 2018). Finally, evaluations in different seasons have led to significant conclusions, and, if the same subjects are assessed, important outcomes on adaptive behaviours can be gathered (BECERRA-SANTACRUZ; LAWRENCE, 2016; MISHRA; RAMGOPAL, 2015). Therefore, this format of survey helps assessing seasonal variability impacting on the operation of buildings, and information regarding differences in systems' adjustments throughout the year can be reported (BELAFI; HONG; REITH, 2018).

Daily-basis questionnaires (both once or more times a day) are a great way to evaluate the responses of people to IEQ conditions and their adaptive behaviours as well, including clothing adjustments (LANGEVIN; GURIAN; WEN, 2015; SUN *et al.*, 2019). As such an intensive data collection can bother respondents in the long term, reducing the intensity of users responses is possible: periodically evaluations (once per week) are feasible for long-term investigations and can gather information related to diverse climate conditions (KIM *et al.*, 2017).

Finally, longitudinal questionnaires are a great way to measure the effectiveness of interventions. For instance, one may use this approach to understand if retrofits played a role regarding indoor conditions (SINGH; MAHAPATRA; TELLER, 2014) or to compare before and after conditions (e.g., if personal devices are given for users aiming to increase their comfort (LIM; KEUMALA; GHAFAR, 2017)). Therefore, it is possible to conduct before-after evaluations with samples of employees before a company decides to change whole-building systems or invest in individual controls like personal cooler/heater. Additionally, before-after evaluations are valid to test behaviour-change interventions, which can rely on constructs of behavioural theories (ANDERSON *et al.*, 2017; MULVILLE *et al.*, 2017; TIMM; DEAL, 2016; UCCI *et al.*, 2014).

3.1.2. Scale of questionnaire/survey

Large-scale evaluations are very important to understand trends among a given population (either on city-, region- or country-levels). Monitoring varied aspects of buildings (including indoor conditions and occupant behaviour) provides meaningful information about the effectiveness of rules created and can inform policy making aiming to promote not only energy efficiency but also conscious behaviours (ELHARIDI; TUOHY; TEAMAH, 2018). However, large-scale monitoring is hardly achieved, time-consuming and expensive; thus, large-scale questionnaire-based surveys are a great option to understand trends among a population and inform different stakeholders that may use those findings. This review found that large-scale surveys were used to gather information about trends on patterns of occupancy (AN *et al.*, 2017; HU *et al.*, 2019), household characteristics and occupant behaviours (FENG *et al.*, 2016; HU *et al.*, 2017), residential heating (HU *et al.*, 2016; LI; LI, 2018) and cooling (AN *et al.*, 2017) use, windows adjustments (LI; LI, 2018), comparison among residential and office air conditioner use (MENG *et al.*, 2018), and indoor environmental quality levels on a national basis (ENGVALL *et al.*, 2014). All those trends related to the human dimension of building performance can be used to improve policies and planning practices in different countries.

Additionally to building-level planning, large-scale surveys are significant for urban planning: by understanding trends on occupant behaviour in different regions, knowledge-oriented urban planning can be designed combining rules for buildings with typical occupant behaviour in computer simulations to reach low-carbon communities (RUAN *et al.*, 2017). Furthermore, besides occupant behaviour aspects, large-scale surveys can be used to understand trends on human intentions like willingness to adapt their behaviour to adopt smart solutions in buildings (LI *et al.*, 2017) or to invest in energy efficiency measures (RAMOS; LABANDEIRA; LÖSCHEL, 2016). Gathering information on those aspects can improve public initiatives by explaining to policymakers the drivers behind energy-efficiency measures adoption. For instance, policies can be improved considering aspects of a target population – e.g., families in economically vulnerable situations can be stimulated to adopt energy efficiency measures in their homes by reducing taxes or providing financial incentives for them.

Another important aspect that concerns large-scale surveys is the use of national databases like census (which can provide depth insights on demographics (GOLDSWORTHY, 2017)) combined to questionnaires. National-level surveys – i.e., the English Housing Survey (EHS) – were used to continually monitor and model building stock to allow computer simulation (ARAGON *et al.*, 2019; TAYLOR *et al.*, 2018). As many countries conduct a national census regularly, energy research can use such information and provide meaningful results to society. Additionally to that, including occupancy evaluation in national censuses is highly recommended (ARAGON *et al.*, 2019). By gathering data on building occupancy, energy planning can be improved as well as energy use in buildings can be benchmarked.

3.1.3. Types of questions

Researchers must be careful to reduce bothering levels of the respondents when planning a questionnaire-based survey (LAVRAKAS, 2009). Therefore, limiting the time and the number of questions, as well as using varied types of questions, may play a role. With diverse formats, people can feel more immersed in the participation and be more likely to answer all questions. Therefore, the most common formats used in energy research are presented in this topic.

3.1.3.1. Closed-ended questions

Closed-ended questions are those in which a fixed number of options are given for the respondents, and they must choose among one (mutually exclusive) or all options that apply (collectively exhaustive). A common practice regarding the use of closed-ended questions is including both Likert-scale (to identify to what extent respondents agree or disagree with the topic, e.g., from "strongly disagree" to "strongly agree") and Likert-like options (which use similar scales compared to Likert questions, but is not limited to agreement levels: researchers may infer satisfaction, frequency, importance, etc.). Throughout this subsection, information about each specific format related to closed-ended questions is presented.

3.1.3.2. Mutually exclusive, Collectively exhaustive, and Ranking questions

Mutually-exclusive questions are those when only one option can be true for a given aspect. This kind of question has been largely used to evaluate comfort or satisfaction with indoor conditions in buildings or when binary ("dummy") options are presented. Its advantage relies on the possibility of placing respondents into categories when analysing responses. It is necessary to guarantee that only one option applies for respondents because otherwise they may be frustrated or confused (LAVRAKAS, 2009). Collectively-exhaustive questions (also known as check-all-that-apply questions) present to respondents a set of answers that can be chosen. As the name suggests, respondents are asked to select as many options as they find suitable for the question. In this regard, it is highly recommended that questionnaire options are based on released studies or pilot experiments, because one may find that the options given do not represent the reality where the survey is conducted. Additionally, some researchers reason that respondents may burden avoidance and choose the first option they consider reasonable, so scramble the order of answers for different participants is a way to minimise bias (LAVRAKAS, 2009). Finally, ranking questions are those in which researchers are interested in understanding the priorities stated by respondents (LAVRAKAS, 2009). In recent years, it has been used to understand what are the first and second actions taken by occupants when they feel discomfort (either hot or cold) in buildings (D'OCA *et al.*, 2017). Although simple, such an approach may help to understand the main adaptive behaviours people perform and discover if their strategies for restoring comfort are passive or active regarding energy use.

3.1.3.3. Likert-scale questions

Likert-scale questions are largely used to study the human dimension of building performance. This approach relies on asking to what extent respondents agree or disagree with a given fact, and the answers can be translated into numbers to analyse trends in the responses. The Likert response sets rely on four or more categories (e.g., “strongly agree”, “agree”, “disagree”, and “strongly disagree”), and when odd numbers are used, a neutral option as “neither agree nor disagree”/“neutral” is added. Attention is needed to guarantee symmetry on the options regarding agreement and disagreement, mainly when bigger scales are used (LAVRAKAS, 2009). In this review, four- (JEBACKUMAR *et al.*, 2018), five- (D’OCA *et al.*, 2017, 2018; LIANG *et al.*, 2019; PAN; PAN, 2018; TETLOW *et al.*, 2015; TIMM; DEAL, 2016; UCCI *et al.*, 2014; VOGIATZI *et al.*, 2018; XUE; MAK; CHEUNG, 2014), six-, (LIM; KEUMALA; GHAFAR, 2017) and seven-point (DAY; GUNDERSON, 2015) Likert-scales were found to measure the agreement of respondents with researched topics.

Although the core concept of Likert-scale relies on measuring the extent that respondents agree or disagree with statements, Likert-like questions are largely used to infer respondent opinions when levels of agreement are not intended. A popular approach is to use the ASHRAE 55 scales (regarding thermal sensations, air movement, air humidity), which are vastly used in the literature (AMIN *et al.*, 2016; CHEN; HWANG; SHIH, 2014; FIELDSON; SODAGAR, 2017; INDRAGANTI; BOUSSAA, 2017; IRULEGI *et al.*, 2017; JAFFAR *et al.*, 2018; KIM *et al.*, 2017; KUMAR *et al.*, 2016; MISHRA; RAMGOPAL, 2015; MUSTAPA *et al.*, 2016; SAFAROVA, 2017; SUN *et al.*, 2018; VELLEI *et al.*, 2016; WEST; WARD; WALL, 2014; YAN *et al.*, 2016). Besides thermal sensations, the literature supports using this format to ask about many aspects. Table 3.3 synthesises different Likert-like scales used in the literature reviewed: it highlights that similarly to Likert-scales, points are used to measure the opinions of respondents; however, other aspects rather than agreement are inferred (e.g., satisfaction, frequency or importance). Major concerns rely on the misuse of words when a set of responses are created: e.g., “frequently” may not present an opposite sense compared to “never”; “not important” may not be comparable to “very important”; “slightly important” may not be associated with a neutral aspect; as well as “sometimes”, which was used both for neutral and negative purposes. After defining words for positive and negative aspects, those words may not be used for the neutral purpose (e.g., “fairly good” may bias the neutral aspect if the word “good” was already used for positive aspect). Therefore, the same number of “negative” and “positive” options must be used to guarantee symmetry. A possible solution for this problem is using antonyms on both parts (e.g., satisfied x dissatisfied, important x unimportant, and negatively x positively) and then adding the same intensifiers on both sides (e.g., very, slightly, somewhat).

Table 3.3. Synthesis of the variability found in the use of Likert-like scales in the literature.

Measure	Reference	-2	-1	0	+1	+2	+3	+4	+5	+6	+7
Satisfaction (regarding indoor conditions)	(INDRAGANTI *et al.*, 2018; SUN *et al.*, 2018)		Dissatisfied	Neutral	Satisfied						
	(PETIDIS *et al.*, 2018)				Comfortable	Neutral	Uncomfortable				
	(MARTINCIGH *et al.*, 2016)				Not satisfied at all	2	3	Very satisfied			
	(HASSANAIN; ALNUAIMI; SANNI-ANIBIRE, 2018)				Very dissatisfied	Dissatisfied	Satisfied	Very Satisfied			
	(SINNOTT, 2016)				Very poor	Poor	Fairly good	Good	Very good		
	(VELLEI *et al.*, 2016)				Very dissatisfying	Slightly dissatisfying	Acceptable	Rather satisfying	Very satisfying		
	(BELAFI; REITH, 2018; D'OCA *et al*, 2018)				Very unsatisfied	Somewhat unsatisfied	Neutral	Somewhat satisfied	Very satisfied		
	(MORA; CARPINO; SIMONE, 2015)				Very satisfied	It doesn't matter	Satisfied	Not satisfied	Don't answer		
	(INDRAGANTI *et al.*, 2018)				Very satisfied	Satisfied	Slightly satisfied	Slightly unsatisfied	Unsatisfied	Very unsatisfied	
	(AMASYALI; EL-GOHARY, 2016)				Very dissatisfied	Dissatisfied	Moderately dissatisfied	Moderately satisfied	Satisfied	Very satisfied	
	(WEST; WARD; WALL, 2014)				Very satisfied	2	3	4	5	6	Very dissatisfied
	(LIM; KEUMALA; GHAFAR, 2017)				Strongly dissatisfied	Dissatisfied	Somewhat dissatisfied	Somewhat satisfied	Satisfied	Strongly satisfied	No opinion
	(KRÜGER; TAMURA; TRENTO, 2018)				Not satisfied						Very satisfied
Clothing insulation	(KIM *et al.*, 2017)				Very light (0.2)	Light (0.4)	Casual (0.6)	Heavy (1.0)			

Table 3.3. Synthesis of the variability found in the use of Likert-like scales in the literature (continuation).

Measure	**Reference**	**-2**	**-1**	**0**	**+1**	**+2**	**+3**	**+4**	**+5**	**+6**	**+7**
Frequency	(JAFFAR *et al.*, 2018)				Once yearly	Twice yearly	Every two years	Randomly			
					Daily	Every other day	Every three days	Once a week			
	(OBAIDELLAH *et al.*, 2019)				Never	Sometimes	Often	Always			
	(AZIZI; WILKINSON; FASSMAN, 2015; SAFAROVA, 2017)				Never	Rarely	Sometimes	Often	Always		
	(AMIN *et al.*, 2016)				Never	Rarely	Sometimes	Often	Frequently		
	(FABI *et al.*, 2017)				Never	Seldom	Occasionally	Often	Always		
	(BAVARESCO; GHISI, 2018)				Always	Frequently	Sometimes	Rarely	Never		
	(XUE; MAK; CHEUNG, 2014)				Always	Often	Sometimes	Rarely	Never		
	(GOLDSWORTHY, 2017)				Continuously	A few hours each day	A few hours each week	Once a week	A few times a month	Rarely or never	
	(OBAIDELLAH *et al.*, 2019)				Throughout the day	Once a day	Couple of times a day	Once a week	Couple of times a month	Once a month	Never
Importance	(AZIZI; WILKINSON; FASSMAN, 2015)				Not important				Very important		
	(PAN; PAN, 2018)				Not important at all	Not important	Neutral	Important	Very important		
	(MARTINCIGH *et al.*, 2016)				Not important at all	2	3	4	Very important		

Table 3.3. Synthesis of the variability found in the use of Likert-like scales in the literature (continuation).

Measure	Reference	-2	-1	0	+1	+2	+3	+4	+5	+6	+7
Importance	(LI *et al.*, 2017)				Very important	Important	Slightly important	Unimportant	Very unimportant		
	(AMASYALI; EL-GOHARY, 2016)				Very unimportant	Unimportant	Moderately unimportant	Moderately important	Important	Very important	
Perceived control	(PETIDIS *et al.*, 2018)				Insufficient	Moderate	Sufficient				
	(VELLEI *et al.*, 2016)				No control	Light control	Medium control	High control	Total control		
Perceived productivity	(INDRAGANTI *et al*, 2018)	Much lower than normal	Lower than normal	Normal	Higher than normal	Much higher than normal					
	(AMASYALI; EL-GOHARY, 2016)				Decrease	No effect	Increase				
	(D'OCA *et al*, 2018)				Very negatively	Somewhat negatively	Neutral	Somewhat positively	Very positively		

3.1.3.2. Open-ended questions

Different from closed-ended questions, open-ended questions allow free texts; although it requires more cognitive efforts from respondents, they may report whatever they find interesting on the topic, and unexpected information can be obtained. Therefore, combining both closed- and open-ended questions is recommended to gather different information from users. In this regard, a general trend in the survey-level is to create questionnaires based on closed-ended questions (because they are easier to answer (FABBRI, 2016)), and include an open-ended question at the end of the survey where respondents may feel free to report their opinions and additional information on the topic (GIUSTI; ALMOOSAWI, 2017). In the question-level, a way to combine both approaches is to include the option "Other" as a possible answer to allow people to write freely about their opinions. Table 3.4 presents examples of collectively-exhaustive (closed-ended) questions that also allow free text if necessary. It may help to understand the respondent perspective considering both building- and user-related aspects (BENNET; O'BRIEN, 2017; BROWN, 2016), as well as culture-related behaviours, can be inferred to explain unforeseen patterns of behaviour (e.g., Hungarian occupants that open windows for five minutes every hour because of their cultural habits (BELAFI; HONG; REITH, 2017)). Similarly, open-ended options also suit Likert-like questions and allow better understating the motivations behind responses (DAY; O'BRIEN, 2017); in this case, a possible solution is asking "Why?" a given fact is true for the respondent.

Table 3.4. Examples of collectively-exhaustive questions with a free-text option (D'OCA *et al.*, 2017).

Measure	Reasons for adjusting thermostat settings	Sources of acoustic discomfort
Options	( ) Indoor temperature too hot	( ) Noise from outside
	( ) Indoor temperature too cold	( ) Noise from inside
	( ) For a co-worker or manager's request	( ) Background noise
	( ) To conserve energy	( ) I don't feel this type of discomfort
	( ) Arrive/leave the office	( ) Other, please specify
	( ) Other (Please describe)	-

3.2. Interviews

Interviews are vastly applied in occupant behaviour research. In a recently released book about methods and challenges in this field, authors highlighted that different approaches can be used to conduct an interview (see Figure 3.2), and both individual (face-to-face, telephone, e-mail or video conferencing) or in-group (focus groups) are valid (WAGNER; O'BRIEN;

DONG, 2017). In Figure 3.2, the basis of the pyramid indicates that responses obtained through such an approach are more easily comparable; therefore, fully-structured interviews may play a role when specific topics need to be understood (ROBINSON; FOXON; TAYLOR, 2015). This literature review found that the majority of studies used semi-structured interviews. However, open-ended interviews have their importance emphasised: first, it may facilitate the discussion between interviewers and interviewed people (ROBINSON; FOXON; TAYLOR, 2015); second, a collection of stories can be used to inform stakeholders on malfunctions and opportunities to improve future buildings, and these stories are expected to be more easily remembered in the future when compared to numbers (DAY; O'BRIEN, 2017). Therefore, throughout this topic, outcomes concerning individual interviews and focus groups are discussed.

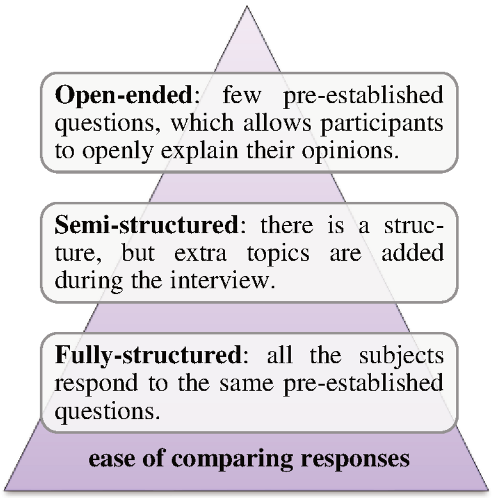

Figure 3.2. Different methods used to conduct interviews - based on Wagner, O'Brien and Dong (2017)).

3.2.1. Individual interviews

Face-to-face interviews can be conducted in the space where researchers are seeking information about (*in situ*) or in a neutral space. *In situ* interviews are more time- and resource-consuming when compared to other approaches, but they allow researchers to probe information about some aspects that people would probably not inform in online surveys (DAY; O'BRIEN, 2017) or observe conditions that subjects may not feel comfortable to state (e.g., mould/smoke smell in houses, indicating low ventilation rates (MONFILS; HAUGLUSTAINE, 2016)). With walkthroughs in a house, interviewers may gather information about everyday practices and behaviours regarding each system (GUERRA-SANTIN *et al.*, 2017). Additionally, interviewers can use tools (e.g., a timeline frame in which participants inform their behaviours by placing corresponding images), as it may improve the conversation flow and enable recall of routine activities (HAINES; KYRIAKOPOULOU; LAWTON, 2019). Ideally, aiming to reduce time and resource consuming, researchers can interview only one person in a given space: a leader or adult member of a household (HAINES; KYRIAKOPOULOU; LAWTON, 2019; MCGILL; OYEDELE; MCALLISTER, 2015; SINNOTT, 2016) or the teacher in a classroom (BELAFI *et al.*, 2018).

Interviews play an important role as complements of other research methods in the field of the human dimension of energy use in buildings. This approach can be used to assess occupancy (CARPINO *et al.*, 2018; MORA; CARPINO; SIMONE, 2018; REN; YAN; WANG, 2014), occupant behaviours and practices (BRÁS; ROCHA; FAUSTINO, 2015; GAUTHIER, 2016; GUTIERREZ-AVELLANOSA; BENNADJI, 2015; MCGILL; OYEDELE; MCALLISTER, 2015; REN; YAN; WANG, 2014; WOLFF *et al.*, 2017; YAN *et al.*, 2016), norms that affect behaviours (BLAY; AGYEKUM; OPOKU, 2019; BELAFI *et al.*, 2018), as well as gather knowledge from different stakeholders: construction company owners or house owners to understand drivers for using energy efficiency technologies (OZARISOY; ALTAN, 2017); professionals involved in building management (BROWN, 2016; JEBACKUMAR *et al.*, 2018; STØRE-VALEN; BUSER, 2019; TIMM; DEAL, 2016); experts in a given field (DAY; GUNDERSON, 2015); possible homebuyers to improve design practices (ZHANG; WEY; CHEN, 2017); or even users of a space before deploying sensors (LANGEVIN; GURIAN; WEN, 2015). This method is also great to hear from users about their constraints in using a given appliance, equipment or system (WOLFF *et al.*, 2017). Therefore, a twofold improvement can be reached in energy research with interview practices: engineers and developers should consider behaviours and preferences of users, while social science researchers can benefit from including such technologies on their analysis.

When monitoring is necessary in occupant behaviour research, *in situ* interviews can be done in the first visit to the place (when sensors or equipment are installed) (KIM *et al.*, 2017), more than once during longitudinal surveys (JAFFAR; ORESZCZYN; RASLAN, 2019), or at the end of the study (GAUTHIER, 2016). “Second interviews” are denoted in the literature as follow-up interviews and can also be used to clarify some misunderstandings about previously asked questions (KALVELAGE; DORNEICH, 2016). Similarly to questionnaire-based surveys, follow-up interviews can be conducted before and after a building intervention to obtain the opinion of users about the effectiveness of the strategy. An important characteristic of follow-up interviews relies on the possibility to narrow down the sample size: after a larger group of subjects be surveyed through a cheaper approach (as questionnaires), researchers can conduct interviews with a smaller sample to obtain information that was not previously clear (ANDERSEN; ANDERSEN; OLESEN, 2016; PAN; PAN, 2018; ROJAS *et al.*, 2016; SDEI *et al.*, 2015).

The literature reviewed presents high variability about the total time needed to conduct an interview, so there is no specific rule regarding this. Although not all the authors state the total time of each interview, a set of durations were found: about 45 minutes (PAN; PAN, 2018), 60 minutes (JAFFAR; ORESZCZYN; RASLAN, 2019), 65 minutes (BLAY; AGYEKUM; OPOKU, 2019), from 30-90 minutes (WOLFF *et al.*, 2017), 60-120 minutes (GUERRA-SANTIN *et al.*, 2017), and 120-150 minutes (HAINES; KYRIAKOPOULOU; LAWTON, 2019). We highlight that subjects may feel fatigued in long interviews; therefore, it is recommended that pointed questions are made to guarantee that subjects will not be bothered during the study.

3.2.2. Focus group

Focus group is a research method that comprises a collective interview conducted from a trained professional and assistants when necessary. As a group of people are placed together during the practice, this method allows communication across participants, which result in dynamic interaction between them and provide valuable insights/information for the interviewer. It can be used to explain previously collected and unclear data (e.g., from questionnaires), as well as to determine what questions are worth asking in a future survey. However, this approach is not recommended in some situations, e.g., when participants are not comfortable with each other, when rigorous statistical data is required, or when confidentiality is needed (LAVRAKAS, 2009). Literature supports that participants may feel social pressure to be sincere in focus groups compared to questionnaires because other participants know them (UCCI *et al.*, 2014). However, literature also shows two bias related to the method: first, the "group effect", when people may agree with the majority of the group even if they think differently; and second, the "moderator effect", when participants try to say what they think that will please the moderator (GAUTHIER; SHIPWORTH, 2015). As shown in previous sections, such biases may be caused by Social Desirability issues.

There is no specific rule to conduct a focus group, and the results obtained are similar to open-ended interviews. However, Likert and Likert-like questions can also be included to guarantee comparability between different groups by asking them to verbalise their rates (LEE;

SHEPLEY, 2018; THOMAS *et al.*, 2015). As shown before, the difference between them relies on the measured aspects: while Likert-scales infer the extent of agreement or disagreement with a statement, Likert-like scales apply similar structure, but other aspects rather than agreement are inferred (e.g., importance, frequency or satisfaction). The literature reviewed supports various outcomes related to diverse stakeholders of building performance. For instance, focus groups were used to evaluate the satisfaction level of residents in apartment blocks (ROJAS *et al.*, 2016); patterns of thermoregulation and behaviours of elderlies (HOOF *et al.*, 2019); to include occupants in the role of behaviour-changing interventions and guarantee persuasiveness of feedbacks (THOMAS *et al.*, 2015); to understand the way professionals apply energy modelling in building design (OLIVEIRA *et al.*, 2017); to compare the opinions of different stakeholders (e.g., residents and professionals of building sector) (LEE; SHEPLEY, 2018); to determine valuable questions for future questionnaire-based surveys (UCCI *et al.*, 2014); or to assess the drivers of home-owners' willingness to refurbish their houses (OZARISOY; ALTAN, 2017). Additionally, focus groups are great to gather knowledge from experts in a given field. In this regard, one may consider using this approach during workshops (as well as conferences or expert meetings) to understand the view of experts in researched topics (ATTIA *et al.*, 2018). This initiative is excellent to establish Key Performance Indicators (KPIs), including different aspects of the human dimension of energy use in buildings.

The literature supports that the most common practices on focus groups include six to eight people with similar backgrounds and last between 90-120 minutes (LAVRAKAS, 2009). Regarding sample, the literature presents variability and range from five (ATTIA *et al.*, 2018; OLIVEIRA *et al.*, 2017; HOOF *et al.*, 2019), six (THOMAS *et al.*, 2015; HOOF *et al.*, 2019), seven (OLIVEIRA *et al.*, 2017; HOOF *et al.*, 2019), eight (ROJAS *et al.*, 2016; HOOF *et al.*, 2019), nine (GAUTHIER; SHIPWORTH, 2015), and ten people (UCCI *et al.*, 2014; HOOF *et al.*, 2019). While duration ranged from 45-50 minutes (LEE; SHEPLEY, 2018), 45-60 minutes (OLIVEIRA *et al.*, 2017), 60 minutes (ROJAS *et al.*, 2016), and 180 minutes (PAN; PAN, 2018).

3.3. Brainstorming

Similarly to focus groups, brainstorming sessions are helpful to gather a considerable amount of knowledge or information from a group of people whose meaningful insights can be extracted from. During focus groups, it is possible to brainstorm solutions to previously identified problems, considering both advantages and disadvantages from different perspectives

(DASGUPTA *et al.*, 2016). Both social dynamics – which includes occupant preferences or behaviours – and requirements for user-centred design may be collected with this method. Along these lines, an innovative approach is the Design Thinking, which is highly used in information technology and business fields, and is a way to combine theories and models from design, psychology, education (DORST, 2011). Although popular in other fields, design thinking may improve building design as well, and brainstorming can complement this method to gather plenty of information that can boost design practices.

With concern to energy-related research, the sustainable development of communities that surround wind farms and other energy renewable sources was evaluated (GONZÁLEZ; GONÇALVES; VASCONCELOS, 2017). As a result of brainstorming sessions, authors created Current Reality Trees: a tool used to identify problems and connect their respective causes and effects. This approach may also be used to determine main problems related to building performances and Future Reality Tree (or Goal Tree) may be created from brainstorming sessions to set goals to solve current issues. This process may provide knowledge from and for different stakeholders related to building performances.

Finally, to improve problem-solving processes, brainstorming may help to analyse practices in creative ways. In this scenario, brainstorming has been related to best practices in education (FEIJOO; CRUJEIRAS; MOREIRA, 2018; KENNEDY; LEE; FONTECCHIO, 2016). Especially in technical fields (like building design), using creativity exercises may improve practices as many perspectives and ideas may be combined. Besides using this method for educational purposes, it may also help professionals to find solutions for challenges in their fields. In this regard, the literature supports to conduct brainstorming sessions during workshops with professionals of the building sector (AL HORR *et al.*, 2017): participants were asked about innovative practices to improve the comfort and productivity of building occupants. Thus, brainstorming practices can improve user-centred buildings in specific contexts (e.g., when designing one) and in broader aspects (e.g., when finding solutions to enhance labelling certificates). Although less present in the literature compared to other qualitative methods reviewed, brainstorming is promising as it can improve information acquisition from different stakeholders. The more used this qualitative method becomes, the more information about challenges and opportunities will be gathered, which may enhance this practice in the future.

3.4. Post-Occupancy Evaluations

Post-occupancy evaluations (POEs) are a great way to obtain feedback from users on success and failures during building operation as design intentions and actual performances can be compared through the opinions of occupants (ALBORZ; BERARDI, 2015). Therefore, some authors state that POEs can enhance building performance during operation (FIELDSON; SODAGAR, 2017) and are as important as the building design (MANAHASA; ÖZSOY, 2016). The significance of POEs has been linked with the advance of green building certificates to test if such buildings perform as expected (DORSEY; HEDGE, 2017; GENG *et al.*, 2019; LI; FROESE; BRAGER, 2018); and pairs of similar buildings (one conventional and one with green features) were compared (GreenPOE) (LEDER *et al.*, 2016). There is no standard protocol to conduct a post-occupancy evaluation (GENG *et al.*, 2019; LI; FROESE; BRAGER, 2018; NKPITE; WOKEKORO, 2017); however, some authors reason that it might be an inherent nature of POEs because purposes and methods are highly dependent on each case (LI; FROESE; BRAGER, 2018). Therefore, POEs can rely on varied techniques (NKPITE; WOKEKORO, 2017) to drive conclusive information, and such tools have been grouped in three categories: perception (e.g., surveys and interviews), monitoring (e.g., measurements and benchmarking), and observation (e.g., walkthroughs and historical records) (VÁSQUEZ-HERNÁNDEZ; ÁLVAREZ, 2017). Furthermore, different performance indicators have been shown as POE results: design quality (e.g., layout, interior and exterior appearance, accessibility), indoor environmental quality (e.g., thermal/visual/acoustic comfort, air quality, fire safety), and quality of services (e.g., water supply, electrical services, washrooms) (MUSTAFA, 2017).

As a result of the high variability of techniques and possible outcomes, POEs have been used to assess varied aspects: health of users (DORSEY; HEDGE, 2017); building energy use (BROWN, 2016) or malfunctions (DAY; O’BRIEN, 2017); occupant behaviour (BELAFI; HONG; REITH, 2017; PRETLOVE; KADE, 2016); features of the customer satisfaction index theory (ZHANG, 2019); as well as occupant satisfaction regarding building physical characteristics (KHAIR *et al.*, 2015), safety attributes of housing (HUSIN *et al.*, 2018), flexibility of workspaces (HASSANAIN; ALNUAIMI; SANNI-ANIBIRE, 2018), and indoor quality levels (BROWN; GORGOLEWSKI, 2014). Additionally, POEs were included in a framework to improve design practices regarding control for adaptive opportunities considering that providing control does not guarantee that users will interact with them as expected (KORSAVI; MONTAZAMI; BRUSEY, 2018). Considering the lack of standardised procedures, the literature supports POE practices in recently built dwellings (SODAGAR; STARKEY, 2016), as well as reasons that at least several years should pass before releasing it (LI; FROESE; BRAGER, 2018). Therefore, it is recommended to consider at least one year of occupation so occupants can understand building performance throughout all the seasons before evaluating it.

Although there is a lack of standards in this field, POEs can result in meaningful information regarding building performances during operation. Building performance could be continually evaluated to guarantee that even changing needs of occupants are met throughout building life cycle (DORSEY; HEDGE, 2017), or to benchmark buildings according to the perception of occupants (MUSTAFA, 2017). However, the practice of POE is not widely adopted due to costs and lack of clarity about who should be the main actors involved (VÁSQUEZ-HERNÁNDEZ; ÁLVAREZ, 2017). Thus, building designers have a fundamental role, and they should contribute to disseminate the practice, even considering barriers that hinder its inclusion in every project (HAY *et al.*, 2017). Some authors reason that more robust, innovative and cost-effective methods are necessary for this field if POEs are expected to be incorporated in the construction sector (SODAGAR; STARKEY, 2016). Figure 3.3 shows the transitions required to improve practices (based on (LI; FROESE; BRAGER, 2018)) and also guidelines for future evaluations (based on (GENG *et al.*, 2019)). With continuous effort from different professionals involved in this field, robust frameworks can be created, and such practice should improve building energy labelling by including aspects related to the building operation on the certifications.

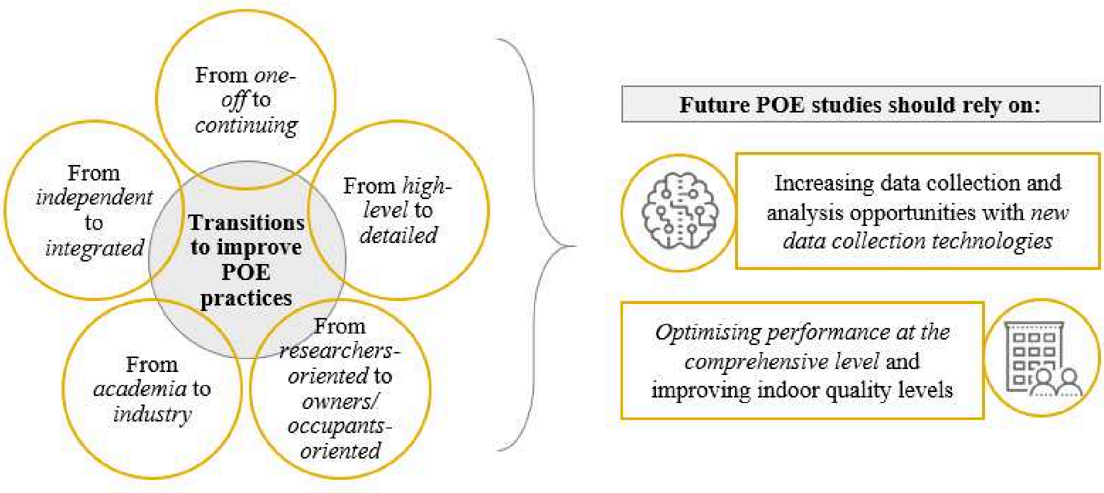

Figure 3.3. Transitions needed to improve POE practices and outcomes - based on Li, Froese and Brager (2018) and Geng *et al.* (2019).

3.5. Personal diaries

Diaries are a self-administered type of questionnaire, in which researchers may obtain both frequent and contemporaneous events. This method is excellent to involve occupants in the role of building performance because when people write about their practices, they become more aware of their impact on the environment (CARLANDER; TRYGG; MOSHFEGH, 2019). There are pros and cons associated with their use: first, information is gathered in natural settings, which may minimise the delay between event and record and reduce retrospective bias; on the other hand, participation involves time commitment, so meagre response rates can be achieved as well as blank answers due to participant forgetfulness (LAVRAKAS, 2009).

In the field of energy research, personal diaries are highly applied in Time Use Surveys (TUS). Generally, it consists in requesting occupants to record their presence and activities in a 10-minute resolution base for 24 hours during a few days (which includes weekdays and weekends). From this method, a massive amount of data may be collected (e.g., Danish TUS with 9,640 answers (BARTHELMES *et al.*, 2018)), and varied knowledge and studies may benefit from them. After gathering all this amount of data, patterns of energy use and occupancy may be found in both local and national levels, which is great to increase knowledge about these aspects for energy-related policy making. Data mining and machine learning techniques are highly recommended to analyse data from TUS; in this regard, the literature supports the use of Markov chain models (BIZZOZERO; GRUOSSO; VEZZINI, 2016; TRÖNDLE; CHOUDHARY, 2017), as well as clustering (BUTTITTA; TURNER; FINN, 2017; WANG; LI; YOU, 2018) and its combination with various methods like Kaplan-Meier estimators (BARTHELMES *et al.*, 2018), neural networks (DIAO *et al.*, 2017), support vector machine (KIM; JUNG; BAEK, 2019), and probabilistic model proposed by Aerts *et al.* (2014). A significant advantage of this approach is the combination of occupancy and activities in a time-dependent base, which allows creating time-dependent models for building simulation.

Besides TUS, personal diaries can be used in other energy-related research or with different features. For instance, instead of structured timeframes (10-min resolution), diaries may capture the beginning and end of activities (HILLER, 2014), which may reduce bothering the participants. This method is also used to collect variables related to thermal comfort studies (as metabolic rate and clothing levels) (IOANNOU; ITARD, 2017); however, a recent review emphasised that, although convenient, this field needs more reliable sources to capture metabolic rates and suggests to develop and validate instruments to measure it (LUO *et al.*, 2018). Additionally, one may combine measurements of building indoor conditions or energy consumption with the use of diaries in which occupants may report their perspectives about building performance (MCGILL; QIN; OYEDELE, 2014; HORST; STADDON, 2018). From occupant-recorded information, building performance simulation models can be created (CARLANDER; TRYGG; MOSHFEGH, 2019; ESCANDÓN; SENDRA; SUÁREZ, 2015), which may improve building simulation reliability. Also, diaries can be used to collect ground truth information about experiments: one may design sensors to capture energy events in buildings, and diaries can be deployed for users to register moments with and without energy consumption to validate the outcomes of sensors, as presented in (LOVETT *et al.*, 2016). Finally, researchers may use different features or technologies along with diaries. In this regard, besides paper-based monitoring, the literature supports using Google's calendar (LOVETT *et al.*, 2016), cameras (visual diaries) (GAUTHIER, 2016; GAUTHIER; SHIPWORTH, 2015), and blogs or web pages (HORST; STADDON, 2018).

As a final remark on this topic, we reason that personal diaries can be used both in short- and long-term experiments. In the case of TUS, short timeframes are asked for each participant, but the vast number of responses results in a meaningful amount of data for further analysis even with low risks of bothering participants due to the short nature of the study. On the other hand, extensive diary-based experiments (as the one presented in (ESCANDÓN; SENDRA; SUÁREZ, 2015), in which participants recorded building aspects during several years) can reveal weakness and strengths of a particular design case, but they rely on participants' interest and commitment, and higher bothering levels may be reported. Both methods can provide meaningful insights for different stakeholders of the building sector.

3.6. Elicitation studies

Elicitation studies have been linked to the Theory of Planned Behaviour (TPB) to determine psychosocial and cognitive aspects of people's intention and behaviour (DOWNS; HAUSENBLAS, 2005), mainly in other fields rather than energy research. However, as shown throughout this review, the TPB itself has been used to study the human dimension of energy use in buildings (see section 0), which opens the room to use elicitation studies to evaluate intentions and behaviours of occupants in buildings. Besides the TPB-related research, the literature also supports using preference and requirement elicitations. In the field of energy research, especially concerning different phases of the life cycle of buildings, both approaches can gather necessary knowledge to support user-centred design and control of buildings.

Preference elicitation can boost smart buildings performance, as users' preferences may be understood regarding systems operation to create preference-dependent schedules for systems in smart buildings (LE *et al.*, 2018), or to understand influencing factors that lead to small power devices control in buildings (TETLOW *et al.*, 2015). Concerning scheduling, a great approach is to ask users to draw simple graphics that represent their preferred times for systems work, which can easily be recognised by software (TRABELSI; BROWN; O'SULLIVAN, 2015). Such an approach aims to reduce bothering levels during participation. Additionally, preference elicitation can improve design practices by including different stakeholders' perspectives throughout the process: mock-ups can be used to elicit practices and preferences of users regarding building or system adjustments (GUERRA-SANTIN *et al.*, 2017), as well as design thinking events can be used to reduce uncertainties related to low acceptance of future technologies (DORTON; TUPPER; MARYESKI, 2017). Finally, preference elicitation plays a role in Recommender Systems (recommendation algorithms are vastly used in online platforms like YouTube, Netflix, and Spotify). A challenge in this aspect is to consider group preferences instead of personalised recommendations (GARCIA *et al.*, 2012), and future research can elicit groups' preferences regarding building control to create recommender systems that provide to users enough knowledge to increase their awareness and reduce energy use.

Requirement elicitation is largely used to create user-centred software as requirements may be included in the development loop (IBRIWESH *et al.*, 2017). This approach may suit energy research as systems to control buildings may be based on users' requirements. To reach this goal, the literature supports that requirement elicitation must be user-centred instead of system-centred (YANG; CHANG; MING, 2017). Such an approach is also valid to understand requirements during building design processes; to optimise it, iterative elicitations have been proposed: during the design process, professionals may be elicited to create the best mock-up, which can be used in follow-up elicitations (YANG; ERGAN; KNOX, 2015). Also, when knowledgeable professionals are elicited, it is denoted as expert elicitation, which plays an important role in the building sector helping to improve energy technologies (VERDOLINI *et al.*, 2018) and the process of policy making (SLEEP *et al.*, 2017). Additionally to the creation of new technologies, elicitation studies are valid to evaluate existing ones. The literature supports the evaluation of air conditioner systems and the willingness of users to pay for energy efficiency labels (JAIN; RAO; PATWARDHAN, 2018). This approach can be used to improve building energy labelling in future studies, by understanding the requirements and needs of building users in the role of energy labelling.

Finally, elicitation studies can also be used to construct Mental Models (MMs) of different stakeholders of buildings. MMs are representations of real-world aspects according to people's past experiences, and they can be used to assess the way people understand complex aspects. In the field of energy research, MMs were constructed to evaluate how building occupants believe that heat operates in their houses (GOODHEW *et al.*, 2017). Understanding the way people think that building systems work is excellent to inform future energy efficiency communications or educational programmes. Additionally, Repertory Grids (RGs) can be constructed from elicitation studies. RG is a cognitive technique based on the Personal Construct Psychology theory, in which humans express their opinions about various aspects, and the answers can cluster a set of features and improve the understanding of human needs (DEY; LEE, 2017). In the role of building performance evaluation, RGs can be used to evaluate different aspects of indoor quality, and the combination may be used to create user-centred benchmarking of buildings. In this regard, rooms of the same building may be compared to understand the spaces in which users feel less satisfied to drive interventions and improve indoor conditions.

3.7. Ethnographic studies

Ethnographic studies comprise a group of qualitative methods (e.g., interviews, observations, photographs, and document analysis) commonly used by Anthropologists to understand cultures, social groups and human behaviours in social settings (LAVRAKAS, 2009). Besides researchers be active in ethnographies, local communities may be included as well: one may provide equipment (like cameras) for them to collect data for further analyses (SJÖLANDER-LINDQVIST; ADOLFSSON, 2015). This method is recommended in the field of energy research, as the techniques involved in the process allow understanding practices related to energy use (CANZLER *et al.*, 2017; SMITH; HIGH, 2017). Although findings from ethnographic studies are hardly generalised (YARROW, 2016), they open the room to understand the embedded culture in energy use (WESTROM, 2018), and this knowledge shows valuable details in which information is necessary. Additionally, considering that users may see and react differently to the same spaces (SHARIF, 2019), ethnographic studies may improve the user-centred design of buildings as empathy may be increased in design processes.

Regarding energy research, this method may result in a great understanding of energy use and policies involved in this role. For instance, energy transitions were explored in different countries – i.e., Senegal (SIMMET, 2018) and Denmark (PAPAZU, 2018) –, and ethnographic studies were used to understand local perspectives rather than internationalist discourses on this topic. Also, the concept of "policy ethnography" was presented (RYDER, 2018). The author reasons that including policy analysis alongside common ethnographical procedures (observations and interviews) may result in nuanced and realistic information about policies, and social aspects may be included on the role of policy making (RYDER, 2018). Similarly, by conducting ethnographies with stakeholders related to heating supply chain (heating installers, plumbers' merchants, and sales representatives), different perspectives can be assessed and included in the role of energy efficiency achievement (WADE; SHIPWORTH; HITCHINGS, 2016). Such an approach would be helpful regarding varied technologies and practices in the building sector. Finally, besides involving different stakeholders in this method, the literature also supports the concept of "auto-ethnography" (HAMPTON, 2018), in which an expert may share her/his point of view on a topic to inform other stakeholders.

Additionally, ethnography is recommended to explore building design processes in a real-life context. One may investigate the way a group of professionals involved in this role interact with each other and gather valuable knowledge to tailor policies related to energy efficiency in buildings. In-depth analyses of building design processes were made to understand what architects are doing to incorporate policy agenda in their daily routine and achieve targets of decarbonisation in buildings (KEROSUO; MÄKI; KORPELA, 2015; ZAPATA-LANCASTER; TWEED, 2014, 2016; ZAPATA-POVEDA; TWEED, 2014). Considering that this method may highlight difficulties that professionals face to comply policies (knowledge gap), the role of policy creation or adaptation may be improved and, as a consequence, acceptance levels may increase.

Besides policies and broad perspectives related to energy use, ethnography may improve research related to specific behaviours or human-system interactions as well. Such a concept has been called "focused ethnography" (THIERBACH; LORENZ, 2014), which is concentrated in action, interaction, and communication related to specific situations. The main difference compared to conventional ethnographies is that visits and observations are generally shorter (THIERBACH; LORENZ, 2014). In the field of human-building interaction, one may conduct focused ethnography to evaluate specific moments like the first arrival to an office (or arrival after lunch break), and gather knowledge on the way the first to arrive set the space.

Ludvig and Daae (2016) investigated how people interact with woodstoves to design a user-centred product that considers user needs, even those implicit and non-verbalised, to reduce firewood consumption. Also, considering the elements presented in the practice theory (materials, competences, and meanings), policies can be tailored to consider target practices and aspects of social life (WESTROM, 2018). This theory has been used to study bath practices in Japanese society, considering that this behaviour is highly related to the local culture (WESTROM, 2018), and also to study home-office practices of work, in which authors concluded that people working from home are willing to accept a wider range of temperatures, because they restore their thermal comfort through creative ways (HAMPTON, 2017). In a broader aspect, this theory can be related to the practice of building retrofits, reasoning that policy intentions for energy efficiency should fit human practices; otherwise, they will have limited reach and impact (JUDSON; MALLER, 2014). Also, the nexus of different actors (professionals, planners and owners) may improve policies for retrofits, and ethnography may help on gathering valuable information (YARROW, 2019).

As a final remark on this topic, it is necessary to inform that ethnographic studies in the building sector consist of spending considerable time in the field to observe the way people experience the spaces. In this regard, different timeframes were found in these studies: researchers have spent 400 hours (WADE; SHIPWORTH; HITCHINGS, 2016), two months (WESTROM, 2018), a whole season (summer) (SHARIF, 2019), four months (YARROW, 2019), five months (PAPAZU, 2018), eight months (SIMMET, 2018), from twelve to twenty-one months (ZAPATA-LANCASTER; TWEED, 2014), and four years (CANZLER *et al.*, 2017). This review found that shorter timeframes can be used to study specific actions or behaviours – as the case of bath practices in Japan, in which researchers spent two months (WESTROM, 2018). However, when broad scopes are defined, larger timeframes can help to achieve meaningful results: e.g., to understand how energy regulations are being considered in design processes, about two years were used (ZAPATA-LANCASTER; TWEED, 2014); as well as to assess trends in collaboration between different sectors, like companies and academic institutions, which used a four-year-long study (CANZLER *et al.*, 2017). Although time-consuming, this method was shown to bridge some knowledge gaps on social aspects related to the human dimension of energy use in buildings.

3.8. Cultural probe

Similar to ethnographic studies, cultural probes may be used to understand people's culture, thoughts, and values. However, in this method, the ethnographer does not need to immerse in the participant real life to gather information; instead, cultural probe kits (e.g., cameras, diaries, and post-cards) are delivered to participants, and they collect as much data as they can regarding their responses to living contexts (LIN; WINDASARI, 2018). Generally, it is open-ended regarding data collection, and components of kits are simple and easy to use; also, they are aimed to create empathy and inspire design (SORO *et al.*, 2016). When the kit is received back, researchers may organise follow-up interviews with participants to understand the probed information (BURROWS; COYLE; GOOBERMAN-HILL, 2018). A major concern regarding this method is that, similarly to personal diaries, as the data collection relies totally on participants' commitment, meagre information may be obtained when the kit is returned. Therefore, gamification approaches are valid, and game-based tasks were comprised in the cultural probe kits to include children in the role of energy research in residential contexts (SAMSO *et al.*, 2018). Additionally, cultural probe is excellent to understand the way people interpret and use technologies in smart homes (BURROWS; COYLE; GOOBERMAN-HILL, 2018; BURROWS; GOOBERMAN-HILL; COYLE, 2015), which is important to inform other stakeholders in this field and fit further technologies with the needs of users.

Although less disseminated in energy-related research in the building sector, cultural probes were found as a promising approach to obtain information from users in their daily lives. Therefore, meaningful information can be gathered if participants are committed to the research purpose, and building designers or technology developers may improve their practices considering what benefit people's practices.

4. Discussion

This literature review has shown opportunities and challenges for applying different qualitative methods to study the human dimension of energy use in buildings. Given how broadly various stakeholders may affect the energy performance of buildings throughout their life cycle, it is essential to determine suitable methods that help to understand their influence, as well as driving conclusions to boost building performance and comfort of occupants. Therefore, this section synthesises the differences between all the methods found in the literature and presents information about ethical requirements to conduct studies with human beings.

4.1. Comparison between methods

As each method was individually presented throughout this literature review, a comparison between all of them is presented in Table 3.5. Such an outcome is aimed to synthesise the pros and cons associated with each method as well as enable easy comparison between two or more of them. By informing professionals about the potential of qualitative methods, broader use of them may be reached. Additionally, professionals may identify possible combinations of methods to improve their practices along with the building sector, especially to design further cases of study. In this regard, a prominent combination can be reached between personal diaries and interviews: if researchers become confused with the diaries' outcomes, they can schedule further interviews with willing participants to clarify their doubts. Similarly, a given POE practice may be a starting point for researchers to train occupants for autonomous data collection (with personal diaries, cultural probe kits or even both). Finally, a questionnaire-based evaluation may help to select specific cases in which attention is needed (e.g., underperforming buildings with a high number of people reporting discomfort) to conduct further assessments in the field: e.g., POE or ethnographic studies to understand the causes for the problems, as well as brainstorming sessions to find solutions for those issues. Besides those specific examples, several combinations are enabled between the qualitative methods presented; therefore, professionals may design experiments according to the pros and cons that suit their purposes.

Table 3.5. Comparison of all the qualitative methods presented in this literature review.

Method	Pros	Cons
3.1 Questionnaire or Survey	- Different types of questionnaires enable gathering data about specific moments: either right-in-time opinions or trends related to a past season; - Different types of questions may assess similar information to test the reliability of self-reported data; - A low-cost aspect is highlighted comparing to the majority of other methods; - The online application reduces time and resources compared to methods that rely on *in situ* evaluations; - Anonymity may be guaranteed when necessary; - A given questionnaire may be used in several studies to compare results from different times or locations;	- Self-reported aspects related to past events may rely on the retrospective bias; - Questionnaire design may be time-consuming because attention to details is necessary to guarantee low bothering and high engagement levels to the participants; - If people are not engaged in the survey, they may report answers that do not help driving conclusions; - If one aim to generalise the results of a case study to the population level, the sample size must be statistically significant, which may increase time and resources necessary; - If paper-based questionnaires are used, data analysis may be exhausting and the low-cost aspect may be lost.

Table 3.5. Comparison of all the qualitative methods presented in this literature review (continuation).

Method	Pros	Cons
3.1 Questionnaire or Survey	- Help to understand subjective constructs related to occupant behaviours (attitudes, social norms, perceived control).	
3.2 Interviews	- Although similar to questionnaires in some aspects, interviews may allow more flexibility as the interviewer has the option to ask respondents why they answered that way; - Allow gathering stories from the participants, which is important to create storytelling in energy research; - *In situ* interviews allow observing the real context of respondents and inferring hidden aspects that they may not feel free to state; - Can work as a complement to other qualitative methods, as selecting key actors to be interviewed help gathering important information; - Can be used to clarify doubts related to field evaluations.	- Data analysis may be more difficult compared to questionnaires because the interviews need to be recorded and transcript; - Although important to create story-telling, open-ended interviews may be difficult to analyse and generalise results; - Although presenting their pros, *in situ* interviews are time- and resource-consuming because the researchers need to go to the place of interest; - The interviewer must be prepared to adverse situations and must keep attention not to induce responses, as well as handle if a given participant is dominating a focus group, and the other participants are not comfortable to speak their mind.
3.3 Brainstorming	- Similarly to group interviews, this method allows combining different expertise from diverse stakeholders, and is especially powerful when problem-solving is necessary; - Involving those who are experiencing a situation in the problem-solving process may help to reach meaningful outcomes; - Causes and effects of real-life problems may be determined, which makes room to set goals to overcome them; - Creative solutions may be found, especially for educational purposes and building design.	- Similarly to group interviews, researchers should be aware that domineering people may centre the discussion, giving low opportunity for others to participate; - Data analysis may be difficult because brainstorm sessions need to be recorded and transcript; - As it involves a group of people, scheduling a time that all of them can attend may be a problem; - If people do not feel comfortable with each other, they may prefer to not show their opinions or suggestions during the sessions.
3.4 Post-Occupancy Evaluations	- Great way to obtain feedback from those who are highly involved with the operation of a building; - It enables professionals to assess if a given building is performing as they expected it to be; - As this practice is known for its high variability of methods, diverse aspects related to the building performance and its influence on occupants may be assessed; - As researchers should visit the building, they can infer aspects that participants may feel uncomfortable to state; - As different methods may be used, a database with diverse formats may allow triangulation to assess the reliability of the data.	- There is no standard protocol to conduct a POE; therefore, various techniques may be combined, and data analysis may become exhausting; - At least one researcher is required during the POE practice in the field, but depending on specific needs of the study this number may increase significantly; - There is still a lack of consensus about who should be the main actors involved in the role of POE practices, which may hinder the application of this method; - Some transitions are necessary to improve POE practices, e.g., changing from researchers-oriented to owners/occupants-oriented and from academia to industry.

Table 3.5. Comparison of all the qualitative methods presented in this literature review (continuation).

Method	Pros	Cons
3.5 Personal diaries	- Due to the right-in-time aspect enabled by this method, retrospective bias related to opinions about past events is expected to be minimised; - Researchers do not need to be present in the space so that data can be collected in several points simultaneously; - If properly used, diaries may result in ground truth information for measurements in field studies; - It may increase consciousness levels by involving occupants in the role of energy use in buildings, as people may become more aware of their practices.	- As the data collection depends totally on the participant, meagre and even blank responses may be received back due to participant forgetfulness; - If participants are required to inform their status several times a day, high bothering levels may be reported; - Paper-based diaries may result in a large amount of information, which is difficult to analyse; - Training sessions are necessary to explain to participants the correct way to fill the diaries, considering both print and online versions.
3.6 Elicitation studies	- It is a great way to assess the constructs of the Theory of Planned Behaviour, which is being used to assess occupant behaviour in buildings recently; - Preference elicitation may facilitate proper control of buildings considering human needs while also boosting energy performance; - Requirements elicitation, which is highly used to develop user-centred software, may benefit energy research to both create and evaluate technologies.	- Biases related to methods used to elicit preferences and requirements from users may reduce the reliability of the results; - If individual preferences are elicited, there is the need to translate it into group preferences, as the majority of buildings are shared between people; - Similarly to POE, ethnographies and cultural probe, several techniques may be used to elicit information; therefore, the elicitor must be aware of specific needs related to each technique to minimise constraints related to them.
3.7 Ethnographic studies	- This method allows understanding cultures and behaviours in social settings, as well as assessing embedded culture in energy use; - Local perspectives can be assessed directly from those involved in the situations; - Auto-ethnography is also allowed, and experts may share their knowledge with other stakeholders; - By understanding practices in real-life contexts, technologies and policies may be adapted to reach broader acceptance and use; - It allows understanding the nexus of different stakeholders of given buildings to improve retrofit practices.	- Similarly to other *in situ* methods, at least one ethnographer must be present in the place of interest to collect data; - Similarly to POE, elicitations and cultural probe, this method comprises several qualitative approaches; therefore, attention is needed to reduce biases related to each of them. - As many approaches may be combined, different formats of data are reached, and analysis may be an exhausting task; - The findings of ethnographies are hardly generalised because they are related to specific social settings; - The timeframe of evaluations are generally significant, and ethnographers have to spend much time *in situ*.
3.8 Cultural probe	- This method can be compared to ethnographies because it allows us to understand trends in social settings; - It does not require the ethnographer presence as the participants are responsible for data collection; - Appealing techniques like gamification may be included to involve different groups of people during data collection; - This method allows for understanding the way people interpret and use technologies in buildings.	- Similarly to diaries, cultural probe can result in a meagre amount of data as it relies on participant commitment; - As a probe kit is given for participants, there is no guarantee that the instruments will be used properly, and people may return them in adverse conditions; - Similarly to diaries, training sessions are necessary to explain the proper way to use the resources provided and to record the data throughout the experiment.

4.2. Ethical board

An additional aspect that researchers must consider when conducting studies with humans is ethical standards. In this regard, either local rules (from a given University) or national rules must be followed. The book "Exploring Occupant Behaviour: Methods and Challenges" contains a chapter on basic guidelines for researchers to approve their work in Ethical Boards considering the reality of several countries (WAGNER; O'BRIEN; DONG, 2017). As emphasised by the authors, ethical consideration must not be a burden, but rather a crucial aspect involved in this field.

From our experience, we add the discussion that the rules of different countries may present some challenges in studies related to the human dimension of building performance. For example, the literature emphasised that giving recompense for participants increase response rates in surveys (e.g., receiving recompenses each full day of participation (LANGEVIN; GURIAN; WEN, 2015) or after the whole study (GOODHEW *et al.*, 2017; THOMAS *et al.*, 2015), as well as entering for a lucky draw after completing attendance (HEWITT *et al.*, 2016; ZOU; YANG, 2014)). Although promising to increase response rates and participants' involvement, we highlight that Brazilian rules do not allow giving any recompense for survey participants. Therefore, researchers should consider this aspect and find solutions to reach the necessary number of answers in their studies. Similarly, researchers from other countries may face local challenges, but they should not demotivate when they happen.

5. Future research opportunities

Great part of energy research relies on qualitative methods; however, questionnaires are still more used compared to other approaches and, in many cases, they are a stand-alone method (KHOSROWPOUR *et al.*, 2018). Although less intrusive compared to other techniques (like interviews, ethnography or cultural probe), questionnaires can drive more meaningful conclusions when combined with other methods. Future research regarding the human dimension of building energy performance may combine various methods presented in this review, which allows understanding cultural-related drivers for energy use. Thus, we highly encourage different stakeholders of the building sector (either researchers or building managers or designers) to apply qualitative methods in their practices, as well as combining techniques to reach more complete outcomes. Besides, another opportunity in this field is to combine technological innovations with qualitative methods to improve data collection. As various technologies are promising to assess and include the human dimension in the building-performance loop (BAVARESCO *et al.*, 2019b), there is an excellent opportunity to include social sciences' approaches and combine qualitative responses with objective measures. Similar to technologies development, if qualitative methods become more popular, fewer constraints will be reported from practitioners; also, future use of those techniques may be improved according to challenges that previous users have reported. For instance, we suggest fit-for-purpose research design considering all the constraints that each method and country reality present.

Along these lines, Annex 66 (YAN *et al.*, 2017) played an important role to formalise experimental research methods, model occupant behaviour and validate it into BPS practices. However, given some unanswered questions and small penetration of advanced occupant modelling into practice, a follow-up research group (Annex 79) is aimed to continue the activities. Annex 79 (Occupant-Centric Building Design and Operation) explores the issues stated while also focusing on application and knowledge transfer to practitioners. Therefore, this review paper is expected to contribute to the efforts of those international research groups as future research in this field are aimed to apply what we learn from human factors into practice. For doing so, different stakeholders should be informed about qualitative methods that suit their practices along with building sector needs.

Therefore, an open research question that came up along with this literature review is: How our research can fit into the agenda of practitioners that have different goals regarding their work? Understanding their needs and preferences as well as documenting hindrances to apply the methods presented in this review is expected to: first, increase the use of qualitative methods in the building sector practices; second, as a consequence, increase the amount of knowledge gathered directly from human factors and boost human-centric design and operation of buildings. Going forward, specific questions about each method may be answered in the future, e.g.: How can we use elicitation studies for designing better buildings? How can we use anthropological research to improve the design of control systems? How can we reach the transitions necessary in post-occupancy evaluation to consolidate this practice over the life cycle of buildings? These and many other specific questions about the use of different qualitative methods may be answered with the collective effort of actors involved in these practices. Finally, frameworks to conduct such studies may also be achieved if they become more popular.

6. Conclusion

This literature review presented an overview of qualitative methods – generally used in social sciences – that can be employed to assess the human dimension of energy use in buildings. Starting from qualitative methods that are commonly used in energy research (questionnaire, survey, interview, diary, and post-occupancy evaluation), this paper assessed the literature published in the last five years (from 2014 up to 2019) to find to what purpose and to which extent those methods are being used. However, throughout the review, additional techniques were found to be suited to this field: focus groups, brainstorming, elicitation studies, ethnographic studies, and cultural probe. Therefore, the final database of papers reviewed comprised all the qualitative methods cited, and a large number of stakeholders are expected to be reached by the outcomes.

Although promising, the broad applicability of qualitative methods to assess humans has some challenges that should be overcome. The most notorious challenge is including less popular methods in the role of energy research: as questionnaires and interviews are highly more used compared to other techniques, stakeholders should be informed about the huge possibility of including some of the methods in their practices. As various stakeholders are related to the energy use in buildings (occupants, designers, managers, technology developers and vendors, policymakers, owners) (D'OCA; HONG; LANGEVIN, 2018), there is confusion about who is responsible for assessing the qualitative aspects of buildings. However, different actors are related to specific phases of building life cycle, and they should be included in this role through various qualitative methods. A remarkable challenge in this field remains related to policy making: as this aspect is associated to all the building life-cycle phases (design, construction, operation, and regulation), qualitative methods can bridge the gap between actual and human-centred policies, which may increase their acceptance and use. Therefore, the more qualitative methods become popular in energy research, the more knowledge and guides for application will be reached, as well as identification of which actors should conduct those evaluations. Another challenge in this field is the difficulty to access different groups of people, mainly linked to time and budget constraints, but also due to real-life obstacles like language barriers. Stakeholders should be aware that some communities use local languages in daily life, and a person from the community can help during experiments (YAN *et al.*, 2016). Finally, confusion in research design (especially with terms used) may reduce studies reliability. Thus, the actors involved in evaluations should be careful to collect meaningful results that can be helpful during different phases of the building life cycle. Also, the questions asked (or other means of the research) are often hidden in the literature; this aspect hinders the future application of qualitative methods, as prior work may guide the path to broader usage of the methods presented herein.

Facing challenges and increasing the use of qualitative methods to assess the human dimension of building energy use represents a twofold improvement in this field. First, as those techniques become more popular, more qualitative aspects will be presented for stakeholders of the building sector. Second, as more qualitative aspects are gathered, more information about them is released, which can enhance practices and determine which stakeholders are responsible for conducting such assessments. As a result, a broad understanding of embedded cultural issues in daily practices, as well as individual and groups' preferences/needs, may be reached; this opens the room for human-centred design and control of buildings. In addition, including qualitative methods in the role of policy making is very important: with a broad understanding of qualitative aspects, human-centred policies may be created, and their acceptance and use may be increased. Finally, with plenty of human-related information, different KPIs (Key Performance Indicators) can be used to assess building performance, which suits rating schemas as well. Concerning this matter, user-centred benchmarking of buildings may consider aspects related to the satisfaction of occupants in the role of assessing buildings.

A final remark on this subject is the possibility to combine several qualitative methods to gather various information related to building performance. With different approaches, various data can be collected and triangulation is enabled, which increases the trustworthiness of the outcomes (BRYMAN; BELL, 2015). However, the inclusion of qualitative methods in stakeholders' practices should not be a tedious or bureaucratic activity. Instead, we suggest fit-for-purpose research designs: each building should be assessed using suitable methods, considering local constraints or hinders. In this aspect, different stakeholders can be responsible for understanding the qualitative aspects of building performance, and they should be informed about the important role they play in this field. An indirect outcome that may be reached is the increase of awareness of those who are involved in such practices. As the human dimension of energy use in buildings become more assessed and understood, the actual humans involved become more aware of the extent their practices impact on energy use.

4. Underlying effects on adaptive behaviour in offices

This chapter is the transcription of the following paper:

> **Assessing underlying effects on the choices of adaptive behaviours in offices through an interdisciplinary framework.**
> Authored by: Mateus Vinícius Bavaresco, Simona D'Oca, Enedir Ghisi, and Anna Laura Pisello.
> Published in Building and Environment (ISSN: 0360-1323), volume 181, in 2020, and catalogued through the DOI: doi.org/10.1016/j.buildenv.2020.107086.

Abstract

This study evaluates subjective aspects related to the control of building systems (HVAC thermostat, windows, lights, and shades/blinds) in offices. The evaluation is based on a new interdisciplinary framework that combines insights from building physics and social science theories, synthesised in a novel survey. A case study in Florianópolis, southern Brazil, was conducted with 278 valid answers achieved. The levels of intention, ease, attitudes and expectations to share the HVAC thermostat control, as well as knowledge for doing so, were the lowest compared to the other systems evaluated. Additionally, the framework was used to perform a theoretical-driven Structural Equation Modelling (SEM) approach and identify underlying effects on choices of adaptive behaviours in offices. From the SEM results, the major constructs related to adaptive behaviours were determined. Intention and perceived behavioural control (PBC) were deemed positive with significant effects on choices for adaptive behaviours related to HVAC control, windows and shades/blinds. The conceptual model did not show a significant relation of intention and PBC on the lighting system adjustments. This outcome allows us to evaluate further theories, considering that habits may play a role in this context. The results provide important information related to the user-centric control of buildings, as well as support theory-driven interventions to improve adaptive opportunities for occupants. In other words, if one aims to increase adaptive opportunities for occupants, the results of this study suggest subjective aspects that may be enhanced in regards to each building system.

1. Introduction

According to the International Energy Agency (IEA), buildings are responsible for about 36% of the final energy used worldwide (GABC, 2019). Technology and envelope-based interventions (considering building physics principles) may be used to increase energy efficiency levels of the building stock. However, it is important to notice that technology alone does not guarantee high levels of energy efficiency in buildings (HONG *et al.*, 2015a) due to the increasingly acknowledged impact of the human dimension of energy use in buildings (D'OCA; HONG; LANGEVIN, 2018). Along these lines, the literature has been stressing the important role that occupants play on the energy use of buildings (DELZENDEH *et al.*, 2017; STAZI; NASPI; D'ORAZIO, 2017; YAN *et al.*, 2017; YOSHINO; HONG; NORD, 2017), emphasising the need to better understand and model occupants' adaptive behaviours in buildings (GUNAY; O'BRIEN; BEAUSOLEIL-MORRISON, 2013). Advances in the state-of-the-art were reached within a research community in the context of the International Energy Agency (IEA) Annex 66 "Definition and Simulation of Occupant Behavior in Buildings" activities (YAN *et al.*, 2017). The main goals of this international effort were to establish a methodological framework for occupant behaviour simulation, considering data collection, modelling and software integration. Researchers highlighted that occupant behaviour modelling present challenges regarding their stochastic, diverse and complex natures. In other words: the stochastic nature represents the variability of behaviours, as occupants do not strictly repeat their actions every day; diversity characterises the different behaviours even when the stimuli are the same, due to personal acceptances and preferences; and complexity encompasses underlying mechanisms influenced by multidisciplinary factors that impact occupant behaviours (YAN *et al.*, 2017).

Some human-building interactions (HBI) may be explained by the Adaptive Principle: "if a change occurs such as to produce discomfort, people react in ways that tend to restore their comfort" (HUMPHREYS; NICOL, 1998). This concept was introduced considering thermal comfort aspects; however, it can be extended to other dimensions of Indoor Environmental Quality (IEQ) satisfaction, as building occupants are continually exposed to combined environmental stimuli (SCHWEIKER *et al.*, 2020). Along these lines, occupants may either adapt themselves (e.g. drinking cold/hot beverages or changing clothes) or adapt the environment (e.g. adjusting a building system or covering a surface) (KEYVANFAR *et al.*, 2014). Therefore, besides impacting occupants' perceived comfort, adaptive behaviours often affect the energy use in buildings as well (GUNAY; O'BRIEN; BEAUSOLEIL-MORRISON, 2013). Considering perceived comfort, a novel framework to measure and analyse data on this field highlighted the importance of investigating environmental parameters from a subjective point of view (PIGLIAUTILE *et al.*, 2020). Authors showed that focusing siloed on environmental data may not be enough to explain human perception, and innovative approaches that include subjective evaluations are necessary. This aspect emphasises the need to improve the understanding and modelling of HBI continually, and a book presenting methods and challenges to explore occupant behaviours in buildings was released recently (WAGNER; O'BRIEN; DONG, 2017). From the comprehensive literature reviews presented throughout the document, authors synthesised factors that stimulate different actions in buildings. For instance, the literature supports that window state in offices are influenced by indoor and outdoor air temperature, time of day/arrival, number of persons in a room, attitudes, personality traits, and perceived control (WAGNER; O'BRIEN; DONG, 2017). It evidences that both objective (e.g. indoor temperature or solar radiation levels) and subjective factors (e.g. fear of bothering coworkers or lack of knowledge about controls) triggers adaptive behaviours in buildings.

All those aspects confirm the previously mentioned stochastic, diverse and complex natures of occupant behaviours in buildings and support the use of varied methods to study it. On the one hand, innovative technologies may play an essential role in assessing objective factors related to adaptive behaviours and improve the development of mathematical models and building performance simulation (BPS) practices, on both deterministic and stochastic basis (BAVARESCO *et al.*, 2019b). On the other hand, those objective approaches may not capture valuable insights presented by subjective aspects related to occupant adaptive behaviours in buildings, and expertise from social sciences may play a role in improving those practices (BAVARESCO *et al.*, 2020b). Some subjective or contextual factors may not improve mathematical models related to building performance; however, they may enhance building design and present to practitioners successful case studies (O'BRIEN; GUNAY, 2014). Therefore, the literature recommends to include social science approaches in energy research practices, making room to this field become more socially oriented, interdisciplinary and heterogeneous (SOVACOOL, 2014).

Even acknowledging the importance of occupant behaviour research, this field still lacks standardised methods, considering both monitoring and model development (STAZI; NASPI; D'ORAZIO, 2017). Along these lines, an interdisciplinary framework presented as an outcome of Annex 66 by IEA aimed at investigating human-building interactions in various buildings and cultures (YAN *et al.*, 2017). The framework comprises an international survey based on theories and insights from building physics and social psychology to study context and occupant behaviour in offices (D'OCA *et al.*, 2017). The interdisciplinary aspect was provided by combining the Drivers-Needs-Actions-Systems (DNAS) framework (HONG *et al.*, 2015a, 2015b) with two theories from social sciences. The first one is the Social Cognitive theory (BANDURA, 1986), able to explain the environmental, cognitive and behavioural factors that affect individual choices in social contexts. The second is the Theory of Planned Behaviour (AJZEN, 1991), which reasons that a significant predictor of human behaviours is the intention towards that behaviour; and the intention, nonetheless, is influenced by attitude, subjective norms, and perceived behavioural control. The framework has already been applied in several countries, and results from the Italian case study were published (D'OCA *et al.*, 2018). It added essential knowledge about subjective aspects that affect human-building interactions in offices. Additionally, a multi-country evaluation related to cooling and heating practices in offices was conducted; and the survey outcomes and subjective aspects related to the choices of technological or personal adjustments were presented (CHEN *et al.*, 2020). Those outcomes may guide both building managers and technology developers to improve their practices and increase user-centric aspects of buildings and their systems.

As emphasised by O'Brien *et al.* (2020), a paradigm shift is necessary in this field as the complex and dynamic bi-directional interactions between occupants and buildings must be comprehended. Therefore, authors introduced IEA EBC Annex 79 "Occupant-Centric Building Design and Operation" as a successor of Annex 66 activities. Along these lines, Heydarian *et al.* (2020) conducted a literature review exploring how behavioural theories from different disciplines can be used to assess occupant behaviour in buildings. Authors identified 27 specific theories in the studies they revised, varying across different disciplines like psychology, sociology, and economics. Conclusions highlighted that psychological theories were more commonly applied, and the Theory of Planned Behaviour (TPB) was the most frequent. In general, the literature normally reports social and psychological factors as drivers for occupant behaviours and perceptions (CHEN *et al.*, 2020; FABI *et al.*, 2012; KIM *et al.*, 2013; STAZI; NASPI; D'ORAZIO, 2017). Therefore, theory-driven studies may play important roles to understand occupant actions as well as propose tailored interventions. For instance, psychological concepts of personality traits may be used to model occupant behaviour for improving BPS (SCHWEIKER; HAWIGHORST; WAGNER, 2016), as well as for evaluating human-building interactions in shared offices (HONG *et al.*, 2020b) and grounding energy conservation measures (SHEN; CUI; FU, 2015). Also, understanding occupant behaviour from behavioural theories' lenses may suggest specific aspects to be improved or focused on, e.g. motivation level can increase energy-savings (LI; MENASSA; KARATAS, 2017), and public feedback may be more effective than private ones (HANDGRAAF; JEUDE; APPELT, 2013). Finally, applying theory-driven frameworks are also expected to improve further research practices: by extending a TPB model with perceived habits, Lo *et al.* (2014) found that habit was the strongest predictor for switching off lights and monitors. Similar outcomes may guide the conception of further studies in this field.

Going further on this topic, it is important to use theory-driven frameworks to determine which subjective aspects influence the choices of adaptive behaviours related to the main building systems (HVAC, windows, lights, and shades/blinds). As the core of the interdisciplinary framework mentioned before relies on constructs of the Theory of Planned Behaviour (attitude, social norms, perceived behavioural control, and intention), it is necessary to evaluate to what extent those constructs affect the choices made by occupants. Along these lines, previous research in varied fields used Structural Equation Modelling (SEM) to capture relations between subjective aspects and test hypotheses based on the Theory of Planned Behaviour. SEM is a statistical method used mainly by biologists, economists, marketing, and medical researchers, as well as social, behavioural and educational scientists (RAYKOV; MARCOULIDES, 2006). Schweiker *et al.* (2020) recommended using SEM on indoor environmental perceptual and behavioural studies as it may capture interactions and their complexity. This method depicts relations among variables (observed and latent) in several theoretical models, providing quantitative tests for the hypotheses of interest (SCHUMACKER; LOMAX, 2015). Considering energy-related research, SEM approaches have been successfully used to assess energy-saving behaviours (DING *et al.*, 2019; LI *et al.*, 2019; ZIERLER; WEHRMEYER; MURPHY, 2017) and consumer behaviour of low-carbon products (HUANG; GE, 2019; GUNARATHNE; KALUARACHCHILAGE; RAJASOORIYA, 2020; TU; YANG, 2019). Experiences found in the literature allow using theoretical-driven approaches (i.e. SEM based on the Theory of Planned Behaviour constructs) to study different aspects of human behaviour, suiting the need to evaluate underlying effects on occupant adaptive behaviours in buildings.

Therefore, this study endeavours to identify underlying effects on occupant adaptive behaviours in offices considering the adjustments of HVAC thermostat, windows, lights, and shades/blinds. It is based on an interdisciplinary framework to assess occupants' intention, ease, attitude, and expectation for sharing systems' control, as well as their knowledge for controlling each system. Another innovation of this piece relies on using a well-established statistical approach (Structural Equation Modelling) to capture relations between observed and latent variables that influence occupant behaviour in offices. The final goal is to include social sciences insights in occupant behaviour research to provide innovative knowledge for building stakeholders about subjective effects that encourage or hinder adaptive behaviours in offices.

2. Method

An internet-based survey (introduced by previous research (D'OCA *et al.*, 2017)) was conducted with employees of the Federal University of Santa Catarina, in Florianópolis, southern Brazil. The statistical approach consisted of carrying out Structural Equation Models (SEM) to analyse the impact of subjective aspects on the choices of adaptive behaviours in offices. This section presents the research procedure conducted in this study.

2.1. Location and climate of Florianópolis

Florianópolis is an island located in the southern region of Brazil, at the latitude of -27º36' and longitude of -48º33'. Its climate is temperate and humid: during the summer, from December to March, it is warm and humid; during the winter, from June to September, it is cool. Figure 4.1 shows the monthly averages for the highest and lowest temperatures as well as relative humidity according to the Brazilian National Institute of Meteorology (INMET) data. Florianópolis is a representative size city, which is great to conduct this initial effort, opening the door to other researchers carry similar approaches and compare trends among locations.

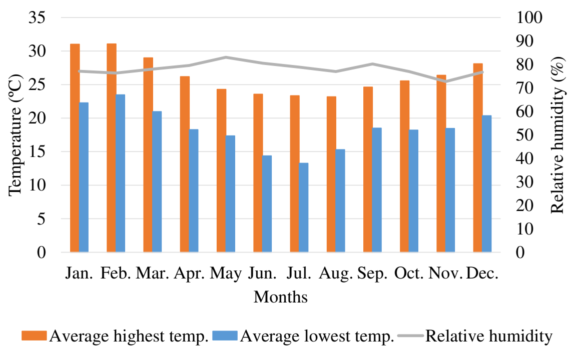

Figure 4.1. Monthly average highest and lowest temperature and relative humidity in Florianópolis during 2017.

2.2 Questionnaire application

This study concerns the Brazilian case study of the interdisciplinary framework to synthesise building physics and social psychology (D'OCA *et al.*, 2017), developed and presented during the Annex 66 activities (YAN *et al.*, 2017). As the survey was created in

English, the first step involved its translation to Portuguese to enable application in Brazil. This process relied on Double Translation Process (DTP) to guarantee semantic and conceptual equivalence; i.e. after being translated into Portuguese, the questionnaire was brought back into English to enable comparison and fix any inconsistencies found. This process allowed comparing both English versions of the survey to improve mistranslations or inconsistencies, as well as minimise cultural gaps between them. Thereafter, the Portuguese version of the survey was submitted to the local ethical board (*Human Research Ethics Committee*) at the University. As the survey questions and style should remain comparable for all the countries, original formats were maintained. Therefore, five-point Likert-like scale questions were used, similarly to the original version of the survey. Appropriate terms were used to guarantee symmetry on the option regarding agreement and disagreement. The guidelines provided by the National Regulation 510/2016 (BRASIL, 2016) were followed through the ethical board analysis. Then, the final version of the questionnaire in Portuguese, as well as the Free and Informed Consent were inserted into the Qualtrics Software. The Paid Panel Service of the programme created individual links to access the questionnaire, which were sent to workers of the Federal University of Santa Catarina (UFSC), in Florianópolis. By workers, we mean faculty members, administrative staff and post-graduate students that regularly occupy office spaces at the University. A list of 3,356 e-mail addresses was gathered in the University and used to send invitations for the survey. An initial request was sent in September 2017, and four follow-up reminders were sent up to November 2017. The local ethical board (*Human Research Ethics Committee*) approved the survey, and data was gathered anonymously throughout the process. Importantly, most of the buildings at the University rely on split air-conditioning instead of central systems. Therefore, they operate under mixed-mode ventilation as occupants may open and close windows as well as adjust HVAC in their offices.

2.3. Data cleanse and preparation

From the 3,356 requests, 345 answers were received – a response rate of 10.3%. However, some answers were deleted according to two rules: first, if more than 50% of the questions were left blank; and second, if the respondent did not work in an office space. After that, a final sample of 278 valid answers was reached and used in the analyses. Considering an infinite population, the necessary sample size is 273 responses for a 90% confidence level and 5% margin of error. Therefore, the final sample used is acceptable in terms of statistical significance.

The Qualtrics output is provided in a crosstab format, valid for Excel, but hardly interpreted in statistical programmes, which usually require data in row format; therefore, the dataset was pivoted from columns to rows. Finally, demographic and building-related data (gender, age rank, work position, hours spent per week, building name, etc.) were associated with each row to enable further analyses. An illustration of the data preparation process is shown in Figure 4.2.

Original data (columns)

Participant ID	Question 1 I can easily share the control of HVAC	Question 2 I can easily share the control of lights	
1	Neutral	Strongly agree	
2	Agree	Neutral	[...]
3	Neutral	Strongly agree	
4	Strongly disagree	Neutral	
[...]	[...]	[...]	

Pivoted data (rows)

Participant ID	Pivot - Questions	Pivot - Answers
1	Question 1	Neutral
2	Question 1	Agree
3	Question 1	Neutral
4	Question 1	Strongly disagree
[...]	[...]	[...]
1	Question 2	Strongly agree
2	Question 2	Neutral
3	Question 2	Strongly agree
4	Question 2	Neutral
[...]	[...]	[...]

Final dataset (joint with demographics)

Participant ID	Pivot - Questions	Pivot - Answers	Gender	Age rank		Numerical answer	
1	Question 1	Neutral	Female	1		3	
2	Question 1	Agree	Female	1		4	
3	Question 1	Neutral	Male	4		3	
4	Question 1	Strongly disagree	Male	2		1	
[...]	[...]	[...]	[...]	[...]	[...]	[...]	[...]
1	Question 2	Strongly agree	Female	1		5	
2	Question 2	Neutral	Female	1		3	
3	Question 2	Strongly agree	Male	4		5	
4	Question 2	Neutral	Male	2		3	
[...]	[...]	[...]	[...]	[...]		[...]	

Figure 4.2. Example of data preparation before conducting the analyses.

2.4. Structural Equation Modelling

From the survey application in the University offices, a set of variables regarding context and aspects related to occupant behaviour were gathered. Latent variables used in the Theory of Planned Behaviour (also called constructs) may not be directly measured; however, observable indicators that affect them may be captured and used to conduct statistical analyses. In light of this concern, Structural Equation Modelling (SEM) was used to assess the influence of the aspects presented in Table 4.1 in the choices of occupant adaptive behaviours in offices. SEM allows representing the relations between observed and latent variables in theoretical models, which enables to quantify their impacts and test hypotheses. In other words, this modelling approach is helpful to define constructs (latent variables) and estimate the impacting parameters as well as relations between them (SCHUMACKER; LOMAX, 2015). Aiming to fit an SEM and draw a path diagram, an important issue is to understand the difference between latent and observed variables (RAYKOV; MARCOULIDES, 2006). In the context of this research, measurable variables (e.g. the ease of sharing the control of different building systems) were used to evaluate the latent variables (constructs previously mentioned). Additionally, SEM should be used to confirm a theory-based model, and not to find relations between subjective aspects that may not be linked to each other. Therefore, this approach was used to evaluate the interdisciplinary framework presented earlier (D'OCA *et al.*, 2017), and several models considering its constructs were created. In this study, the models presented are those with more acceptable fit indices. As shown in the literature (SCHUMACKER; LOMAX, 2015), there are some steps to conduct an SEM:

- Model specification: determine the model structure based on previous theoretical frameworks or theories, confirming the relations among latent variables – for this part, we used the interdisciplinary framework presented earlier (D'OCA *et al.*, 2017), which combine insights from building physics and social psychology considering the Social Cognitive Theory, the Theory of Planned Behaviour and the Driver-Needs-Actions-Systems framework;
- Model identification: establish models with degrees of freedom (df) equal to or greater than 1; smaller values indicate either saturated (df = 0) or under-identified ($df < 0$) models;
- Model estimation: respect the assumptions related to each estimation method that fit the research problem;
- Model testing: testing for fit indices to evaluate if the original variance-covariance matrix and the one inferred by the model are similar to each other – thresholds for subjective aspects used as guides for the analysis are presented in Table 4.2;
- Model modification: based on values of residual matrix or previous theories, modifications are allowed to reach better fit with the model – iterative processes were made to reach a model structure with high fit indices.

Table 4.1. Survey questions used to conduct the Structural Equation Modelling.

Aspects based on the interdisciplinary framework	Question	Response options
Behavioural belief	Coworkers sharing control of the *[building system*]* in a shared office is...	Five-point scale: from 1=very bad to 5=very good.
Normative belief	The majority of my coworkers expect me to share control over the *[building system*]*.	Five-point Likert scale: from 1=strongly disagree to 5=strongly agree.
Motivational drivers	How would you best describe your personal workspace?	Private enclosed office; Shared enclosed office; Shared open office; Cubicle; Other.
Motivational drivers	In a typical week, how many hours do you spend in your personal workspace?	1-10; 11-20; 21-30; 31-40; 41-50; More than 50.
Motivational drivers	What is your age range?	18-28 years; 29-39 years; 40-50 years; 51-61 years; 62 years or older; other or prefer not to answer.
Motivational drivers	What is your gender?	Male; Female; Other or prefer not to answer.
Knowledge of controls	I know how to adjust *[a building system*]*.	Five-point Likert scale: from 1=strongly disagree to 5=strongly agree.
Ease to share controls	If I want to, I can easily share the control of *[a building system*]*.	Five-point Likert scale: from 1=strongly disagree to 5=strongly agree.
Perceived comfort	To what extent are you satisfied or not satisfied with the following conditions in your workspace? (five aspects of IEQ)	Five-point scale: from 1=very unsatisfied to 5=very satisfied.
Intention	I am willing to *[adjust a building system*]* based on the majority of my coworkers' opinions	Five-point scale: from 1=very unlikely to 5=very likely.

*building system: HVAC thermostat, windows, lights, and shades/blinds; each question related to them was asked once for each building system.

To run the analysis, the lavaan.survey package (OBERSKI, 2014) for R programme (language and environment for statistical computing) was used. This package allows for complex survey analysis and was validated to apply Structural Equation Modelling in survey data. The core constructs from the Theory of Planned Behaviour (attitude, subjective norms, perceived behavioural control, and intention), combined with other aspects from the framework (presented in Table 4.1) were used to specify the model in the lavaan.package. The model was then estimated, tested and modified in the lavaan.package to improve the results with this iterative process and reach representative thresholds for fit indices. The final framework obtained is illustrated in Figure 4.3.

Table 4.2. Fit indices and acceptable thresholds – based on Nimlyat (2018) and Schumacker and Lomax (2015).

Fit indices	Thresholds considered acceptable
Chi-square (χ^2)	p-value > 0.05
Goodness-of-fit index (GFI)	0 (not fit) to 1 (perfect fit) values close to 0.90 or 0.95 reflect good fits
Standardised root-mean square residual (SRMR)	< 0.05
Root-mean square error of approximation (RMSEA)	< 0.07
Normed fit index (NFI)	0 (no fit) to 1 (perfect fit) values close to 0.90 or 0.95 reflect good fits
Comparative fit index (CFI)	≥ 0.95
The ratio of Chi-square and degrees of freedom (χ^2/df)	< 3.0

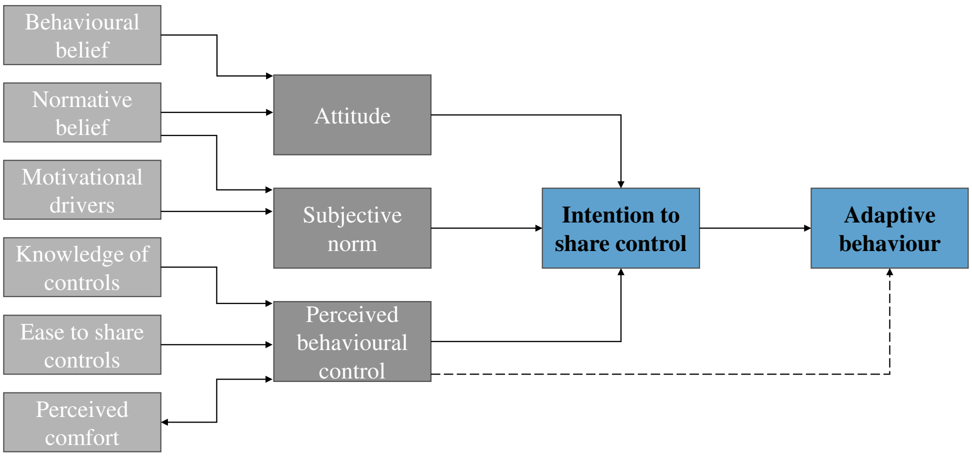

Figure 4.3. Structure reached in this study and used to calculate the relations among parameters in the lavaan.package.

Finally, applying the structure in the lavaan.package, path coefficients analyses were conducted – such path coefficients should be interpreted as statistical estimates of direct effects, i.e. regression coefficients in multiple regressions (KLINE, 2011). Therefore, the strength and significance level of the relations between observable and latent variables, as well as between latent variables themselves were presented.

3. Results

3.1. Characterisation of the sample

A total of 278 valid responses were obtained out of the 3,356 e-mails that were sent out. Average completion time was 38 minutes, and the median for completion time was 18 minutes.

Some demographics and other information were gathered to characterise the sample. Among the valid responses, there is a difference between participants' gender: 34% were male, and 66% were female. By analysing other demographics, we found that this difference is mainly influenced by the post-graduation-students' gender (more than 75% of them are female), as well as the administrative-staff profiles, which comprised the majority of responses and most of them are also women. Respondents also informed age ranges, and the final sample is characterised as follows: 24% belongs to the "18-28 years" age range, 41% to the 29-39 years, 20% to the 40-50 years, and 15% were 51 years or older. Work position is also slightly different between the target population, and the majority of respondents are administrative staff: 29% faculty members, 45% administrative staff, 23% post-graduation students, and 3% researchers. Finally, considering the amount of time spent at the office in a typical week, the majority of respondents spend at least 31 hours per week: 17% spend 1-20 hours in a typical week, 19% spend 21-30 hours, 30% spend 31-40 hours, and 34% spend 41 hours or more.

3.2. Underlying effects related to control of building systems

This subsection synthesises the respondents' intention, ease, attitudes and expectations related to sharing the control of building systems, as well as the knowledge for doing so. Each aspect is presented thoroughly in the following subtopics, and general comparisons are presented in this subsection.

Table 4.3 shows the average and the standard deviation for the respondents' opinions about different aspects of controlling building systems. The answers were coded in five-point numerical scales: i.e. negative options like "strongly disagree" = 1, while positive options like "strongly agree" = 5. The averages for all the subjective aspects evaluated are smaller for the HVAC control compared to other systems. In other words, occupants find it harder to both control and share the HVAC control in comparison with windows, lights and blinds/shades. Furthermore, Table 4.4 shows that gender plays a role when it comes to controlling HVAC: men reported lower intention to share the control of HVAC and also perceived lower expectations from their coworkers to share it. Similarly, they reported lower intention to share the control of lights as well compared to women.

Table 4.3. Average and standard deviations calculated for each subjective aspect related to the control of building systems.

Subjective aspects related to the control of building systems	Building system			
	HVAC	Windows	Lights	Blinds/shades
Intention to share	$\bar{x}$ = 4.14* *sd* = 1.21	$\bar{x}$ = 4.28** *sd* = 1.10	$\bar{x}$ = 4.17 *sd* = 1.17	$\bar{x}$ = 4.23 *sd* = 1.06
Ease to share	$\bar{x}$ = 3.94* *sd* = 1.33	$\bar{x}$ = 4.28** *sd* = 1.06	$\bar{x}$ = 4.24 *sd* = 1.15	$\bar{x}$ = 4.27 *sd* = 1.12
Attitudes related to sharing	$\bar{x}$ = 3.46* *sd* = 1.17	$\bar{x}$ = 3.69 *sd* = 1.09	$\bar{x}$ = 3.68 *sd* = 1.11	$\bar{x}$ = 3.70** *sd* = 1.10
Expectations of sharing	$\bar{x}$ = 3.98* *sd* = 1.12	$\bar{x}$ = 4.11** *sd* = 1.02	$\bar{x}$ = 4.07 *sd* = 1.06	$\bar{x}$ = 4.07 *sd* = 1.05
Knowledge to control	$\bar{x}$ = 4.41* *sd* = 1.06	$\bar{x}$ = 4.85 *sd* = 0.53	$\bar{x}$ = 4.90** *sd* = 0.36	$\bar{x}$ = 4.76 *sd* = 0.68

*lowest value for each subjective aspect (rows); **highest value for each subjective aspect (rows)

Table 4.4. Chi-square goodness-of-fit indicators to assess the influence of gender on the subjective aspects related to the control of building systems.

Influence of gender	Building system			
	HVAC	Windows	Lights	Blinds/shades
Intention to share	χ^2 = 10.41 p-value = 0.03*	χ^2 = 8.70 p-value = 0.07	χ^2 = 15.26 p-value = 0.00*	χ^2 = 8.25 p-value = 0.08
Ease to share	χ^2 = 2.49 p-value = 0.64	χ^2 = 3.99 p-value = 0.40	χ^2 = 6.22 p-value = 0.18	χ^2 = 7.70 p-value = 0.10
Attitudes related to sharing	χ^2 = 5.08 p-value = 0.27	χ^2 = 9.20 p-value = 0.06	χ^2 = 5.08 p-value = 0.28	χ^2 = 6.82 p-value = 0.15
Expectations of sharing	χ^2 = 10.65 p-value = 0.03*	χ^2 = 6.10 p-value = 0.19	χ^2 = 5.69 p-value = 0.22	χ^2 = 6.09 p-value = 0.19
Knowledge to control	χ^2 = 5.51 p-value = 0.24	χ^2 = 1.37 p-value = 0.85	χ^2 = 0.14 p-value = 0.93	χ^2 = 1.16 p-value = 0.88

Throughout subsections 3.2.1–3.2.5, Figures showing the Likert-type answers are presented. They show the total percentage that comes from neutral to positive (very likely, strongly agree, very good) as well as the overall percentage that comes from neutral to negative evaluation (very unlikely, strongly disagree, very bad) of each aspect. As the framework used five-point scales, numerical analyses were enabled, and the average for each piece was presented to allow comparisons.

3.2.1. Intention to share control of building systems

The intention to share control of building systems was measured in the questionnaire using a Likert-like scale, in which respondents showed their willingness to share the control of HVAC thermostat, windows, lights, and shades/blinds according to the following statement: "I am willing to *[control a building system]* based on the majority of my coworkers' opinions." Figure 4.4 shows the results according to a scale ranging from 1 (very unlikely) to 5 (very likely), and a label with the average of all the responses for each building system. The results show a lower intention to share the control of HVAC (accept indoor temperature settings) compared to the other systems. On the other hand, occupants reported the highest willingness to adjust windows based on the majority's opinion. As gender was associated with the intention to share the control of HVAC and lights (see Table 4.4), the averages were calculated separately: considering male respondents, it was found $\bar{x} = 4.04$ for the intention to share control over the HVAC, while females reported $\bar{x} = 4.24$ on a five-point basis. Similarly, men reported lower intentions to share the control of artificial lights ($\bar{x} = 3.91$) compared to women ($\bar{x} = 4.33$). As a conclusion, it was found that gender plays a role in the intention to share control of both HVAC thermostats and lighting, as shown in Figure 4.5. This outcome suggests that, in general, women are more willing to accept adjustments in HVAC and lighting based on the majority's opinion compared to men.

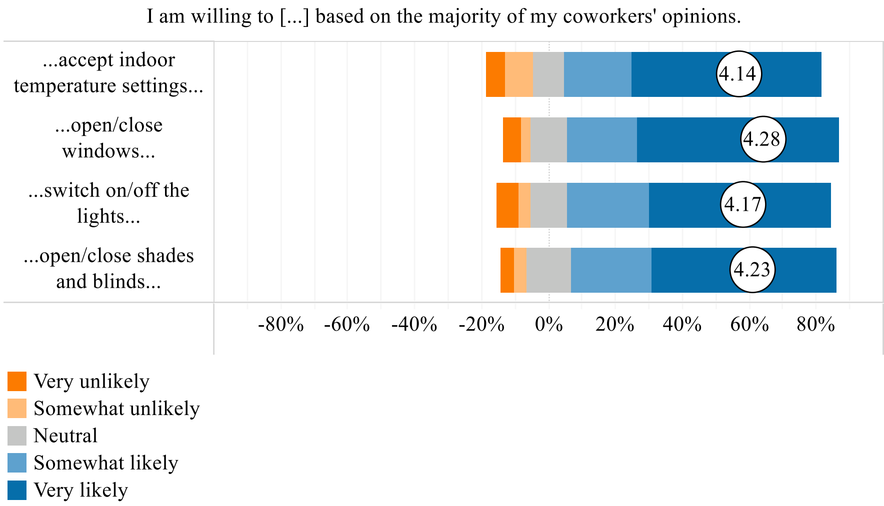

Figure 4.4. Intention to share control of devices in the workplace.

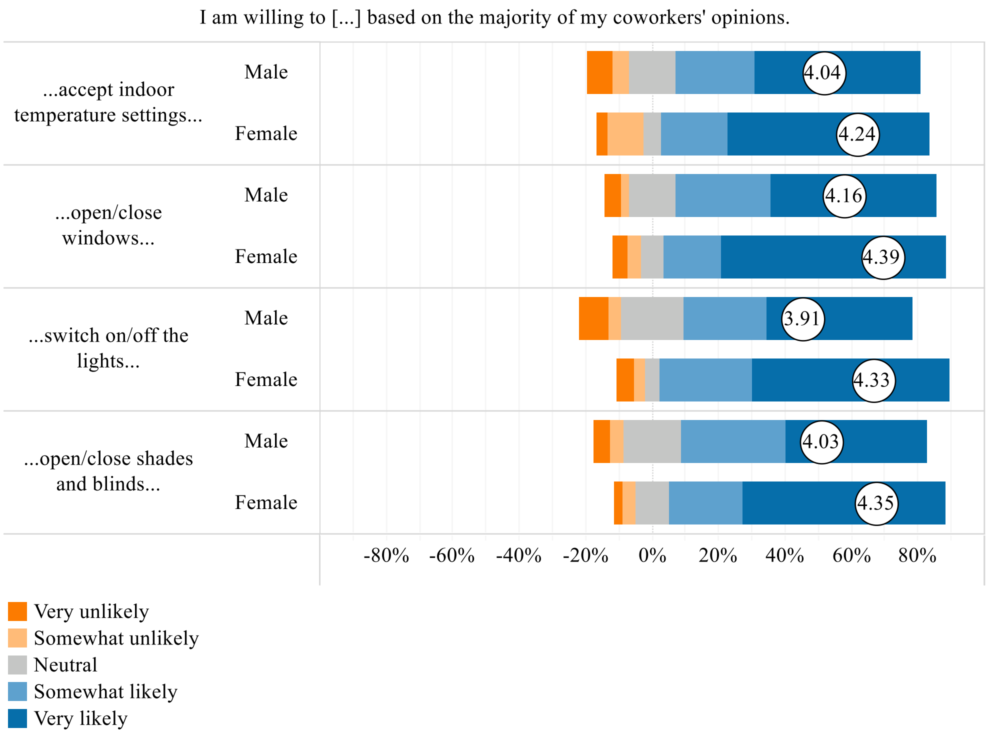

Figure 4.5. Intention to share control of devices in the workplace according to the respondents' gender.

3.2.2. Ease to share control of building systems

The ease of sharing control of building systems was measured using a Likert-scale question in which respondents should state to what extent they agree or disagree with the following statement: "If I want to, I can easily share the control of *[building system]*". Figure 4.6 show the results according to a scale ranging from 1 (strongly disagree) to 5 (strongly agree). Each building system was considered separately in the survey and results highlight that occupants struggle the most to share the control of HVAC thermostats ($\bar{x}$ = 3.94) compared to other systems. On the opposite, occupants find it easier to share the control of windows and shades/blinds ($\bar{x}$ = 4.28 and $\bar{x}$ = 4.27, respectively). This outcome is a little different from the cross-country evaluation that showed windows as the second more difficult system to share the control with coworkers and artificial lighting as the easiest one (CHEN *et al.*, 2020). It is important to notice that the cross-country evaluation included locations with cold winters (e.g. Poland, Switzerland, and Italy), in which occupants may not rely on natural ventilation. As Florianópolis has a mild climate and a latitude that favours daylight use, it may affect the subjective aspects related to adjustments of windows and artificial lights, as those systems are related to the use of natural ventilation and daylight.

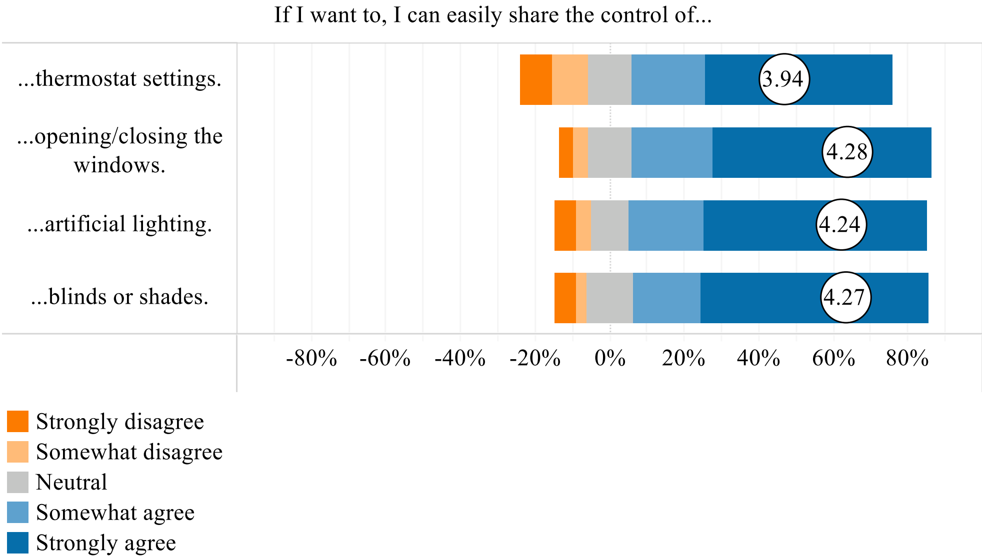

Figure 4.6. Ease to share control of devices in the workplace.

3.2.3. Attitudes related to sharing control of building systems

Attitudes related to sharing control of building systems were measured according to the respondents' opinion about the following statement: "Coworkers sharing the control of *[building system]* is…". Results are presented in Figure 4.7, with a scale ranging from 1 (very bad) to 5 (very good). Again, it is evident that attitudes related to sharing control of HVAC systems are smaller than those for the other systems. However, comparing with the intention and ease to share controls, the averages for the attitudes of sharing controls were lower for all the systems. The neutral option (fair) was the most frequent response for all the systems: 38.0% for artificial lighting, and 39.0% for HVAC, windows, and shades/blinds. Additionally, considering both "bad" and "very bad" feelings of attitudes related to sharing control of devices, the higher percentages were found compared to previous results: 17.5% of respondents chose one of those options for HVAC, 9.2% for windows, 10.4% for lighting, and 9.4% for shades/blinds. When it comes for differences according to genders, no statistically significant variation was found according to Chi-square goodness-of-fit tests' indicators.

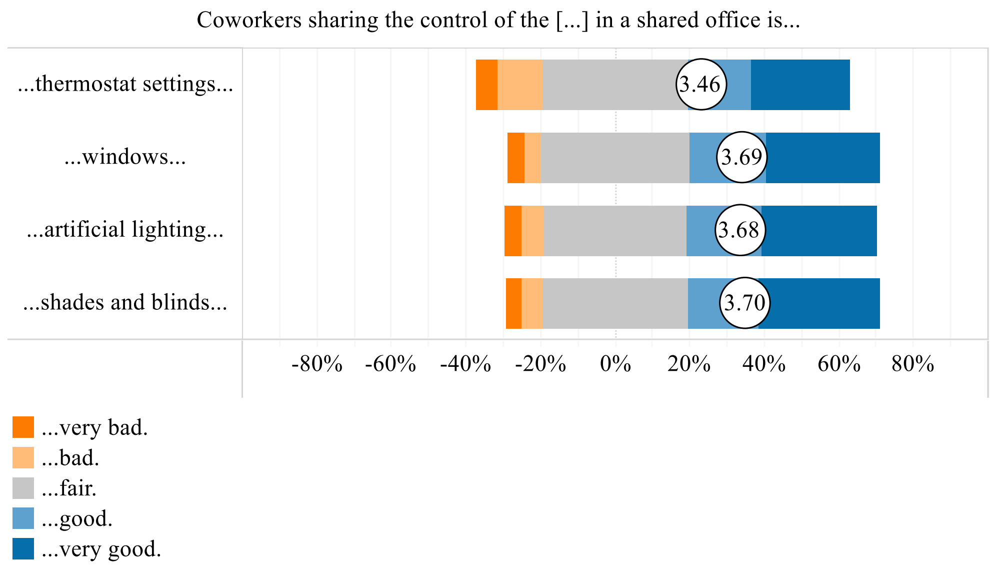

Figure 4.7. Attitudes related to the role of sharing control of devices in the workplace.

3.2.4. Expectations of sharing control of building systems

In order to measure the expectations of the occupants related to sharing control of building systems, respondents were asked about their (dis)agreement with the following statement: "The majority of my coworkers expect me to share control over the *[building system]*". Figure 4.8 shows the results according to a scale ranging from 1 (strongly disagree) to 5 (strongly agree). This outcome highlights the influence of social dynamics on the role of building control: the majority of respondents strongly agree that their coworkers expect them to share control of all systems (HVAC: 45%; windows and lights: 48%; and shades/blinds: 47%). Considering all the systems, results show that occupants expressed lower expectations to share control of HVAC thermostat and higher expectations considering the windows (HVAC: $\bar{x}$ = 3.98 and windows: $\bar{x}$ = 4.11). The influence of gender was statistically significant considering the expectation of sharing control of HVAC thermostat, as showed the Chi-square goodness-of-fit tests' indicators (HVAC: χ^2 = 10.65, p-value = 0.03). The influence of gender indicates that men perceived lower expectations of sharing the control of HVAC from their coworkers ($\bar{x}$ = 3.88) than did women ($\bar{x}$ = 4.07). As the previous results showed, men also stated lower intention to share the control of HVAC compared to women; it may explain why women tend to choose personal adjustments (such as putting on extra clothes) over the adjustments of HVAC (CHEN *et al.*, 2020).

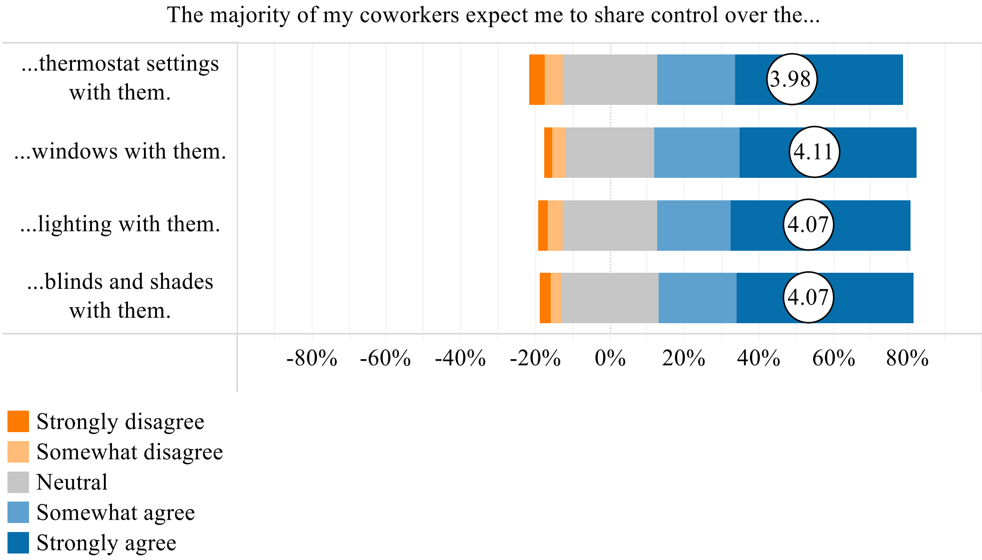

Figure 4.8. Expectations of sharing control of devices in the workplace.

3.2.5. Knowledge of control building systems

Knowledge about control devices in workplaces was measured according to the respondents' opinions about the following statement: "I know how to control *[building system]*". Figure 4.9 shows the results according to a scale ranging from 1 (strongly disagree) to 5 (strongly agree). It is evident that the majority of respondents know how to control devices in their workplaces, and the highest averages were found for all the systems evaluated compared to previous results. The percentage of people who declared that knowledge is not a problem for them to adjust building systems is high, and one may not worry about lack of knowledge leading to improper control of buildings. Considering the percentage of those who either "somewhat" or "strongly agree" with the statement, 83.0% of the respondents know how to adjust the HVAC thermostat, 97.0% know how to open/close windows, 98.0% know how to switch on/off the lights, and 94.0% know how to open/close the shades/blinds. On the other hand, excluding the neutral responses, some people either "somewhat" or "strongly disagree" with the statement: 8.0% declared that do not know how to adjust HVAC thermostat, 1.0% about opening/closing windows, and 2.0% about opening/closing the shades/blinds. This outcome supports the need to educate key stakeholders related to the human dimension of energy use in buildings (D'OCA; HONG; LANGEVIN, 2018). In this case, occupants should receive instructions about how to properly control all the building systems in order to increase their adaptive opportunities.

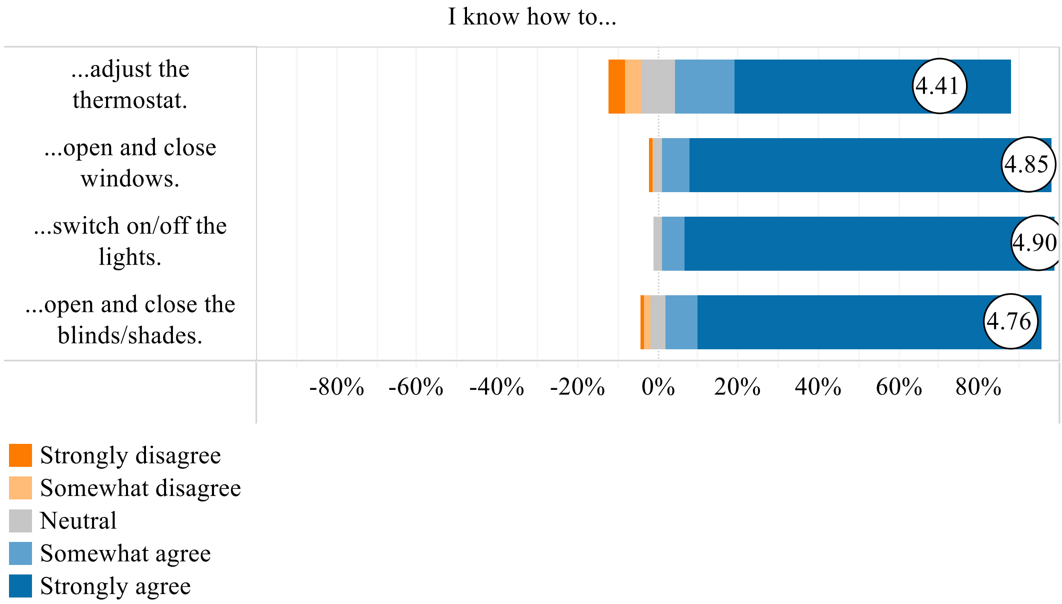

Figure 4.9. Knowledge of control devices in the workplace.

3.3. Structural Equation Modelling to assess the proxies for adaptive behaviour

As highlighted throughout section 3.2, it is evident that social dynamics play an important role in sharing control of building systems in offices. Therefore, a Structural Equation Modelling (SEM) approach was tested to assess the extent that subjective aspects influence the choice of adaptive behaviours (adjustments of HVAC thermostat, windows, lights, and blinds/shades). The subjective aspects tested are the constructs of the Theory of Planned Behaviour (TPB) – attitude, social norms, perceived behavioural control, and intention. Table 4.5 shows the model fit indices according to each building system evaluated. Throughout this section, the results of SEM and the corresponding path analyses are presented.

3.3.1. HVAC system

Figure 4.10 shows the hypothesised model with the constructs related to the control of the HVAC thermostats in workplaces. Considering the TPB constructs, our findings show that attitude ($\beta = 0.93$, p-value ≈ 0.00), and perceived behavioural control ($\beta = 0.48$, p-value ≈ 0.00) are related to the intention to share the control over HVAC thermostat in offices. Additionally, intention ($\beta = 0.99$, p-value ≈ 0.00) and perceived behavioural control ($\beta = 0.52$, p-value ≈ 0.00) are correlated to the choice of adaptive behaviours related to this system. In other words, the SEM approach highlighted that the choices for adaptive behaviours related to the adjustment of HVAC thermostat are influenced by the perceived behavioural control and the intention to share controls. Moreover, the intention is influenced by personal attitude and perceived behavioural control. Considering other aspects included in the interdisciplinary framework that based this study (D'OCA *et al.*, 2017), a higher broad of related factors were evaluated. Therefore, it was found that behavioural belief (β = 0.68, p-value ≈ 0.00) and normative belief (β = 0.88, p-value ≈ 0.00) are related to the attitude towards sharing HVAC control. Normative belief (β = 0.37, p-value ≈ 0.00) is related to the subjective norm. Finally, ease to share controls (β = 0.79, p-value ≈ 0.00) and perceived comfort (β = 0.20, p-value = 0.01) are related to the perceived behavioural control.

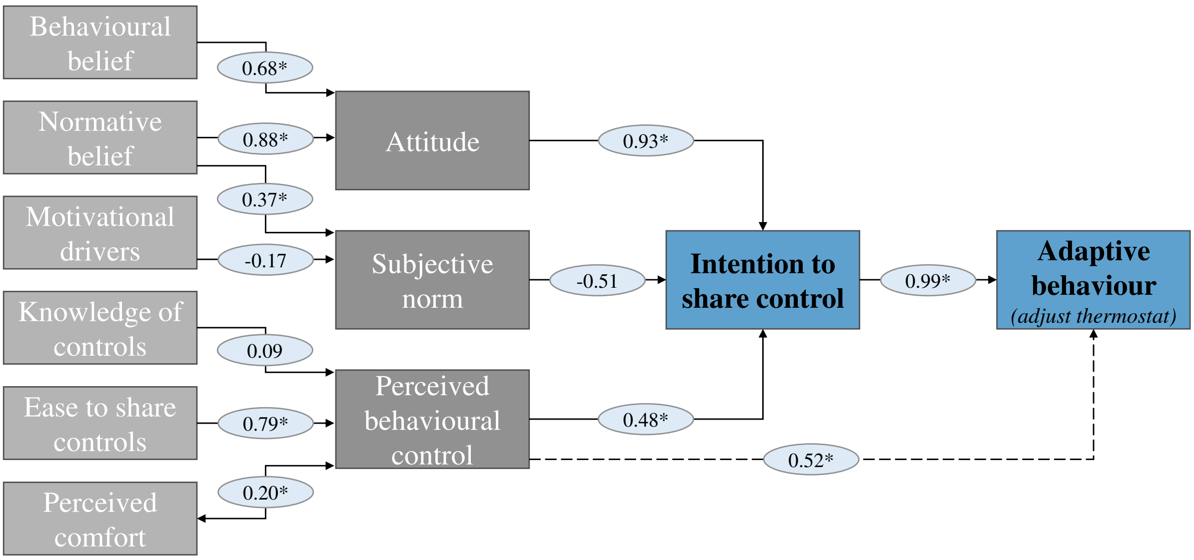

Figure 4.10. Path coefficients related to the choice of adaptive behaviour to control HVAC. (* means p-value < 0.01)

Table 4.5. Fit indices for the models related to each building system.

Building system	χ^2	df	χ^2/df	RMSEA	CFI	GFI	NFI	SRMR
HVAC	54.68	44.00	1.24	0.024	0.985	0.997	0.895	0.045
Windows	71.38	48.00	1.49	0.044	0.940	0.998	0.844	0.053
Lights	32.18	34.00	0.95	≈ 0.000	1.000	0.999	0.906	0.035
Shades/blinds	53.31	48.00	1.11	0.021	0.984	0.998	0.867	0.046

3.3.2. Windows

Figure 4.11 shows the SEM using the aspects linked to the control of windows. When it comes to the TPB constructs, it was found that attitude (β = 0.71, p-value ≈ 0.00) is related to the intention to share the control over windows. Additionally, intention (β = 0.99, p-value ≈ 0.00) and perceived behavioural control (β = 0.50, p-value ≈ 0.00) are related to the adaptive behaviour. Considering the broader scope of the framework evaluated, behavioural belief (β =

0.75, p-value ≈ 0.00) and normative belief (β = 0.49, p-value ≈ 0.00) are related to the attitude; normative belief (β = 0.39, p-value ≈ 0.00) is related to subjective norm; and ease to share controls (β = 0.73, p-value ≈ 0.00) is related to perceived behavioural control.

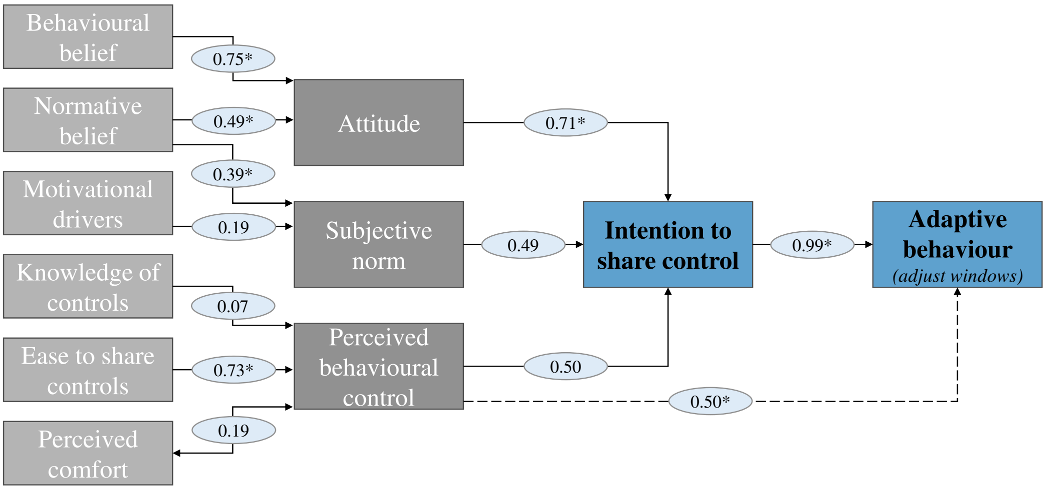

Figure 4.11. Path coefficients related to the choice of adaptive behaviour to adjust the windows. (* means p-value < 0.01)

3.3.3. Lights

The model associated with the control of lights is presented in Figure 4.12. In view of the TPB constructs, the results highlight that attitude (β = 0.94, p-value ≈ 0.00) and subjective norms (β = -0.78, p-value = 0.01) are related to the intention to share the control over lights. Differently from the other systems evaluated, adaptive behaviours related to adjusting lights had both smaller and non-significant impact of intention to share control and perceived behavioural control. Such an outcome suggests that future research should focus on deeply understanding the role of lighting adjustments in offices and looking for other theories to boost this comprehension. Regarding the other aspects measured in the framework, it was found that behavioural belief (β = 0.66, p-value ≈ 0.00) and normative belief (β = 1.00, p-value ≈ 0.00) are related to the attitude; motivational drivers (β = -0.39, p-value = 0.02) are related to subjective norm; and ease to share controls (β = 0.99, p-value = 0.01) is related to perceived behavioural control.

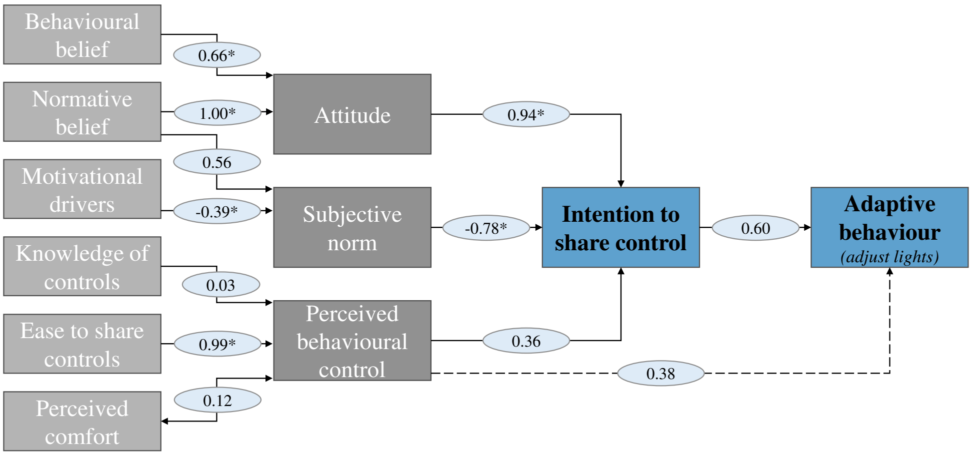

Figure 4.12. Path coefficients related to the choice of adaptive behaviour to switch on/off lights. (* means p-value < 0.01)

3.3.4. Shades/blinds

The SEM related to the control of shades/blinds is presented in Figure 4.13. As for the TPB constructs, the results show that attitude (β = 0.78, p-value ≈ 0.00), subjective norms (β = 0.56, p-value = 0.01), and perceived behavioural control (β = 0.51, p-value ≈ 0.00) are related to the intention to share the control over shades/blinds. Additionally, intention (β = 0.99, p-value ≈ 0.00) and perceived behavioural control (β = 0.49, p-value ≈ 0.00) are related to the choice of adaptive behaviour. Going further on the aspects hypothesised in this study, our findings suggest that behavioural belief (β = 0.68, p-value ≈ 0.00) and normative belief (β = 0.51, p-value ≈ 0.00) are related to attitude; normative belief (β = 0.39, p-value ≈ 0.00) is related to subjective norm; and ease to share controls (β = 0.71, p-value ≈ 0.00) is related to perceived behavioural control.

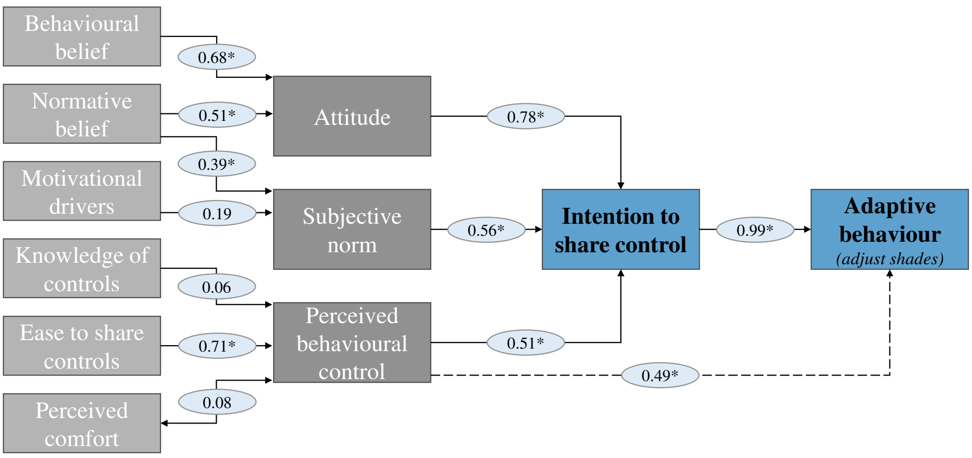

Figure 4.13. Path coefficients related to the choice of adaptive behaviour to open/close the shades/blinds. (* means p-value < 0.01)

4. Discussions

4.1. Subjective aspects that influence occupant behaviour

Providing options for adaptive behaviours in offices is a great way to increase occupant perceived comfort, as well as give opportunities to reduce energy use in buildings (GUNAY; O'BRIEN; BEAUSOLEIL-MORRISON, 2013). As the literature highlights that subjective aspects also influence the occupants' comfort perception (CASTALDO *et al.*, 2018), it is essential to identify underlying factors related to the choices of adaptive behaviours regarding the adjustments of different systems in buildings. Considering the four systems evaluated in this study (HVAC, windows, lights, and shades/blinds), all the assessed aspects (intention, ease, attitude, expectation, and knowledge) related to the control of HVAC was smaller than the indicators found for the other systems. Additionally, considering individual differences, both intentions and expectations associated with the control of HVAC thermostats are affected by gender. Besides reporting lower intention to share the control of HVAC thermostats, males also stated that they feel like their coworkers expect them to share the control of this system less than females do. This outcome is aligned with the fact that women are more likely to make personal adjustments when feeling either too cold or too hot instead of standing up and adjusting a control system (CHEN *et al.*, 2020), even being more critical over their thermal environment compared to men (KARJALAINEN, 2007).

The differences among underlying aspects related to sharing control of HVAC compared to other systems may be related to the variability of thermal preferences in offices, which is highly denoted in the literature and is influenced by individual traits (CHOI; AZIZ; LOFTNESS, 2010; INDRAGANTI; OOKA; RIJAL, 2015; MAYKOT; RUPP; GHISI, 2018; RUPP *et al.*, 2018; RUPP; VÁSQUEZ; LAMBERTS, 2015; WANG *et al.*, 2018). The outcomes of this study highlight the potential of providing Personal Comfort Systems (PCS) to reduce the need for sharing control of thermostats in offices (SHAHZAD *et al.*, 2018). Additionally, André *et al.* (2020) highlighted the advantages of implementing PCS in shared offices by associating personal comfort models with user-centred environmental controls. Granting individualised opportunities for occupants may enhance their perceptions of IEQ, which is expected to increase their satisfaction levels. On the one hand, as our results suggest, occupants may struggle to share the control and accept the majority's opinion when adjusting HVAC thermostat compared to the other systems evaluated (windows, lights and shades/blinds). On the other hand, considering a broad aspect of human dimensions of energy use in buildings, this finding supports the inclusion of other practitioners in the role of HVAC control to achieve environments that are more comfortable and reduce energy consumption. In other words, diverse professionals may learn from subjective features and reach practical insights to further design and control buildings. As individual differences play an important role in thermal comfort levels, shifting from a "one-size-fits-all" approach to a more individualised control of thermal environments is essential (WANG *et al.*, 2018).

The highest levels of intention, ease and expectations were reported for sharing control over the windows (opening/closing) compared to the other systems. This outcome is important as it may lead to more adaptive behaviours towards mixed-mode offices, which improves natural ventilation practices – necessary in climates similar to the one in the city studied (RUPP; GHISI, 2014). Considering naturally-ventilated offices, results from field studies in Florianópolis showed that occupants adapted easier to temperature fluctuations (RUPP; GHISI, 2017; RUPP; DEAR; GHISI, 2018). Therefore, positive intention, ease and expectations about sharing the control of windows in offices are important to enable adaptive opportunities for occupants. Besides parameters largely related to the control of windows – seasons, temperatures, time of the day, previous window state – the literature also highlights the impact of relations between coworkers when the control over windows is shared (ROETZEL *et al.*, 2010). As those parameters influence the effectiveness of natural ventilation, future research should focus on what practical aspects (window type, size, placement, etc.) encourage or hinder sharing control over the windows. It is then expected to provide for building practitioners insights to improve user-centric practices to enhance the use of natural ventilation in offices.

4.2. Capturing correlations between observed and latent variables

Results of the Structural Equation Modelling (SEM) indicate that intention to share the control and perceived behavioural control have a positive and significant effect on the choices for adaptive behaviours related to adjustments on HVAC thermostat, windows, and shades/blinds. It seems that for adjusting lighting, the intention to share the control and PBC do not play a role in the choice of adaptive behaviour for the sample of the study. As shown in the literature, there are clusters of occupants who totally disregard the natural lighting and rely entirely on artificial lighting. Additionally, occupancy-dependent aspects (entering or leaving a building) is highly linked with the probability of switching on/off this system (FABI; ANDERSEN; CORGNATI, 2016). Although further studies are necessary, these first outcomes support the use of other theories and frameworks to study lighting behaviours – e.g. Self-Reported Habit Index (SRHI), which captures automaticity related to behaviours, suggesting that habit is also a psychological construct (VERPLANKEN *et al.*, 1998; VERPLANKEN; ORBELL, 2003). Indeed, Lo *et al.* (2014) have extended a Theory of Planned Behaviour model with perceived habit and concluded that habit was the strongest predictor for switching lights off compared to intentions.

Considering the TPB's constructs affecting the intention to share the control of systems (attitude, subjective norm and perceived behavioural control), only attitude affected significant and positively the intention to share the control of all systems studied (HVAC, windows, lights, and shades/blinds). The highest effect of this construct (β = 0.94, p-value ≈ 0.00) was found for the intention to share control of lights, and the lowest one (β = 0.71, p-value ≈ 0.00) was found for the intention to share control of windows. Subjective norms had significant effects on the intention to share control over lights and shades/blinds. However, a negative effect was found for the intention to share control over lights (β = -0.78, p-value = 0.01) and a positive effect was found for the intention to share control over shades/blinds (β = 0.56, p-value = 0.01). Finally, perceived behavioural control had significant and positive effects on the intention to share control of HVAC systems (β = 0.48, p-value ≈ 0.00) and shades/blinds (β = 0.51, p-value ≈ 0.00).

Although these first outcomes may seem abstract, such theory-driven conclusions may play a role to improve the operation of systems in the future: e.g. if one is preparing an intervention to increase the choices of adaptive behaviours related to the HVAC use, our results suggest that increasing the intentions to share these controls may play an important role. For doing so, we suggest stimulating positive attitude and increasing perceived behavioural control levels of occupants. Before-after surveys have proved that awareness campaigns can increase levels of different constructs of TPB (as attitudes and perceived behavioural control) (STARK; BERGER; HÖSSINGER, 2018). It may be a new path for practitioners of the building sector to lead future buildings to a more user-centric control. In other words, introducing evidence-based improved attitudes towards adaptive behaviours may play a role to increase IEQ levels and reduce energy use in buildings. Considering attitudes, SEM results showed that behavioural belief is significant and positively related to sharing the control of all the systems evaluated. Taking into consideration examples from other fields, this information may be explained as follows: a student who studies hard for a test (the behaviour) believes that, as a consequence, he/she may succeed as intended (behavioural belief), which leads to a positive attitude related to studying (CHAMBERS, 2018). Similarly, changing the behavioural belief related to adaptations in buildings (i.e. some adjustments may reduce energy use while improving comfort levels), attitudes related to sharing the control of devices in offices may become more positive.

Subjective norms represent the expectations of others towards a behaviour (LI *et al.*, 2019); in the case of this study, this construct reflects the expectations of coworkers regarding the share of controls. Results of the SEM indicate that this construct is significantly linked with the intention to share control over the lights and shades/blinds. However, it is important to note that for the lights a negative path coefficient was found (β = -0.78, p-value = 0.01), indicating an inverse relation: the higher the subjective norm, the smaller the intention to share the control over lighting fixtures. Although not significant at 95% level (p-value > 0.05), social norms were also found to have a negative relationship over the control of HVAC thermostat (β = -0.51) – both systems are technology-related when compared to windows and shades/blinds. This outcome provides insights about sharing technological controls in offices, which is still underexplored by researchers. Therefore, future experiments should be designed to study the impact of social norms on the intention to share technological controls like HVAC thermostat and lighting, both directly related to energy use in offices.

Our findings show that ease to share the controls with coworkers is significant and positively linked with perceived behavioural control over all the systems evaluated (HVAC: β = 0.79, p-value ≈ 0.00; windows: β = 0.73, p-value ≈ 0.00; lights: β = 0.99, p-value = 0.01; shades/blinds: β = 0.71, p-value ≈ 0.00). Additionally, the literature supports that perceived behavioural control is linked to increases in productivity and satisfaction of occupants (GUO; MEGGERS, 2015; LANGEVIN; WEN; GURIAN, 2012; THOMAS, 2017). Therefore, besides providing actual control over building systems, it is important to provide easy-to-use and easy-to-share controls in offices to increase levels of perceived behavioural control. As occupants may change throughout a building life cycle, it is also important to continually evaluate which are the impactful factors related to those aspects. By gathering knowledge about underlying effects on occupant adaptive behaviours during building operation, it would be easier to understand what kind of building features occupants rate as easier to share the control. By providing more significant comprehension about the relation between physical and non-physical parameters, user-centric design and control of buildings are enabled.

4.3. Limitations of this study and future developments

Finally, this study comprises some limitations that should be mentioned. As the sample size is a critical issue to reduce biased results, high response rates are intended. A great way to increase response rates is providing respondents with incentives (WAGNER; O'BRIEN; DONG, 2017); however, Brazilian laws for human research ethics prohibits giving any recompense for research participants. Therefore, a low response rate was reached – about 10% of people invited provided a valid answer to the survey. However, the final sample (278 responses) is acceptable in terms of significance. Furthermore, self-reported data are criticised due to influences of Hawthorne effect and social desirability bias (i.e. when respondents provide answers that are socially acceptable instead of truthfully) (WAGNER; O'BRIEN; DONG, 2017). However, as the evaluated aspects in this research rely on subjective features, the inclusion of objective approaches (e.g. measurements based on sensors) would not play a role because they cannot capture the needed information. Yet, future research should apply more qualitative methods (e.g. face-to-face interviews or focus groups) to enable triangulation of the responses obtained from questionnaires and attempt to minimise those bias. In addition, data comes from Florianópolis, southern Brazil, and some differences may be found in other locations due to culture or climate variations. For instance, the willingness to share the control of thermostat could be even smaller in extreme climatic conditions (either too cold or too hot). However, this study opens the door to evaluate such subjective aspects under a well-established statistical approach and further international assessments may provide detailed comparisons. Finally, the survey focused especially on subjective aspects related to sharing the control over building systems. Future research should focus on objective aspects that may influence this role: e.g. how many zones the HVAC system covered, what type of systems were installed, how many people share a space, etc. However, in this case, researchers should consider dealing with possible bias in the results when surveys are submitted to general audiences. As presented in our results, respondents reported lack of knowledge to control some systems; thus, researchers are likely to obtain inconclusive answers from technical questions (e.g. HVAC zoning or specific control settings). A possible alternative is evaluating carefully each building the survey will be applied to assess technical aspects instead of asking for participants to provide this information.

5. Conclusions

The purpose of this work was to evaluate the underlying effects on occupant adaptive behaviours in offices. Therefore, knowledge from social psychology was used to assess different constructs related to choices of behaviours (attitude, social norms, perceived behaviour control, and intention). A questionnaire-based application was used to evaluate those constructs related to adjustments on HVAC thermostat, windows, lights, and shades/blinds. The questionnaire used in this study comprises the interdisciplinary framework created to merge building physics and social psychology (D'OCA *et al.*, 2017) – an outcome of the Annex 66 research (YAN *et al.*, 2017). Answers related to adjusting each building system were analysed, and a Structural Equation Modelling (SEM) approach was applied to assess the latent variables (constructs of the Theory of Planned Behaviour) and their relations with adaptive behaviours.

Firstly, results show that occupants find it more challenging to share the control of HVAC thermostat compared to the other systems assessed (windows, lights, and shades/blinds). As the literature has been emphasising that individual differences play a significant role in thermal comfort votes and thermal preferences, this aspect was also tested in this study. Results show that gender plays a role to share the control of HVAC thermostat in offices: males reported lower intention to share the control of this system while also perceived lower expectations from their coworkers for doing so when compared to females. Such an outcome supports that providing Personal Comfort Systems (PCSs) for occupants is highly recommended to reduce bothering levels of occupants due to controlling shared systems. Additionally, although relatively less expressive, some respondents also reported a lack of knowledge to control HVAC thermostat, lights and shades/blinds. HVAC was the system with the highest number of people who reported a lack of knowledge to control (8.0% of respondents). Such an outcome provides evidence-based arguments to include other building stakeholders in the loop of building control, instead of it relying only on the occupants. By training occupants about how to adjust systems, for instance, higher levels of knowledge may be found in the future – ideally, 100% of occupants should know how to adjust all the systems to have possible ways to restore their comfort during work.

Secondly, results from the SEM approach suggest that intention to share control and perceived behavioural control have positive and statistically significant effects on adaptive behaviours related to HVAC thermostat, windows, and shades/blinds. For the lights, although a positive effect was found, it was not statistically significant. This result shows room to study occupants' adjustments of lighting through another lens: e.g. by conducting field studies using Self-Reported Habit Index (SRHI), which suggest that habit is also a psychological construct related to behaviours. Although there are differences, this study bridges the gap between the adaptive behaviours themselves and the underlying effects that are related to those choices. Practical advice may be given for stakeholders according to the results: as each building system is affected by specific social psychological constructs, it is recommended to focus on impactful constructs when interventions are necessary. For instance, as perceived behavioural control was found as a positive and significant impact on the intention to share control of HVAC thermostats and shades/blinds, when low intention and consequently low choices to adjust those systems are found, interventions to increase it could focus on increasing perceived behavioural control levels. While for windows and lights, our results suggest focusing on changing attitudes related to sharing control when higher intentions are expected.

Finally, as this survey gathered data anonymously, it is impossible to reach those who declared lack of knowledge to control building systems or low scores for aspects related to sharing control over systems, as well as associate participant's responses with technical information of building systems. However, the results presented enable further studies to evaluate which kind of building systems are perceived as harder to adjust and share control with coworkers. Future research should focus on those aspects to add valuable pieces of information to facilitate the user-centric design of buildings.

5. Subjective and comfort-related drivers for occupant behaviour

This chapter is the transcription of the following paper:

> **Triggering occupant behaviour for energy sustainability: Exploring subjective and comfort-related drivers in Brazilian offices.**
> Authored by: Mateus Vinícius Bavaresco, Enedir Ghisi, Simona D'Oca, and Anna Laura Pisello.
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Abstract

Indoor environmental quality, socio-psychological aspects, as well as contextual and personal factors, can be considered as multi-domain drivers for occupant behaviour (OB). Therefore, this study relies on a survey that bridges the gap between building physics and social psychology to implement an interdisciplinary framework into OB research. A case study was conducted in Florianópolis, southern Brazil. Results show that the impact of Indoor Environmental Quality (IEQ) parameters on respondents' satisfaction is correlated with their influence on perceived productivity. Besides this stand-alone effect, IEQ-beliefs related to indoor temperature and air quality are correlated. The main sources of environmental discomfort and reasons for OB were analysed and provided a basis for further evaluations. Then, the twofold relation between multi-domain discomfort and OB were represented in a flowchart. Our conclusions support that OB must be treated as multi-physics and multi-domain-comfort issues, as adaptive behaviours to restore occupants' comfort may result in additional sources of discomfort. Finally, all the surveyed aspects – IEQ-beliefs, subjective, contextual, and personal factors – were used to perform decision-tree-based analyses to find the main predictors for behaviours. The first takeaway is that control over building systems is the principal driver for adjustments. Additionally, subjective aspects like IEQ-beliefs, frequency of negotiation to control building systems, attitudes, ease and intention towards sharing their control were also important predictors. It evidences that increased data-driven knowledge about those relations is essential in this field, and future monitoring and modelling approaches may be enhanced by incorporating them instead of focusing siloed on environmental parameters.

1. Introduction

Literature highlights that buildings are responsible for one of the largest share of energy used worldwide, and this consumption is increasing rapidly and continuously (GABC, 2019). Another fact is that people are spending about 90% of their time inside buildings in modern societies (ZOMORODIAN; TAHSILDOOST; HAFEZI, 2016). During this considerable amount of time spent indoors, occupants interact with different systems – air conditioning, windows, blinds/shades, lighting fixtures, etc. – to meet their needs and preferences regarding indoor environmental quality (IEQ). State-of-the-art literature presents great efforts to evaluate the extent to which occupant behaviour impacts on building energy use (D'OCA; HONG; LANGEVIN, 2018; STAZI; NASPI; D'ORAZIO, 2017). IEA-EBC Annex 66 was an important initiative to improve occupant behaviour research in terms of data collection, model representation and evaluation, as well as the integration of created models to building performance simulation programmes (YAN *et al.*, 2017). Along these lines, it is evident that understanding drivers for occupant behaviour is essential to improve the performance of buildings since their design stage (DELZENDEH *et al.*, 2017), and many studies provided valuable information about the impact of environmental drivers on adjustments of building systems. For instance, indoor (HALDI; ROBINSON, 2008; LIN *et al.*, 2016) and outdoor temperature (HALDI; ROBINSON, 2008; SCHWEIKER; SHUKUYA, 2010; ZHANG; BARRETT, 2012) have been related to window, blind/shade and HVAC control; solar radiation to blind/shade control (BAVARESCO; GHISI, 2020; O'BRIEN; KAPSIS; ATHIENITIS, 2013); and CO_2 concentration to window control (CALÌ *et al.*, 2016; NASPI *et al.*, 2018). More detailed information is available on (WAGNER; O'BRIEN; DONG, 2017); the authors conducted an extensive literature review and presented several triggers for human-building interactions. However, not only environmental variables impact occupant behaviours: Hong *et al.* (2015a) proposed the DNAS (Drivers, Needs, Actions, and Systems) framework claiming that the human cognition encompasses the connection of human "inside world" inputs (Drivers and Needs) and the "outside world" outputs (Actions and Systems). Similarly, further advances in the field are showing that subjective aspects do play important roles in occupant behaviour. The literature already supports the impact of Theory of Planned Behaviour constructs (attitude, subjective norms, perceived behavioural control, and intention) (D'OCA *et al.*, 2018), values (AMASYALI; EL-GOHARY, 2016; HEWITT *et al.*, 2016), cultural differences (CHEN *et al.*, 2020; MA *et al.*, 2017), and personality traits (AHMADI-KARVIGH *et al.*, 2017; HONG *et al.*, 2020b).

Along with updates on the literature regarding occupant behaviour, acceptable thresholds for IEQ are also extensively studied. Thermal (RUPP; VÁSQUEZ; LAMBERTS, 2015), visual (GALASIU; VEITCH, 2006), acoustic (MA; WONG; MAK, 2018), air quality (MA; WONG; MAK, 2018), and multiphysics comfort able to link at least two of the physical spheres (PIGLIAUTILE *et al.*, 2020; SCHWEIKER *et al.*, 2020) are being evaluated throughout the world, as highlighted by state-of-the-art reviews. International efforts to study thermal comfort are consolidated, and standards are available, as well as a global database on field studies across the world (LIČINA *et al.*, 2018). With many advances in this field, there is evidence supporting that demographics (age, gender, weight, thermal history), environmental variables (humidity, air movement, controls), and building-related aspects (naturally ventilated, air-conditioned or mixed-mode) may affect thermal comfort of occupants (RUPP; VÁSQUEZ; LAMBERTS, 2015). However, occupants are not exposed to stand-alone sources of discomfort; instead, multi-domain combinations are continually affecting them inside buildings (HEYDARIAN *et al.*, 2020). In office contexts, multiple interaction means (e.g., operable building systems) and various triggers (e.g., sources of discomfort) coexist (OZCELIK; BECERIK-GERBER; CHUGH, 2019). Therefore, multi-domain comfort studies, also supported by a more holistic design for human building interfaces (DAY *et al.*, 2020), are emerging as promising ways to assess occupants' preferences considering at least two dimensions of IEQ (e.g., thermal and visual), as changes in one aspect may affect the way occupants react to another one.

Along these lines, studies are showing relations between several environmental factors and adjustments on building systems. Occupant actions differ when they are exposed to "no discomfort" compared to "multi-domain discomfort" situations (OZCELIK; BECERIK-GERBER; CHUGH, 2019). Under simultaneous visual and thermal discomfort, occupants tended to adjust first the blinds, while under the no discomfort scenario, the first option was changing desk fans (OZCELIK; BECERIK-GERBER; CHUGH, 2019). As the literature supports that both thermal and visual aspects play important roles when it comes to blind/shade control (O'BRIEN; KAPSIS; ATHIENITIS, 2013), the adjustments of internal blinds/shades should be considered under multi-domain comfort lenses. Although window control is primarily associated with indoor/outdoor temperatures to develop models (RIJAL *et al.*, 2007; ZHANG; BARRETT, 2012), there are suggestions also to include aspects like indoor air quality, rain, and noise level (FABI *et al.*, 2012; HALDI; ROBINSON, 2008), supporting that it is a multi-domain-triggered action. Even thermal behaviours (i.e., changing clothes) have been related to visual-comfort aspects. Experimental results showed that lighting systems with low colour temperature impacted positively on the thermal comfort of participants (HUEBNER *et al.*, 2016).

Besides environmental aspects that affect human-building interactions, both contextual and personal factors are also meaningful in this field. Considering cooling and heating practices, social-psychological, contextual and personal aspects affected occupants thermal actions in offices (CHEN *et al.*, 2020). Social-psychological constructs were also linked to energy-saving behaviours in offices, namely opportunity, motivation and ability reported by occupants (LI *et al.*, 2019). Exploring constructs to understand energy use behaviours may provide practical advice to policy-makers regarding which aspect is worth addressing to achieve effective outcomes (BAVARESCO *et al.*, 2020a; LI; MENASSA; KARATAS, 2017). Similarly, personality traits have been proved to influence human-building interactions in shared offices (HONG *et al.*, 2020b). Non-physical and subjective aspects also influenced the way occupants perceive environmental comfort, and psychological factors related to company policies may positively affect occupants' comfort perception (CASTALDO *et al.*, 2018). Field studies in Indian offices also confirmed that non-thermal factors are related to the adjustment of windows (INDRAGANTI *et al.*, 2015). The authors concluded that barriers could be either beyond or within occupants' realm, suggesting that efforts to improve occupant operation of controls involve different phases of building life cycle. Specific underlying aspects like the colour temperature of the illumination was also associated with the thermal comfort of occupants in chamber-based studies (HUEBNER *et al.*, 2016). Assessing the influence of combined effects is an innovative approach in occupant perception and behaviour studies. However, most previous research focused on specific topics, like window operation or HVAC adjustments, and broader views are still missing (HARPUTLUGIL; WILDE, 2021).

Indeed, a recent literature review highlighted the need to consider relations and interactions among multi-domain physical variables, contextual and personal factors (SCHWEIKER *et al.*, 2020). The authors presented physical variables that are typically measured and considered as triggers for occupant behaviour. Nevertheless, there are still uncertainties to select and report appropriate contextual and personal variables, which can be reached through the implementation of interdisciplinary frameworks. As recently presented by Day *et al.* (2020), although the literature has increased fast in the last few years, more work is still necessary to assess and understand how occupants use different building systems. Enriching knowledge about multi-domain stimuli for occupant behaviours is expected to boost the operation in building-level scales as occupants may have user-centric control features. Therefore, detailed evaluations may present to building stakeholders practical advice to improve IEQ in built environments. Moreover, such practice may also improve model developments, as choosing correct predictor variables is a fundamental role in modelling occupant behaviour for Building Performance Simulations (CARLUCCI *et al.*, 2020).

In this panorama, the purpose of this study is to empirically evaluate the effect of multi-domain triggers on occupant behaviour by implementing an interdisciplinary framework in Brazilian offices. Its theoretical basis relies on the combination of different theories that synthesise building physics and social psychology to study occupant behaviour (D'OCA *et al.*, 2017). Such an approach is aligned with a recent literature review that evidenced the importance of using behavioural theories to assess occupant interactions with building systems (HEYDARIAN *et al.*, 2020). Multi-domain aspects were surveyed on the case study conducted, and three main foci were given to the analysis. First, IEQ-beliefs consisting of occupants' satisfaction and perceived productivity influenced by indoor environmental parameters were evaluated. Second, the main sources of environmental discomfort, as well as the reasons to adjust building systems during different seasons, were assessed and provided the basis for further analyses. Considering the clear relation between sources of environmental discomfort and reasons to adjust building systems, a flowchart linking environmental triggers with occupant behaviour in offices was proposed. Finally, a noteworthy takeaway of this research relies on the use of a machine learning algorithm to combine all the surveyed information and determine the main predictors for occupants' adaptive actions at work. For doing so, IEQ-beliefs, subjective, contextual and personal factors were included under the proposed formulation to boost the multi-domain evaluation conducted. As presented by Heydarian *et al.* (2020), it is necessary to deepen the evaluations about drivers for occupant behaviour in buildings. Moreover, the authors emphasised that it is important to conduct such research in developing countries to enrich the findings with a broader geographical spectrum, as most studies are still conducted in Western Europe, the United States and China.

2. Method

Previous research developed an interdisciplinary framework that synthesises building physics and social psychology to study occupant behaviour in offices (D'OCA *et al.*, 2017). By combining knowledge from different fields, the authors presented a questionnaire to investigate human-building interactions in offices based on three theories:

- Social Cognitive Theory (SCT), explained by Bandura (1986), relates human behaviour with personal and environmental factors, reasoning that what people perceive, believe and do affect their further actions as well as other's behaviours;
- Drivers-Needs-Actions-Systems (DNAS) framework (HONG *et al.*, 2015a, 2015b), used to explain impacting factors on human-building interactions, which supports that the "inside world" (drivers and needs) affects the "outside world" (actions and systems);
- Theory of Planned Behaviour (TPB), introduced by Ajzen (1991), which highlights the impact of individual intention to behave on the exercised behaviour. Also, the theory argues that attitude, subjective norms and perceived behavioural control are key factors impacting one's intention.

The present study relies on the implementation of this framework to evaluate the influence of multi-domain triggers on occupant behaviour in workspaces of the Federal University of Santa Catarina (UFSC) campus, located in Florianópolis, Southern Brazil. The approach adopted is aimed to combine core elements deemed as key facets in energy social research by Sovacool *et al.* (2018). Indeed, by asking relevant questions that are based on a conceptual framework, this study is expected to bring innovation to occupant behaviour modelling studies. Additionally, this section presents all the details on the research design to facilitate its evaluation and enable replicability.

2.1. Details about the questionnaire application

The survey instrument consisted of an internet-based questionnaire (D'OCA *et al.*, 2017), developed and presented along with the Annex 66 activities (YAN *et al.*, 2017). As it was initially created in English, a version in Portuguese was achieved using the Double Translation Process (DTP). After being translated into Portuguese, the questions were brought back to English to enable comparison and fix inconsistencies found. Ethical board at the University (*Human Research Ethics Committee*) approved the Portuguese version of the survey under National Regulation 510/2016 requirements (BRASIL, 2016). After that, the questionnaire was inserted into the Qualtrics Software and individual links to access it were sent to 3,356 employees at the Federal University of Santa Catarina. Among them, 345 employees accepted the invitation and participated in the survey; however, 67 answers were excluded because they were either uncompleted or came from people who did not work in office spaces. Data collection occurred from September to November 2017, comprising an initial invitation and four follow-up reminders.

2.2. Location and climate of the city

This research comprises a case study conducted in Florianópolis, southern Brazil, at the Federal University of Santa Catarina. Florianópolis is located at the latitude of -27º36’ and longitude of -48º33’, with a temperate and humid climate (warm and wet during the summer – from December to March; and cool during the winter – from June to September). Figure 5.1 presents details about the city climate according to data from the Brazilian National Institute of Meteorology (INMET).

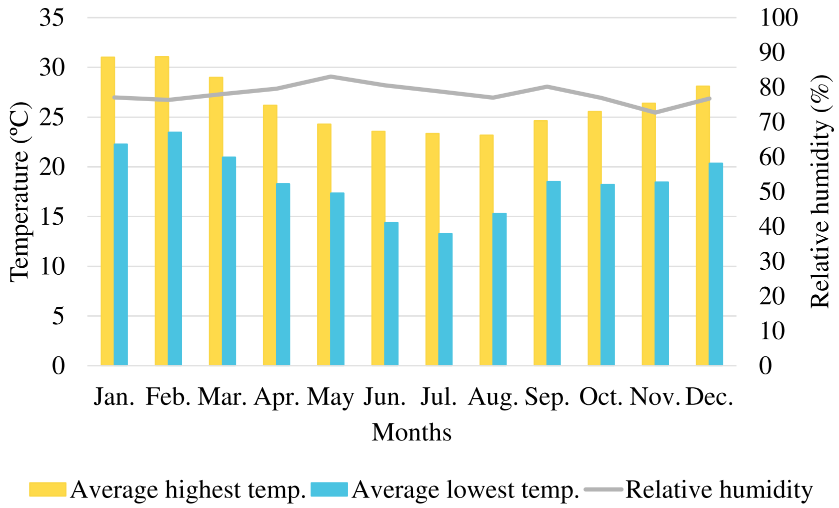

Figure 5.1. Florianópolis climate during 2017.

2.3. Characteristics of the buildings

Employees working in different buildings on campus accepted the invitation and responded to the survey. Although the participation was anonymous and responses were not linked to the invitation e-mail, participants were allowed to inform in which University building they were used to work in. Therefore, Figure 5.2 shows Google street view images of buildings that were reported by some of them. Despite the fact that several characteristics (e.g., solar orientation, window-to-wall ratio, solar absorptance, number of floors, etc.) are building-dependent, some similarities among buildings are evident. Such a trend is especially valid considering building systems. For instance, all the buildings operate under mixed-mode ventilation (operable windows and HVAC); additionally, to the best of authors’ knowledge, buildings on campus do not rely on automated control for the systems evaluated on this study – HVAC, windows, lighting, and blinds. In other words, occupants are responsible for adjusting them during occupied hours.

It is also important to highlight some specific characteristics of each system. Regarding the HVAC systems, the most common type are mini-split units (both wall or ceiling-mounted) attached to an outdoor compressor. Therefore, each zone has its control and occupants are responsible for adjusting indoor temperature as well as balancing between natural and artificial ventilation. Regarding windows, both slider and top-hung models are common at the University buildings, and occupants are expected to adjust them. A greater option of shades/blinds can be found on campus, as vertical-fabric blinds, Venetian blinds and roller shades are used. Most buildings rely on external shading (i.e., *brise soleil*) considering that Florianopolis is a cooling-dominated climate. Finally, tubular fluorescent lamps are frequently used on the University offices, and the indoor target illuminance required by national standards is 500 lux on offices' working areas (ABNT, 2013).

Figure 5.2. Characterisation of University buildings with images from Google street view.

  

Figure 5.2. Characterisation of University buildings with images from Google street view (continuation).

2.4. Aspects surveyed

This study did not rely on field measurements, and answers are not linked with indoor or outdoor monitoring; instead, subjective information was collected to evaluate the extent that multi-domain triggers may affect human-building interactions. The wide variety of historical perceptions reported by participants is presented in this subsection to contextualise further analysis.

2.4.1. IEQ-beliefs

These variables were surveyed according to occupants' satisfaction and perceived productivity influenced by different IEQ parameters: indoor temperature, indoor air quality, natural lighting, artificial lighting, and acoustics. Respondents stated to what extent they were satisfied or dissatisfied with each IEQ parameter and how those conditions influenced their current productivity at work using five-point Likert-like scales. Data were coded from 1 (very unsatisfied and very negatively) to 5 (very satisfied and very positively).

2.4.2. Subjective aspects

Social-psychological factors included intention, ease, attitudes, and expectations to share the control of each building system (windows, blinds/shades, HVAC, and lighting), as well as knowledge for doing so. Each aspect was surveyed in a five-point Likert-like scale, where 1 represented very negative answers, and 5 described very positive answers. Additionally, the frequency of negotiation to adjust each system was surveyed, asking "How often do you negotiate with your co-workers about sharing the control of the following devices?". Each building system was evaluated separately, and five options were used to measure it: 1: never negotiate; 2: less than once a week; 3: once a week; 4: once a day; 5: more than once a day.

2.4.3. Contextual factors

Contextual factors included occupancy (hours spent at work per week, surveyed with brackets from “1–10 hours” to “more than 50 hours” with 10-hour intervals), office type (private or shared offices), accessibility to control building systems as well as the number of people sharing their control. Accessibility was surveyed asking “Do you have control to… *[adjust each building system]* …in your workspace?”. Answers were dummy categorised as 1 when the answer was “yes” and 0 when it was “no” or “I do not know”. Finally, it was asked “How many people in your workplace share (with you) the control of the following devices?”. Each building system was evaluated separately, and four options were used to measure it: 1: only me; 2: one other co-worker; 3: two or more co-workers; 4: I do not know.

2.4.4. Personal factors

Respondents informed their gender, and the answers were dummy coded as 0 for “females” and 1 for “males”. Age was surveyed with brackets from “18–28 years” to “62 years or older” using 11-year intervals.

2.4.5. Main sources of multi-domain discomfort

Four questions asked the primary sources of discomfort considering thermal, visual, acoustic, and air quality aspects. Check-all-that-apply formats were used to allow occupants selecting as many options as desired. Additional sources could be provided under the option “Other, please describe”.

2.4.6. Main reasons to adjust building systems

Respondents provided the main reasons to adjust HVAC thermostat and to open and close windows and blinds/shades across seasons, as well as the main reasons to switch on and off the lighting system. Such check-all-data-apply questions enabled to understand the impact of seasonality on occupant behaviour in offices as well as calculating the number of adaptive opportunities that each respondent considers to be performing throughout the year. The total adaptive opportunities were used as dependent variables in the predictive modelling technique used in this study. Then, we evaluated what factors are the main predictors for occupant behaviour in offices, and all the details about this part are presented in subsection 2.5.2.

2.5. Data analyses

Two main analyses were performed in this study. First, responses to IEQ-beliefs were in-depth evaluated. Second, a machine learning technique was applied to identify triggers for human-building interactions considering all the systems evaluated in the survey. This subsection presents details about both aspects.

2.5.1. Evaluation of IEQ-beliefs, sources of discomfort and reasons to adjust systems

Firstly, a correlation matrix was performed to evaluate if different aspects of IEQ satisfaction and IEQ-productivity-belief are linked. For doing so, the function "rcorr" under the "Hmisc" package (HARRELL JR., 2020) for R software was used. Along with this function, Spearman's rho rank correlation coefficients were calculated using algorithms from Press *et al.* (1992). Regarding the main sources of discomfort and reasons to adjust systems, calculated fields in Tableau software (TABLEAU, 2020) allowed the determination of the appropriate percentages for each question. Therefore, images synthesising all the information from those check-all-that-apply questions were created.

2.5.2. Machine learning technique

In this study, decision trees were used to evaluate the main predictors for human-building interactions. Decision trees are highly used in machine learning studies and consists of dividing a database into several predefined classes (HAN; KAMBER; PEI, 2011). Such a model results in a flowchart-like tree structure, and each internal node represents a test made for an attribute; then, each branch denotes the outcomes of the trials, and the leaf nodes show the results for all the paths. Decision trees follow logic rules to assess how a target variable can be predicted by a series of predictor variables, which can describe, categorise and generalise datasets (YU *et al.*, 2010). In the present study, classification trees were used to evaluate the influence of IEQ-beliefs, subjective aspects, contextual and personal factors on the reported adaptive behaviours performed throughout the year. This subsection presents details about the approaches used on such analyses.

2.5.2.1. Data

The main objective of a decision tree is to establish a classification model to predict a label attribute based on several predictor attributes (D'OCA; HONG, 2014). In the context of this study, the label attributes are related to the main reasons to adjust building systems through building interfaces reported by the participants on the survey. As shown in subsection 2.3.6, the total adaptive opportunities were calculated and used as the label attributes on the decision trees. In other words, we assessed the possible reasons for each respondent to adjust building systems in their offices throughout the year. As a result, an integer number synthesising all the potential triggers was found. Then, this number was used to evaluate to what extent a combination of multi-domain triggers may affect the way occupants adjust building systems. In other words, according to the final number, it was possible to know if a given occupant is likely to adjust or not each system throughout the year. Discretisation was then performed to group the outcomes in the following classes: “no interactions”, when occupants do not adjust a given system throughout the year; “low” or “high” when occupants adjust a given system, according to two discretisation approaches. The discretisation is used to reduce the number value of continuous attributes into intervals, and it is advantageous when decision-tree-based classification is intended (HAN; KAMBER; PEI, 2011). Two unsupervised discretisers were tested on this study: Equal Width and Equal Depth. Both techniques consist of binning data according to their distribution, i.e. each bin has the same range in an equal-width histogram, while each bin has the same frequency in an equal-depth histogram (HAN; KAMBER; PEI, 2011). Both strategies were tested, and better outcomes were achieved using equal-depth discretisation, so this approach was used in all the decision trees created. Similarly, the number of classes used to discretise label attributes was based on model outcomes. By assuming only two classes, the models would fail to detect either the “no interaction” or the variations on responses from occupants who do adjust their workspace. Also, adopting more than three classes reduced the reliability of the models created.

2.5.2.2. Algorithm used

The “rpart” package (Recursive Partitioning and Regression Trees) (THERNEAU; ATKINSON; RIPLEY, 2019) from R software was used to develop the decision trees on this study. The first step consisted of the learning process, where the dataset was randomly divided into two categories: training (80% of data) and testing (20% of data). Then, the “training” dataset was used as input for the “rpart” model created. Such a model was built considering the classes mentioned above that express how likely occupants are to adjust building systems (“no interactions”, “low” or “high”) as a label attribute. At the same time, the multi-domain triggers (IEQ-beliefs, subjective aspects, contextual and personal factors) represented the predictor attributes. In general, building a decision tree consists of splitting attributes to determine the best split and, then, creating partitions using them (DU; ZHAN, 2002). Common approaches to assess the goodness of such splitting schemes are the *Gini index* and *Entropy*. If a given dataset *W* presents *n* classes, Gini(W) and Entropy(W) can be calculated according to Equations 1 and 2, respectively. After that, those indexes are used to determine the information gain if an attribute A is used to partition the dataset W. Information gain synthesises whether a given attribute is a good predictor for classifying the variable, i.e. higher information gains represent better predictors (RYU; MOON, 2016). Considering both Gini index and Entropy, information gain can be calculated according to Equations 3 and 4.

$$Gini\ index(W) = 1 - \sum_{j=1}^{n} {P_j}^2 \tag{1}$$

$$Entropy(W) = -\sum_{j=1}^{n} P_j \log P_j \tag{2}$$

$$Gain\ (W, A) = Gini\ index(W) - \sum_{v \in A} (\frac{|W_v|}{|W|} * Gini\ index(W_v) \tag{3}$$

$$Gain\ (W, A) = Entropy\ (W) - \sum_{v \in A} (\frac{|W_v|}{|W|} * Entropy(W_v) \tag{4}$$

Where: P_j is the proportion of j found in W; v is a possible value of attribute A; W_v is a subset of W in which attribute A has the value of v; $|W_v|$ is the size of subset Wv; $|W|$ is the size of W.

Regarding “rpart” package used in this study, the splitting index can be set under the “parms” argument; “gini” is the default, but users can set Entropy by changing it to “information” (THERNEAU; ATKINSON; RIPLEY, 2019). Both splitting indexes were tested, and Gini index was chosen based on the decision trees’ fit. After that, the testing dataset was submitted to the classification path of the decision tree achieved, and the predictions were compared to the actual values of the dataset using confusion matrix enabled by the “caret” package (Classification And Regression Training) (KUHN, 2020) on R software. Finally, this evaluation enabled iterative processes to improve the models by applying the concept of pruning on the created trees. Pruning is important to remove leaves that do not add useful information; as a consequence, a previously over-fitted tree may become more reliable for unseen datasets (D'OCA; HONG, 2014). Pruning is an alternative englobed on the "rpart" package under the "rpart.control" argument. As explained on the "rpart" documentation, the pruning is based on the complexity parameter (cp), which is a threshold to recursively snipping off the least important splits on a created tree (KUHN, 2020). In other words, cp is used to evaluate if created splits decrease the overall lack of fit on the model by a factor of cp. When it does not happen, the algorithm excludes such split to save computational time, and the outcome is likely to be more accurate. Each decision tree was set a specific cp ranging from 0.010 to 0.035 – open windows = 0.010, close windows = 0.020, open blinds = 0.035, close blinds = 0.025, adjust the HVAC thermostat = 0.015, turn on and turn off the lights = 0.020. Finally, the "rpart.plot" package (MILBORROW, 2020) was used to plot the decision trees and include some details on their leaves. Under the argument "extra" on the package, it was set that leaves should present the predicted class, the probability per class of observation, and the percentage that each leaf represents considering the training data. Details about these aspects are presented in Figure 5.3. Considering the examples from the models, it is possible to see that the first leaf (class "low") synthesises 17% of all data on the model, which 88% actually belongs to this class on the training dataset. Similarly, the example leaf from a "high" class represents 3% of all the data of the corresponding model, in which 80% of the data is actually from this class.

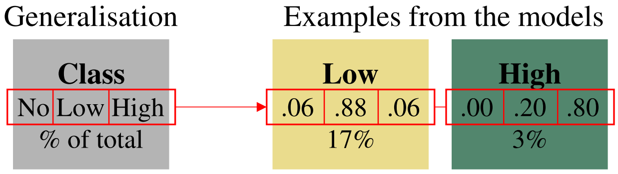

Figure 5.3. Illustration of the information presented in decision trees' leaves.

3. Results and discussion

The total sample comprised 278 complete pre-validated responses, and it included occupants with a variety of profiles. This subsection presents and discusses the outcomes reached with this study, and a brief characterisation of the sample is also worth. The main differences were found for occupants' gender: 34% were male and 66% female. However, recent data from the University showed that, as a general trend, the gender distribution is uniform among employees: about 49% men and 51% women (UFSC, 2019). This outcome suggests that women were more willing to accept the invitations to participate in the survey, especially considering that invitations were sent to all the e-mail addresses available.

Considering work position, 45% of participants were administrative staff, 29% faculty members, 23% post-graduation students, and 3% were researchers. Age ranges comprised 24% of participants in the "18–28 years" interval, 41% in the "29–39 years", 20% in the "40–50 years", and 15% were "51 years or older". Considering the time spent weekly in the office, 17% of respondents spend 20 hours or less, 19% spend 21–30 hours, 30% spend 31–40 hours, and 34% spend 40 hours or more.

3.1. Influence of IEQ parameters on occupant satisfaction and productivity

To assess the perceived satisfaction and the influence of IEQ on occupants' productivity, participants rated different IEQ parameters (indoor temperature, indoor air quality, natural lighting, artificial lighting, and acoustics) according to a five-point Likert-like scale. The worst scenarios (very unsatisfied or very negatively) were coded as 1, and the better ones (very satisfied or very positively) were coded as 5. Figure 5.4 shows the percentage of positive and negative answers for each aspect, as well as circles with their averages.

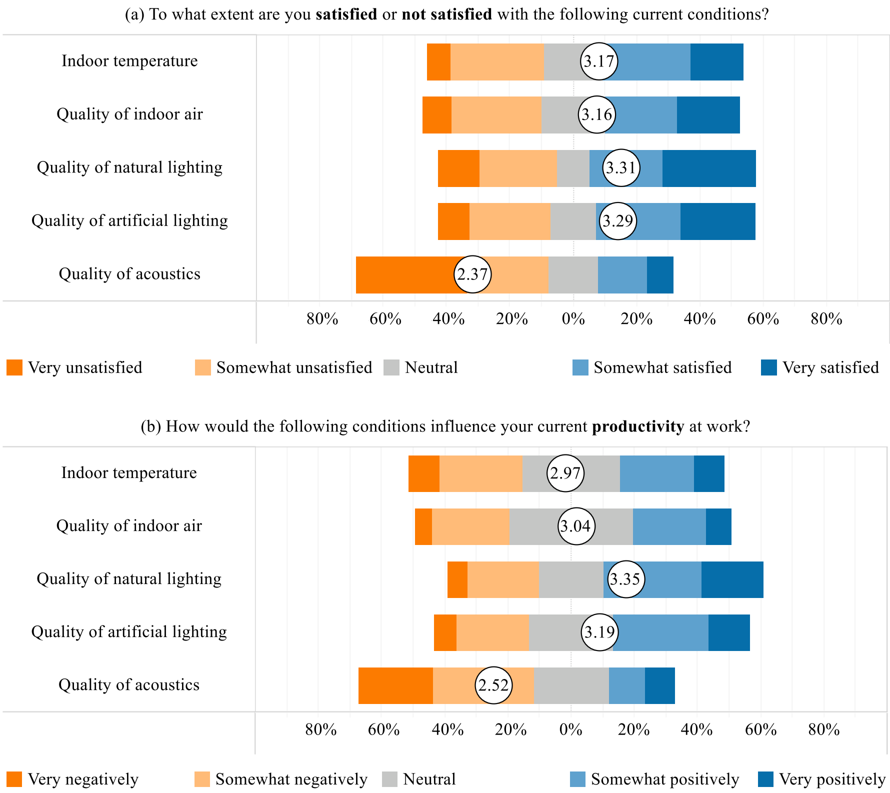

Figure 5.4. The self-reported impact of IEQ parameters on (a) satisfaction and (b) productivity of occupants.

Our results suggest that occupants may be conservative to rate the influence of IEQ on their productivity. Indeed, participants reported more neutral opinions about the impact of IEQ on productivity compared to their satisfaction with IEQ. Although this trend is evident for all the parameters evaluated, outcomes regarding indoor air quality (IAQ) stress this tendency. While 20.0% of respondents are neither satisfied nor dissatisfied with IAQ, 39.0% reported a neutral opinion regarding its influence on their productivity. Importantly, a recent study proposed a multi-dimensional framework to specifically study the impact of IEQ on occupant perceived productivity (CHEN *et al.*, 2020). The authors concluded that IEQ satisfaction is the major predictor for IEQ-productivity belief; however, other aspects like cultural differences, attitudinal-behavioural factors, and accessibility to building controls play important roles. Our results also show that quality of acoustics needs to be further explored and improved at the evaluated offices. In essence, 60.4% of the respondents are very or somewhat unsatisfied with it, and 55.3% of them consider that acoustics impacts their productivity in very or somewhat negatively ways. The high percentage of negative responses can be seen through the averages obtained: $\bar{x} = 2.37$ considering self-reported satisfaction, and $\bar{x} = 2.52$ regarding its impact on productivity. Quality of natural lighting, on the other hand, was the most positively-rated aspect: 52.4% of the respondents are very or somewhat satisfied with it, and 50.5% of them stated that natural light impacts their productivity in very or somewhat positively ways.

Besides the siloed effect of each evaluated aspect, it is also important to understand if the influence of IEQ aspects on satisfaction and productivity are mutually correlated with each other. Table 5.1 shows a correlation matrix between all the self-reported impacts of IEQ variables on occupants' satisfaction and productivity. The satisfaction with all IEQ parameters is correlated ($\rho > 0.5$ and p-value < 0.01) with the perceived productivity related to the same parameter. Correlations higher than 0.5 were highlighted on the cells: absolute correlations ($\rho = 1.0$) are presented in grey cells, while correlations higher than 0.7 are red, $\rho > 0.6$ are orange, and $\rho > 0.5$ are yellow. All the correlations highlighted are statistically significant (p-value < 0.01). Thus, increasing occupants' satisfaction levels with IEQ may lead to a consequent increasing in their perceived productivity, as supported by the literature (CHEN *et al.*, 2020; LAMB; KWOK, 2016).

However, the other way around may also be hypothesised: when occupants consider that a given IEQ parameter positively influence their productivity, they may feel more satisfied with indoor conditions. Further studies can focus specifically on evaluating these hypotheses about which belief causally precedes the other. Additionally, it was found that satisfaction with indoor temperature is correlated with satisfaction with air quality ($\rho = 0.543$) as well as the influence of indoor temperature on productivity is correlated with the influence of air quality on productivity (ρ = 0.723). Some previous works found associations between the thermal environment and air quality evaluation by occupants. For instance, even by increasing the airspeed – which reduces thermal discomfort in hot climates (BUONOCORE *et al.*, 2018) – occupants may associate it with fresh air and report higher perception of air quality (ARENS *et al.*, 2008). Finally, the influence of natural lighting on productivity is correlated with the influence of artificial lighting on productivity (ρ = 0.573).

Table 5.1. Correlation matrix for the self-reported influence of IEQ aspects on occupant satisfaction and productivity.

IEQ-beliefs		**Satisfaction with the following IEQ aspects**					**Influence of the following IEQ aspects on self-reported productivity**				
		Te.	**I.A.**	**Ac.**	**N.L.**	**A.L.**	**Te.**	**I.A.**	**Ac.**	**N.L.**	**A.L.**
Satisfaction with the following IEQ aspects	Temperature (Te.)	1.00									
	Indoor Air (I.A.)	.543	1.00								
	Acoustics (Ac.)	.251	.305	1.00							
	Natural Light (N.L.)	.243	.424	.329	1.00						
	Artificial Light (A.L.)	.298	.356	.304	.444	1.00					
Influence of the following IEQ aspects on productivity	Temperature (Te.)	.621	.436	.268	.227	.228	1.00				
	Indoor Air (I.A.)	.378	.573	.213	.294	.243	.723	1.00			
	Acoustics (Ac.)	.215	.145	.605	.117	.174	.433	.375	1.00		
	Natural Light (N.L.)	.161	.266	.233	.627	.328	.378	.464	.345	1.00	
	Artificial Light (A.L.)	.206	.229	.291	.341	.650	.395	.437	.385	.564	1.00

Going further on this topic, it is also important to discuss the cumulative effect that the associations of perceived quality of different IEQ aspects may present on occupants' actions (YUN; STEEMERS; BAKER, 2008). Considering that the evaluated buildings rely on mixed-mode ventilation, the correlation between thermal and air quality factors may explain some occupants' adaptive actions. For instance, the literature supports that perceived control over temperature and air quality are linked with the proportion of time a window was open in offices (YUN; STEEMERS; BAKER, 2008). Additionally, a recent comparison among three offices found varied window and HVAC operations performed by the occupants, but similar indoor conditions (NEVES *et al.*, 2020). The authors argue that occupant behaviours, although diverse, led indoor conditions of monitored buildings to be similar. Previous field studies in mixed-mode ventilated buildings reported a twofold thermal comfort response, as occupants may feel excessive cold during HVAC use and a tendency towards warm discomfort when natural ventilation takes place (VECCHI *et al.*, 2017), highlighting the complex underlying aspects of such operation mode. Along these lines, our results support that both thermal and air quality preferences must be comprehensively understood to improve user-centric design and operation of mixed-mode ventilated buildings, as such parameters may be strictly linked to occupant behaviour. In a broader perspective, Haldi and Robinson (2010) related occupants' actions and comfort sensations to present a formulation about adaptive behaviours as responses to environmental discomfort. The authors then argue that occupants' actions may represent adaptive increments in comfort sensations. Along these lines, future research could rely on the association between thermal and air quality subjective evaluations to formalise a possible interconnection criterion for controlling mixed-mode ventilation buildings.

3.2. Main sources of discomfort reported in this study

The primary sources of discomfort in the offices – in terms of thermal, visual, acoustics, and air quality – are presented in Figure 5.5. It shows the absolute number of respondents that selected each option (column), as well as their corresponding percentage and confidence intervals with 95% probability. Such an evaluation may lead to intervention-based improvements in the University offices. By recognising unknown sources of discomfort, practitioners may conduct field studies to discover objective information related to them and provide helpful insights for future work. Along these lines, 16% of the respondents stated that windows being too close to their position is a thermal discomfort source, while 9% said so when windows are too far. Similarly, 31% of respondents reported that artificial lighting is not enough, while 9% stated the contrary. Therefore, field studies may result in practical advice to improve building design as well as office layouts, considering acceptable distances between occupants and windows and comfortable lighting levels for the majority of employees. Comprehensive field studies may also positively impact on the design of building systems: e.g., some may discover window interfaces that help increasing occupant perceived satisfaction.

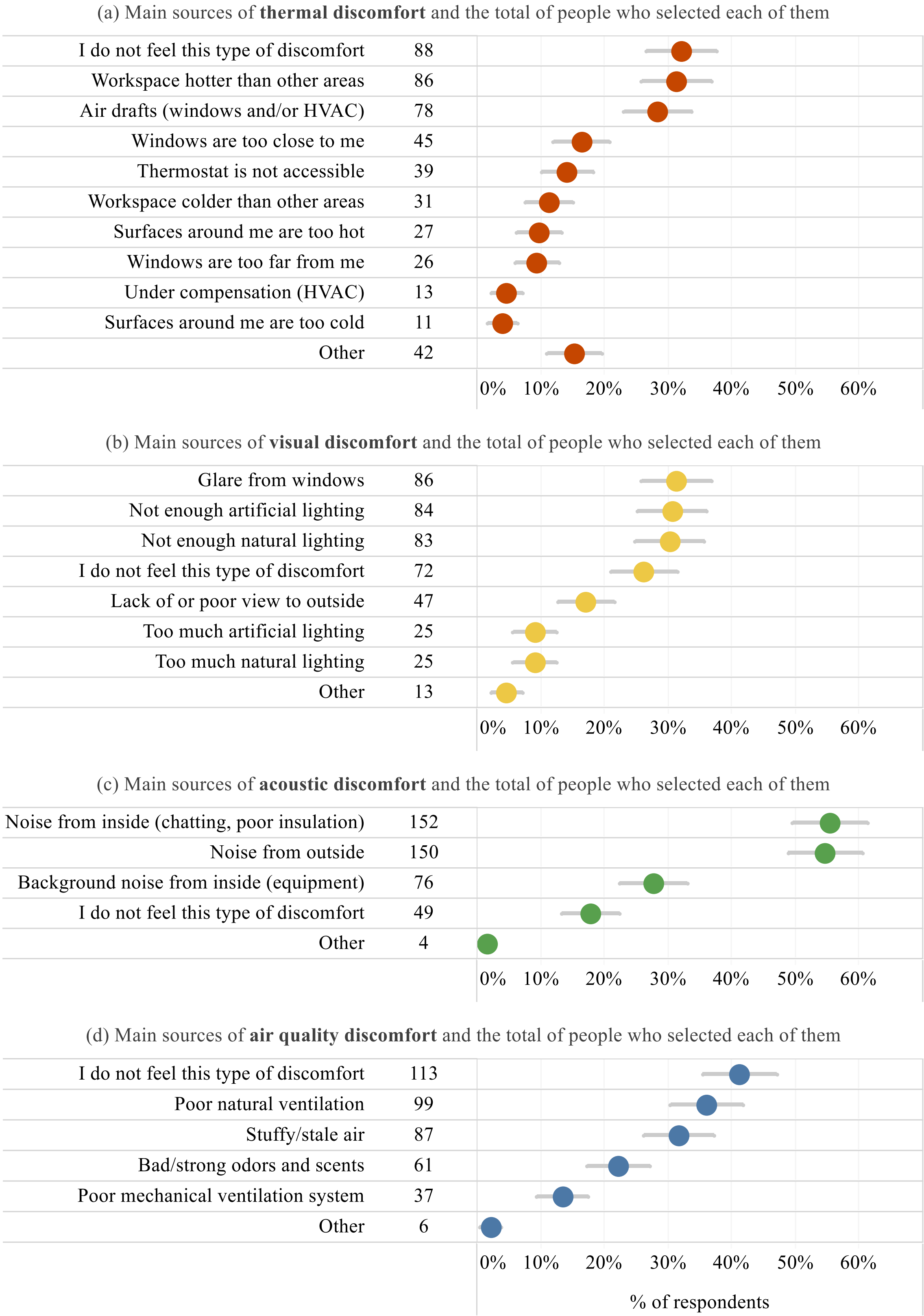

Figure 5.5. Main sources of (a) thermal, (b) visual, (c) acoustic, and (d) air quality discomfort reported by the participants.

Emphasising previously presented results about the quality of acoustics, Figure 5.5 shows that more participants reported sources of acoustic discomfort compared to the other aspects. Inside and outside noise was reported by 55% of respondents; contrarily, none of the potential sources of different kinds of discomfort was stated by more than 36% of participants. When it comes to occupants who reported that he/she does not feel discomfort at work, different proportions were found according to each IEQ aspect: 41% for air quality discomfort, 32% for thermal discomfort, 26% for visual discomfort, and 18% for acoustic discomfort.

3.3. Subjective aspects related to human-building interactions

Results from the survey allowed assessing triggers for occupant behaviour throughout the year. Sections 3.3.1-3.3.4 show the issues related to adjustments of windows, blinds/shades, HVAC thermostat and lighting. Additionally, decision trees were created considering the interrelated influences on human-building interactions. The first takeaway from those analyses represents the impact of actual control over building systems: zero adaptive opportunities were predicted for people that perceive no control over the windows, blinds/shades, HVAC, and lighting. However, when occupants do have control over building systems, several subjective, contextual and IEQ-related aspects were predictors for a higher number of interactions throughout the year. The following subsections present innovative knowledge about the primary triggers driving occupant behaviour, including detailed information about the influence of seasonality on such adjustments. This knowledge may therefore enhance the representation of occupant behaviour when non-probabilistic fit-for-purpose modelling is intended (GAETANI; HOES; HENSEN, 2016), as even static models could be tailored to context-driven information. Additionally, machine learning algorithms returned the main predictors for each behaviour evaluated, which may guide future field studies as well as the development of models.

3.3.1. Adjusting windows

Figure 5.6 shows the self-reported motivational drivers for opening and closing the windows at work. It was created to synthesise the outcomes of check-all-that-apply questions, and that is why the sum of responses is greater than 100%. Each percentage represents the proportion of a given action (e.g., open windows during the summer to have fresh air) in relation to all possible ones. The same approach was used to evaluate the main triggers to adjust the other systems in the following figures. Personal needs play a significant role in opening windows across all seasons – having fresh air: up to 91% of respondents stated so; and reducing outdoor noises: up to 53% of them. Habits/rules are also important: arrive/leave the office were indicated by 57% of the respondents; such time-dependency is supported by the literature (D'OCA; HONG, 2014; YUN; STEEMERS, 2008). Furthermore, the triggers for opening and closing windows in offices highlight that it can be interpreted as a multi-domain issue (SCHWEIKER *et al.*, 2020). On the one hand, people tend to open windows to have fresh air (improving air quality levels as well as increasing air velocity, which also impacts on thermal sensation). On the other hand, once open, windows may become a source of acoustic discomfort and occupants tend to close them to reduce outdoor noises.

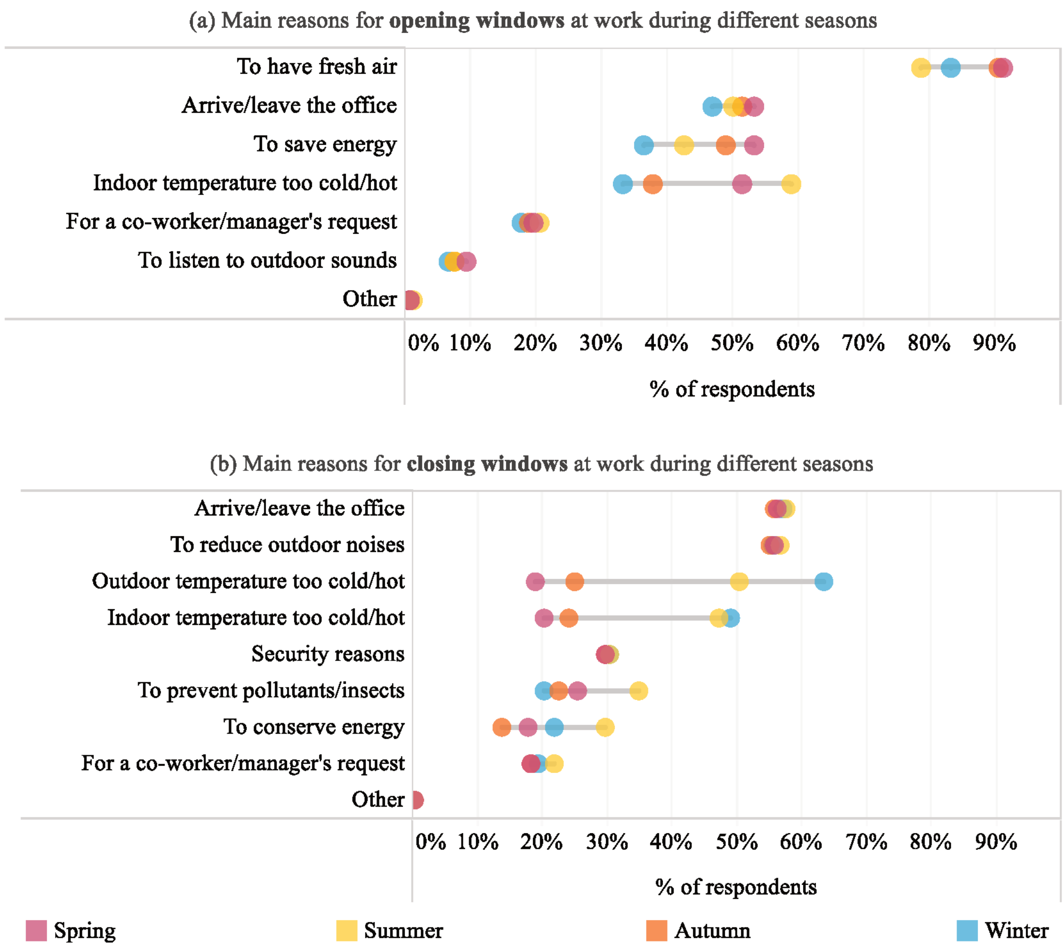

Figure 5.6. Main reasons for (a) opening and (b) closing windows at work throughout the year.

Some motivational drivers seem to be unaffected by seasons: request of others was reported by 20% of the respondents as a trigger to open and close the windows; outdoor noises were reported by 9% to open windows (listen to them) and by 56% to close windows (reduce them); leave the office (57%) and security reasons (30%) also triggered closing the windows. However, other influencing aspects are affected by seasons. First, some motivational drivers differ comparing hotter and colder seasons: about 33% of respondents tend to open the windows during the winter due to the indoor temperature; in comparison, about 59% of them do the same during the summer. Second, some triggers differ comparing milder seasons (spring and autumn) to hotter/colder ones (summer and winter): while 36–43% of respondents open windows to save energy during winter and summer, 49–53% do the same during autumn and spring; while 19–25% close windows due to the outdoor temperature during spring and autumn, 50–63% do the same during summer and winter; while 20–24% close windows due to the indoor temperature during spring and autumn, 47–49% do the same during summer and winter. Third, some triggers for closing the windows are more evident in the summer compared to other seasons: about 35% of respondents close the windows to prevent pollutants and insects from coming in during the summer (different seasons rated from 20–25%); and 30% of respondents close the windows to save energy (other seasons rated from 14–22%).

As recently argued by Day *et al.* (2020), although operable windows are widely-studied in this field, there is no general agreement about the reasons why people adjust windows or the main triggers for those actions. Therefore, decision trees comprising window adjustments are presented in Figure 5.7 to evaluate the main predictors for those actions. The models reached 82% accuracy regarding open windows and 73% for window closing. Considering occupants who have control over the windows, the biggest predictors for the adjustments are action-dependent: IEQ-productivity-belief played the major role to open windows (higher IEQ-productivity-belief resulted in more adaptive opportunities); while the frequency of negotiation with co-workers played the biggest role to close them (people who negotiate once a week or more reported more adaptive opportunities compared to those who do so less often). Additionally, an inverse relation between satisfaction and window adjustments was found. While occupants that are less satisfied with indoor conditions tend to open the windows more than others, this relation is inverse while considering closing behaviours. Occupants that are more satisfied with indoor conditions tend to close the windows more often than others. Finally, multi-domain aspects like IEQ-productivity-belief, attitudes towards sharing window control, frequency of negotiation as well as occupants' age may predict more active behaviours towards window control. As shown in the literature, the inclusion of habit on window opening models may result in improvements compared to models focusing siloed on environmental conditions

(VERBRUGGEN *et al.*, 2019). Therefore, understanding subjective predictors of window control is important to both improve future practices of occupant behaviour monitoring as well as modelling it.

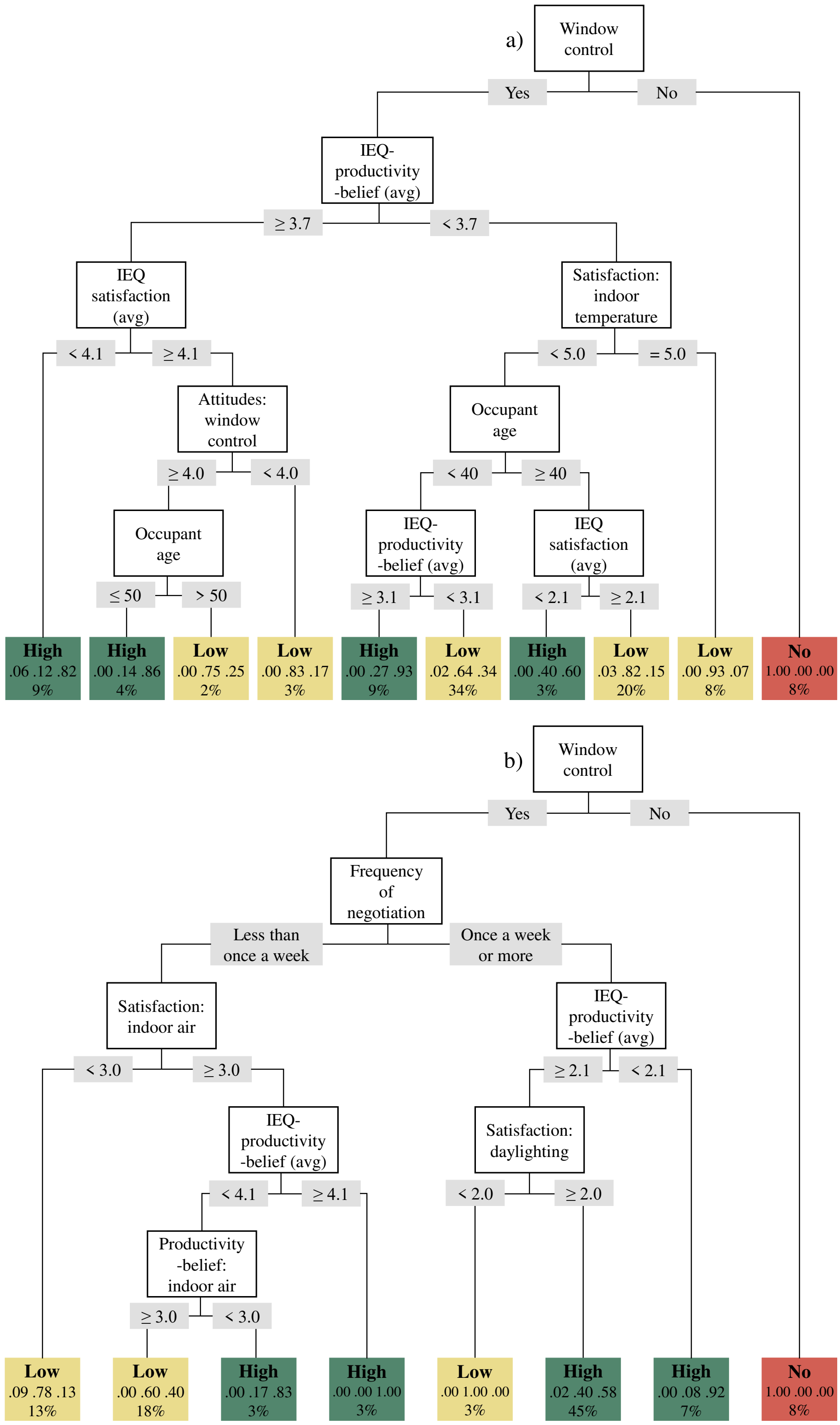

Figure 5.7. Decision trees to assess the adjustments of windows considering (a) opening and (b) closing behaviours.

3.3.2. Adjusting blinds/shades

Motivational drivers for opening and closing blinds/shades are presented in Figure 5.8. Similarly to window adjustments, there is a clear influence of multi-domain comfort: 90% of the respondents open the blinds to let more daylight in (visual preference) across seasons; however, 58% close the blinds during summer to reduce overheating (thermal preference). Although not representing multi-domain comfort drivers, some triggers may cause blinds' opening and closing: 70% of respondents open the blinds to have a view to the outside across seasons, while 25% close them to block the view and reduce privacy concerns. The results highlight that adjustments of blinds/shades, as expected, is conducted the most to improve visual and thermal issues during work; as shown in previous research (BAVARESCO; GHISI, 2018). Our results are aligned with the fact that occupants tend to open internal blinds due to psychological factors and view, but tend to close them due to physiological aspects (DAY, 2012). Additionally, time-dependent adjustments (i.e., opening blinds/shades upon arrival and closing them upon departure) were reported by 40% of respondents. Finally, this system seems to boost indoor quality in opposite climate scenarios: 43% of the respondents open the blinds/shades to warm up the office during winter, while 58% of them tend to close the blinds/shades to reduce overheating during summer. Previous simulation-based research found that internal blind finishing impacts the operative temperature in offices (BAVARESCO *et al.*, 2019a). Therefore, this system is important regarding thermal adaptive actions, especially considering that occupants find it easier to share the control of blinds/shades than the control of thermostat (D'OCA *et al.*, 2018), which may reduce social-norms-related constraints for adaptive behaviours.

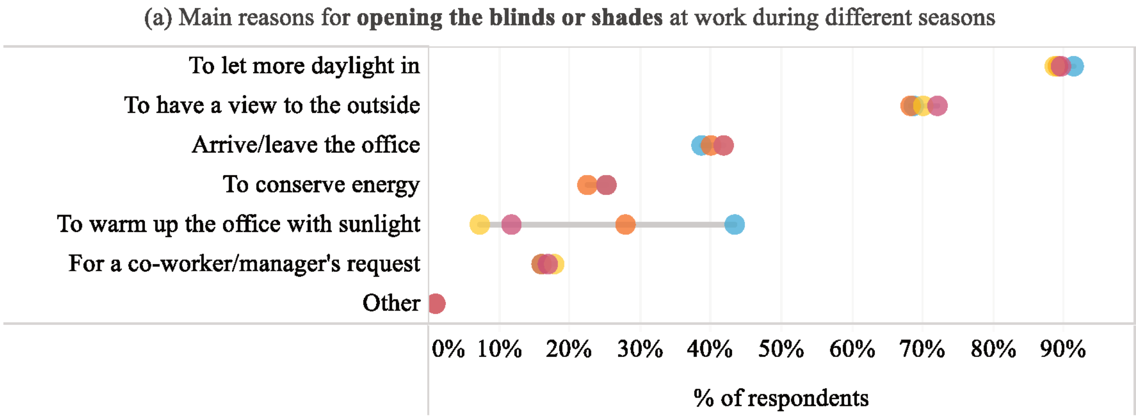

Figure 5.8. Main reasons for (a) opening and (b) closing the blinds/shades throughout the year.

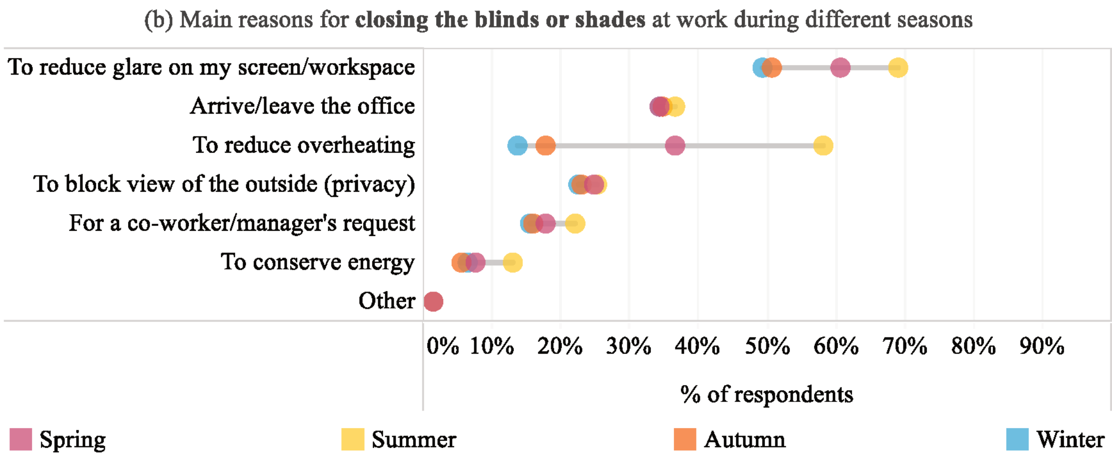

Figure 5.8. Main reasons for (a) opening and (b) closing the blinds/shades throughout the year (continuation).

Decision trees related to the control of blinds/shades are presented in Figure 5.9. The models achieved 71% accuracy for blind opening and 72% for blind closing. Regarding occupants who reported control over the blinds/shades, the most significant predictors differ considering its opening (intention to share the control) and its closing (attitudes towards control). Similarly to the window control, the influence of satisfaction was inverse considering opening and closing behaviours. While occupants less satisfied with indoor conditions tend to open the blinds more often, those more satisfied are responsible for closing them more often. Additionally, as shown by Day *et al.*(2020), spoken or unspoken constraints in shared spaces is a phenomenon that suppresses interactions with shades/blinds. Our results confirm this trend as intention, attitudes and ease to share the control of blinds, as well as frequency of negotiation, were important predictors for shades/blinds adjustments. As a trend, occupants with more positive opinions about sharing the control of internal blinds and those who negotiate more frequently with their co-workers adjust the internal blinds more often. Therefore, it is suggested that such trends are considered in further occupant behaviour models, as not only weather parameters trigger such adjustment (DAY, 2012; O'BRIEN; KAPSIS; ATHIENITIS, 2013; SCHWEIKER; WAGNER, 2016).

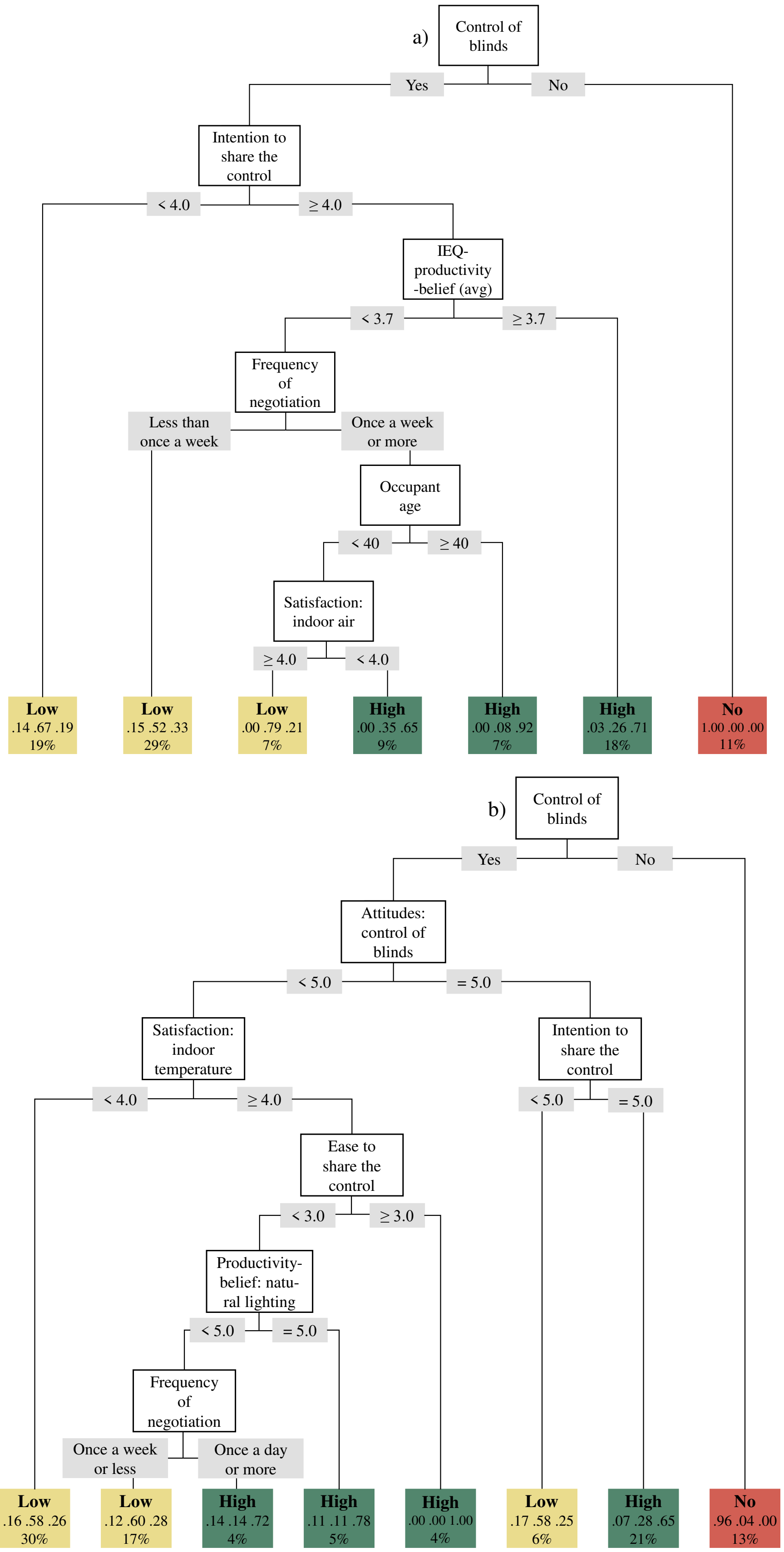

Figure 5.9. Decision trees to assess the adjustments of blinds/shades considering (a) opening and (b) closing behaviours.

3.3.3. Adjusting HVAC thermostat

As shown in Figure 5.10, indoor temperature too hot is the main reason for adjusting HVAC. This outcome is more evident during the summer (about 86% of the respondents reported it) and the spring (about 54% of them). Indoor temperature too cold is an issue for about 13% up to 37% of the respondents across seasons. Although much more influencing in winter (37%), 18% of the respondents also reported it as a cause for adjusting HVAC in summer. Besides being IEQ-related, adjusting the HVAC because indoor temperature is too cold during the summer may be related to the way occupants control this system – e.g., keeping cold indoor temperatures. Therefore, when it comes to evaluating IEQ and its impact on occupant satisfaction, productivity and behaviour, it is crucial to consider several contextual factors to represent it better (CHEN *et al.*, 2020). By comparing HVAC adjustment with other systems, the influence of social dynamics is evident. While no more than 22% of respondents reported adjustments of other systems caused by co-workers/managers' requests, this aspect motivates up to 35% of respondents to adjust the HVAC. It emphasises the need to qualitatively assess occupant behaviour in offices in further mathematical models and computer simulations. Additionally, although Florianópolis present mild climate that benefits using natural ventilation especially during spring and autumn, some occupants rely on artificial ventilation throughout the year: from 15% up to 25% of the respondents adjust the thermostat when arrive/leave the office. This aspect is more evident during the summer (25% of the respondents). It is necessary to explore it further in various buildings at the University to assess if issues are hindering natural ventilation in those offices; for doing so, field evaluations applying different qualitative methods are encouraged (BAVARESCO *et al.*, 2020b).

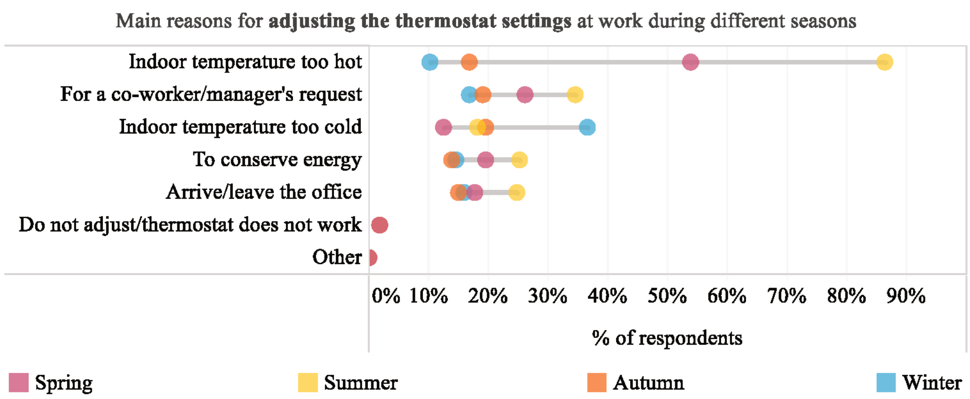

Figure 5.10. Main reasons for adjusting the HVAC thermostat throughout the year.

Figure 5.11 shows the main predictors for HVAC adjustments according to the decision tree results. This model achieved 75% accuracy. It is evident that subjective and contextual factors play significant roles regarding this system. The major predictor for HVAC adjustments is the frequency of negotiation, and people who negotiate less frequently tend to adjust the HVAC less often compared to those who do so more often. Importantly, previous research showed that more occupants reported lack of knowledge to control HVAC compared to other building systems (BAVARESCO *et al.*, 2020a). Our study added that lack of knowledge might actually be similar to lack of control, as both aspects predicted no HVAC adjustments according to the decision tree.

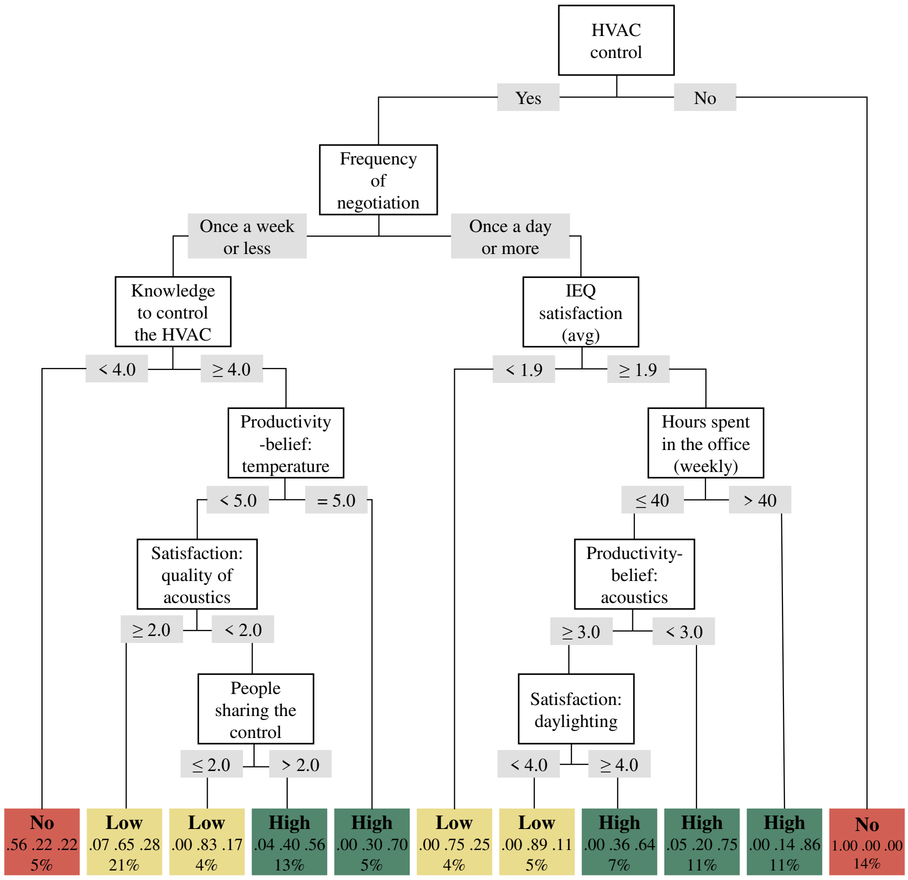

Figure 5.11. Decision tree to assess the adjustments of HVAC thermostat.

In fact, the literature supports that lack of knowledge may be similar to the lack of perceived control of building systems (DAY *et al.*, 2020). This result emphasises the importance of teaching occupants about the proper use of building interfaces as well as the important role that other stakeholders have on this aspect, such as for designing occupant-centric controls (PARK *et al.*, 2019). Although more adaptive opportunities may result in a higher probability of achieving comfort, shared spaces with rare negotiation may result in occupants controlling systems considering only their preferences; therefore, an adaptive behaviour may become a source of discomfort for co-workers.

Considering that up to 35% of occupants adjust HVAC based on others' requests, this outcome may negatively impact on the satisfaction levels with IEQ and, consequently, hinder occupants' productivity. Finally, an important relation was found regarding the influence of acoustics and HVAC control: people less satisfied with acoustics and people with a smaller IEQ-productivity-belief tend to adjust the HVAC more often. In fact, such an outcome may be system-related as many occupants reported on the survey that their offices are noisy when HVAC is on. As shown in subsection 2.3, the most common system at the University consists of split HVAC with an outdoor compressor, which is sometimes located near working stations and may disturb occupants.

3.3.4. Adjusting lighting

Differently from the other systems, lighting adjustments were assessed disregarding the season, and the results are presented in Figure 5.12. Motivational drivers are oppositely related to switching on and off the lighting: what stimulates turning a light on is not essential regarding its shutdown. Although the amount of light on the workspace is related to lighting adjustments, people seem to turn the light on when they perceive low lighting level (91% of the respondents) much more frequently compared to turning it off when there is too much light (36% of the respondents). Regarding time-dependent aspects, people tend to turn lights on when arriving (about 75% of respondents), and turn them off when leaving the office (about 85% of them); such a time-dependent aspect has also been reported in the literature (SILVA; LEAL; ANDERSEN, 2013). Our results add that occupants tend to turn on the light either when arriving at the office or when they consider it too dark; on the other hand, they turn it off much more frequently when leaving the office compared to when there is too much lighting. In other words, visual discomfort caused by lack of light (both natural and artificial) is more impactful than the excess of light considering occupant behaviour. It is aligned with our results (see subsection 3.2), showing that although up to 84% of respondents stated that not enough lighting cause visual discomfort, only 25% of the respondents reported the same from excessive lighting. It emphasises the need to include natural lighting in buildings, as suggested by the Brazilian labelling for energy efficiency in commercial buildings (CB3E, 2017). The labelling process requires that lighting fixtures near sources of natural lighting should be controlled independently from the other ones. By teaching occupants, they can reduce the usage of lighting fixtures near windows and minimise building energy consumption as a consequence.

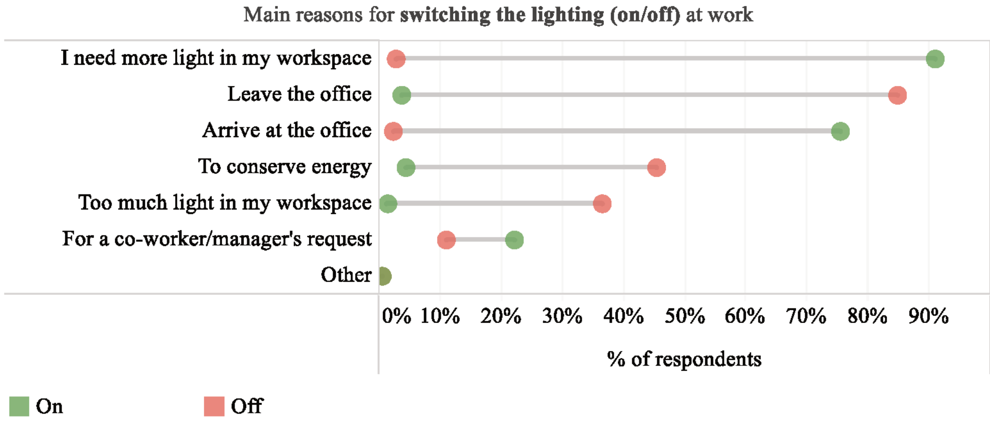

Figure 5.12. Main reasons for adjusting the lights at the workspace.

The decision trees created to assess lighting adjustments are presented in Figure 5.13. The model concerning turning on the lights achieved 85% accuracy and the one for turning off reached 75% accuracy. Regarding switching on behaviours, the major predictors are IEQ-related: satisfaction with IEQ and influence of daylight on occupant productivity. While occupants less satisfied with IEQ turn lights on more frequently, the influence of daylighting on occupant productivity had an inverse effect: smaller beliefs cause less interaction with the lighting system. When it comes to turning off behaviours, the major predictor is the number of people sharing the control: if the control is shared by three or more occupants, more actions to turn off the lighting were reported. Although having the possibility to adjust systems is essential, more adaptive actions in such cases may represent scenarios in which people adjust systems to improve the indoor conditions based on their preferences, which may result in discomfort for co-workers. Finally, the literature supports that accurate evaluations about occupants'ooccupants' habits, preferences, and indoor perceptions of IEQ are missing and those investigations are expected to improve model development (CARLUCCI *et al.*, 2020). Our results emphasise that such knowledge could improve occupant behaviour understanding as they are important predictors of the frequency of light adjustments, which has to be properly modelled for reliable simulations.

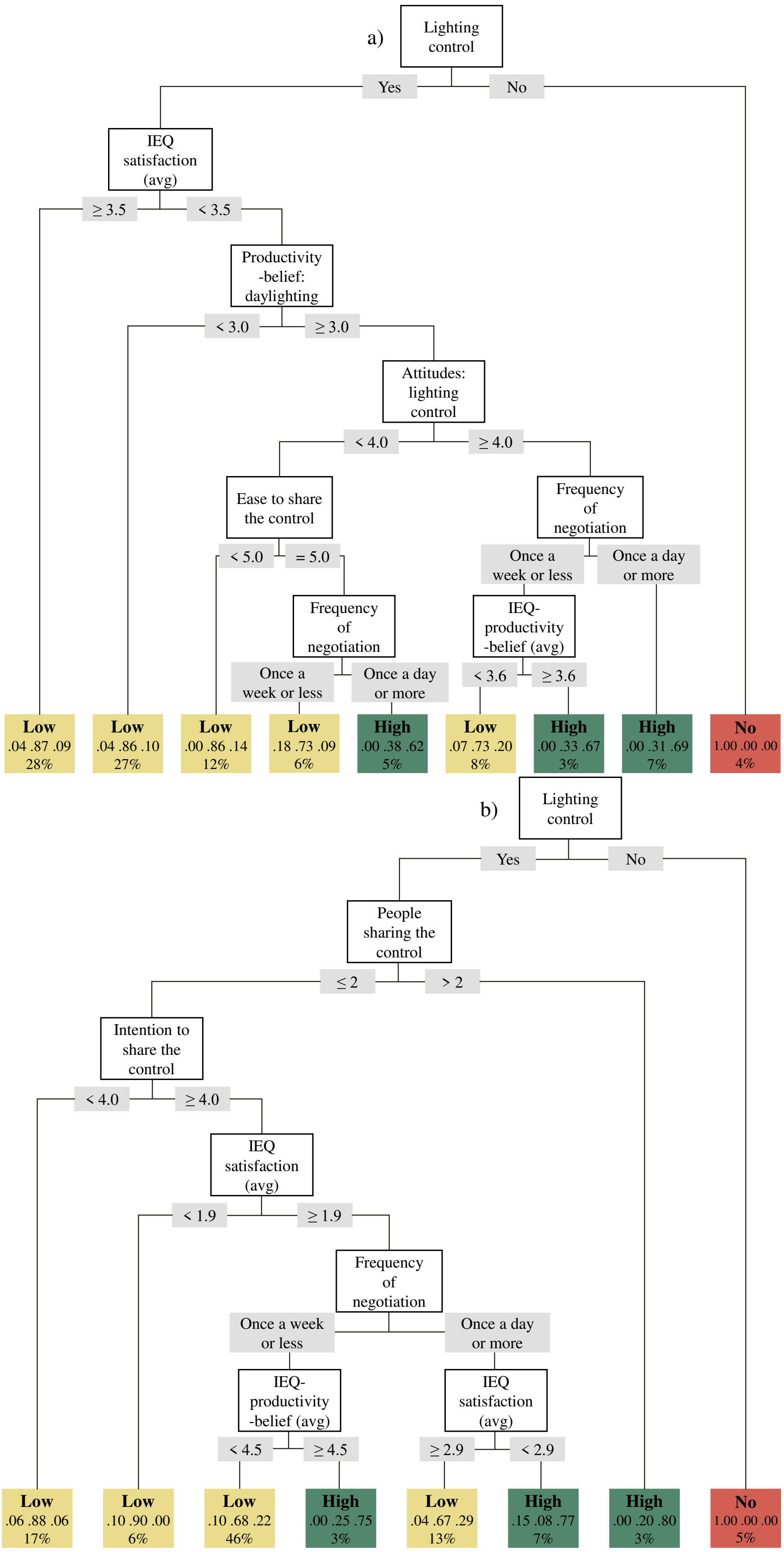

Figure 5.13. Decision tree to assess (a) switching on and (b) switching off the lighting system.

4. A conceptual flowchart about multi-domain comfort stimuli on occupant behaviour

Our results showed that satisfaction levels with the evaluated IEQ parameters are correlated with perceived productivity influenced by the same parameter. The literature supports that boosting IEQ conditions does not necessarily increase energy consumption in U.S. office buildings; instead, it can be reached with small increases in energy cost or even with simultaneous energy savings (FISK; BLACK; BRUNNER, 2011). The authors show that eliminating high indoor temperatures (> 23ºC) during heating seasons is an effective alternative. Our results show that about 18% of respondents adjust the HVAC system during the summer because the indoor temperature is too cold. Therefore, specifying minimum temperatures during summer can reduce energy consumption as well as minimise cold discomfort during this period, similarly to the U.S. case study reported. Other improvements may increase the building cost; however, benefits can be expected from both personal (higher occupant satisfaction) and economic sides (higher productive and smaller absences during the year) (SINGH *et al.*, 2011).

Additionally, occupants deal with different sources of multi-domain discomfort at work. In descending order, the two primary sources of discomfort were: workspace hotter than other areas and air drafts from windows or HVAC (thermal); glare from windows and not enough artificial lighting (visual); noise from inside and noise from outside (acoustics); and poor natural ventilation and stuffy air (air quality) – see Figure 5.5. Our results also showed that occupants adjust building systems mainly to improve indoor quality and reach personal needs or preferences. Chen *et al.* (2020) grouped the reasons for operating building systems as follows: habit/rule, energy-saving, request of others, and personal needs. The authors conducted a comprehensive cross-country evaluation and showed that personal needs represent the majority of triggers for human-building interactions. In the context of this research, personal needs synthesise comfort-related adjustments of windows, blinds/shades, HVAC, and lighting (e.g., to have fresh air, indoor temperature too cold, to have a view to the outside, etc.).

Therefore, it is essential to confront the main sources of discomfort with human-building interactions driven by personal needs. By doing so, some relations can be explained: 22% and 32% of the respondents stated that bad odours/scents and stuffy/stale air, respectively, are sources of air quality discomfort. When it comes to opening windows, 91% of respondents stated that they do so to have fresh air during mild seasons (autumn and spring), which may hinder some of the sources of air quality discomfort reported. However, opening windows may increase the air velocity and characterise an air draft, which has been reported by 28% of the respondents as a source of thermal discomfort. At some point after that, closing windows may be quite probable as 19−25% of the participants close windows due to outdoor temperatures too cold/hot during mild seasons. Lack of both artificial and natural lighting was reported by 31% and 30% of the respondents, respectively, as sources of visual discomfort. While 90% of the respondents open the blinds/shades to let more daylight in disregarding the season and 91% switch on the artificial lighting because they need more light in his/her workspace. Also, 31% of the respondents reported glare as a visual discomfort source, as well as too much lighting, which was reported by 9%. As a consequence, 49−69% of the respondents tend to close blinds/shades to reduce glare on their computer screen/workspace. Although such visual-comfort-related trigger to close blinds/shades, about 58% of the respondents close them during the summer to reduce overheating, emphasising the role that multi-domain comfort aspect plays on occupant behaviour. Similarly, 17% of the respondents reported a lack of outside view as a visual discomfort source, as well as 70% open the blinds/shades to have a view to the outside.

It is clear that occupant behaviour and multi-domain comfort represent an inseparable twofold issue: besides some interactions are adaptations to multi-domain discomfort, they can also result in a new source of discomfort. In other words, we claim that although discomfort in offices leads to human-building interactions – i.e., adaptive behaviours – the actual adjustments may be a further source of discomfort either for the occupant who acted or for co-workers in shared spaces. This aspect was already presented in the literature as a reversal of adaptive behaviour (GUNAY; O'BRIEN; BEAUSOLEIL-MORRISON, 2013), but in-depth evaluations are still necessary. Therefore, Figure 5.14 presents a conceptual flowchart that synthesises how conflicting needs may result in discomfort or in adjustments of building systems, as well as such adjustments may lead to new sources of discomfort. The first part represents the interrelated aspects of multi-domain comfort and human-building interactions in offices. The second one depicts appropriate relations between sources of discomfort and adjustments in windows, blinds/shades, HVAC, and lighting. Each domain of IEQ (thermal, visual, acoustic, and air quality) was represented with colour to enable distinction. Importantly, continuous arrows characterise adjustments in building systems caused by a specific source of discomfort; in contrast, dashed arrows represent sources of discomfort that may be created after one adjusts building systems. Based on the survey responses, it was concluded that occupant behaviours are either influenced by or can influence different domains of IEQ. Window control is related to thermal, acoustic and air quality concerns; blinds/shades to visual and thermal concerns;

HVAC to thermal, acoustic and air quality concerns; and lighting system is mostly affected by visual concerns.

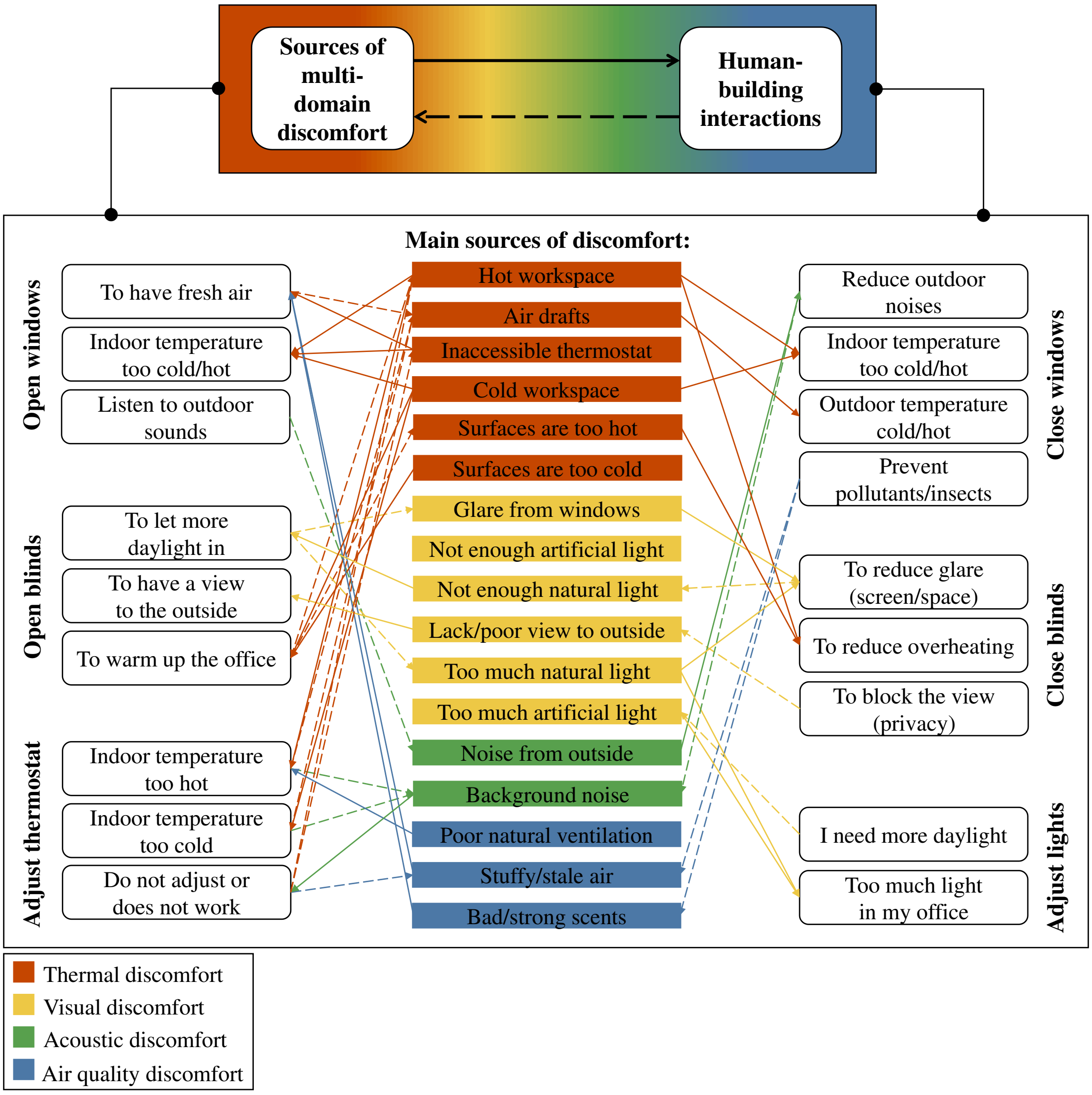

Figure 5.14. Conceptual flowchart of the interrelation between multi-domain comfort and human-building interactions in offices.

The results provided by the conceptual flowchart give practical perspectives for the building sector. Firstly, it is essential to continuously assess occupants' opinions about the primary sources of multi-domain discomfort and to what extent they influence on human-building interactions. Some aspects may not represent a source of discomfort for all the occupants due to personality traits (HONG *et al.*, 2020b), individual preferences (WANG *et al.*, 2018), gender (MAYKOT; RUPP; GHISI, 2018; RUPP *et al.*, 2018) or age (HOOF *et al.*, 2017). However, by understanding both individual and group preferences, it is more likely to reach comfortable thresholds for the majority of occupants during working hours. Such qualitative knowledge may inform building managers to improve conditions of actual buildings as well as building designers to adapt their projects to current discoveries. In light of this concern, several qualitative methods have been presented as ways to assess the opinions and needs of different stakeholders of the building sector (BAVARESCO *et al.*, 2020b). It is vital to understand what is boosting or hindering occupants' satisfaction at work to improve unpleasant conditions. Knowledge from social scientists is fundamental in this role, and the literature highlights the need for multidisciplinary efforts to improve building sector outcomes (SOVACOOL, 2014).

Secondly, efforts of different stakeholders may improve the development and use of devices to provide occupants with ways to individually restore their comfort at work, as individualised features to control IEQ may minimise the role of a consequent source of discomfort after one adjusts a building system. When occupants are provided with features to adapt their microclimate, especially in shared offices, they tend to reduce their impacts on the room conditions. Most probably, the increasingly frequent use of indoor separation furniture due to the present COVID-19 emergency conditions may lead toward a better individual microclimate separation and a possible improvement in self-assessment and self-controlling operations and interfaces. Indeed the literature already supports the use of several personal comfort systems (ANDRÉ; VECCHI; LAMBERTS, 2020), including like desk fans (HE *et al.*, 2017), chair-based personalised ventilation (SHAHZAD *et al.*, 2018), as well as personal lighting control (DAY *et al.*, 2020; ROSSI *et al.*, 2015). Additionally, technological innovations are significant in this scenario as occupants may be included in the loop of building control with up-to-date sensing features and Internet-of-Things (IoT) devices, for example (BAVARESCO *et al.*, 2019b). Finally, innovations like smart desks may also be used to adapt IEQ in a microlevel allowing occupants to adjust surrounding conditions according to their preferences (ARYAL *et al.*, 2019).

5. Limitations

This research has a number of limitations specifically reported below for a better replication of the study and its validation.

First, a low response rate was reached: about 10% of the invited employees accepted to participate in the survey. It is important to mention that National Regulation 510/2016 prohibits providing incentives for research participants in Brazil (BRASIL, 2016), which is a known strategy to increase response rates in surveys worldwide (WAGNER; O'BRIEN; DONG, 2017). However, considering an infinite population, the needed sample size is 273 responses for a 90% confidence level and 5% margin of error. Therefore, the final sample of 278 responses can be considered as acceptable in terms of statistical significance for this study.

Second, all data apply to Florianópolis, southern Brazil, and some variations are expected in other locations and cultures, which may hinder the generalisability of the outcomes. However, the results presented herein are more likely generalisable to different cooling-dominant climates compared to the current state-of-the-art in this field, which is mostly from heating-dominant climates. Additionally, the promising findings are likely to motivate further similar research, especially in other developing countries.

Third, the building stock on campus is quite diverse, and many participants on the survey did not inform in which building they were used to work in. Therefore, small subsamples can be available if data were stratified according to the buildings reported. Nevertheless, survey invitations were sent out to a large group of employees, and responses came from varied contexts in terms of rooms' thermal characteristics, solar orientation, layout, floor level, and so forth. Such a variety of features is expected to increase the reliability when the decision models are generalised to all the buildings on campus.

6. Conclusions

The purpose of this study was to evaluate multi-domain triggers for occupant behaviour related to the interaction with windows, blinds/shades, HVAC, and lighting in office settings. The survey-based analyses were grounded in an interdisciplinary framework that synthesises building physics with social psychology, and a case study was conducted in Florianópolis, southern Brazil. Compared with previous research in the field, this study adds significant knowledge about multi-domain comfort issues related to occupant behaviour in buildings. Also, by including machine learning techniques (such as decision trees) in this qualitative evaluation, this study brings innovation to assess triggers for human-building interactions at work considering the impact of IEQ-beliefs, subjective, contextual and personal factors. The main conclusions of the study can be summarised accordingly:

- Occupants' satisfaction with each IEQ parameter evaluated (indoor temperature, indoor air, natural lighting, artificial lighting, and acoustics) is correlated with the influence of the same parameter on occupant productivity. Besides this stand-alone facet, there are also paramount multi-domain relations: IEQ-beliefs related to indoor temperature impact the same aspects of indoor air, considering both satisfaction and perceived productivity. This outcome emphasises the complexity of mixed-mode ventilation control in offices, as balancing between natural and artificial ventilation use may result in cumulative variation of IEQ perception;

- The main sources of multi-domain discomfort were also assessed, and contrasting information was found: while 16% of the respondents consider that windows being too close is a source of thermal discomfort, 9% reported so about distant windows. Likewise, although 31% of the respondents reported that the lighting level is not enough, 9% considered it too excessive. Such variation may guide field studies to discover practical information about building design and control: i.e., determining an ideal distance between occupants and windows to improve office layout as well as defining a comfortable lighting level considering local perspectives. Additionally, characteristics of building interfaces that enhance occupants' perceptions may also be tested;
- The predictive modelling approach used herein (decision trees) proved that actual control over building systems is the primary driver for adaptive opportunities in offices. Besides that, each system evaluated resulted in different complexity levels and important predictors. This machine-learning-based evaluation reached hypotheses that may be tested in future research, such as including subjective aspects found as important predictors on both monitoring and modelling occupant behaviours. For instance, frequency of negotiation to control building systems as well as attitudes, ease, and intention towards sharing the control were deemed as important predictors. However, these aspects are still missing in current evaluations. Also, satisfaction with indoor conditions and IEQ-productivity-belief were important predictors to the adjustments performed throughout the year. This outcome supports that future monitoring studies should include subjective evaluations of indoor conditions instead of focusing siloed on measurements of environmental parameters;
- Finally, a conceptual flowchart was proposed to synthesise the twofold relation between multi-domain comfort aspects and human-building interactions. Our results showed that although most adjustments are triggered by personal needs (i.e., comfort-related issues, like indoor temperature too cold/hot), the interactions may characterise a new source of multi-domain discomfort. Such an outcome is most evident in shared offices, where individual preferences tend to

be different as the literature already confirms. It enables building stakeholders to assess the comfortable thresholds of occupants, as well as to provide them with personal features to adjust IEQ at a micro-level.

Further research will focus on assessing multi-domain comfort in offices combining questionnaire applications with indoor monitoring. Additionally, new multi-domain experimental techniques are much needed to reproduce multiphysics triggers and to analyse physiological and neurological feedbacks. Such more objective indicators may drive towards more reliable models, to be validated through a classic survey-based approach. Such an approach may indeed provide quantitative information about acceptable thresholds for indoor conditions as well as how they are interrelated. In other words, field studies may show to stakeholders if occupants' satisfaction with one IEQ parameter is affected by others. The activities within the framework of Annex 79 by IEA EBC are giving the required answers to this and other research issues (HEYDARIAN *et al.*, 2020; O'BRIEN *et al.*, 2020; SCHWEIKER *et al.*, 2020). Data-driven knowledge is vital to understand individualised preferences and tailor policies to acceptable thresholds for the majority of workers. Such improvements are also crucial in a managerial point of view, as more satisfied occupants tend to be more productive at work.

6. Optimising window operation monitoring in offices

This chapter is the transcription of the following paper:

Optimising window operation monitoring in buildings: A data-driven approach based on information theory concepts and deep learning.

Authored by: Mateus Vinícius Bavaresco, Ioannis Kousis, Ilaria Pigliautile, Anna Laura Pisello, Cristina Piselli, and Enedir Ghisi.

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Abstract

Occupant control of windows is a meaningful way to regulate natural ventilation rates with evident implications in buildings' energy and indoor environmental quality performance. Although window operation is influenced by contextual factors like seasons and indoor and outdoor physical variables, several strategies may monitor occupant behaviour. Therefore, the primary goal of this study is to propose guidelines for the optimisation of window monitoring to reach reliable data-driven models using data from a multi-year-long evaluation in offices. Information theory concepts (entropy, conditional entropy, mutual information, and cross-entropy) were used as proxies for the uncertainty and uncertainty reductions of window operation distribution and to calculate the divergence between subsets and the entire database. Thereafter, a recursive strategy enabled to train more than 7,000 deep neural networks using subsets of the full database comprising different lengths and initial months combined with different predictors (the combination of indoor and outdoor variables, only indoor, or only outdoor variables). Each model was tested using the remaining data of the whole database. From the information-theoretic metrics, results support that indoor-related variables can most reduce the uncertainty related to window operation, and subsets influenced by autumn and winter diverge the most compared to the full database. Considering the modelling approach, results showed that by including indoor-related variables in the loop, higher shares of good performing models were achieved, and smaller databases were needed as well. Finally, the main conclusions led to an optimisation strategy that considers the predictors available from field monitoring and the influence of seasonality to balance the need for big data while reducing the chance of achieving underperforming data-driven models.

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1. Introduction

The high share of energy used in buildings worldwide is vastly discussed in the literature, as well as its rapid and continuous increasing trend (GABC, 2019), which places strategies for reducing such energy use in a prominent position. Although technology may play an essential role in this scenario, it is evident that the human dimension should also be considered to improve the energy efficiency of buildings (HONG *et al.*, 2015a). The literature shows there is a potential to reduce the energy use in buildings from outcomes of interactions between occupants and building systems (MASOSO; GROBLER, 2010). Consequently, the comprehension of energy-related occupant behaviour is an essential step towards buildings' performance evaluation and optimisation since the design phase (DELZENDEH *et al.*, 2017). Regarding occupant behaviour research, important advances in the state-of-the-art were reached in the last few years, especially considering methodological frameworks for occupant behaviour simulation (YAN *et al.*, 2017). Although there have been advances, there is no standardised approach for field monitoring (STAZI; NASPI; D'ORAZIO, 2017). In other words, it means that such assessments are context-related, and practitioners rely on the available resources to monitor building operations. For instance, season-related monitoring is handy to provide occupant behaviour models valid for this specific context (YUN; STEEMERS, 2008). In such cases, attention for representativeness is needed by considering longer periods and year-based evaluations of building energy use through computer simulations. A common practice is to monitor conditions during several months to account for rare interactions and those that exhibit seasonal variations (YAN *et al.*, 2015). Indeed, gathering data to influence building operation and occupant behaviour was presented as the next frontier in sustainable design (HONG *et al.*, 2016), and several technological innovations can be used in this field (BAVARESCO *et al.*, 2019b).

A recent literature review also highlighted the impact of big data requirements in building science, considering communities and urban scales as well (DONG *et al.*, 2021). Consequently, big data analytics to post-occupancy evaluations is growing in interest and importance (HONG *et al.*, 2020c). In general, big data stands for collecting and analysing large amounts of complex data originating from various and different sources that traditional data-processing methods cannot manage (RANJAN; FOROPON, 2021). Within the last decade, big data emerged as a part of mainstream practices involving different sectors and demonstrating broad applications, such as decision-making, modelling, forecasting and enhancing organisations intelligence. Yet, big data is still in an early stage of development, hence, there are various ongoing challenges for rendering big data efficient, cost-effective, scalable, and reliable (SIVARAJAH *et al.*, 2017). In fact, multi-source and heterogeneous data collection, as well as their corresponding storage, processing and analysis are continuously assessed for exploiting big data potentiality. The amount of available data grows at an increasing rate. Data derived from social media, websites, e-mails, e-commerce and so forth are stored and used by different sectors such as industry, business, policymakers and academia.

Several variables are reported to regulate big data, e.g. volume, velocity, value, variety, variability, virality, viscosity, and veracity. The successful process of large amounts of data (volume) at high speed (velocity) under a multidisciplinary approach exploiting various sources (variety) is considered the defining key concepts of big data (CHEN; YANG; SONG, 2016). The increasing rate of available data leads to a great volume of databases that, in many cases, pose substantial challenges to their efficient management. In order to efficiently deal with such great volumes of data, organisations shift from desegregated data to more sophisticated sources such as data lakes and warehouses. Both data lakes and warehouses are used for storing big data, but serve different purposes. Data lakes comprise raw data with a yet undefined purpose, i.e. unstructured data (MILOSLAVSKAYA; TOLSTOY, 2016). They are massive and scalable storage repositories that can store almost any data structure. On the other hand, data warehouses comprise data obtained from operational and transactional applications already processed and filtered for a defined purpose, i.e. highly structured data (SANTOSO; YULIA, 2017). Big data velocity is another parameter with a substantial impact on the big data framework. Data need to be generated, acquired, processed and utilised at a fast rate. Conventional batch processes are not sufficient to handle such large amount of available data that currently are streamed in a continuous fashion. Considering the growing framework of Internet of Things (IoT), there is a great demand for efficient real-time data aggregation, management, and analysis. Unlike past decades when organisations used to deal mainly with internal data sources, there is currently an immense amount of diverse data sources that can be extremely useful for organisations' function and intelligence. Managing and classifying simultaneously incoming structured, semi-structured, and unstructured data originating from various sources demands distinct processing capabilities and specialist algorithms that, in many cases, are applied using Artificial Intelligence (AI) approaches (HAIMED *et al.*, 2021).

Big data analytics can also be implemented for assessing and improving the built environment (WANG *et al.*, 2019). A recent literature review highlighted the potential of using machine learning (ML) throughout buildings' life cycle, considering their design, construction, operation, maintenance, control and retrofit (HONG *et al.*, 2020c). For instance, personal comfort models to predict individual thermal preferences based on ML reached higher accuracy than conventional comfort models, namely PMV (predicted mean vote) and adaptive (KIM *et al.*, 2018b). ML algorithms were also used to couple physiological signals and human subject responses to different thermal stimuli (PIGLIAUTILE *et al.*, 2020). Accuracies up to 84% may open the door to improving building control and energy management with real-time monitoring. The use of ML in the field of occupant behaviour modelling has also increased recently. Indeed, a comprehensive deep-learning-based approach to model window opening in offices was proposed by Markovic *et al.* (2018). The authors relied on extensive hyperparameter search to propose a generic window operation model and showed its associated practical implication in terms of model implementation in energy simulation. The literature also supports the use of other algorithms such as Bayesian Network (BARTHELMES *et al.*, 2017) and Gauss distribution (PAN *et al.*, 2019) to successfully evaluate window operation in buildings. Additionally to behaviours, ML is an emerging and promising way to improve current practices in forecasting, modelling and simulating occupants' presence and movements in buildings (CARLUCCI *et al.*, 2020).

All the advances related to data collection and evaluation allow for objective assessments of strategies to improve buildings' energy and indoor environmental quality performance. One solution in this context is natural ventilation, which is presented as a passive-cooling strategy to reduce buildings' energy use while accounting for indoor thermal and air quality conditions in tropical climates (AFLAKI *et al.*, 2015). Benefits were also achieved in colder regions since natural ventilation has been recommended for decreasing overheating during warm periods in subtropical (FOKAIDES *et al.*, 2016) or cold continental climates (BRAMBILLA *et al.*, 2018). A recent literature review confirmed the potential of natural ventilation for energy savings, thermal comfort, air quality in buildings in many countries (SAKIYAMA *et al.*, 2020). Another critical aspect in this field is occupant control in naturally or hybrid ventilated buildings (ROETZEL *et al.*, 2010), as the balance between natural and artificial ventilation is usually complex (BAVARESCO *et al.*, 2021). Indeed, occupant-related aspects are considered the leading factors in buildings' energy consumption and can affect it even more than technical and physical factors (YOSHINO; HONG; NORD, 2017). Besides contextual factors, windows control in buildings is primarily influenced by different physical drivers (FABI *et al.*, 2012), which should be monitored to reach reliable models. Indeed, different strategies have been adopted in this field, and previous research relied on different field monitoring durations, such as less than one year (e.g., three months (YUN; STEEMERS, 2008), at least six months (JEONG; JEONG; PARK, 2016; SCHWEIKER *et al.*, 2012), and eight months (ANDERSEN *et al.*, 2013)) or more than one full year (e.g., about two years (D'OCA; HONG, 2014; MARKOVIC *et al.*, 2018), four years (CALÌ *et al.*, 2016), as well as up to almost seven years (HALDI; ROBINSON, 2009)).

In this panorama, it is evident that recent developments support the use of ML by building stakeholders in energy-related applications. Additionally, as natural ventilation is a passive strategy that can improve building performance, understanding typical window operation patterns performed by occupants is essential. Although recent pieces of research have focused on window operation, there have been disagreements about the duration of monitoring and the predictors used. As previously stated, no standardised method is available for similar research, and practitioners rely on the available resources (e.g., different indoor and outdoor sensors) and feasible monitoring duration for each situation.

Therefore, this research article aims to guide the optimisation of field studies considering different predictors (i.e., the combination of indoor and outdoor variables, only indoor or only outdoor ones) and their implications on the minimum duration needed to reach reliable models. For doing so, information theory concepts (entropy, conditional entropy, mutual information, and cross-entropy) were used to assess which variables can reduce the uncertainty of window operation data to the maximum, as well as to determine how wrong one is likely to be when using data from small monitoring campaigns instead of long-term ones. Information theory concepts have been applied in previous energy-related research comprising occupancy detection (ZOU *et al.*, 2018), calibration of building energy models (CHONG *et al.*, 2017), optimal sensor placements (LEE; DIWEKAR, 2012), and proposition of a sustainability index (PAWLOWSKI *et al.*, 2005). This work is innovative considering the application of information-theoretic concepts to frame hypotheses about feasible optimisation in occupant behaviour research. Additionally, the method includes a comprehensive modelling strategy based on deep-learning algorithms to test the hypotheses reached with information theory metrics and translate the results into practical recommendations for building stakeholders. Both steps relied on data collected at the Environmental Applied Physics Living Lab of the University of Perugia throughout six whole years, comprising indoor and outdoor-related variables.

2. Method

The research procedure implemented in this study consists of three main steps, as shown in Figure 6.1. The first step comprised long-term monitoring of indoor and outdoor variables related to offices in Perugia, Italy. The second part encompassed the initial data analyses using information theory metrics. Such metrics enabled the evaluation of uncertainty-related aspects linked to the window operation and formulated hypotheses about the impact of the measured variables and the seasons. Finally, the third step focused on testing such hypotheses using deep learning algorithms by training neural networks using subsets of the whole dataset considering different predictor combinations. This section presents detailed descriptions of each step included in the study.

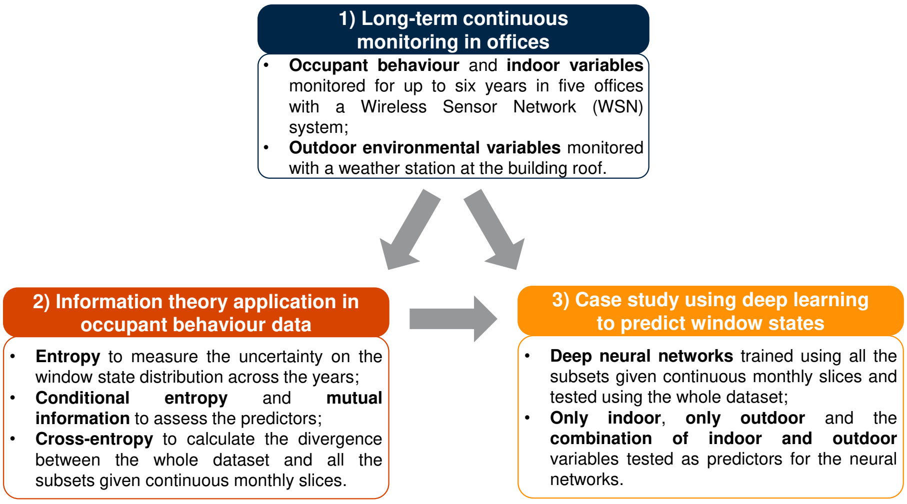

Figure 6.1. Outline of the main steps conducted throughout this study.

2.1. Data collection and preparation

2.1.1. Experimental campaign

This research leans upon a big dataset collected at the Environmental Applied Physics Living Lab (EAPLL) of the University of Perugia throughout six years of operation, since April 2015. The EAPLL consists of five offices on the first floor of a two-storey university office building, i.e. the Interuniversity Research Centre on Pollution and Environment "Mauro Felli" (CIRIAF), located in Perugia, central Italy. The city is located in Cfa zone according to the Köppen-Geiger international climate classification, i.e. humid subtropical climate. The building is rectangular-shaped with a flat roof and has average energy performance according to the Italian energy certification. The offices of the EAPLL have the same characteristics in terms of geometry, orientation, systems, and are occupied by peers, as explained in detail in (PISELLI; PISELLO, 2019; PISELLO *et al.*, 2016) and shown in Figure 6.2. Each office hosts two or three persons in working stations. They all have two operable French windows providing direct access to the external gallery but could be partially opened as vasistas windows, which were shown in (PISELLI; PISELLO, 2019; PISELLO *et al.*, 2016).

The EAPLL is continuously monitored by means of a Wireless Sensors Network system comprising five nodes, one for each monitored room, and a gateway saving on-board and, then, on-cloud data retrieved via wireless from the nodes every 5 minutes. Each node is connected via cable to several sensors that allow to obtain the following data: internal air temperature in the middle of the room at desk height (range: -20°C to 60°C; accuracy: < 0.15 °C), illuminance level at the desk plane (range: 20 lx to 2000 lx; accuracy: < 5%), electrical consumption of single workstations or clusters of two workstations (AC measured using an ammeter – range: 10 A to 400 A; accuracy: < ±1%), and window and door operation (magnetic sensor – on/off). Furthermore, a weather station located on the rooftop of the building hosting the EAPLL continuously collects external air temperature, relative humidity, global solar radiation, rainfall, and wind speed and direction data every 10 minutes. More detailed information on the monitoring setup is described in (PISELLI; PISELLO, 2019; PISELLO *et al.*, 2016).

Figure 6.2. Details about the indoor characteristics of a typical monitored office room.

2.1.2. Data preparation for the analyses proposed

After an initial data cleaning and preparation process, data from the indoor and the outdoor monitoring were merged into a common dataset. The main changes comprised the exclusion of outliers in both indoor and outdoor continuous data and checking the consistency of window and door measurements over time. Also, the continuous variables (i.e. indoor and outdoor environmental variables) were discretised using equal width and equal frequency strategies (HE; MIN; ZHU, 2014) to enable further tests. This dataset comprises the data monitored from April 2015 to March 2021, i.e. 72 months. The dataset was used to conduct the further analyses proposed in this study, and all the metrics that comprise the whole distribution of interest were computed considering it. However, critical points of this study rely on evaluating the impact of the subsets' length on their representativeness compared to the entire dataset. Such a test is crucial in occupant behaviour research since no standardised method is available, and studies are generally context-related. Therefore, the strategy adopted in this study comprised the complete dataset slicing in all the possible combinations of continuous monitoring in terms of months. For instance, starting in April 2015, one can have continuous subsets with lengths in integer values of months like a one-month-long subset considering the whole month of April 2015, a two-month-long subset from April to May 2015, and so on up to a 72-month-long considering the whole dataset. Similarly, starting in May 2015, one can have a one-month-long subset with this whole month, a two-month-long subset from May to June 2015, and so on up to a 71-month-long subset from May 2015 up to March 2021. This strategy was implemented considering all the possible initial months and lengths available in the full dataset, and an illustration of this process is shown in Figure 6.3. More than 2,500 subsets were reached throughout this process and used to conduct further analyses.

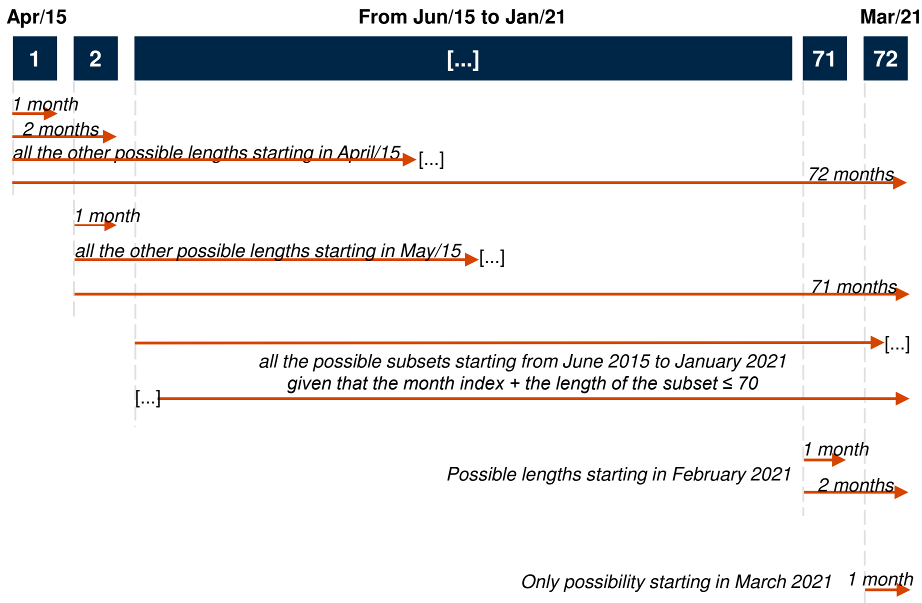

Figure 6.3. The strategy adopted to divide the whole database.

2.2. Core concepts of information theory

The first part of the data-driven approach is based on fundamental quantities of information theory – namely entropy, conditional entropy, mutual information and cross-entropy – all functionals of probability distributions and closely related (COVER; THOMAS, 2006). Such metrics were first used to assess which variables could most reduce the uncertainty regarding window operation in offices. Second, they enabled to evaluate the impact of seasonality on the divergence of smaller subsets compared to the whole dataset. Understanding these divergences is a key aspect to plan future field monitoring campaigns. All the information-theoretic methods were calculated using the MIT-licensed library pyitlib implemented in Python and NumPy.

2.2.1. Entropy

The initial approach of this analysis comprised the calculation of the entropy of the target variable (window operation). The entropy of a random variable is a measure of its uncertainty and the amount of information required to describe this random variable. Considering *X* as a discrete variable with alphabet χ and probability mass function (PMF) *p(x)* = $\Pr\{X = x\}$, $x \in \chi$, the entropy *H(X)* can be estimated using Equation 1 (COVER; THOMAS, 2006). When using the log to the base 2, the entropy unit is bits. Thus, all the entropy-related calculations in this study are presented in bits.

$$H(X) = -\sum_{x \in \chi} p(x) \cdot log_2 p(x) \qquad ((1)$$

Where: *p(x)* denotes the PMF of the random variable *X*.

2.2.2. Conditional entropy and mutual information

The second step comprised the calculation of conditional entropies given other random variables available. Letting w be the random variable window state (i.e. windows being open or closed) and *H(w)* its entropy, each one of the other random variables (e.g., $Predictor_n$) has an associated conditional entropy $H(w|Predictor_n)$, which was calculated using Equation 2. According to Cover and Thomas (2006), this metric can be defined as the entropy of a random variable conditioned on the available knowledge about another random variable. The initial uncertainty is reduced due to the mutual information among them, and this metric may provide the most informative predictors. The variables shown in Table 6.1 were used to assess the conditional entropies. All the continuous random variables were discretised to be included in such analysis using equal width and equal frequency strategies (HE; MIN; ZHU, 2014). Throughout this process, the output on the conditional entropies indicated that equal frequency represented better outcomes for the tests made, and this approach was adopted herein.

Table 6.1. Predictors used throughout the analyses carried out in this study.

Category	Predictors	Name used
Contextual aspects	Month	Month
	Offices – five options available	Office
	Hours – grouped in 4-hour intervals to minimise the number of bins	Hours
	Day of the week	Day
Indoor variables	Indoor air temperature (°C)	Ind-temp
	AC waveforms current at the workstation level as an energy use indicator (Hz)	AC-curr
	Indoor illuminance (lx)	Lux
	Door state (open or closed)	Door
Outdoor variables	Outdoor air temperature (°C)	Out-temp
	Outdoor air relative humidity (%)	Hum
	Direct solar radiation (W/m²)	Sol-rad
	Wind direction (degrees)	Wind-dir
	Wind speed (m/s)	Wind-speed
	Rain (mm)	Rain

$$H(X|Y) = -\sum_{y} p(y) \sum_{x} p(x|y) \cdot log_2 p(x|y) \tag{(2)}$$

Where: *p(y)* denotes the PMF of the random variable *Y*; *p(x|y)* denotes the conditional PMF of the random variable *X* given the random variable *Y*.

Besides using the predictors available (i.e. indoor and outdoor variables) to calculate conditional entropies of window state, the mutual information between the predictors was calculated using Equation 3. Cover and Thomas (2006) stated that such a metric measures the amount of information that one random variable contains about the other. Also, the mutual information between one random variable and itself is the same as the actual entropy of this given variable. Therefore, entropy may also be considered as the self-information of a variable. Understanding the amount of information that each predictor shares with each other is a great way to assess the most informative ones for window operation to add new information to the distributions.

$$I(X;Y) = \sum_{x,y} p(x,y) \cdot log \frac{p(x,y)}{p(x) \cdot p(y)} \tag{3}$$

Where: *p(x)* denotes the PMF of the random variable *X*; *p(y)* denotes the PMF of the random variable *Y*; *p(x,y)* denotes the joint PMF of random variables *X* and *Y*.

2.2.3. Cross-entropy and Kullback–Leibler divergence

A final step relying on the information-theoretic metrics used in this study was to compare all the small subsets derived from the whole dataset to calculate the differences among them. Kullback–Leibler (KL) divergence was the metric used to calculate such differences. According to Cover and Thomas (COVER; THOMAS, 2006), KL divergence can be used to compare two probability distributions, p and q, and indicate the inefficiency of assuming that the distribution is q when it is p. In other words, it measures the "distance" between the probability mass functions p and q, and it is calculated according to Equation 4.

$$D_{KL}(p||q) = -\sum_{x} p(x) \cdot log_2 \frac{p(x)}{q(x)} \tag{4}$$

Where: *p(x)* and *q(x)* denote PMFs of the random variable *X*.

For each subset (see section 2.1.2), the corresponding KL divergence was calculated concerning the whole dataset. In other words, one calculated the "distance" between each of the subsets and the whole distribution to estimate how wrong one would be if assuming that the actual data distribution occurs as in each small dataset. Cross-entropies of subsets are expected to converge to the total dataset entropy as the size of the subset increases. However, such a trend is not expected to be linear, especially regarding occupant behaviour and the uncertainties related to the stochastic nature of human-building interactions. Thus, this analysis provided an overview of field studies' duration needed to represent window operation.

2.3. Case study using deep feed-forward neural networks

Another goal of this study was to implement machine learning techniques for predicting the state of windows, i.e. open or closed, concerning occupants' behaviour. Under this scenario, one assessed different combinations of predictors and subsets of the whole database as modelling approaches. Initially, the whole database was used to fit a deep feed-forward neural network to predict window states according to knowledge transferred from the work by Markovic *et al.* (2018). Indeed, this existing work comprised a massive set of tests in terms of hyperparameters to propose an optimised window opening model, and the results indicated satisfying generalisation capabilities and robustness of the final proposition. Based on such satisfactory outcomes, a five-hidden layer neural network (number of neurons per hidden layer: 64, 94, 81, 10, 25) using the activation function Rectified Linear Unit (ReLU) was tested in this study. Although the Sigmoid activation function can also be used in binary classification, the literature supports that using ReLU can avoid easy saturation because this function maintains most features that make linear models easy to optimise (GOODFELLOW; BENGIO; COURVILLE, 2016). The number of predictors available for each test was set as the number of neurons for the input layer, while the output layer had one neuron because the outcome is a binary variable. The main performance metrics used here are based on the associated confusion matrix (which includes true positive rate (TPR), true negative rate (TNR), false positive rate (FPR), and false negative rate (FNR). Such performance metric has been used in other machine-learning-based assessments of occupant behaviour in buildings (MARKOVIC *et al.*, 2018). TPR and FPR were preferred over accuracy measures because the window operation data represents an unbalanced database (in which more "negatives" are observed since the windows stay more closed than open throughout the year).

Insights from the information theory metrics calculated were used to set different characteristics for the models, as shown in Figure 6.4. First, considering the variations found on the cross-entropy of the subsets and the whole dataset, each one of the subsets (see section 2.1.2) were used to train a neural network. Thus, for each subset that started in month m and had a duration n (with m and n varying from 1 to 72), one deep feed-forward neural network was trained using 80% of the subset data and tested using the other 20% combined with the remaining data of the whole dataset. Second, considering the variations observed on the conditional entropies of the window state given the available predictors and the mutual information between them, different predictors were used.

Therefore, three groups of predictors were tested: indoor variables, outdoor variables, and the combination of both. Considering all the possibilities comprised throughout this iterative process, more than 7,000 neural networks were evaluated. The True Positive Rates and False Positive Rates of each neural network were then used to build receiver operating characteristics (ROC) diagrams to visualise their performance (FAWCETT, 2006). The diagonal line ($y = x$) representing the strategy of randomly guessing a class was used as a proxy to determine the out and the underperforming models. In-depth evaluations were then carried out within the poor models to evaluate common characteristics and provide recommendations in terms of optimisations for further field studies.

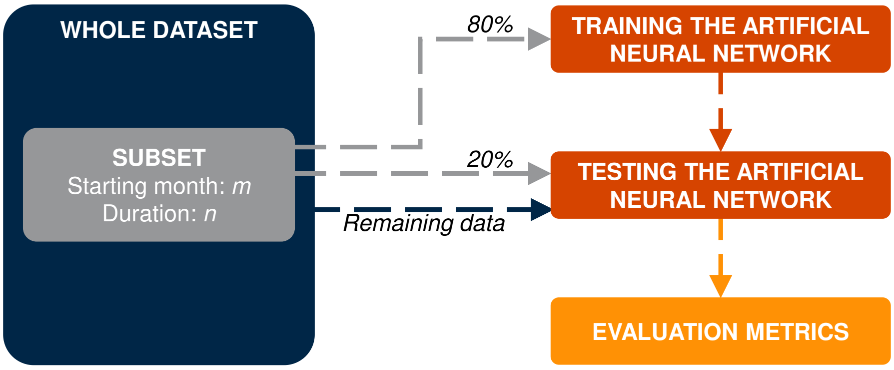

Figure 6.4. Illustration of the iterative process adopted to train and test the neural networks.

3. Results and discussion

The results achieved are presented and discussed in two parts. In the first one, outcomes from the information-theoretic metrics applied herein are introduced and used to hypothesise optimisations regarding window operation monitoring and modelling. The second one shows the results achieved throughout the tests based on deep learning to assess the hypotheses.

3.1. Core concepts of information theory applied to occupant behaviour research

3.1.1. Entropy, conditional entropy and mutual information

The first information-theoretic metric obtained was the entropy of the window operation distribution. Considering the whole dataset (six years of monitoring), the associated entropy ($H(w)$) was 0.7771 bits. As previously discussed, this value can be understood as an uncertainty measure, and further calculations used it as a reference. First, the other random variables available in the dataset were used to calculate the conditional entropy of the window operation given each of them (i.e. indoor and outdoor-related variables). Results are presented in Table 6.2. Considering the uncertainty reductions, one may determine the most informative variables regarding the window operation. The first outcome of this analysis is that contextual variables (e.g., month and the office evaluated) are important to reduce the uncertainty about the window operation. In those cases, the resulting conditional entropies were 0.6841 bits for month and 0.7570 bits for office. Indeed, different months say a lot about the window operation: during cold periods, the windows remain closed longer than they do throughout milder and hotter months. A practical application regarding this fact is that contextual variables – which represent no additional costs in terms of sensor installation or maintenance – should always be considered when window models are created. In fact, including various contextual variables is a good practice in the field (FABI *et al.*, 2012). Previous research concluded that some clusters of window operation are influenced by contextual aspects more than by physical ones (D'OCA; HONG, 2014). Additionally, the office-related entropy reduction supports previous conclusions that peers behave differently even in equivalent spaces (PISELLO *et al.*, 2016).

Table 6.2. Conditional entropies considering single predictors and their associated reduction compared to the reference value.

Predictor	**H(w|Predictor) measured in bit**	**H(w|Y)/H(w)**
Month	0.6841	0.8802
Out-temp	0.7073	0.9100
AC-curr	0.7292	0.9382
Ind-temp	0.7321	0.9419
Office	0.7570	0.9740
Sol-rad	0.7602	0.9781
Hum	0.7682	0.9884
Lux	0.7634	0.9822
Door	0.7741	0.9960
Hours	0.7750	0.9972
Wind-dir	0.7753	0.9975
Wind-speed	0.7762	0.9987
Day	0.7764	0.9989
Rain	0.7767	0.9993

Going further on this topic, it is also important to evaluate the difference between indoor and outdoor variables regarding uncertainty reduction of the window operation distribution. Although combining indoor and outdoor variables is a good practice and has been used in most previous research (D'OCA; HONG, 2014; FABI *et al.*, 2012; MARKOVIC *et al.*, 2018; PISELLO *et al.*, 2016), it is interesting to understand the feasibility of reducing the number of sensors to minimise the associated costs of field monitoring in the future. Based on the conditional entropies, it is evident that both classes of variables are handy to reduce the uncertainty of window operation. However, only this metric may not be enough to determine which group of variables are more informative for this context. One may argue that since there are more outdoor-related variables available than indoor ones, their combination may play an essential role regarding the uncertainty reduction of the target variable. A follow-up evaluation comprised the mutual information between each pair of predictors, and the results are presented in Tables 6.3 and 6.4.

Table 6.3. Mutual information between indoor variables.

Variables	**Mutual information**			
	Ind-temp	**AC-curr**	**Lux**	**Door**
Ind-temp	-	-	-	-
AC-curr	0.0563	-	-	-
Lux	0.0878	0.2122	-	-
Door	0.0231	0.0344	0.0415	-

Table 6.4. Mutual information between outdoor variables.

Variables	Mutual information					
	Out-temp	**Sol-rad**	**Hum**	**Wind-dir**	**Wind-speed**	**Rain**
Out-temp	-	-	-	-	-	-
Sol-rad	0.3516	-	-	-	-	-
Hum	0.3830	0.2481	-	-	-	-
Wind-dir	0.0880	0.1072	0.0823	-	-	-
Wind-speed	0.0596	0.0738	0.1680	0.0993	-	-
Rain	0.0082	0.0088	0.0216	0.0016	0.0011	-

There are trends regarding the mutual information between each pair of indoor and outdoor variables representing the smaller conditional entropies (see Table 6.3) that need clarification. Considering indoor-related variables, the smaller conditional entropies were observed with the energy consumption at the workstation, air temperature, and illuminance. When it comes to the mutual information between them, the highest share was observed for the indoor illuminance and the energy use at workstations, which represented 0.2122 bits. In other words, it means that the indoor variables that reduced the uncertainty about window operation the most do not share much information. However, a different trend was observed considering the mutual information between outdoor variables that most reduced the uncertainty about window operation – namely air temperature, air relative humidity, and solar radiation. In all the cases, the shares of mutual information were higher than the biggest one found for the indoor-related variables. As shown in Table 6.4, the mutual information between outdoor temperature and relative humidity was 0.3830 bits, for outdoor temperature and solar radiation was 0.3516 bits, and for solar radiation and relative humidity was 0.2481 bits. Consequently, individual entropy reductions of window operation distribution may overlap, considering that such variables share similar knowledge.

The results obtained herein support that, although more outdoor-related variables are available because climate stations generally comprise more sensors than indoor-based stations, it is clear that the most informative predictors from outdoors share much information. Consequently, combinations of the available indoor-related variables are more likely to reduce the uncertainty on the window distribution than combinations of outdoor-related values. This trend was obvious in this study, but the same calculations may be done using other databases relying on the same or new predictors to provide comparison metrics. However, based on the knowledge gathered herein, it was hypothesised that indoor-related variables are more informative in terms of window operation, which was tested in the second part of this study using deep learning algorithms. Another critical aspect to consider is that the literature supports using other indoor-related variables like CO_2 concentration (FABI *et al.*, 2012; STAZI; NASPI;

D'ORAZIO, 2017; ZHANG *et al.*, 2018) and objective measurements of room occupancy (GUNAY; O'BRIEN; BEAUSOLEIL-MORRISON, 2013; HALDI; ROBINSON, 2009). Although CO_2 was not considered in this work, the energy use at workstations may be a proxy for occupancy in the offices, as supported by previous research (MORA *et al.*, 2019; WANG; DING, 2015). Indeed, this variable was the indoor-related one that most reduced the uncertainty on window operation, followed by the indoor air temperature.

3.1.2. Cross-entropy

The second part of the evaluations based on information theory metrics comprised the calculation of cross-entropies of all the subsets according to the slicing strategy adopted (see Figure 6.3). Firstly, it is essential to highlight that the reference value H(w) = 0.7771 bits for the entropy of the window operation distribution is also important here. Indeed, the higher the cross-entropy between two random variables' distributions, the greatest the divergence between them. Consequently, no divergence is found when comparing two identical distributions, and the cross-entropy calculated equals the entropy itself. Therefore, considering the window operation distributions evaluated in this study, convergence to the reference value of $H(w)$ = 0.7771 bits is expected when bigger subsets are compared to the whole dataset. Indeed, this trend can be observed in Figure 6.5, where the average cross-entropy for each monthly-sliced subset is presented considering its associated starting season. The corresponding cross-entropy of a given length (x-axis) in Figure 6.5 represents the average cross-entropy for all the subsets with this particular length. Additionally, such values were calculated considering the season in which each specific subset started, and such distinctions were made in the graph.

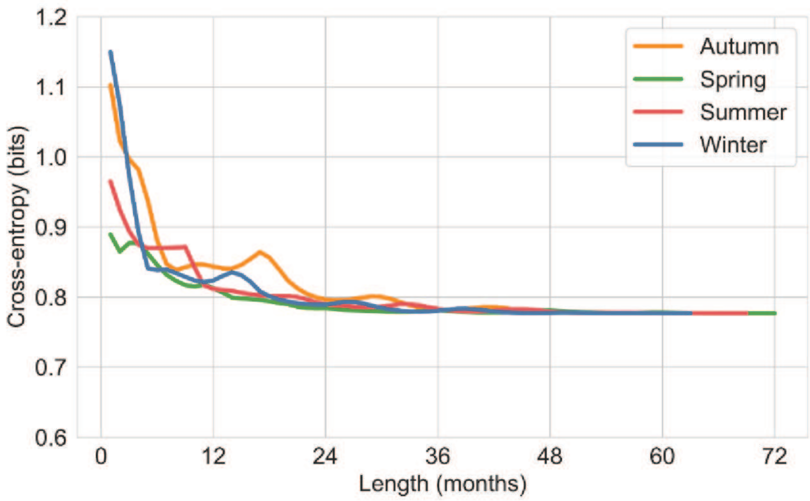

Figure 6.5. Cross-entropy variation between subsets and the whole database.

Based on the cross-entropies of the subsets and the whole database, it is clear that smaller continuous monitoring is very likely to diverge a lot from the total distribution of the variable. In other words, continuous field monitoring campaigns with just a few months of duration are likely to diverge a lot compared to long-term window operation patterns. Different trends may be found when small subsets from different seasons are combined – i.e. measurements that are not continuously conducted in offices (PEREIRA, RAMOS; SIMÕES, 2020). Additionally, the seasonality effect on the divergence between smaller subsets and the whole database is evident. The most considerable divergences were found for winter and autumn, colder seasons in which windows are more likely to be closed. Additionally, the influence of the winter throughout the time series is apparent. Besides being responsible for the highest cross-entropies when considering just a few months of monitoring, the inclusion of winter-related data tends to increase the divergence of the subsets starting in other seasons. This tendency can be observed from 6-9 months after starting in summer, 9-12 months after commencing in spring, 12-15 months after starting in winter, and 15-18 months after beginning in autumn. Using the same terminology from the predictors, it is clear that summer and spring can be considered more informative seasons than autumn and winter since subsets starting from them resulted in smaller divergences. It means that one is more likely to be wrong by assuming that window operation distributions biased towards winter are similar to those observed in the long term.

Another important outcome that came from the cross-entropies is some convergence points. The clearest one occurs after 48 months of monitoring when the influence of winter is quite imperceptible. However, smaller lengths also represented some interesting convergences. The first one is observed between nine and twelve months, where the high divergences initially observed with small datasets are reduced. However, as previously discussed, including periods representing further winters are likely to increase the cross-entropy again, especially when the monitoring started either in autumn or winter. Consequently, the results show that 12, 24, 36, and 48 months can be considered different convergence points. However, lengths between those thresholds are biased by so-called less informative seasons. Thus, noticeable increases were observed from the 12th up to the 24th month and again up to the 36th and 48th months. It is also important to highlight that the bigger the sample, the smaller the variability observed between these convergence points. In other words, by including new data after one full year of monitoring, some increases in cross-entropy are expected. However, the longer one monitors, the less impactful such divergences' increase become. This tendency can be confirmed with variations observed between 12-24 months, 24-36 months, and 36-48 months, which show yearly reductions.

3.2. Case study using deep learning

More than 7,000 deep feed-forward neural networks were trained using different subsets of the whole database considering different predictors and used to test the hypotheses framed in the first part of this study. ROC diagrams were used to evaluate the True Positive and False Positive Rates (TPR and FPR) as performance metrics of the models, which enabled to compare the influence of indoor and outdoor monitored variables on the outcomes. The outcomes of each model were plotted in a corresponding ROC diagram, as shown in Figure 6.6. Considering the diagonal line in each diagram as a random guess (TRP equals FPR), the results are presented in blue when the model outperformed the random guess and in red otherwise.

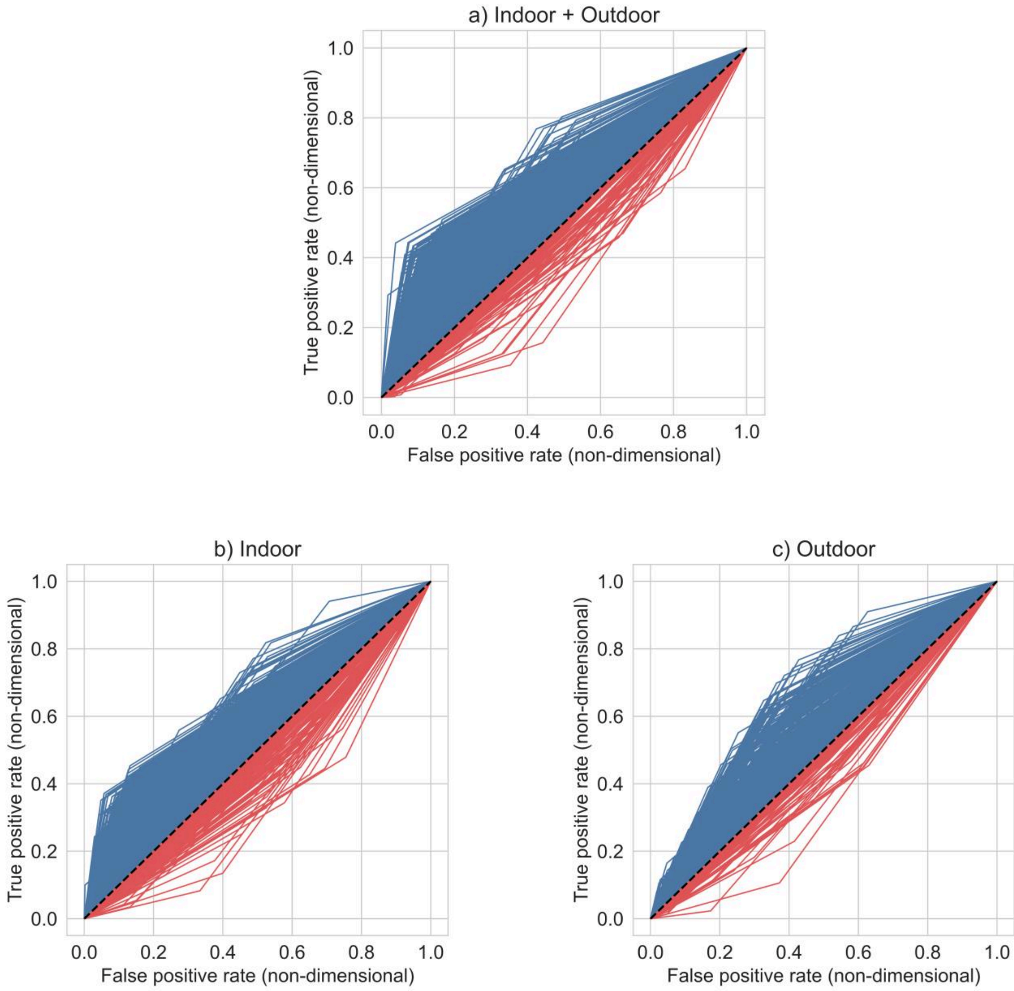

Figure 6.6. ROC diagrams considering the models created with: a) indoor and outdoor data; b) only indoor data; and c) only outdoor data.

The first outcome from this analysis was the rates of models that outperformed the guess line: 90.6% of the models considering indoor and outdoor predictors, 86.6% of the models considering only indoor variables, and 83.1% of those based on outdoor variables. Relying on the information-theoretic concept that information never hurts (THIESEN; DARSCHEID; EHRET, 2019), this study showed that the best approach to reach higher reliabilities when modelling window operation in offices comprises monitoring indoor and outdoor variables. This combination is aligned with most previous research in this field (D'OCA; HONG, 2014; FABI *et al.*, 2012; MARKOVIC *et al.*, 2018; PISELLO *et al.*, 2016). Another conclusion from these results is that indoor-related data should be preferred over outdoor-related data when one of them needs to be chosen for any reason. This result is aligned with the hypothesis formulated in the first part of this study. Indeed, outcomes from conditional entropies and mutual information led to the belief that indoor variables were more likely to reduce the uncertainty of window operation, and deep-learning-based models confirmed such a tendency.

Besides assessing the variables that resulted in higher rates of outperforming models, it is necessary to understand the trends and similarities among the underperforming ones. Such knowledge is helpful to provide recommendations for further studies aiming at optimal experiment designs. Initially, boxplots were constructed considering the poor models built with different predictors (Figure 6.7). The results highlight a clear reduction in minimum lengths needed when indoor variables are included in the loop of window operation monitoring and modelling. Since upper quartiles represent 75% of the points in each boxplot, these thresholds were considered paramount values in terms of the minimum lengths. From them, it is clear that building stakeholders should consider at least nine months to be more likely to achieve good-performing window operation models based on both indoor and outdoor variables. However, minimum durations based on upper quartiles increased only when indoor or outdoor data were included. For the indoor variables, at least one year of continuous monitoring is recommended, while outdoor variables require more than two years of evaluation. These thresholds are related to the initial convergence points observed with the cross-entropy calculations (see Figure 6.5).

A follow-up test based on Kernel Density Estimation of cumulative density functions was used to determine if the upper-quartile criterion can be considered a straightforward recommendation. According to Figure 6.8, high densities are observed for the thresholds reached considering the upper-quartile criterion. For instance, a density of 0.8 is reached when models based only on indoor data reach the threshold of one year of monitoring. Similar trends are observed for the other cases – about nine months when indoor and outdoor variables are combined and more than two years when only outdoor data is used.

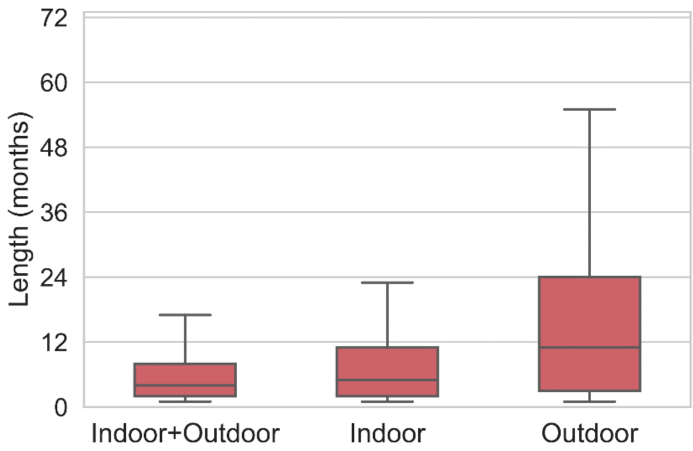

Figure 6.7. Synthesis of the most recurrent lengths of subsets that resulted in underperforming models according to the predictors used.

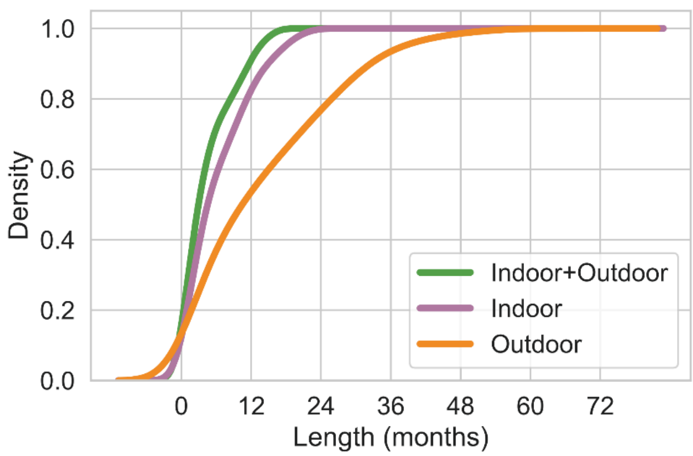

Figure 6.8. Cumulative distribution of the dataset length of underperforming models considering different predictors.

The previous recommendations based on the upper-quartile criterion and confirmed by corresponding cumulative density functions can be considered initial guidance on the minimum lengths of monitoring for creating window models. They can be interpreted as a good practice, at least in terms of durations that should be avoided. However, there is still one unanswered question on the other way around: how much should we enlarge the field monitoring for each scenario using the upper-quartile values as thresholds? Indeed, one may argue that 25% of the underperforming models were still based on monitoring campaigns bigger than these values. Thus, the upper limits (and lengths with densities equal to 1.0 in Figure 6.8) can be considered the most reliable thresholds for future measurements. In this case, the durations are as follows:

a) 1.5 years or more of continuous monitoring when indoor and outdoor data are considered; b) 2 years or more when only indoor data are considered; and c) more than 4.5 years when only outdoor variables are used as predictors. Although these values may be deemed safety factors for further experiments, they represent a considerable amount of data, especially when only outdoor variables are considered. Additionally, the question presented above is somehow unanswered if only the maximum values are given as recommendations.

To bridge this gap, in-depth analyses were carried out considering the underperforming models with associated lengths between the upper quartiles and the upper limits (Figure 6.7). As shown in Figure 6.9, the results indicate a strong influence of seasonality on these models. The lowest shares of underperforming models were achieved using subsets that started in the summer and spring. As previously discussed (see Figure 6.5), greater divergences were found among subsets that started in both winter and autumn and the whole dataset. Therefore, a recommendation for practitioners in this field comprises relying on the influence of seasonality to minimise the lengths of further experiments without compromising the outcomes. Indeed, the most recommended season to start such monitoring would be the summer, especially when outdoor variables are included in the loop.

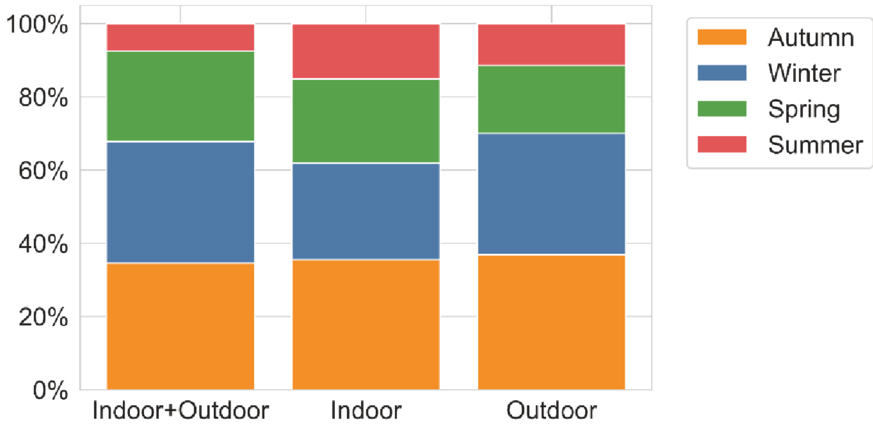

Figure 6.9. Illustration of the season in which the subsets that resulted in underperforming models started.

According to the results, summer-starting subsets represented the lowest share of underperforming models in all the cases tested: 7.4% when indoor and outdoor predictors are used, 15.1% with only indoor ones, and 11.4% using outdoor-related variables. In all the cases, starting the monitoring in winter or autumn is not a good practice – 62% up to 70% of underperforming models were created with subsets that started in such seasons. According to the best of the authors' knowledge, this is the first work that combined insights from information theory and machine learning to provide optimisation guidelines for further evaluations. Therefore, the method can be applied to other databases, given that specific culture and climate conditions may play a role in the outcomes and context-related guidelines are likely to be achieved.

The seasonality effect on window operation is highly discussed in the literature. A comprehensive body of research supports that windows remain more time closed during cold months (D'OCA; HONG, 2014; FABI *et al.*, 2012; HERKEL; KNAPP; PFAFFEROTT, 2008). This study added an information theory metric (cross-entropy) to calculate the season-influenced divergence and a machine-learning-based approach to test its effect in occupant behaviour models. Indeed, both approaches shed light on the fact that winters and autumns can increase the uncertainty in window operation. A practical implication is that new data can also incorporate new uncertainties into the models. Hence, even smaller subsets are more likely to result in good models than bigger subsets biased towards colder seasons. Additionally, an interesting implication of the results reached in this study regards the situation where only outdoor data is used to train window operation models. In this case, more than 4.5 years of continuous monitoring were needed to be sure about achieving good-performing models (see Figure 6.7).

However, a cost-effective strategy could be to perform shorter monitoring campaigns (at least longer than two years) starting from the summer. This approach can be feasible when it comes to big buildings that need to be thoroughly monitored, as well as for real-state marketing analyses. In this case, only one climate station on the rooftop can monitor the predictors for modelling all the offices. Consequently, thousands of indoor-related sensors can be disregarded, reducing associated costs with installation and maintenance. It is then up to the companies to define the most feasible solution between managing more comprehensive databases or relying on smaller ones, leading to higher initial costs. Additionally, building stakeholders from developing countries may also rely on the guidelines to optimise field monitoring and achieve less expensive evaluations than long-term campaigns. As a consequence, it can stimulate and popularise occupant behaviour evaluations across the world. Such a trend would play a critical role in the field since most of the available occupant models come primarily from North America, Europe, and China (CARLUCCI *et al.*, 2020).

4. Conclusion

This study proposed an innovative approach based on information theory metrics and deep learning to guide optimisations on window operation assessments in offices. The optimisations comprised the determination of minimum durations of field monitoring that lead to accurate window state models in offices. The method relied on a dataset with six years of continuously monitored indoor and outdoor variables, which enabled the calculation of information-theoretic metrics as proxies for uncertainty and uncertainty reductions concerning the windows' operation. These uncertainty reductions relied on the concept that different random variables share varying amounts of information (mutual information), which can be used to assess and reduce the uncertainty of each other. Additionally, a monthly-based slicing was applied to determine the divergence of each subset compared to the whole dataset (i.e.~~,~~ how wrong one will be if assuming data from short field studies to model long-term window states), as well as to train and test deep feed-forward neural networks to draw the conclusions and recommendations for further studies. According to the best of the authors' knowledge, this work is the first to summarise information theory concepts and deep-learning-based models to advance occupant behaviour research practices, and the main findings can be summarised as follows:

- Different uncertainty reductions were reached by evaluating the conditional probability distribution of window operation given other random variables available in the dataset. The results confirmed that not only indoor and outdoor physical variables are essential in this field, but also contextual aspects like the month (which is a proxy for the season) and the office (which is a proxy for different occupants' preferences and attitudes).
- Information-theoretic metrics showed that, considering the variables measured in the scope of this study, indoor variables share lower rates of information compared to outdoor ones and, as a consequence, individual entropy reductions enabled by outdoor variables may overlap and become less significant when combined. This tendency led to the hypothesis that indoor variables are more informative regarding window operation in offices. Additionally, subsets biased towards winter and autumn had higher divergences concerning the whole database with six years of continuous monitoring. This aspect led to the hypothesis that practitioners should consider the season before starting field monitoring.

- The performance of deep learning models trained considering different predictors (i.e. the combination of indoor and outdoor variables, only indoor, and only outdoor variables) and different subset lengths confirmed the hypotheses initially framed. First, the inclusion of indoor-related variables increased the share of good-performing models according to their true and false-positive rates. Second, an enlargement on the monitoring duration is needed when indoor variables are disregarded. For instance, while all the underperforming models that included indoor variables had lengths shorter than two years, using only outdoor variables required at least 4.5 years before being sure about the quality of randomly selected models. Finally, it was concluded that building stakeholders might use the influence of seasonality to balance the need for big data and a reasonable minor chance of achieving poor data-driven models. Therefore, feasible optimisation strategies would rely on starting field monitoring in spring or summer and adjusting its duration according to the variables monitored, as follows: at least nine months of continuous monitoring when using indoor and outdoor variables; at least one full year if only indoor variables are used; and more than two years when only outdoor data are considered.
- The results of this study provide building stakeholders with the opportunity to define the most feasible choice regarding the combination of more extended field monitoring with the installation of few sensors or vice-versa. Also, the proposition of this method may encourage its replication with various datasets to achieve more generalisable strategies for future monitoring campaigns. Such strategies are likely to benefit practitioners from developing countries to choose cost-effective solutions that still lead to reliable models. According to the promising findings, future studies should evaluate if similar optimisation strategies are reached for other kinds of human-building interactions (e.g., adjustments of internal blinds or thermostats). Moreover, as future development, similar metrics can be used to assess optimal sensor quantity and placement in buildings to reduce the associated costs of field monitoring.

7. Discussions

This work provided evidence that qualitative and quantitative methods play essential roles in occupant behaviour research. The former gathers subjective data related to the human dimension of building performance that is essential to either contextualise objective information or reach new insights to optimise building control and assess occupants' preferences. On the other hand, the latter provides objective, sensor-based information from varied aspects like indoor environmental quality, human-building interactions, and person-related data like physiological measurements. Consequently, they comprise complementary approaches towards better understanding and representing the human dimension of buildings' performance.

The first part of this thesis, which was based on comprehensive literature reviews, contributed to the field by documenting both technological innovations and qualitative methods that may be used in the future. First, from the technological innovations point-of-view, there are many possibilities to assess and include the human dimension in the loop of building performance with positive impacts in the short and long-term horizons. Building stakeholders still need to understand the human dimension to reach user-centric smart buildings. Technology acceptance is a fundamental aspect in this context, and the innovations themselves cannot exclude human perspectives. Indeed, such human-in-the-loop systems are expected to enable high indoor environmental quality levels while also reducing the energy use in buildings. Finally, considering the qualitative methods from social science perspectives, an initial contribution relies on providing technology-driven systems with subjective information, critical to improving the occupant-centric aspect. Additionally, this part can help to systemise the knowledge and opportunities from this field, providing an overview of methods that suit this context. If there are more explicit paths that building stakeholders may follow to approach specific questions, it is expected that qualitative methods become increasingly more common in the building sector practices.

In a stricter scope, but still considering the knowledge gathered from the literature reviews, qualitative and quantitative-based insights are likely to improve the practices of building stakeholders in developing countries. From the technological innovations point-of-view, it was important to provide a general overview of opportunities given that the current developments are likely to reduce the costs of many devices and increase their availability across the world. As recently highlighted by Hong *et al.* (2020a), future perspectives on data and computational tools on occupant behaviour monitoring and modelling should communicate the developments with a building industry moving forward in terms of technology adoption.

Indeed, as the authors discussed, low-cost and reliable methods and tools are key to collect high-quality occupant-related data, which is essential to establish mathematical models of occupant behaviour. Therefore, documenting these opportunities may provide stakeholders with insights for better assessing occupant behaviours and including them in their daily practices. Indeed, as many buildings do not rely on automation systems, self-made prototypes or low-cost sensors will play essential roles, and the information presented is likely to guide this path. From the opportunities related to social science methods, their popularisation may bridge the gap between current and human-centred policies, increasing their acceptance and use. Such a paradigm shift is fundamental regarding the human dimension of building performance in developing countries. As previously stated, most of the knowledge gathered so far in this area comes from different cultures and climates – i.e. developed countries.

The outcomes from evaluations based on the framework (D'OCA *et al.*, 2017) that combines DNAS (Drivers, Needs, Actions, and Systems) with Theory of Planned Behaviour (TPB) and Social Cognitive Theory (SCT) constructs helped to rationalise motivations for energy-related evaluations in Brazilian offices. Indeed, such an online data collection proved that low-cost and non-invasive methods are handy and may collect important information related to the human dimension of building performances. Indeed, by relying on similar approaches, occupants of target buildings may be continually asked about different aspects that influence their perceptions about the workplace. Building managers may use similar surveys to assess specific buildings and understand the most problematic aspects hindering occupant satisfaction and productivity at work. For instance, the literature review about qualitative methods emphasised the feasibility of longitudinal surveys also to conduct before-after evaluations. Linking these opportunities with the findings from the two following studies presented (articles 3 and 4), one may assess the underlying effects on adaptive behaviours and the primary sources of discomfort or subjective constraints that hinder proper adaptations throughout the year. Indeed, with continuous evaluations, different changes may be proposed (e.g., layout adaptations, lighting changes, fixing noisy or broken systems, awareness campaigns to increase levels of different constructs of TPB, and so on) and have the effectiveness checked using before-after evaluations.

Last but not least, a final step of this research provided objective insights for occupant behaviour monitoring. As the literature supports that most of the work done so far comes from Europe, North America and China (CARLUCCI *et al.*, 2020; HEYDARIAN *et al.*, 2020; SCHWEIKER *et al.*, 2020), the final step of this research was to propose a method to optimise future window monitoring campaigns aiming to determine the minimum duration of field experiments that are likely to result in reliable models. This method relied on data from Europe (specifically, from Perugia – Italy) to propose initial guidelines towards such an optimisation. Importantly, as it comprises a data-driven evaluation, the outcomes fit the local reality perfectly, and future work is still needed in knowledge transferability. However, as the optimisations are primarily related to seasonality (mainly because the windows remained closed for a longer time in colder seasons), this knowledge can be initially transferred to subtropical areas with defined seasons, such as Southern Brazil. Notably, the proposition of this method with a theoretical foundation in core concepts of Information Theory and machine learning algorithms encourages its replication with different datasets to achieve increasingly generalisable guidance. Knowledge from tropical regions is still missing, and similar approaches may propose specific guidance for those places. Additionally, the method proposed may be adjusted to determine other optimisation strategies, like the minimum number of sensors needed for obtaining reliable results.

The successful case studies conducted (using qualitative and quantitative data collection) confirmed the importance of data-driven evaluations in this field. Although qualitative data can be obtained by means of inexpensive equipment, this is not the case with sensor-based objective evaluations. The importance of objective data collection was highlighted by Hong *et al.* (2016), a study considered an Engineering Advance research. Based on the comprehensive overview provided, the authors argued about occupants' critical role in buildings and the importance of gathering data in this field. Regarding space data (e.g., indoor environmental parameters like air temperature or humidity, as well as occupant-related aspects like window or blind states), most of them are suggested to be collected with Building Management Systems (BMS) or Energy Management Systems (EMS). However, many buildings in developing countries are not equipped with automation and high-level management systems, and monitoring human-building interactions is not common. A concept from Peter Drucker comes from Business School and fits this lack: "*if you can't measure it, you can't improve it*" (DRUCKER, 2007). Therefore, providing opportunities for building stakeholders in developing countries to monitor building operation is also a way to encourage them to improve it.

Insights from the first literature review (chapter 2) can be used by professionals in the building industry from developing countries to create their pieces of equipment to enable data collection in buildings. In a broader perspective, different information collected throughout this work also emphasise the importance of such developments. First, occupant behaviour research is still underrepresented in developing countries. Second, data collection in this field is not easy in developing countries because most facilities do not rely on automation or management systems with attached sensors, commonly used to collect occupant-related data. Third, technological innovations like the IoT are evolving rapidly and provide great opportunities to assess and include the human dimension in the building performance loop. Finally, occupant behaviour and multi-domain comfort are closely linked and objectively assessing the relations among them will boost advances in this field.

Therefore, developers can use low-cost equipment − microcontrollers like Arduino, and microprocessors like Raspberry Pi − to develop IoT-based tools to monitor human-building interactions triggered by multi-domain environmental triggers. The literature shows some previous works that developed similar equipment to solve specific needs. An IoT-based device was developed to evaluate indoor air quality considering different pollutants, indoor temperature and humidity (MUMTAZ *et al.*, 2021). Another device to monitor indoor thermal conditions (temperature and humidity) by integrating sensors into a microcontroller to transmit data was developed (VALINEJADSHOUBI *et al.*, 2021). Such a device enabled integrating observed data into a Building Information Modelling (BIM) model to provide a big picture of low and medium-rise buildings. Besides indoor temperature and humidity, IoT systems may also monitor energy use (MATALOTO *et al.*, 2021). Regarding indoor environmental quality data collection, Parkinson *et al.* (2019) developed a comprehensive IoT-based device to monitor indoor conditions in buildings continuously, and some results from field studies were recently published (POLLARD *et al.*, 2021). Additionally, Luna-Navarro *et al.* (2021) also proposed a comprehensive data collection approach to IEQ and occupants' interactions with building façade. However, an open-source option that combines indoor quality monitoring with occupant presence and actions is still missing. Such a tool would fit the need to advance occupant behaviour research in Brazil or other developing countries where similar data is not commonly collected.

8. Conclusions

This work explored the potential of applying qualitative and quantitative methods in occupant behaviour research in developing countries. Initially, challenges and opportunities were gathered through comprehensive literature reviews of indexed articles recently published. Then, a case study was conducted in offices at the Federal University of Santa Catarina using a framework that synthesises building physics with social psychology constructs to evaluate underlying effects and triggers for adaptive behaviours. A second case study relied on objective data from long-term continuous monitoring in Perugia, Italy. Information Theory concepts and deep learning algorithms were used to propose an innovative method to guide optimisations in future field studies of window operation in offices. Each part of the thesis added evidence about the importance of qualitative and quantitative methods in occupant behaviour research as their outcomes are complementary. Based on the detailed documentation of the approaches used herein and the results achieved, this thesis provides building stakeholders from developing countries with a range of opportunities and recommendations to encourage occupant behaviour research in those countries. Therefore, the objectives of this work were achieved, and the main conclusions can be summarised as follows:

- Buildings are emerging as Cyber-Physical-Social Systems, which places innovative technology, humans, and their interactions in a prominent position to achieve low-energy use and comfortable buildings. As shown in the literature, various technologies can be used: active and passive sensors, Kinect technology, Internet of Things (IoT), human-in-the-loop approaches, virtual reality and immersive environments. One clear benefit of relying upon technological innovations is the possibility of gathering and analysing significant amounts of data, which can be used to optimise building design and control. A chain reaction is expected since higher acceptances may increase the adoption of such technologies (i.e. more people may buy and install them in), and higher adoption may result in large-scale productions with consequent cost reductions;
- Assessing human perspectives through qualitative methods is also encouraged. Several methods used in social sciences (questionnaires, interviews, brainstorming, post-occupancy evaluation, personal diaries, elicitation, ethnography, and cultural probe) can help building stakeholders gather qualitative knowledge to contextualise and inform decision-making. As most social science methods represent low-cost opportunities compared to sensor-

based monitoring, presenting and popularising these opportunities in developing countries is needed. By increasing the use of these approaches, outcomes from developing countries will become more popular, and the knowledge gap highlighted in the literature (i.e. most occupant-related research comes from Europe, North America and China) can be bridged;

- Intention to share the control and perceived behavioural control have positive and statistically significant effects on adaptive behaviours involving HVAC, windows, and shades/blind. Additionally, occupants find it more challenging to share HVAC control compared to windows, lights, and shades/blinds. Occupants' gender also influences this aspect: as opposed to women, males reported lower intention to share the HVAC control and also perceived lower expectations coming from their co-workers for doing so. Such subjective outcomes may guide interventions considering that practitioners may focus on the most impactful constructs for each system. Combined with that, qualitative methods can be used in longitudinal evaluations to assess the intervention impacts using before-after trends;
- Subjective and comfort-related triggers are also important regarding commonly performed adaptive actions. According to the outcomes from the machine learning algorithm, the frequency of negotiation to control building systems in shared spaces and attitudes, ease, and intention towards sharing such controls were deemed significant predictors to occupants' performing higher numbers of adaptive actions in offices. Additionally, this research evidenced the inseparable two-fold relation between occupant behaviour and multi-domain comfort: besides some interactions are adaptations to multi-domain discomfort, they can also result in a new source of discomfort;
- The data-driven approach proposed with Information Theory concepts and deep learning algorithms was successfully used to guide optimisations for future studies about window operation in buildings. The main conclusion is that when indoor-related variables are included in field monitoring, smaller experiments can support the development of reliable models compared to those based only on outdoor variables. Also, when small campaigns are intended to reduce the constraints related to big data collections, practitioners should pay attention to

the so-called "less informative seasons" since starting window monitoring in winter or autumn reduces the likelihood of achieving reliable models.

8.1. Limitations

This work has a number of limitations specifically reported below to enable better replications and validations of the outcomes:

- A low response rate (about 10%) was reached in the case study carried out at the Federal University of Santa Catarina. However, the final sample of 278 valid responses was deemed acceptable with a 90% confidence level and 5% margin of error;
- The Brazilian results apply to Florianópolis, Southern Brazil, and some variations are expected to other locations and cultures. However, these results are more likely to be generalised to cooling-dominant climates, especially considering that other trends in the literature come mostly from heating-dominant locations;
- As the survey-based evaluation was anonymous, it was impossible to reach those who declared lack of knowledge to control building systems or low intention of sharing the control over them to conduct follow-up evaluations and have a broader understanding of such constraints. Also, other information like the building where the respondent works was provided only by a few participants, and relations between building characteristics and occupant behaviour were not assessed;
- Self-reported data (as in the Brazilian case study) may be influenced by the Hawthorne effect and social desirability bias, influencing occupants to change their behaviours or provide socially acceptable instead of truthfully answers;
- Considering the method proposed to optimise window operation monitoring, the main limitation comprises the broad generalisation of the outcomes. Indeed, as it is a data-driven approach, the results fit most the local reality. However, the proposition of such a method may encourage further research using other databases to increase the knowledge transferring and results generalisability that are needed to guide stakeholders in developing countries;
- The choice of the deep learning algorithm used in the method was based on previous work about window operation modelling. There are several other

methods available, but this work focused only on one algorithm instead of comparing many of them because of the high computational cost related to testing all the subsets according to the slicing criteria proposed in this research;

- The optimisation strategies focused the most on monitoring duration and combining all indoor sensors with all the outdoor sensors. However, mainly considering indoor data, optimisation strategies regarding the reduction of sensor installation would also play a role in costs reductions, especially when massive buildings are monitored.

8.2. Recommendations for future developments

Given the limitations and opportunities highlighted by this work, some recommendations for future work are provided:

- Field studies to develop objective relations of multi-domain comfort are highly encouraged. For doing so, IEQ conditions of shared spaces can be monitored while right-here-right-now questionnaires are applied to occupants. This method would enable a broader understanding of crossed and combined effects between different domains on occupants' comfort. Different facilities can also be used for such assessments: field studies in buildings, test-room-based evaluations, and living labs can provide complementary pieces of knowledge to advance this field;
- With a better understanding of multi-domain comfort trends in offices, their relations with occupant behaviour are also more likely to be determined. Such developments could assess the aftermaths of human-building interactions to ascertain if building adjustments may result in further sources of multi-domain discomfort, especially in shared offices;
- In-depth evaluations about the influence of building interfaces on underlying effects of adaptive behaviours are also necessary. Additionally, understanding the physical configuration of offices regarding occupants' position to such interfaces may also guide layout planning;
- Advances on occupant behaviour modelling by combining qualitative and quantitative data would also play an essential role in this field. By doing so, integrated models that account for different human-building interactions while

also considering personal aspects can be achieved in the future (e.g. using agent-based modelling);

- The development of IoT-based tools to monitor human-building interactions is highly encouraged. As presented in chapter 7, the creation of open-source equipment able to monitor indoor conditions and occupant behaviours would be an advance with practical implications for building stakeholders in developing countries.

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Appendix A – Shared authorship agreements

All the co-authors of the five articles that comprise this thesis provided written consent to include them herein. The consents are presented in this Appendix.

Term of Agreement

This document attests that **Simona D’Oca**, co-author of the following articles:

- *Technological innovations to assess and include the human dimension in the building-performance loop: A review*. Published in Energy and Buildings (doi.org/10.1016/j.enbuild.2019.109365);
- *Methods used in social sciences that suit energy research: A literature review on qualitative methods to assess the human dimension of energy use in buildings.* Published in Energy and Buildings (doi.org/10.1016/j.enbuild.2019.109702);
- *Assessing underlying effects on the choices of adaptive behaviours in offices through an interdisciplinary framework.* Published in Building and Environment (doi.org/10.1016/j.buildenv.2020.107086);
- *Triggering occupant behaviour for energy sustainability: Exploring subjective and comfort-related drivers in Brazilian offices.* Published in Energy Research & Social Science (doi.org/10.1016/j.erss.2021.101959).

AGREES with the use of these articles in the Doctoral thesis of Mateus Vinícius Bavaresco (first author), supervised by Professor Enedir Ghisi from the Graduate Program of Civil Engineering (PPGEC) at the Federal University of Santa Catarina (UFSC). Dr Simona D’Oca co-supervised this work and guided the development of the articles mentioned above.

Perugia, August 2nd, 2021.

Simona D’Oca

Term of Agreement

This document attests that **Roberto Lamberts**, co-author of the following articles:

- *Technological innovations to assess and include the human dimension in the building-performance loop: A review*. Published in Energy and Buildings (doi.org/10.1016/j.enbuild.2019.109365);
- *Methods used in social sciences that suit energy research: A literature review on qualitative methods to assess the human dimension of energy use in buildings.* Published in Energy and Buildings (doi.org/10.1016/j.enbuild.2019.109702).

AGREES with the use of these articles in the Doctoral thesis of Mateus Vinícius Bavaresco (first author), supervised by Professor Enedir Ghisi from the Graduate Program of Civil Engineering (PPGEC) at the Federal University of Santa Catarina (UFSC).

Florianópolis, August 5th, 2021.

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This document attests that **Anna Laura Pisello**, co-author of the following articles:

- *Assessing underlying effects on the choices of adaptive behaviours in offices through an interdisciplinary framework.* Published in Building and Environment (doi.org/10.1016/j.buildenv.2020.107086);
- *Triggering occupant behaviour for energy sustainability: Exploring subjective and comfort-related drivers in Brazilian offices.* Published in Energy Research & Social Science (doi.org/10.1016/j.erss.2021.101959);
- *Optimising window operation monitoring in buildings: A data-driven approach based on information theory concepts and deep learning*. This one is in the submission process.

AGREES with the use of these articles in the Doctoral thesis of Mateus Vinícius Bavaresco (first author), supervised by Professor Enedir Ghisi from the Graduate Program of Civil Engineering (PPGEC) at the Federal University of Santa Catarina (UFSC). Professor Anna Laura Pisello hosted the student at the University of Perugia and supervised his activities during the exchange period.

Perugia, August 2nd, 2021.

Anna Laura Pisello

Term of Agreement

This document attests that **Ilaria Pigliautile**, co-author of the article entitled *"Optimising window operation monitoring in buildings: A data-driven approach based on information theory concepts and deep learning"*, **AGREES with the use of this article in the Doctoral thesis of Mateus Vinícius Bavaresco** (first author), supervised by Professor Enedir Ghisi from the Graduate Program of Civil Engineering (PPGEC) at the Federal University of Santa Catarina (UFSC). This article was written during the student's exchange period at the University of Perugia and is now in the submission process.

Perugia, August 2nd, 2021.

Ilaria Pigliautile

Term of Agreement

This document attests that **Ioannis Kousis**, co-author of the article entitled *"Optimising window operation monitoring in buildings: A data-driven approach based on information theory concepts and deep learning"*, **AGREES with the use of this article in the Doctoral thesis of Mateus Vinícius Bavaresco** (first author), supervised by Professor Enedir Ghisi from the Graduate Program of Civil Engineering (PPGEC) at the Federal University of Santa Catarina (UFSC). This article was written during the student's exchange period at the University of Perugia and is now in the submission process.

Perugia, August 2nd, 2021.

Ioannis Kousis

Term of Agreement

This document attests that **Cristina Piselli**, co-author of the article entitled *"Optimising window operation monitoring in buildings: A data-driven approach based on information theory concepts and deep learning"*, **AGREES with the use of this article in the Doctoral thesis of Mateus Vinícius Bavaresco** (first author), supervised by Professor Enedir Ghisi from the Graduate Program of Civil Engineering (PPGEC) at the Federal University of Santa Catarina (UFSC). This article was written during the student's exchange period at the University of Perugia and is now in the submission process.

Perugia, August 2nd, 2021.

Cristina Piselli

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