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Paula Brumer Franceschini Kagan

OCCUPANT BEHAVIOUR MODELLING FOR BUILDING PERFORMANCE SIMULATION OF NATURALLY VENTILATED SCHOOL CLASSROOMS

MODELAGEM DO COMPORTAMENTO DO USUÁRIO PARA A SIMULAÇÃO DO DESEMPENHO DE SALAS DE AULA NATURALMENTE VENTILADAS

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Thesis presented to the Faculty of Civil Engineering, Architecture and Urban Design of the University of Campinas in partial fulfillment of the requirements for the degree of Doctor in Architecture, Technology and City, in the area of Architecture, Technology and the City.

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Supervisor: Prof. Dr. Leticia de Oliveira Neves

Co-supervisor: Prof. Dr. Vanessa Gomes da Silva

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- ORCID do autor: https://orcid.org/0000-0002-2356-6731
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Tese de Doutorado aprovada pela Banca Examinadora, constituída por:

Profa. Dra. Leticia de Oliveira Neves
Presidente e Orientadora/ FECFAU/UNICAMP

Prof. Dr. Roberto Lamberts
Universidade Federal de Santa Catarina

Prof. Dr. Caio Frederico e Silva
Universidade de Brasília

Profa. Dra. Clarice Bleil de Souza
Cardiff University

Profa. Dra. Doris Catharine Cornelie Knatz Kowaltowski
Universidade Estadual de Campinas

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ABSTRACT

Most studies on occupant behaviour (OB) in school classrooms are focused on window operation in oceanic climates. In naturally ventilated schools, thermal comfort and indoor air quality are mainly affected by OB with respect to window, door and fan operation. In addition, the COVID-19 pandemic underscored the importance of indoor air quality, particularly in densely occupied buildings such as schools. Therefore, this study aimed to identify and quantify the influence of multi-domain factors (including thermal, indoor air quality, contextual and multi-behaviour domains) on window, door, and fan status in naturally ventilated school classrooms in a humid subtropical climate, in order to predict OB. A systematic literature review was carried out to raise up information about existing models of occupant behaviour for school buildings. A data collection of 66 public schools located in the state of Sao Paulo, Brazil, was performed to identify envelope and construction characteristics and select representative school buildings for a field campaign. Environmental variables, manual operation of windows, doors and fans, and occupancy rate were monitored and questionnaires were applied in a set of classrooms of selected school buildings. During part of the physical monitoring, restrictive occupancy measures due to the COVID-19 pandemic were observed. Statistical analysis was applied to assess the influence of the recorded parameters on the window, door, and fan status and to generate OB predictive models. An OB model was implemented in building performance simulations to predict OB over a year and compare it to optimized scenarios, considering thermal comfort and indoor air quality requirements. Results showed that indoor environmental variables influenced window, door, and fan status in school classrooms, with few exceptions. Yet, the models including school routines, social norms and teachers' behaviour as predictors led to the highest accuracy. This suggests that, while a more complex model with additional predictors can provide more accurate predictions of OB, it also becomes more context-dependent and less generalizable. The trade-off between model complexity and generalizability is an important consideration in this research study, and it highlights the nuanced relationship between multi-domain factors affecting occupant behaviour in school buildings. The comparison between real and optimized occupant behaviours revealed variations of up to 42.5% in CO_2 levels and up to 9% in discomfort hours, highlighting the potential to enhance indoor conditions by adjusting occupant behaviour. Finally, the optimal strategies varied by school, emphasizing the importance of evaluating recommendations within each specific context.

Keywords: occupant behaviour, school building, natural ventilation, multi-domain, building performance simulation.

RESUMO

A maioria dos estudos sobre o comportamento do usuário em salas de aula de escolas concentra-se na operação das janelas em climas oceânicos. Em escolas naturalmente ventiladas, o conforto térmico e a qualidade do ar interior são afetados principalmente pelo comportamento do usuário com relação à operação de janelas, portas e ventiladores. Além disso, a pandemia da COVID-19 ressaltou a importância da qualidade do ar interior, especialmente em edifícios densamente ocupados, como as escolas. Nesse contexto, esta pesquisa teve como objetivo identificar e quantificar a influência de fatores de múltiplos domínios (incluindo os domínios térmico, de qualidade do ar interior, contextual e de múltiplos comportamentos) sobre o *status* de janelas, portas e ventiladores em salas de aula de escolas naturalmente ventiladas em um clima subtropical úmido, a fim de prever o comportamento do usuário. Uma revisão sistemática da literatura foi realizada com o objetivo de levantar informações sobre os modelos existentes de comportamento do usuário para edificações escolares. Os projetos de 66 escolas públicas localizadas no estado de São Paulo, Brasil, foram analisados com o objetivo de identificar as características da envoltória e da construção. As variáveis ambientais, a operação manual de janelas, portas e ventiladores e a taxa de ocupação foram monitoradas e questionários foram aplicados em um conjunto de salas de aula de escolas selecionadas. Durante parte do monitoramento, foram observadas medidas restritivas de ocupação devido à pandemia da COVID-19. Análises estatísticas foram aplicadas para avaliar a influência dos parâmetros registrados no *status* das janelas, portas e ventiladores e para gerar modelos preditivos do comportamento do usuário. Um modelo foi implementado em simulações do desempenho da edificação para prever o comportamento do usuário ao longo de um ano. O comportamento real foi comparado com cenários otimizados, considerando parâmetros de conforto térmico e qualidade do ar interior. Os resultados mostram que as variáveis ambientais internas influenciaram no *status* de janelas, portas e ventiladores das salas de aula, com poucas exceções. No entanto, os modelos que incluíram rotinas escolares, normas sociais e comportamento dos professores como preditores levaram a uma maior precisão. Isso sugere que, embora um modelo mais complexo, com preditores adicionais, possa fornecer previsões mais precisas do comportamento do usuário, ele também se torna mais dependente do contexto e menos generalizável. O equilíbrio entre a complexidade e a generalização do modelo é uma consideração importante nesse estudo e destaca a relação entre os fatores de vários domínios que afetam o comportamento dos usuários em edificações escolares. A comparação entre os comportamentos de ocupantes baseados em dados reais ou otimizados revelou variações de até 42,5% nos níveis de CO_2 e de até 9% nas horas de desconforto, destacando o potencial para melhorar as condições internas por meio do ajuste do comportamento dos usuários. Por fim, as estratégias otimizadas variaram de acordo com a escola, enfatizando a importância de avaliar as recomendações em cada contexto específico.

Palavras-chave: comportamento do usuário, edificação escolar, ventilação natural, múltiplos domínios, simulação do desempenho da edificação.

LIST OF PUBLICATIONS DURING THE DOCTORAL PROGRAM

1. **FRANCESCHINI, P.**; NEVES, L. O impacto da operação de janelas no desempenho térmico das edificações escolares. In: ENCONTRO NACIONAL DE TECNOLOGIA DO AMBIENTE CONSTRUÍDO, 18., 2020, Porto Alegre. **Anais...** Porto Alegre: ANTAC, 2020. Available at: https://entac2020.com.br/anais-2020/
    - Awarded as the best article in the workgroup of Environmental Comfort and Energy Efficiency.

2. SILVA, V. G.; LOCHE, I.; SAADE, M. R. M.; PULGROSSI, L. M.; **FRANCESCHINI, P. B.**; RODRIGUES, L. L.; PIMENTA, R. G.; NEVES, L. O.; KOWALTOWSKI, D. Operational and embodied impact assessment as retrofit decision-making support in a changing climate. In: Windsor Conference, 11., 2020, Windsor. Anais […]. The Windsor Conference: Windsor, 2020.

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    - Awarded with the IV Mauricio Roriz Prize for best articles.

5. **FRANCESCHINI, P. B.**; NEVES, L. O. A critical review on occupant behaviour modelling for building performance simulation of naturally ventilated school buildings and potential changes due to the COVID-19 pandemic. **Energy and Buildings**, [s. l.], v. 258, n. 2022, p. 111831, 2022. DOI: 10.1016/j.enbuild.2022.111831

6. **FRANCESCHINI, P. B.**; LIGUORI, I. N.; NEVES, L. O. Condições de conforto térmico e QAI em salas de aula naturalmente ventiladas durante a pandemia de COVID-19. **Ambiente Construído**, Porto Alegre, v. 22, n. 4, p. 217-231, out./dez. 2022. DOI: 10.1590/s1678-86212022000400637

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8. **FRANCESCHINI, P. B.**; SCHWEIKER, M.; NEVES, L. O. Investigation of window operation behaviour in naturally ventilated classrooms during the COVID-19 pandemic. In: 18^{th} Healthy Buildings Europe Conference, 2023, Aachen. **Proceedings...** Aachen, Germany: 2023.

9. SHIMASAKI, N. S.; **FRANCESCHINI, P. B.**; NEVES, L. O. Análise comparativa de conforto térmico e ventilação natural entre edifícios escolares com e sem a certificação ambiental AQUA-HQE. In: ENCONTRO NACIONAL DE CONFORTO NO AMBIENTE CONSTRUÍDO, 17., 2023, São Paulo. Anais... São Paulo: ANTAC, 2023.

10. **FRANCESCHINI, P. B.**; SCHWEIKER, M.; NEVES, L. O. Predictive modelling of multi-domain factors on window, door, and fan status in naturally ventilated school classrooms. **Building and Environment**, v. 264, p. 111912, 2024.

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1 Introduction

Occupant behaviour (OB) plays an important role on the building performance in all its aspects, such as indoor conditions, usability, functionality and energy use (O'BRIEN; TAHMASEBI, 2023). Occupants interact with buildings' controls or interfaces, in order to adapt the environment to their needs (e.g., window, blinds, lighting and air-conditioning operation) or to adapt themselves to the environment (e.g., clothing adjustment and drinking hot or cold beverage), aiming to maintain their comfort and preferences (DELZENDEH et al., 2017; HONG et al., 2016b; O'BRIEN; TAHMASEBI, 2023). They usually respond in different ways to the built environment, since there are many factors, such as external (environmental factors, time-related factors, contextual factors) and internal factors (physiological factors, psychological factors, social factors), that influence their decision-making process (O'BRIEN et al., 2016; YAN et al., 2017). Challenges in studying OB in buildings include its complexity and dynamicity in nature, privacy issues, which difficult the data collection, and the relatively high costs to acquire various types of sensors to monitor OB (DONG et al., 2022).

Due to OB uncertainty and unpredictability, this parameter is often oversimplified in building performance simulation (BPS) and, as a consequence, it is one of the main causes of a performance gap between buildings' performance prediction versus reality (SHI et al., 2019; WANG; HONG; JIA, 2018). In this context, occupant modelling has gained attention by researchers and practitioners, due to its impacts, which can increase the performance gap; the increasing interest in occupant wellbeing; and the increased computational and simulation capabilities (O'BRIEN; TAHMASEBI, 2023). More than 500 papers have been published on the topic of OB over the last decade, including data regarding occupancy (e.g., occupant presence and movement) and occupants' actions (e.g., windows and door operation, blinds/ solar shading operation, thermostat or air-conditioning adjustment) (DONG et al., 2022). OB models from these studies have been developed to predict and represent human behaviour in BPS, aiming at optimizing the building design and, therefore, reducing the performance gap, and also to better understand comfort and adaptive opportunities and to help develop strategies toward healthy indoor spaces (O'BRIEN; TAHMASEBI, 2023).

The International Energy Agency (IEA), that co-ordinates international energy research and development activities, had two projects in this research area: Annex 66 (Definition and Simulation of Occupant Behaviour in Buildings), conducted between 2013 and 2017, and Annex 79 (Occupant-Centric Building Design and Operation), conducted between 2018 and 2023. The main objectives of the Annex 66 were to set up a standard OB definition platform, to establish a quantitative simulation methodology to model OB in buildings and to understand the influence of OB on building energy use and on the indoor environment (IEA, 2018). The Annex 79 aimed to integrate and implement occupancy and OB into the design process and building operation to improve both energy performance and occupant comfort (O'BRIEN et al., 2020). One outcome of these two research projects was the development of the ASHRAE occupant behaviour database, which consists of 34 datasets from 39 institutions located in 15 countries and 10 climate zones (DONG et al., 2022). These datasets cover 11 types of OB measurements (window, door, fan, lighting and shading status, plug loads, HVAC measurements, occupancy, occupant number and others) and three building typologies classified according to the room type: commercial (office), educational (office, classroom and study zone) and residential (apartment, dorm and single-family house) (DONG et al., 2022).

So far, the human-building interaction has been studied mainly in residential and office contexts (DELZENDEH et al., 2017). In the Annex 66 and Annex 79, for example, all proposed models and case studies focused on these two building typologies (IEA, 2018; O'BRIEN; TAHMASEBI, 2023). School buildings are different from offices, residential buildings and other educational buildings (e.g., universities), since primary and secondary schools are occupied mainly by children, in specific periods of the year and with different daily timetables, more group rules and less freedom of action (BELAFI et al., 2018). The investigation of OB in school classrooms is far recent, with most studies published in the last five years. Three datasets regarding OB data collection in school classrooms were included in the ASHRAE occupant behaviour database, with data from the United Kingdom, China and Australia (DONG et al., 2022). The OB most addressed in the studies published in this research field included window (BELAFI et al., 2018; DUTTON; SHAO, 2010; ENGLUND et al., 2020; HERACLEOUS; MICHAEL, 2020; KORSAVI; JONES; FUERTES, 2022b; PISTORE et al., 2019; STAMP et al., 2020; STAZI; NASPI; D'ORAZIO, 2017a) and lighting operation (BERNARDI; KOWALTOWSKI, 2006; LOURENÇO; PINHEIRO; HEITOR, 2019; SIMANIC et al., 2020; ZHANG; BLUYSSEN, 2021) and the studies were conducted mainly in an oceanic climate. The most investigated drivers in these studies were the environmental factors, such as indoor and outdoor temperature, relative humidity, and CO_2 concentration. Also, the teacher was identified as the main active occupant regarding the environment adjustment, with the decision-making process relying mostly on collective needs and school rules (BERNARDI; KOWALTOWSKI, 2006; PISTORE et al., 2019).

Most school buildings located in tropical or subtropical climates are partially or fully naturally ventilated, with manually operable windows, which reinforces the occupant's role over the environment's performance (YAN et al., 2017). In the state of Sao Paulo, Brazil, for example, all public-school buildings maintained by the Foundation for Education Development (*Fundação para o Desenvolvimento da Educação*, FDE) have manually operable windows to provide natural ventilation, and most of them also have manually operable fans. Natural ventilation, beyond influencing the classroom's thermal performance, also impacts on its indoor air quality (IAQ) (STABILE et al., 2017) and, consequently, on students' health and learning process (PEREIRA *et al.*, 2017).

In 2020, due to the COVID-19 pandemic, the IAQ became particularly relevant to prevent airborne virus transmission in indoor environments (FRANCO, 2020), especially in high occupancy environments, such as school buildings' classrooms (LIPINSKI et al., 2020). Therefore, several guidelines to improve air renewal in classrooms were published between 2020 and 2021, suggesting measures related to, among other issues, mechanical ventilation and, in a lower proportion, operation of windows (JONES *et al.*, 2020; VAN DIJKEN, 2020; WORLD HEALTH ORGANIZATION, 2020). In addition, recent studies investigated the impact of the COVID-19 pandemic on the classrooms' IAQ and thermal comfort (ALONSO et al., 2021; KONSTANTINOU et al., 2022; MORI et al., 2022) and the infection risk regarding ventilation and occupancy rates, window opening behaviour and the use of masks (ARJMANDI et al., 2021; HOU; KATAL; WANG, 2021; OROSA; NEMATCHOUA; REITER, 2020; PARK et al., 2021; ZIVELONGHI; LAI, 2021). However, whilst occupant behaviour and daily routine in schools were affected by COVID-19 response measures, to what extent these behaviour changes will be durable is still unknown and must be investigated (FELL et al., 2020). Also, since COVID-19 impacts and restrictions were different in each place, the potential changes on action drivers may be different and not comparable between and within countries (FELL et al., 2020).

In Brazil, most of the research studies in school buildings focus on building design and environmental comfort aspects, without investigating the OB (ALEXANDRUK, 2015; BENDER, 2013; DELIBERADOR; KOWALTOWSKI, 2011; GEMELLI, 2009; GERALDI, 2021; KOWALTOWSKI et al., 2017; KOWALTOWSKI; DELIBERADOR, 2014; MARÇAL, 2016; MOREIRA, 2005; NOGUEIRA, 2011; OLIVEIRA, 2016; PEREIRA; KOWALTOWSKI, 2011). Also, a systematic literature review regarding BPS in Brazil showed that OB was poorly explored in this context (LOPES; SILVA, 2019). Brazilian publications related to OB focus, mainly, the residential context (GIGLIO, 2015; SORGATO, 2015) and office buildings (BAVARESCO, 2016, 2021; GRASSI, 2021; HAZBOUN, 2018; NEVES et al., 2020; RUPP et al., 2021), and only one study was found with a focus on school buildings (BERNARDI, 2001). Lastly, few studies consider the COVID-19 pandemic impacts on the occupant behaviour and built environment. Therefore, this study aims to fill this research gap by investigating the occupant behaviour in naturally ventilated school classrooms, focused on thermal comfort and indoor air quality, and providing data and information related to the humid subtropical climate of the state of São Paulo, Brazil.

1.1 Objectives

Main Objective (MO) - This study aims to identify and quantify the influence of multi-domain factors (including thermal, indoor air quality, contextual and multi-behaviour domains) on window, door, and fan status in naturally ventilated school classrooms in a humid subtropical climate, in order to improve the ability to predict occupant behaviour.

The specific objectives (SO) are related to the objectives of the papers that compose this thesis and include:

SO1 – Identifying and analysing existing occupant behaviour models for naturally ventilated and mixed-mode school buildings.

SO2 – Investigating potential impacts on occupant behaviour due to restrictions implemented during the COVID-19 pandemic in school buildings.

SO3 – Developing predictive occupant behaviour models based on the collected data.

SO4 – Analysing potential conflicts between thermal comfort and indoor air quality, regarding triggers for manual operation of windows in naturally ventilated school classrooms and identifying optimal situations of balance between both drivers.

1.2 Hypothesis and research questions

Considering the research problem addressed and the proposed objectives, the main hypothesis of this research study is that investigating and including multi-domain factors in occupant behaviour models for school classrooms can improve the prediction of occupant behaviour in the building performance simulation.

Based on this statement, the following research questions were elaborated in order to better explain the problem:

- Do the drivers for window, door, and fan operation vary between school classrooms and teachers?
- Which factors (including thermal, indoor air quality, contextual and multi-behaviour domains) have greater influence on window, door, and fan operation in school classrooms?
- Are school classrooms' occupants operating windows near optimal conditions, considering the balance between thermal comfort and indoor air quality?

1.3 Thesis structure

The structure of this thesis is based on the requirements of Resolution CPPG-ATC/FEC-051/2015 and is composed, apart from the Introduction and Conclusion chapters, of five papers reporting the work performed during the doctorate (Table 1.1). Four papers are presented as chapters, and they were transcribed as they were published or submitted with the layout adjusted to this document. A fifth paper is currently in development and its preliminary results are presented in Chapter 6. Also, all the references are presented at the end of this document for conciseness. An overview of the thesis structure is presented in Figure 1.1 and described below.

Table 1.1 – Papers included in this thesis.

Thesis structure	Paper title	Journal/ Conference	Status
Chapter 2	A critical review on occupant behaviour modelling for building performance simulation of naturally ventilated school buildings and potential changes due to the COVID-19 pandemic	Energy and Buildings	Published in January 2022
Chapter 3	Condições de conforto térmico e QAI em salas de aula naturalmente ventiladas durante a pandemia de Covid-19	Ambiente Construído	Published in October 2022
Chapter 4	Investigation of window operation behaviour in naturally ventilated classrooms during the COVID-19 pandemic	18th Healthy Buildings Europe Conference	Presented and published in June 2023
Chapter 5	Predictive modelling of multi-domain factors on window, door, and fan status in naturally ventilated school classrooms	Building and Environment	Published in August 2024
Chapter 6	Thermal comfort and perceived indoor air quality optimization with respect to occupant behaviour in naturally ventilated school buildings	Preliminary results	

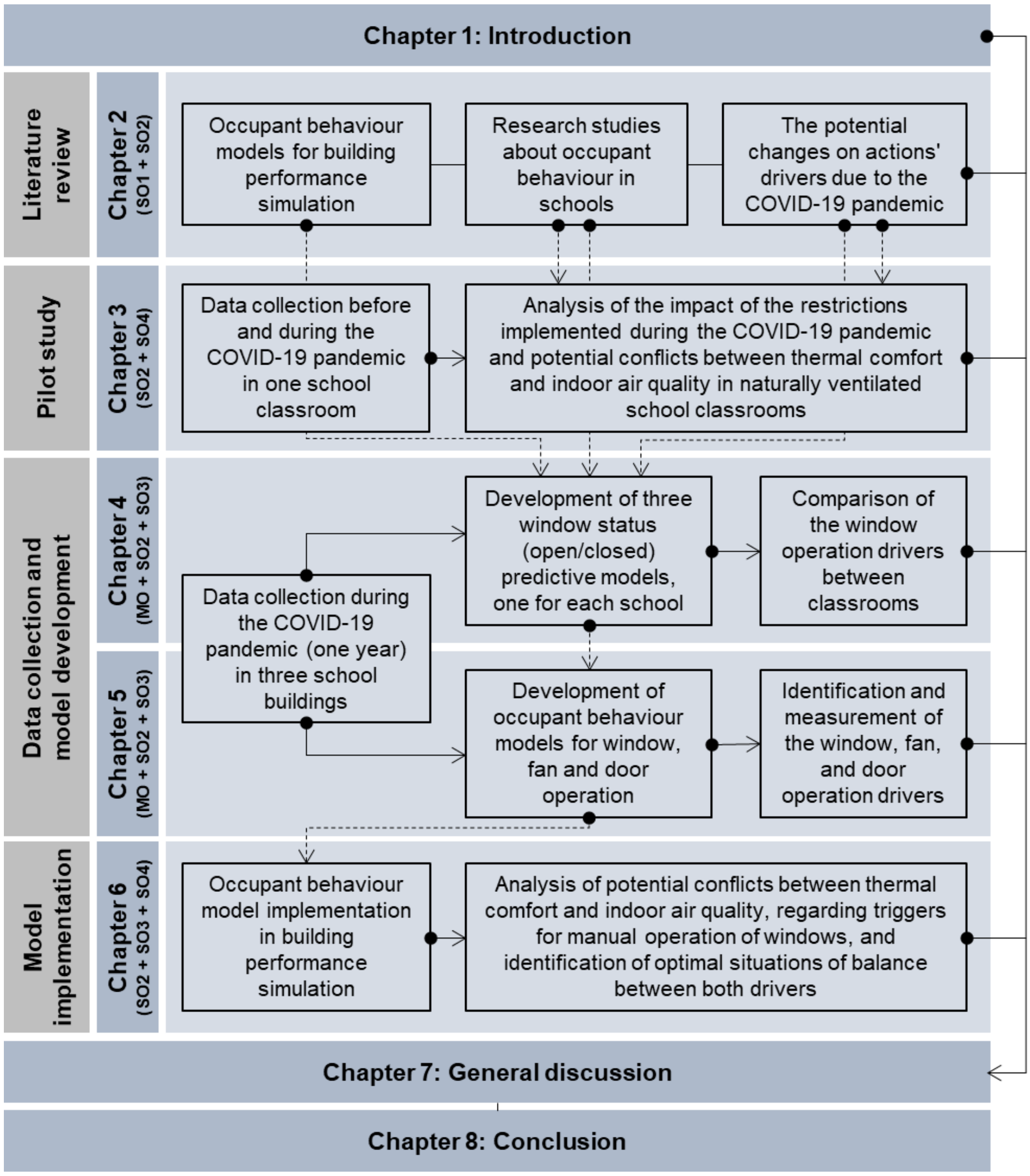

Figure 1.1 – Thesis structure

Chapter 2 presents the literature review, that addresses (i) occupant behaviour models for building performance simulation, (ii) research studies about occupant behaviour in schools and (iii) the potential changes on action drivers due to the COVID-19 pandemic (specific objectives 1 and 2 of this thesis). Three main steps to represent the OB modelling approach were identified in the literature: the data collection (pre-processing, step 1), the OB model development and evaluation (processing, step 2) and the OB model implementation in building performance simulation (post-processing, step 3) – which were used to structure this thesis (Figure 1.1). The main findings regarding the existing OB models for school buildings are discussed in this chapter. In addition, the outcomes support the need to investigate the behaviour changes, their action drivers and their impacts on the built environment due to the restrictions implemented during the COVID-19 pandemic. Complementary literature reviews are presented in the following papers with updated studies regarding each subject.

In 2020, due to the COVID-19 pandemic, all public-school buildings in the state of Sao Paulo were closed and, therefore, the data collection (step 1 of this research study) had to be postponed. The three schools selected for the study, that had already agreed to participate, remained closed until August 2021. Therefore, a pilot field study was conducted in a different school building, which was selected due to having already gone through previous data collection, before the COVID-19 pandemic (in 2019 by Liguori (2020)). This study, presented in **Chapter 3**, compares data collected before (2019) and during (2021) the COVID-19 pandemic in one school classroom located in Campinas, Brazil, in order to analyse the impact of the restrictions implemented during the COVID-19 pandemic (specific objective 2) and potential conflicts between thermal comfort and indoor air quality in naturally ventilated school classrooms (specific objective 4). Indoor environmental variables were monitored during both periods and were used to calibrate a simulation model, using EnergyPlus. Theoretical scenarios varying the number of occupants and the air change rates were simulated, in order to assess their impact on the indoor air quality (CO_2 concentration) and thermal comfort (indoor operative temperature) and identify scenarios that contribute to reducing the risk of spreading the SARS-CoV-2 virus. The results suggest that the restrictive measures implemented during the COVID-19 pandemic, which are related to occupant behaviour (opening windows and doors and reducing the number of occupants), can help to reduce the CO_2 concentration and the probability of infection, in addition to improving the thermal comfort of the analysed classroom. Yet, the measures adopted by schools must be analysed for each specific climate and context and in order to balance potential benefits and risks to occupants.

The research framework is presented in Figure 1.2. The first steps, data collection (pre-processing, step 1) and the model development and evaluation (processing, step 2), are presented in chapters 4 and 5. The data collection was conducted in three school buildings located in the cities of Campinas and Sao Paulo, which were selected from a database of 66 public-school buildings, and included the monitoring of indoor environmental variables, number of occupants and manual operation of windows, door and fans (physical monitoring) and the application of questionnaires with teachers and students (occupant investigation).

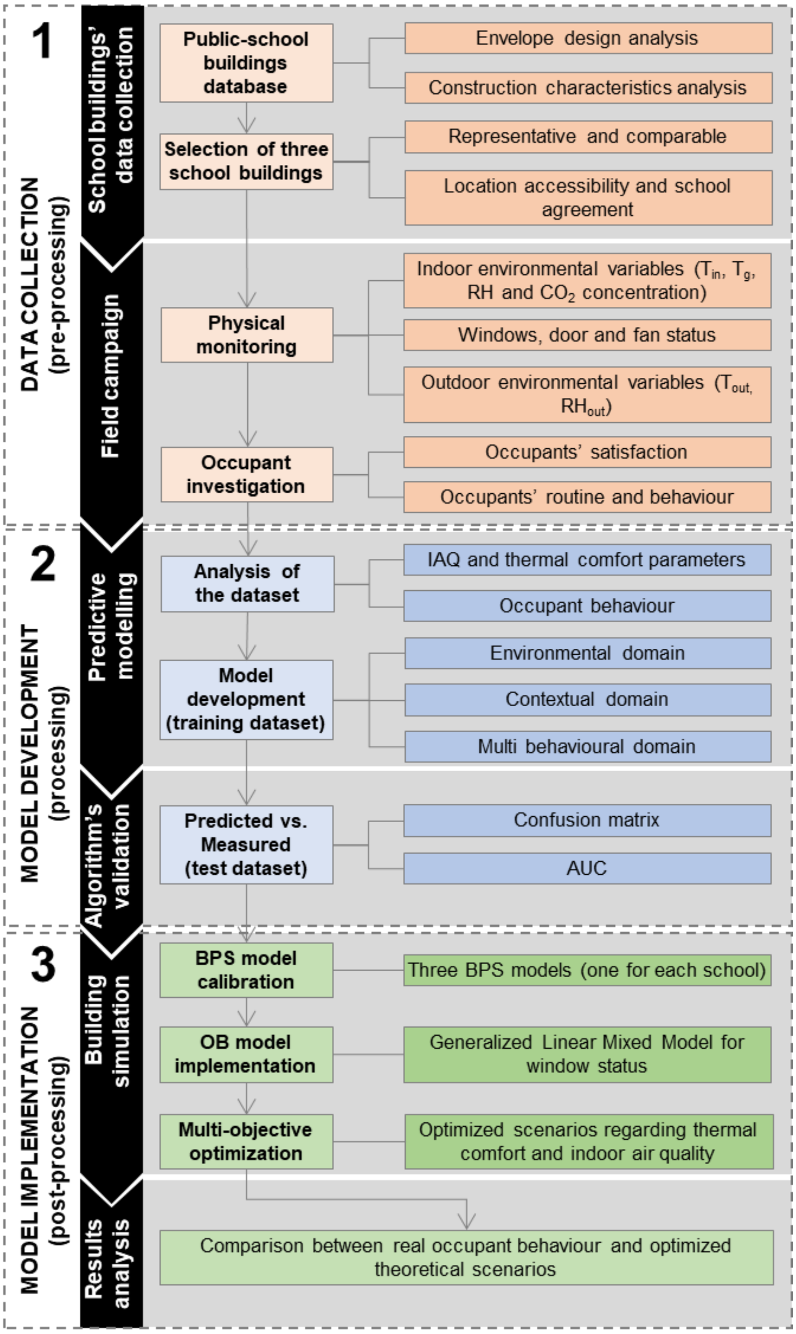

Figure 1.2 – Research framework

Chapter 4 presents the development of three window status predictive models, one for each school classroom, in order to compare the window operation drivers between classrooms – addressing the main objective, specific objective 2 and specific objective 3 of this thesis. Generalized linear models (GLM) were applied to assess the influence of the recorded parameters over the window status. Indoor operative temperature, relative humidity, CO_2 concentration and the restrictions imposed during the COVID-19 pandemic were identified as triggers for window operation in all schools. In addition, the differences between the school classrooms suggest that occupant behaviour is context dependent, being highly influenced by rules and habits, as confirmed by the outcomes from the generalized linear models and the questionnaires responses.

Chapter 5 presents the development of occupant behaviour models for window, fan and door operation, aiming to identify and quantify the influence of multi-domain factors (including thermal, indoor air quality, contextual and multi-behaviour domains) on their status – also addressing the main objective, specific objective 2 and specific objective 3 of this thesis. Generalized linear mixed models (GLMM) were applied to assess the influence of the recorded parameters over the window, door and fan status. In addition to the predictors included in the previous models (environmental domain – indoor operative temperature, relative humidity, CO_2 concentration – and contextual domain – the COVID-19 restrictive measures), other predictors regarding contextual (time of the day, teacher, number of occupants) and multi-behavioural domains were included to create more complex and real models. The results highlighted that other predictors, such as the teachers' behaviour and the COVID-19 restrictions, could have a greater influence on occupant behaviour than environmental variables, indicating the relevance of investigating other domains in behavioural studies. Also, the models including additional predictors were the ones with better results during the validation phase, suggesting that, while more complex models can provide more accurate predictions of occupant behaviour, they also become more context-dependent and less generalizable.

Chapter 6 presents the preliminary results and discussion regarding the model implementation in building performance simulation (post-processing, step 3) (Figure 1.2). By implementing the OB models into the BPS, the aim of this chapter is to analyse potential conflicts between thermal comfort and indoor air quality, regarding triggers for manual operation of windows in naturally ventilated school classrooms, and to identify optimal situations of balance between both drivers (specific objective 4). This chapter presents the preliminary results of a paper currently in development, which was also part of Prof. Leticia de Oliveira Neves' research project titled "Thermal Comfort and Perceived Indoor Air Quality Optimization with Respect to Occupant Behavior in Naturally Ventilated School Buildings" (FAPESP BPE Grant n. 2021/11903-8).

Chapter 7 presents a general discussion regarding the results of the previous chapters and **Chapter 8** provides a conclusion for all the chapters, including the main contributions of this thesis, its limitations, and suggestions for future research.

2 Literature Review

This chapter is the transcription of the following paper:

A critical review on occupant behaviour modelling for building performance simulation of naturally ventilated school buildings and potential changes due to the COVID-19 pandemic

Authored by Paula Brumer Franceschini and Leticia Oliveira Neves

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Abstract

Occupant behaviour (OB) is one of the main causes of the energy performance gap between buildings' performance prediction versus reality, since, due to its uncertainty and unpredictability, it is often oversimplified in the building performance simulation (BPS). Hence, previous studies developed OB models, mainly in the residential and office contexts, in order to predict and represent human behaviour in BPS. Yet, school buildings are different from other typologies due to contextual factors (e.g., occupants' age, different daily timetables and group rules) and are in a unique position to promote energy efficiency for tomorrow's citizens. Assessing OB in schools can lead to an improvement of the indoor environment, especially in naturally ventilated buildings, where window operation behaviour directly impacts on the air change rates and, consequently, on the indoor air quality. This study addresses the knowledge gap on OB modelling for naturally ventilated (NV) and mixed-mode (MM) school buildings. The reviewed papers were organized in three main themes, namely (i) OB models for BPS of NV and MM buildings, (ii) OB research studies in NV and MM school buildings and (iii) potential changes on OB in school buildings due to the COVID-19 pandemic. The analysis focused on three phases of the OB modelling framework: data collection (pre-processing), model development (processing) and model implementation (post-processing). Important research gaps are identified, such as the reduced number of studies that cover the three phases of the modelling framework within the school buildings context and the need to better investigate the

teachers' behaviour and collective actions as important OB drivers in classrooms. Future research topics are also identified, such as which are the potential changes on actions' drivers due to COVID-19 pandemic in naturally ventilated classrooms and to what extent they will be durable or ephemeral.

Keywords: occupant behaviour, behaviour model, building performance simulation, school buildings, natural ventilation, COVID-19

2.1 Introduction

The driving factors of energy use in buildings are climate, building envelope, building energy and services systems, indoor design criteria, building operation and maintenance and occupant behaviour (IEA, 2016), which are mostly considered in a building performance simulation (BPS). However, frequently the predicted performance (simulated during the design phase) is different from the real one (measured during the operation phase), resulting in an energy performance gap (SHI et al., 2019). One of the most important causes of this gap is the occupant behaviour (OB) (CHEN; HONG; LUO, 2018; FABI et al., 2012; SHI et al., 2019) – which refers to occupants actions and responses to stimuli (SHI et al., 2019), being responsible for up to 71% of the energy demand variation in buildings (IEA, 2016). The energy performance gap occurs mainly due to OB uncertainty and unpredictability in the design phase (SHI et al., 2019), which, as a consequence, often oversimplifies the occupant behaviour models in BPS (WANG; HONG; JIA, 2018). In BPS tools, the occupant's impact is mainly considered only in the occupancy section and the input data is generally limited to occupants' presence in fixed and scheduled patterns, which do not reflect reality (DELZENDEH et al., 2017).

During the last decade, studies about OB in buildings were conducted aiming to better represent this parameter in the BPS through OB modelling, thus reducing the energy performance gap. For instance, the International Energy Agency (IEA) has two projects in this research area: the concluded Annex 66 (Definition and Simulation of Occupant Behaviour in Buildings) and the ongoing Annex 79 (Occupant-Centric Building Design and Operation). Also, several reviews about OB modelling for BPS were conducted in the last decade, focusing mainly on office and residential contexts (Table 2.1).

Table 2.1 – Previous reviews on OB modelling for BPS

Publication	Temporal coverage	Building typology	Scope
Azar et al. (2020)	Up to 2019	All	Occupant-centric building design applications: metrics, modelling and simulations tools, design methods and supporting practices and mechanisms
Berger and Mahdavi (2020)	2010 – 2018	All	Application of agent-based modelling in the built environment domain: model purpose, domain knowledge and implementation tools
Carlucci et al. (2020)	Up to 2019	All	Modelling techniques to represent occupant behaviour (presence and actions) on building performance simulation
Laaroussi et al. (2020)	1995 - 2019	Residential	Current approaches for occupant behaviour analysis
Li et al. (LI et al., 2019)	Up to 2018	All	Environmental and individual adjustments for OB modelling purposes
Balvedi, et al. (2018)	2008 - 2018	Residential	Occupant behaviour in residential buildings
Dong et al. (2018)	Up to 2017	All	Current modelling efforts of occupant behaviour
Hong et al. (2018)	Up to 2017	All	Approaches to representing and implementing OB models in building performance simulation tools
Zhang et al (2018)	Up to 2017	All	OB model approaches and the energy-saving potential: focus on window opening behaviour, lighting control behaviour, and space heating/cooling behaviour
Delzendeh et al. (2017)	Up to 2016	All	Influence of occupant behaviour on building energy consumption
Gaetani et al. (2016)	Up to 2015	All	Modelling complexity for occupant behaviour in building energy simulation
Yan et al. (2015)	Up to 2014	All	Occupant-related data collection and monitoring, modelling approaches, model evaluation, and model implementation
Gunay et al. (2013)	Up to 2013	Office	Findings and limitations of the occupant behaviour research, including observational, modelling, and simulation methodologies
Parys et al. (2011)	Up to 2010	Office	Models of occupant control of shading devices, windows, lighting, appliances and thermal environment

School buildings are in a unique position to promote energy efficiency for tomorrow's citizens (KATAFYGIOTOU; SERGHIDES, 2014). This building typology is different from others (e.g. residential and office buildings) due to contextual factors, since primary and secondary schools are occupied mainly by children, in specific periods of the year and with different daily timetables, more group rules and less freedom of action (BELAFI et al., 2018). Assessing its OB can lead to an improvement of the indoor environment, which is very important in school buildings, not just in terms of energy use, but also for students health and education (BELAFI et al., 2018). The indoor environment of school buildings (e.g. noise levels, indoor temperature, air quality and light) influences students health and sense of well-being (KATAFYGIOTOU; SERGHIDES, 2014; MONTAZAMI; GATERELL; NICOL, 2015; PEREIRA et al., 2017). A more comfortable and safe environment can also boost students' productivity in many activities (FRANCO, 2020) and reduce students' absenteeism (PEREIRA et al., 2017). Yet, there is a gap in the study of the impact of OB on building energy performance of school buildings, since the subject has been studied mainly in the residential and office contexts (DELZENDEH et al., 2017). For example, the majority of the review papers here mentioned (Table 2.1) present a general scope and very few of them discuss school buildings: just seven papers about school buildings were included in five of the above-mentioned literature reviews (CARLUCCI et al., 2020; DELZENDEH et al., 2017; GAETANI; HOES; HENSEN, 2016; GUNAY; BRIEN;

BEAUSOLEIL-MORRISON, 2013; LI et al., 2019). The systematic literature review presented by Carlucci et al. (2020) confirms the fact, since only 5% of the 278 studies identified by the authors about OB modelling addressed educational buildings, showing that this building typology requires further analysis.

Most school buildings located in tropical or subtropical climates are partially or fully naturally ventilated (KAPOOR et al., 2021; SHRESTHA; RIJAL, 2021; VAN DIJKEN, 2020; WORLD HEALTH ORGANIZATION, 2015). Since natural ventilation depends on the outdoor conditions, adequate air change rates cannot be guaranteed all the time (VAN DIJKEN, 2020). Indeed, previous studies demonstrate that naturally ventilated classrooms often fail to achieve recommended levels of ventilation (DENG; ZOU; LAU, 2021; DUTTON; SHAO, 2010) and, as consequence, exceed the satisfactory limit of pollutants (DORIZAS et al., 2015). In fact, window operation behaviour plays an important role on indoor air quality (IAQ) and indoor air temperature (DUTTON; SHAO, 2010; IEA, 2018; SCHIBUOLA; TAMBANI, 2021), contributing to improve or to worsen the indoor environment conditions in naturally ventilated school buildings.

School buildings have high occupancy rates which, in addition to poor IAQ, can provide the optimum conditions for rapid disease spread (LIPINSKI et al., 2020). A study conducted in 114 European schools, of which 86% were naturally ventilated, showed that in overcrowded classrooms (less than 1.5 m² per child) the concentration of pollutants increased significantly and more children suffered from respiratory symptoms (e.g., chronic cough, earache, sinusitis) compared to classrooms with adequate space and well ventilated (WORLD HEALTH ORGANIZATION, 2015). In 2020, due the COVID-19 pandemic, the IAQ in school buildings became particularly relevant (PULIMENO et al., 2020). The IAQ was brought up as a fundamental path to prevent airborne virus transmission and to maintain low levels of pollutants in indoor environments (FRANCO, 2020), especially those with poor ventilation and high density and exposure time, such as school classrooms (HOU; KATAL; WANG, 2021). A study conducted in naturally ventilated classrooms revealed an infection risk ranging from 1.9% (all occupants wearing an US N95 mask) to 56% (all occupants without masks) in the presence of one asymptomatic individual (SCHIBUOLA; TAMBANI, 2021). Thus, recent publications recommended opening windows always as possible, as one of the main measures to reduce airborne virus transmission in naturally ventilated classrooms (JONES et al., 2020; VAN DIJKEN, 2020; WORLD HEALTH ORGANIZATION, 2020). Moreover, due to COVID-19 response measures (e.g., window opening, social distancing, masks) and restrictions (e.g., schools closure), current research studies anticipate that there will be important changes in behaviours and daily routines, which will affect directly the decision-making (FELL et al., 2020).

Yet, the potential changes in OB due to COVID-19 pandemic were not covered in existing reviews on OB modelling (Table 2.1), since the reviewed papers were published up to 2019.

This review paper aims to address the knowledge gap on occupant behaviour modelling for naturally ventilated school buildings and understand the potential changes on actions' drivers due to the COVID-19 pandemic. Therefore, we identify and analyse here the existing occupant behaviour models for naturally ventilated and mixed-mode school buildings, highlight the main findings in the current scientific literature and discuss the potential changes on occupant behaviour due to COVID-19 pandemic, especially related to window operation and natural ventilation. As to the latter, we consider it an important research topic also in phases without a pandemic, since it focuses on human and especially children's health and long-term well-being.

2.2 Method and material

This research study adopted the systematic review method to conduct the literature review, including two systematic literature reviews (SLR) and one literature review (LR) using a snowball strategy. The literature search process aimed to answer the following questions: (i) Which are the existing occupant behaviour models for building performance simulation focused on naturally ventilated and mixed-mode buildings? (SLR 1); (ii) What is the status quo on research studies about occupant behaviour in naturally ventilated school buildings? (SLR 2); (iii) What are the potential changes on research studies about occupant behaviour in school buildings due to the COVID-19 pandemic? (LR 3).

The SLR 1 and SLR 2 searches were conducted in Web of Science (WoS) and Scopus databases on 19th April, 2021 and followed the steps proposed in the PRISMA Statement (LIBERATI et al., 2009): identification, screening, eligibility and inclusion. The string used for the SLR 1 included ‘occupant behaviour model’ and ‘building performance simulation’ (and similar words, such as ‘user’ and ‘behavior’) in the title, abstract and keywords fields. The string used for the SLR 2 included ‘occupant behaviour’ and ‘school building’ (and also similar words) in the title, abstract and keywords fields. After excluding the duplicated results, the title and abstract were analysed and results not related to the review questions were excluded. The final selection resulted in 46 papers, whose distribution is presented in Figure 2.1. Most of them were published in the last decade (Figure 2.2), demonstrating that it is a relatively new research theme.

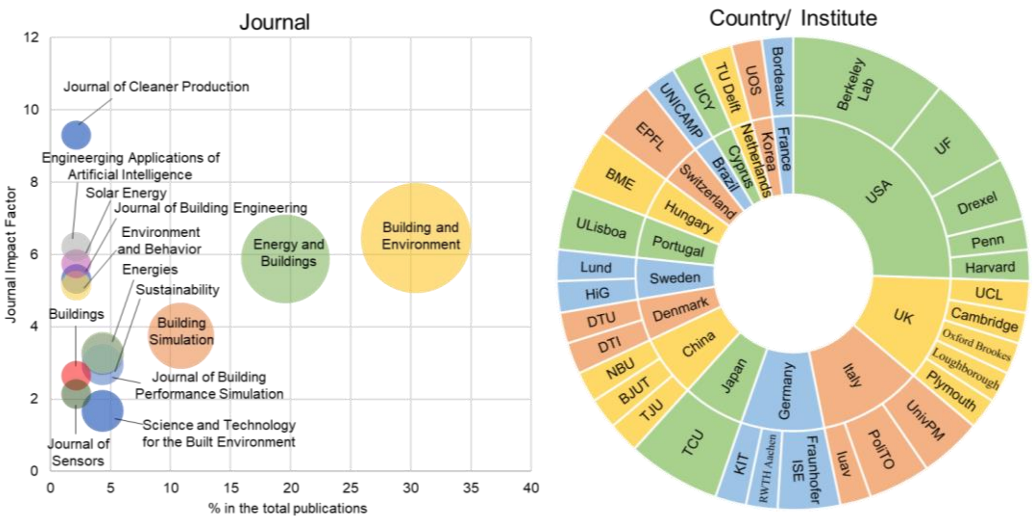

Figure 2.1 – Distribution of publications (SLR 1 and SLR 2)

Berkeley Lab – Lawrence Berkeley National Laboratory; UF – University of Florida; Drexel – Drexel University; Penn – University of Pennsylvania; Harvard – Harvard University; UCL – University College London; Cambridge – University of Cambridge; Oxford Brokes – Oxford Brookes University; Loughborough – Loughborough University; Plymouth – Plymouth University; UnivPM – Università Politecnica delle Marche; PoliTO – Politecnico di Torino; Iuav – Iuav University of Venice ; Fraunhofer ISE – Fraunhofer Institute for Solar Energy Systems; RWTH Aachen - RWTH Aachen University; KIT – Karlsruhe Institute of Technology; TCU – Tokyo City University; TJU – Tianjin University; BJUT – Beijing University of Technology; NBU – Ningbo University; DTI – Danish Technological Institute; DTU – Technical University of Denmark; HiG – University of Gävle; Lund – Lund University; ULisboa – University of Lisbon; BME – Budapest University of Technology and Economics; EPFL - Ecole Polytechnique Federale de Lausanne; UNICAMP – University of Campinas; UCY – University of Cyprus; TU Delft – Delft University of Technology; UOS – University of Seoul; Bordeaux – University of Bordeaux.

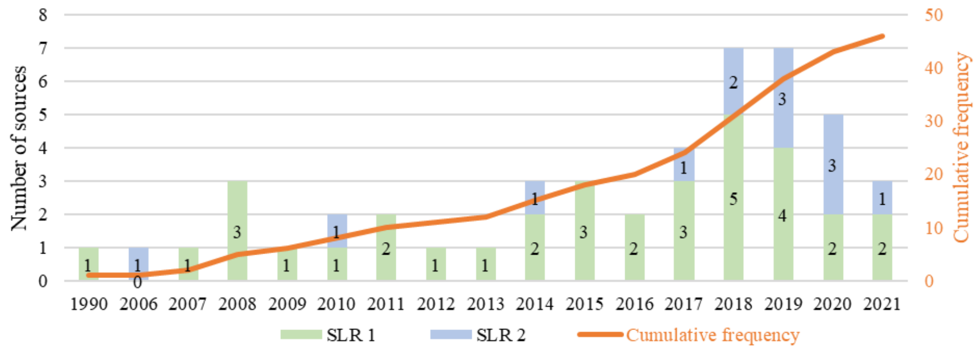

Figure 2.2 – Year of publication of SLR 1 and SLR 2 results

For the literature review regarding the potential changes on OB due to COVID-19 pandemic (LR 3), the search included papers, scientific reports and documents addressing the relation between natural ventilation, indoor environment, especially school buildings, and COVID-19 airborne transmission. The snowball strategy was adopted to extend the search, identifying other documents in the reference list of the first results. After selection, 26 publications were included in this review, published in 2020 (13 documents) and 2021 (13 documents).

2.3 Occupant behaviour modelling for building performance simulation

Occupant behaviour is defined as the occupant's interaction with building systems in order to adapt to the building environmental conditions (LAAROUSSI et al., 2020), aiming to obtain thermal, visual and acoustic comfort (DELZENDEH et al., 2017). According to Fabi et al. (2012), it includes unconscious and conscious actions to control the physical parameters based on the comparison of the perceived environment and past experiences. Hong et al. (2016a) distinguish non-adaptive behaviours, which include occupant presence and appliances use, from adaptive behaviours, which include changes to adapt the environment to their needs (e.g., window, blinds, lighting and air-conditioning operation) and changes to adapt themselves to the environment (e.g. clothing adjustment and drinking hot or cold beverage).

Occupants usually respond in different ways to the built environment, since there are many factors that influence their decision-making process (O'BRIEN et al., 2016). For example, occupancy patterns in buildings are influenced by contextual factors such as occupancy density and occupancy type (e.g., occupants movements and activities) (CHEN; HONG; LUO, 2018). Brien et al. (2016) identified other driven factors that contribute to occupant behaviour diversity, such as activity type, personal health and wealth, job type and lifestyle. Delzendeh et al. (2017) suggested the use of occupant profiling based on occupants' energy behaviour to lead to more accurate assumptions in energy analyses. He et al. (2021) and Causone et al. (2019), for example, identified behaviour styles to represent occupant diversity based on occupant energy-saving consciousness. D'Oca et al. (2014) classified occupant profiles to represent window opening behaviour and thermostat adjustment. In addition, occupant behaviour can be even more diverse when comparing different building typologies and location (e.g., climate, culture and energy conservation consciousness) (HE; HONG; CHOU, 2021). In the school building typology, for example, rules and habits can vary between different schools, climates and cultures (BELAFI et al., 2018). Thus, to be fully understood, occupant behaviour diversity requires investigation in both boundary and contextual conditions, as well as a more detailed and dynamic representation than predefined schedules (BELAFI et al., 2018).

Occupants have a significant impact on building energy performance and on occupants comfort through their with building systems (GILANI et al., 2016; HONG et al., 2016a; PUTRA; HONG; ANDREWS, 2021). Previous studies reviewed by Zhang et al. (2018) showed that improving occupant behaviour in buildings results in an energy-saving potential ranging between 5% and 30% for total energy consumption, varying according to the building typology (residential or office buildings) and the building system (air-conditioning, lighting and appliances). Occupant behaviour models are developed in order to predict and represent human behaviour in building performance simulation, optimizing the building design and reducing the performance gap (CARLUCCI et al., 2020). Therefore, occupant diversity, although bringing more uncertainty for BPS, can contribute to reduce energy peak demand (O'BRIEN et al., 2016). Parys et al. (2011) proposed three methods to represent occupant behaviour diversity in BPS: (i) explicit modelling of variability by randomly sampling, using real measured occupant data as input, (ii) calculating standard deviations to the averaged probability functions, and (ii) clustering of occupant type, as defining representative active and passive users.

Previous studies identified the main steps to represent OB modelling approach (BALVEDI; GHISI; LAMBERTS, 2018; GUNAY; BRIEN; BEAUSOLEIL-MORRISON, 2013; YAN et al., 2015, 2017). The first step refers to data collection, including occupant monitoring, system observation and data validation. The second step consists in the development and evaluation of the OB model, aiming to accurately predict occupants' behaviour in buildings. The last step involves the OB model implementation in building performance simulation, which requires the integration between the developed OB model and an existing building simulation tool and application. Figure 2.3 synthetises the OB modelling approach based on the reviewed publications. In Table 2.2, we identify 27 existing occupant behaviour models for naturally ventilated and mixed-mode buildings, based on the analysis of the methods section of 33 publications. Most of the presented models were developed for office buildings (63%, 17 models), are based on a mixed-mode ventilation system (70%, 19 models), and were developed for regions located in the oceanic climate – Cfb (52%, 14 models). The classification here presented is detailed in the following sub-sections.

2.3.1 Data collection (pre-processing)

The first step of the OB modelling approach is the data collection, which includes physical monitoring, occupant investigation and validation of the collected data (BALVEDI; GHISI; LAMBERTS, 2018; YAN et al., 2017). The data collection is an efficient approach for OB analysis (LAAROUSSI et al., 2020) and is used for the identification of driving factors and patterns for specific behaviours (BALVEDI; GHISI; LAMBERTS, 2018). The method selection for the data collection depends on the purpose of the research study (e.g., represent window operation or occupant presence), that will dictate the required information to use as input in the BPS.

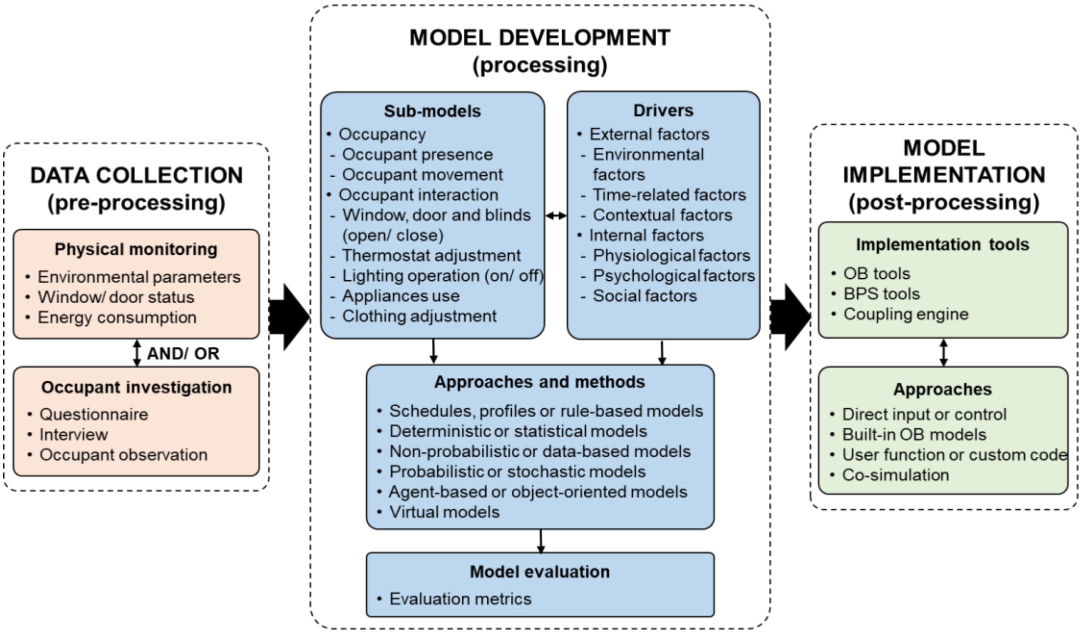

Figure 2.3 – OB modelling framework

Table 2.2 – Reviewed OB models (SLR 1)

Publication	Building typology	Ventila-tion system*	Location	Climate **	Sub-model	Method		
						Data Collection	Model Development	Model Implementation
Mun et al. (2021)	Residential	MM	South Korea	Dwa	Window and air-conditioning	-	Stochastic/ Probabilistic	Co-simulation
Jia et al. (2021); Jia and Srinivasan (2020); Jia et al. (2019)	Faculty office	MM	USA	Am	Window and blinds	Physical monitoring and occupant investigation	Agent-based	Co-simulation
Imagawa et al. (2020) and Rijal et al. (2018)	Residential	MM	Japan	Cfa	Window, fan, air-conditioning	Physical monitoring and occupant investigation	Stochastic/ Probabilistic	-
Micolier et al. (2019)	Residential	MM	France	Cfb	Window, blinds, thermostat, clothing and appliances	Physical monitoring and occupant investigation	Agent-based	Co-simulation
Pan et al. (2019)	Office	MM	China	Dwa	Window	Physical monitoring and occupant investigation	Stochastic/ Probabilistic	-
Mo et al.(2019)	Residential	NV	China	Dwa	Window	Physical monitoring	Stochastic/ Probabilistic	-
Belafi et al. (2018)	School	MM	Hungary	Cfa	Window	Physical monitoring and occupant investigation	Stochastic/ Probabilistic	-
Yao (2018)	Residential	MM	China	Cfa	Air-conditioning	Physical monitoring	Stochastic/ Probabilistic	User function or custom code
Naspi et al. (2018)	Faculty office	NV	Italy	Csa	Window and lighting	Physical monitoring and occupant investigation	Stochastic/ Probabilistic	Co-simulation
Markovic et al. (2018)	Faculty office	MM	Germany	Cfb	Window	Physical monitoring and occupant investigation	Data mining and machine learning	Co-simulation
Laurent et al. (2017)	University dormitory	NV	USA	Dfa	Window	Physical monitoring and	Stochastic/ Probabilistic	User function or custom code

						occupant investigation		
Chen et al. (2017)	Office	MM	USA	Am	Window, blinds, thermostat, lighting and appliances	-	Agent-based	Co-simulation
Jones et al. (2017)	Residential	MM	UK	Cfb	Window	Physical monitoring	Stochastic/ Probabilistic	-
Langevin et al. (2016); Langevin et al. (2015)	Office	MM	USA	Dfa, Csb, Cfa, Csa	Window, fans, thermostat and clothing	Physical monitoring and occupant investigation	Agent-based	Co-simulation
Hong et al. (2016a); Hong et al. (2015b); Hong et al. (2015a)	Office	MM	USA	Am	Window, lighting, blinds and thermostat	-	Stochastic/ Probabilistic	Co-simulation
Lee and Malkawi (2014)	Office	MM	USA	Dfa	Window, blind, thermostat, fan and clothing	-	Agent-based	Co-simulation
D'Oca et al. (2014); Fabi et al. (2013)	Residential	NV	Denmark	Cfb	Window and thermostat	Physical monitoring	Stochastic/ Probabilistic	Direct input or control
Schwiker et al. (2012)	Residential and office	NV / MM	Switzerland and Japan	Cfb, Cfa	Window	Physical monitoring and occupant investigation	Stochastic/ Probabilistic	-
Andersen et al. (2011)	Office	NV / MM	Denmark	Cfb	Window and thermostat	Physical monitoring and occupant investigation	Stochastic/ Probabilistic	-
Rijal et al. (2011)	Office	NV / MM	Europe and Pakistan	Csa, Csb, Cfa, Cfb, BWh, BSk	Window and fans	Physical monitoring and occupant investigation	Stochastic/ Probabilistic	Direct input or control
Wei et al. (2010)	Faculty office	NV	UK	Cfb	Window, blinds and clothing	Occupant investigation	Stochastic/ Probabilistic	-
Haldi and Robinson (2009)	Office	NV	Switzerland	Cfb	Window	Physical monitoring	Stochastic/ Probabilistic	-
Rijal et al. (2008)	Office	NV / MM	UK	Cfb	Window	Physical monitoring and occupant investigation	Stochastic/ Probabilistic	Direct input or control
Yun and Steemers (2008)	Office	NV	UK	Cfb	Window	Physical monitoring and occupant investigation	Stochastic/ Probabilistic	-
Herkel et al. (2008)	Office	NV	Germany	Cfb	Window	Physical monitoring	Stochastic/ Probabilistic	-
Pfafferott and Herkel (2007)	Office	NV	Germany	Cfb	Window, lighting, blinds and appliances	Physical monitoring	Stochastic/ Probabilistic	Direct input or control
Fritsch et al. (1990)	Office	MM	Switzerland	Cfb	Windows	Physical monitoring	Stochastic/ Probabilistic	-

*NV – natural ventilation; MM – mixed-mode.

**Am – Tropical monsoon; BWh – Hot desert; BSk – Cold semi-arid; Cfa – Humid subtropical; Cfb – Oceanic; Csa – Hot-summer Mediterranean; Csb – Warm-summer Mediterranean; Dfa – Hot-summer humid continental; Dwa - Monsoon-influenced hot-summer humid continental.

The physical monitoring is a quantitative approach and includes objective measurements (physical sensing), that are realized using specific equipment (BALVEDI; GHISI; LAMBERTS, 2018; HONG et al., 2016a). It can be realized in-situ, collecting data in occupants natural environment, usually for a long period, or in a laboratory, where the researchers have more control over different environmental conditions (YAN et al., 2017). The methods used for the physical monitoring include energy metering, measurement of indoor and outdoor environmental parameters (e.g., air temperature, relative humidity and CO_2 concentration) and occupant interaction with building systems or presence through sensors (e.g. window and door status – open/close) (HONG et al., 2016a). From the reviewed publications, 33% used only physical monitoring for data collection, while 48% used the integration of physical monitoring with occupant investigation methods. As to the monitoring parameters, 78% measured environmental variables, 56% monitored window and/or door status and 11% measured energy consumption.

The occupant investigation is a qualitative approach and includes subjective measurements (non-physical sensing) to monitor OB based on self-reported data (BALVEDI; GHISI; LAMBERTS, 2018; HONG et al., 2016a). It includes questionnaires, interviews, focus groups, surveys, diaries, perception, observation and opinions (LAAROUSSI et al., 2020). The occupant investigation often involves ethical issues regarding participant recruitment and risks, requiring the approval of ethics protocols, privacy issues and informed consent before the data collection, in order to preserve the identity of the participants (LAAROUSSI et al., 2020; YAN et al., 2017). From the reviewed papers, 52% performed occupant investigation: 33% applied questionnaires or surveys, 15% realized interviews and 4% realized occupant observation in-situ.

The validation of the collected data is addressed in few cases, which may be explained by the lack of guidelines on how to validate occupant measurements (YAN et al., 2017). Yan et al. (2017) suggest and explain the calculation of measurements uncertainties to quantify data quality.

Also, 15% (4 models) of the OB models analysed (Table 2.2) did not realize the data collection step, using data from previous studies to the OB modelling. In order to support OB model development, occupant behaviour databases are emerging during the last years, which can provide a more robust basis for OB modelling with different building typologies and climates (PUTRA; HONG; ANDREWS, 2021). For example, the ASHRAE Global Thermal Comfort Database II is an online open-source database that includes more than 80,000 sets of data collection about occupant comfort and preferences from field studies conducted since 1995 (LIČINA et al., 2018).

2.3.2 OB model development (processing)

Understanding the correlation between drivers and occupants' interactions is an essential part of the OB modelling (LAAROUSSI et al., 2020). Different approaches were proposed in the reviewed literature to represent this correlation through OB modelling.

2.3.2.1 Sub-models

Previous studies classified OB models in sub-models, which were divided in two groups. The first group refers to occupancy and includes occupant presence and movement (BALVEDI; GHISI; LAMBERTS, 2018; GAETANI; HOES; HENSEN, 2016; HE; HONG; CHOU, 2021; LAAROUSSI et al., 2020; PARYS; SAELENS; HENS, 2011). Occupant presence can be detailed as occupant detection (presence and absence), estimation (occupancy count) and prediction (to forecast the occupancy in a future time window), and occupant movement can be detailed as occupant activity recognition (to identify or forecast a particular activity) and occupant movement between zones (the transition from one room to another inside a building) (CARLUCCI et al., 2020).

The second group of sub-models refers to occupants' interactions with building systems to meet individual needs (CARLUCCI et al., 2020; LAAROUSSI et al., 2020), which includes, mainly, windows and door operation, blinds/ solar shading operation, thermostat or air-conditioning adjustment (cooling and heating systems), artificial lights control, appliances use and clothing adjustment (BALVEDI; GHISI; LAMBERTS, 2018; CARLUCCI et al., 2020; GAETANI; HOES; HENSEN, 2016; PARYS; SAELENS; HENS, 2011). Putra et al. (2021) also differs actions driven by individual needs from collective actions, which are influenced by social interaction and requires a group decision process (e.g., majority decision or hierarchical decision).

A comprehensive behaviour model should include more than one sub-model to represent a combination of occupants' interactions, since one action can influence the other and vice-versa (GAETANI; HOES; HENSEN, 2016). The combination could refer to two or more occupancy sub-models, such as combining lighting and blinds control (CARLUCCI et al., 2020) or combining occupancy with occupants' interactions sub-models, since occupant must be present to interact with the building systems (MURONI et al., 2019). From the reviewed studies, 52% combined two or more sub-models, from which 26% combined window operation with thermostat adjustment and 19% with blinds control. Fan operation, lighting control and clothing adjustment were present in 15% of the cases, appliances use and air-conditioning in 11% of the cases and occupant movement in 4% of the cases.

2.3.2.2 Drivers

Each OB sub-model is stimulated by one or more drivers or driving factors, also called in the specific literature as triggers, predictors or influencing variables (BALVEDI; GHISI; LAMBERTS, 2018; CARLUCCI et al., 2020; FABI et al., 2012; LANGEVIN; WEN; GURIAN, 2015; MAHDAVI et al., 2021; STAZI; NASPI; D'ORAZIO, 2017b; YAN et al., 2017). Drivers can be classified in two main categories: external (environmental factors, time-related factors, contextual factors) and internal (physiological factors, psychological factors, social factors) (YAN et al., 2017). Other authors use this same categories to classify energy-related drivers, also including, in the list, random factors (FABI et al., 2012; LAAROUSSI et al., 2020; STAZI; NASPI; D'ORAZIO, 2017b).

External factors are objective and easier to measure and compare (STAZI; NASPI; D'ORAZIO, 2017b). Environmental factors include indoor and outdoor conditions, such as air temperature, relative humidity, illuminance and CO_2 concentration (FABI et al., 2012; STAZI; NASPI; D'ORAZIO, 2017b). Time-related factors include, for example, time of the day (e.g., morning, noon), day of the week, season and occupant routine (e.g., arrival and departure) (HONG et al., 2015a; LAAROUSSI et al., 2020). Contextual factors include building characteristics, building location, building orientation, etc. (FABI et al., 2012).

Internal factors concern the individual and are more difficult to collect, quantify and analyse (STAZI; NASPI; D'ORAZIO, 2017b). Physiological factors include occupant's physiological condition, such as age, gender, health situation, clothing, activity level), individual sensitivity to brightness and other variables (FABI et al., 2012; STAZI; NASPI; D'ORAZIO, 2017b). Psychological factors include individual perception, expectations, habits and lifestyle (FABI et al., 2012). Social factors refer to the interaction between occupants and include, for example, organization policy (FABI et al., 2012; STAZI; NASPI; D'ORAZIO, 2017b). Random factors are uncertain and not quantifiable factors, which cannot be synthesised with association rules and, therefore, are very little addressed in OB modelling (BALVEDI; GHISI; LAMBERTS, 2018; STAZI; NASPI; D'ORAZIO, 2017b).

The majority of the reviewed publications used external factors as drivers. The environmental were the most addressed: indoor temperature (93%), outdoor temperature (85%), CO_2 concentration (37%), relative humidity (37%), illuminance or daylight (33%), wind speed (22%) and noise (4%). Time-related factors were considered in 33% of the reviewed OB models, including time of the day and occupant routine, in special occupant arrival and departure. Only one publication considered internal factors as a driver (physiological crossed with clothing insulation). Also, 56% of the reviewed papers considered a combination of four or more drivers.

2.3.2.3 Approaches and methods

The literature review mentions different approaches to model OB, which can vary according to the model complexity, the input data required by the model, the level of implementation and the research goals (DONG et al., 2018; JIA; SRINIVASAN; RAHEEM, 2017). Hong et al. (2016a) classified the approaches in two groups: implicit, which are related to the physical systems of the building, and explicit, which are directly related to the occupant. As to the OB model complexity, several authors classify it in (with minor changes between each author): schedules (or profiles, rule-based), deterministic (or statistical), non-probabilistic (or data-based, data mining, data-driven), probabilistic (or stochastic, machine learning), agent-based stochastic (or object-oriented) and virtual OB models (CARLUCCI et al., 2020; DONG et al., 2018; GAETANI; HOES; HENSEN, 2016; JIA; SRINIVASAN; RAHEEM, 2017; YAN et al., 2017).

Schedules, profiles or rule-based models represent a simplified scenario (the lowest level of complexity), introducing occupant behaviour as a static variable (DONG et al., 2018; GAETANI; HOES; HENSEN, 2016). These models include either deterministic rules, where actions are direct consequences of drivers, or occupant profiles, representing average and predictable behaviours (CARLUCCI et al., 2020; GAETANI; HOES; HENSEN, 2016). In general, schedules are the most used model category, since they can be directly implemented on BPS tools (DONG et al., 2018).

Deterministic or statistical models specify more action drivers than the previous model category, increasing the model resolution (GAETANI; HOES; HENSEN, 2016). These models use traditional regression methods or generalized linear methods to quantitatively determine the relationship between drivers (independent variables) and occupant behaviour (LI et al., 2019). One limitation of this approach is that a larger sample size and data input of many variables are required to capture and describe occupant behaviour (ZHANG et al., 2018).

Non-probabilistic or data-based models are determined by training a profile that include factors resulting from data-mining (GAETANI; HOES; HENSEN, 2016), which consists one of the approaches to extract occupant behaviour from occupancy related data (DONG et al., 2018; GAETANI; HOES; HENSEN, 2016). This approach allows integrating machine learning to data-mining through a clustering analysis to group data into categories based on measurements of inherent similarity or distance (DONG et al., 2018). Methods used for data-mining and machine learning models include k-means clustering, decision tree, Bayesian network, artificial neural network and support vector machine (DONG et al., 2018; LI et al., 2019).

Probabilistic or stochastic models use stimuli (drivers) as influencers within the probability function for an action to occur (GAETANI; HOES; HENSEN, 2016). Thus, behaviour results from a complex relationship between drivers and may evolve over time and vary between occupants (CARLUCCI et al., 2020). These models consider only the interactions between building and occupants and require a high number of simulation runs to increase resolution and achieve reliable results (GAETANI; HOES; HENSEN, 2016). The most common methods used to develop these models are Markov chain, Logit analysis (or logistic regression analysis), Survival analysis, Poisson process, Probit analysis, Monte Carlo method and random sampling (CARLUCCI et al., 2020; DONG et al., 2018; GAETANI; HOES; HENSEN, 2016; LI et al., 2019; PARYS; SAELENS; HENS, 2011).

Agent-based or object-oriented models have a more complex simulation framework, combining learning and simulation algorithms (DONG et al., 2018; GAETANI; HOES; HENSEN, 2016). These models predict occupants behaviour by modelling the behaviour of each occupant independently, instead of in a group-level (GAETANI; HOES; HENSEN, 2016; LI et al., 2019). The model complexity varies according to the sub-models included, but it usually requires a large amount of information (GAETANI; HOES; HENSEN, 2016).

Virtual models are a recent approach and, different from the above-mentioned approaches, do not rely on measured data and surveys (DONG et al., 2018). Instead, this approach is supported by immersion techniques into virtual reality, which provide images, sound and other stimuli to simulate the human-building interaction (DONG et al., 2018).

The majority of the reviewed publications present probabilistic/ stochastic OB models (78%), using techniques such as Logit analysis (56%), Markov chain (15%), survival analysis (4%) and Monte Carlo method (4%). 19% of the reviewed papers used the agent-based approach and 4% used the data-mining and machine learning approach, adopting the neural network method.

2.3.2.4 Model evaluation

An evaluation of the OB model should be performed in order to verify if is reliable and effective, by considering its intended application (YAN et al., 2015). Several evaluation metrics can be found in the literature, such as prediction accuracy, precision, recall, f-1 score, mean average error (MAE), mean average percentage error (MAPE) and root mean squared error (RMSE) (CARLUCCI et al., 2020). Yan et al. (2017) suggest that an external model evaluation, rather than an internal evaluation, is essential to prevent bias and to provide more convincing evidence of the model's reliability. The model evaluation should result in a report detailing its specificities and applicable limitations (YAN et al., 2015).

The evaluation metrics used in several of the reviewed papers are the coefficient of determination (R^2), RMSE, recall, precision, accuracy and f-1 score (JIA et al., 2019; LANGEVIN; WEN; GURIAN, 2015; NASPI et al., 2018). However, not all studies include the model evaluation. The model evaluation is a challenge due to the lack of established standard evaluation protocols for OB modelling and the limited availability of occupant behaviour data, requiring further investigation to demonstrate the validity of the developed behaviour models (CARLUCCI et al., 2020; YAN et al., 2017).

2.3.3 Model implementation (post-processing)

This step involves the implementation of the developed OB model in a building energy model (HONG et al., 2018). The implementation tools can be divided in three categories: representation of people (OB tools), representation of the environment (BPS tools) and their interactions (coupling engine) (BERGER; MAHDAVI, 2020). The most popular OB tools include NetLogo, AnyLogic, Occupancy Simulator, Repast Symphony, PMFserv, MATLAB, Unity 3D, obFMU and obXML (BERGER; MAHDAVI, 2020; YAN et al., 2017). The most popular BPS tools include DOE-2, EnergyPlus, DeST, ESP-r, IDA ICE, TRNSYS, IES VE and TRACE (HONG et al., 2018). Examples of coupling engines used to integrate OB and BPS tools are Building Control Virtual Test Bed (BCVTB) and Lightweight Communications and Marshalling (LCM) (BERGER; MAHDAVI, 2020).

Four implementation approaches were found in the reviewed literature: (i) direct input or control, (ii) built-in OB models, (iii) user function or custom code and (iv) co-simulation (HONG et al., 2018; YAN et al., 2017). Direct input or control refers to the implementation of the occupant related inputs directly through BPS tool semantics and is supported by almost all BPS programs (AZAR et al., 2020; HONG et al., 2018). The built-in approach uses OB models already implemented in BPS tools (HONG et al., 2018; YAN et al., 2017). Despite its easy implementation, there is a limited numbers of built-in OB models in few BPS tools, which is the main limitation of this approach (HONG et al., 2018). The user function or custom code approach allows users to write functions or custom codes as part of the building energy model input file, allowing to overwrite existing values or add new values to an existing code (BALVEDI; GHISI; LAMBERTS, 2018; HONG et al., 2018). The co-simulation approach allows the integration of the OB tools and BPS tools by real-time exchange of information (BALVEDI; GHISI; LAMBERTS, 2018) and it can be realized using two methods: the middleware coupling method, which uses a middle data exchange tool to manage the integration between OB and

BPS tools and requires users' familiarity with different data coding format; and the standardized coupling method, which provides a uniform interface for information and data exchange, allowing the direct link between both tools (LI et al., 2019). So far, co-simulation was already implemented in EnergyPlus and ESP-r (YAN et al., 2017).

A total of 56% of the reviewed publications implemented OB models in BPS tools. From this percentage, 33% used the co-simulation approach, 15% used the direct input or control approach and 7% used the user function or custom code approach. The most popular BPS tool was EnergyPlus (30%), but others were also used, such as ESP-r (11%), IDA ICE (4%) and IES VE (4%). Regarding the OB tools, MATLAB and obFMU were used by 22% of the studies and PMFserv, AnyLogic and Occupancy Simulator were used by 12% of the studies. BCVTB was used as a coupling engine in 15% of the studies.

2.4 Occupant behaviour investigation and modelling in school buildings

Occupant behaviour has a significant impact on IAQ and on building thermal and energy performance, especially in high-occupancy density environments, such as school classrooms (DUTTON; SHAO, 2010). Nevertheless, few publications address this building typology. Table 2.3 presents the results from SLR 2, which aimed to investigate the *status quo* on research studies about occupant behaviour in naturally ventilated and mixed-mode school buildings. The data collection (pre-processing phase) has been widely adopted as a research method and can be identified in all the reviewed studies. The inclusion of model development (processing phase) and model implementation (post-processing phase) are still limited, showing an important research gap.

2.4.1 Data collection (pre-processing)

The reviewed papers adopted, for the data collection, physical monitoring methods (38%), occupant investigation methods (8%) or a combination of both (54%). The measurement of environmental parameters was the most used physical monitoring method (85%), followed by energy metering (31%) and window and/or door status measurement (23%). Occupant observation (31%), questionnaires (23%) and interviews (15%) were adopted as occupant investigation methods. Important findings from occupant investigation include the identification of the teacher as the main active occupant regarding the environment adjustment, while students are more passive users and rely on the teacher to adjust uncomfortable conditions, since they often have limited freedom of action (BERNARDI; KOWALTOWSKI, 2006; PISTORE et al., 2019).

Table 2.3 – Reviewed studies on occupant behaviour in school buildings (SLR 2)

Publication	School level	Ventilation system*	Location	Climate**	Sub-model	Method		
						Data collection	Model development	Model implementation
Zhang and Bluyssen (2021)	Primary school	MM and NV	Nether-lands	Cfb	Lighting operation and thermostat adjustment	Physical monitoring and occupant investigation	-	-
Stamp et al. (2020)	Secondary school	MM	UK	Cfb	Window operation	Physical monitoring	-	-
Simanic et al. (2020)	Primary and lower secondary school	MV	Sweden	Dfb	Thermostat adjustment, occupant presence, lighting operation and appliance use	Physical monitoring (Previous collected data)	Stochastic/ Probabilistic	Direct input or control
Englund et al. (2020)	Secondary school	MM	Sweden	Dfb	Window and door operation	Physical monitoring	Schedules and Deterministic	Direct input or control
Heracleous and Michael (2019)	Secondary school	NV	Cyprus	BSh	Window operation	Physical monitoring and occupant investigation	-	-
Pistore et al. (2019)	Secondary school	MM	Italy	Cfb	Window and blinds operation, clothing adjustment	Occupant investigation	-	-
Lourenço et al. (2019)	Secondary school	MM	Portugal	Csa	Window, blinds and lighting operation	Physical monitoring and occupant investigation	Schedules	Direct input or control
Belafi et al. (2018)	Elementary school	MM	Hungary	Cfa	Window operation	Physical monitoring and occupant investigation	Stochastic/ Probabilistic	-
Heebøll et al. (2018)	Primary school	MM	Denmark	Cfb	Window operation	Physical monitoring	-	-
Stazi et al. (2017b)	Secondary school	NV	Italy	Cfa	Window operation	Physical monitoring and occupant investigation	Stochastic/ Probabilistic	-
Lourenço et al. (2014)	Secondary school	MM	Portugal	Csa	Thermostat adjustment and water heating	Physical monitoring and occupant investigation	-	-
Dutton and Shao (2010)	Primary school	NV	UK	Cfb	Window operation	Physical monitoring	Stochastic/ Probabilistic	Direct input or control
Bernardi and Kowaltowski (2006)	Primary school	NV	Brazil	Cfa	Door, window, blinds, fan and lighting operation	Physical monitoring and occupant investigation	-	-

* NV – natural ventilation; MM – mixed-mode; MV – mechanical ventilation.

** BSh – Subtropical steppe; Cfa – Humid subtropical; Cfb – Oceanic; Csa – Hot-summer Mediterranean; Dfb – Warm-summer humid continental.

2.4.2 OB model development (processing)

The reviewed literature showed as main scopes of OB investigation in school buildings the OB impact on energy consumption (38% of the reviewed papers), followed by indoor environmental quality (IEQ) (23%) and IAQ (23%), thermal comfort (15%) and visual comfort (8%). The addressed sub-models are mostly related to the occupants' interactions with the building systems, such as window operation, thermostat adjustment, lighting operation and appliances use (Simanic et al., 2020). Examples of sub-models associated to energy consumption investigations are the thermostat adjustment and water heating consumption sub-models, which were investigated in eight Portuguese schools, in terms of energy and gas consumption (Lourenço et al., 2014). Lourenço et al. (2014) identified as the main occupant behaviour driver the time span between the discomfort perception, the action taken and the expected feedback. The lighting operation sub-model, also associated to energy consumption, was observed in nine Dutch school buildings (Zhang & Bluyssen, 2021). Results showed a negative relationship between the frequency of use of artificial lights and energy consumption: less electricity was consumed when the teachers triggered the light control more often. The window operation sub-model is mainly associated to IAQ and thermal comfort investigations (Belafi et al., 2018; Dutton & Shao, 2010; Englund et al., 2020; Heebøll et al., 2018; Heracleous & Michael, 2019; Stamp et al., 2020; Stazi et al., 2017b). Stamp et al. (2020) analysed the IAQ in UK non-domestic buildings including one MM school building, showing that higher outdoor air temperatures increased the use of natural ventilation (window opening) and, consequently, reduced the IAQ due to increased summertime natural ventilation use against controlled mechanical ventilation. Heebøll et al. (2018) compared a classroom with manually operable windows (original configuration) to three retrofitted classrooms with mechanical ventilation and automated windows, showing that the controlled system provided better IAQ (lower CO_2 concentrations).

The drivers for the window operation sub-model were identified as being, mainly, the indoor and outdoor air temperatures (DUTTON; SHAO, 2010; HERACLEOUS; MICHAEL, 2019; STAZI; NASPI; D'ORAZIO, 2017a). Dutton and Shao (2010), for example, identified correlations between the window closing behaviour and the indoor air temperature during unheated periods or the outdoor temperature during heated periods. The window opening behaviour had correlations with the outdoor air temperature, the CO_2 concentration and the vapour pressure. Stazi et al. (2017a) highlighted the indoor and outdoor air temperatures as the main drivers for window operation, while the association of window operation with CO_2 concentration was rated as weak. Conversely, Heracleous and Michael (2019) identified the CO_2 concentration and the outdoor air temperature as the main drivers for window opening behaviour due to poor indoor air quality or thermal discomfort, and the indoor air temperature as the main driver to window closing behaviour due to thermal discomfort. Belafi et al. (2018) identified different drivers for different case studies: in one case, window operation was driven by habits and time-dependent actions, since the teacher opened the windows during breaks, regardless of the environmental conditions or students' complains, while in the other case, window operation was driven by indoor and outdoor air temperatures, since the teacher operated the window based on students' observations and complains.

Although all the reviewed studies considered in their methodology the correlation between occupant interaction (sub-models) and drivers, only 46% actually presented the resultant OB model. Lourenço et al. (2019), for example, used the lighting operation behaviour sub-model as an input to model the occupant behaviour and compared simulation results with measured data to evaluate the OB model adequacy. Simanic et al. (2020) developed a stochastic OB model to predict energy use by adopting the random sampling method to determine the combination of user-related parameters (occupancy rate and energy use for hot water supply, lighting and appliances). As to the natural ventilation system operation, Englund et al. (2020) developed a deterministic model of airing behaviour and window and door operation using linear regression analysis to correlate daily heat power and outdoor temperature. Stazi et al. (2017a) and Dutton and Shao (2010) developed stochastic models of window operation using logistic regression analysis to determine the contribution of environmental variables on the window operation behaviour. Belafi et al. (2018) developed a stochastic model of window operation by combining regression analysis and absolute thresholds.

2.4.3 Model implementation (post-processing)

Only 31% of the reviewed studies implemented the OB models in a BPS tool. Dutton and Shao (2010) used their OB stochastic model to schedule window opening in an EnergyPlus model. Simanic et al. (2020) used a set of combinations of user-related parameters as input for BPS in IDA ICE software. Lourenço et al. (2019) simulated lighting operation scenarios based on the behaviour patterns observed *in loco*, by using Radiance and Energy Plus software tools, through the Design Builder interface. Englund et al. (2020) calibrated a model in IDA ICE software based on measured data and implemented a deterministic OB model to determine heat losses resultant from OB.

2.5 Potential changes on naturally ventilated school buildings design and occupant behaviour due to the COVID-19 pandemic

Since March 2020, the COVID-19 pandemic not just renewed but also emphasized the interest and urgency on investigating deficient IAQ and thermal comfort conditions in school classrooms, since the majority of the COVID-19 infections occur in public indoor environments

(ALONSO et al., 2021; AZUMA et al., 2020; MOKHTARI; JAHANGIR, 2021; QIAN et al., 2021). Recent research studies highlighted the association between indoor occupation and risk of infection, showing that the SARS-CoV-2 reproduction rate (contagiousness) in indoor environments is three to four times higher than in outdoor environments (DIETZ et al., 2020; QIAN et al., 2021). Also, the airborne transmission was found to be the main infection route, especially in indoor environments with poor ventilation, high occupancy and high exposure time, such as school buildings (HOU; KATAL; WANG, 2021).

In order to reduce the COVID-19 transmission, most of the governments temporarily closed schools facilities in 2020 and some of them remained closed during the beginning of 2021 (KAPOOR et al., 2021). However, while the COVID airborne transmission in school buildings is a challenging issue, especially in naturally ventilated classrooms, which rely only on occupants to achieve good IAQ conditions through manual operation of windows, the necessity to keep schools opened led to the rapid development of guidelines to improve IAQ in classrooms (ALONSO et al., 2021; KAPOOR et al., 2021). Such guidelines and protocols were developed by international organizations and associations (ASHRAE, 2020a; CIBSE, 2020; VAN DIJKEN, 2020; WORLD HEALTH ORGANIZATION, 2020) and specific literature, but few of them focus specifically on naturally ventilated buildings. Table 2.4 presents the research and review papers selected in LR 3, which aimed to investigate the potential changes on occupant behaviour in school buildings due to the COVID-19 pandemic.

2.5.1 Guidelines to improve IAQ in classrooms and the occupants' role

Special attention to the IAQ in school buildings has led to the use of ventilation protocols developed by associations throughout the world. The World Health Organization (WHO) and the Chartered Institution of Building Services Engineers (CIBSE), for example, proposed strategies to ensure adequate ventilation in classrooms, such as the use of natural ventilation to increase dilution of indoor air pollutants and the increase of airflow supply to ensure adequate ventilation (CIBSE, 2020; WORLD HEALTH ORGANIZATION, 2020). The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) also published a guidance towards the reopening of schools, suggesting strategies regarding ventilation (to provide a good supply of outside air), filtration (to use MERV-13 filters or portable HEPA air cleaners) and air cleaning (to use a germicidal ultraviolet air disinfection device to supplement ventilation and filtration) (ASHRAE, 2020a). The Federation of European Heating, Ventilation and Air Conditioning Associations (REHVA) published recommendations especially related to the classrooms' ventilation, such as installing CO_2 monitors to indicate when extra ventilation is necessary and installing mechanical ventilation systems to ensure a continuous air renewal throughout the year (VAN DIJKEN, 2020). The German Federal Environmental Agency (UBA) suggested ventilation strategies which includes to maintain a minimum outdoor air ventilation rate of 3 ACH, to open windows during intervals and every 20 minutes for 3 to 5 minutes during winter or for 10 to 20 minutes during summer (UBA, 2021).

Table 2.4 – Reviewed research and review papers on OB in school buildings during the COVID-19 pandemic (LR 3)

Publication	Ventilation system *	Location	Climate **	Objective	Method
Alonso et al. (2021)	MV and NV	Spain	Csa	Analyse the effects of the COVID-19 pandemic on thermal comfort and IAQ conditions in winter	Field measurements and questionnaires
Arjmandi et al. (2021)	MV	-	-	Perform numerical modelling of infection control to reduce the risk of infectious exposure while improving thermal comfort parameters	Computational Fluid Dynamics (CFD) simulation and multi-objective optimization
Asanati et al. (2021)	MV and NV	-	-	Propose mitigation strategies for school buildings, especially regarding ventilation and testing	Literature review
Deng et al. (2021)	MV	USA	BSk	Investigate the influence of IAQ and thermal comfort on students’ illness-related absenteeism	Field measurements and statistical analysis (negative binomial model)
Ding et al. (2021)	NV and MV	-	-	Evaluate the ventilation strategies currently adopted in school buildings regarding their efficiency of reducing infectious aerosols in the indoor environment	Literature review
Hou et al. (2021)	MV and NV	Canada	Dfb	Estimate ventilation rate and airborne infection risk of COVID-19	Field measurements and sensitivity analysis (Bayesian calibration and Markov Chain Monte Carlo).
Kapoor et al. (2021)	NV	-	-	Identify the necessity of IEQ in NV school buildings during the COVID- 19 pandemic	Systematic literature review
Park et al. (2021)	MV and NV	Korea	Dwa	Quantify the natural ventilation performance according to the window opening conditions and infection probability.	Field measurements and calculation procedure
Schibuola and Tambani (2021)	MV and NV	Italy	Cfa	Investigate the possibility to contain COVID-19 via increasing ventilation rates obtained through high energy efficiency systems.	Field measurements and calculation procedure
Zivelonghi and Lai (2021)	NV	-	-	Propose and analyse strategies to mitigate airborne infection risk	Calculation procedure (GN-Riley model)
Orosa et al. (2020)	MV and NV	Spain	Csa	Define the optimal moment and the exact increment of the number of air changes to lower energy consumption.	Calculation procedure.

*NV – natural ventilation; MM – mixed-mode; MV – mechanical ventilation.

**Am – Tropical monsoon; BWh – Hot desert; BSh – Subtropical steppe; BSk – Cold semi-arid; Cfa – Humid subtropical; Cfb – Oceanic; Csa – Hot-summer Mediterranean; Csb – Warm-summer Mediterranean; Dfa – Hot-summer humid continental; Dfb – Warm-summer humid continental; Dwa - Monsoon-influenced hot-summer humid continental.

Three review articles associating the subjects airborne virus transmission in indoor environments and school buildings were found. Ding et al. (2021) investigated ventilation strategies adopted in schools, aiming to outline future possible solutions to control virus airborne transmission. The authors concluded that both natural and mechanical ventilation can reduce airborne transmission if properly designed, operated and maintained, but standards and guidelines are still lacking. Kapoor et al. (2021) discussed the impacts of COVID-19 on naturally ventilated classrooms and highlighted that most guidelines regarding natural ventilation during the pandemic do not consider a specific building typology, which demonstrates the need of guidelines focused on school buildings. Asanati et al. (2021) presented a short communication discussing ventilation, testing and vaccination in school buildings, suggesting that increasing ventilation in classrooms is an important approach to lower the concentration of indoor air pollutants and contaminants, thus reducing the risk of infection. The authors proposed a model for ventilation and filtration in schools that suggests implementing air ducts to increase the air change rate and adding HEPA filters in existing HVAC units or in portable units.

Original research papers recently published have shown the importance of air renewal to dilute contaminants and, consequently, to reduce airborne infection risks, both in naturally and mechanically ventilated school environments (PARK et al., 2021). The indoor CO_2 levels may be used as an index to estimate the ventilation rate and, therefore, the airborne transmission of diseases (BHAGAT et al., 2020; HOU; KATAL; WANG, 2021). Hence, its concentration rate is widely used as an indicator of IAQ (CHATZIDIAKOU; MUMOVIC; SUMMERFIELD, 2015). As a result, the current pandemic brought into discussion which CO_2 levels and ventilation rates thresholds would be adequate to reduce the probability of infection in school classrooms, since recommendations from standards could not be enough to prevent airborne transmission (HOU; KATAL; WANG, 2021).

Schibuola and Tambani (2021) investigated the COVID-19 infection risk in both naturally ventilated and mechanically ventilated school buildings located in Italy, by calculating the air change rates and measuring and simulating the CO_2 concentration. Results showed that the mechanical ventilation could considerably reduce indoor viral concentration and, consequently, the infection risk – with the reproduction number decreasing from 13.1 in a naturally ventilated classroom without the use of facemasks to under 1 in a classroom with high ventilation rates and facemasks' filtration, which is considered a safe limit to stop the outbreak. Hou et al. (2021) analysed the ventilation rate and airborne infection risk in three Canadian schools through a one-day measurement of CO_2 levels. Results showed that outdoor ventilation rates between 3 and 8 ACH and a CO_2 concentration around 500 ppm are the thresholds to prevent COVID-19 airborne transmission in classrooms during a school day (less than 8 hours of continuous use). Park et al. (2021) analysed the natural ventilation performance and the infection probability in a Korean school building by using air temperature, relative humidity, wind velocity and CO_2 concentration data measured during the COVID pandemic. The authors found out that a window opening ratio of 15% could provide a ventilation rate of 6.5 ACH, which, in addition to restricting exposure time to less than 3 hours and wearing facemasks, would be adequate to maintain infection risk at less than 1%. Mokhtari and Jahangir (2021) analysed the effects of indoor occupancy on COVID-19 infection risk in an Iranian university classroom, concluding that an optimum occupant distribution could reduce the number of infected people by up to 56%. The authors also showed that increasing ventilation rates and reducing classes duration could help airborne transmission prevention. Zivelonghi et al. (2021) applied the GN-Riley infection risk model in a classroom scenario and proposed mitigation interventions regarding ventilation, occupancy, classroom's volume and CO_2 monitoring. The authors concluded that regular window opening could almost halve the infection risk in classrooms and, if added to facemasks use, could achieve acceptable levels of airborne transmission risk. Other suggested interventions were class splitting and CO_2 sensors installation.

Recent research studies also focus on the relationship between IAQ and students' health and thermal comfort. Alonso et al. (2021) analysed the effects of the COVID-19 pandemic on thermal comfort and IAQ conditions in two mixed-mode classrooms of southern Spain, comparing CO_2 concentration, air temperature and relative humidity data collected before and during the pandemic. Results showed that CO_2 concentration weekly average decreased from values around 1000 ppm before pandemic (medium quality category) to 600-750 ppm during pandemic (optimum quality category). However, since IAQ was the main priority and classrooms were only naturally ventilated due to security measures, comfort conditions worsened, increasing from 50-60% of discomfort hours before pandemic to more than 80% of discomfort hours during pandemic. Deng et al. (2021) investigated the relationship between classrooms' IAQ and thermal comfort and students' illness related to absenteeism by analysing data collected before the pandemic in 85 American school buildings. Results showed that the majority of the classrooms were poorly ventilated and students' absenteeism were associated to the elevated CO_2 concentration only during the heating season. Arjmandi et al. (2021) analysed the COVID-19 infection risk in school classrooms in order to reduce airborne transmission and improve thermal comfort, by using Computational Fluid Dynamics to simulate the performance of five mechanical ventilation systems (with different inlet and outlet vents position). Results showed the best scenario as the one with individual inlets and outlets located on the floor and ceiling of the teacher and each student's desk, since the particles exit through the shortest and straightest path-line.

Most strategies suggested by the reviewed research papers to improve IAQ in classrooms rely on the occupant behaviour, especially in naturally ventilated buildings. Nevertheless, only two research papers mention the occupants' role as part of the solution to the problem. Schibuola and Tambani (2021) emphasizes the arbitrariness of natural ventilation management due to its dependence on the OB, which contributes to the lack of acceptable IAQ conditions in naturally ventilated classrooms. Zivelonghi and Lai (2021) consider OB and exposure time to model the SARS-CoV2 emission rates inside a classroom.

2.5.2 Potential changes on actions' drivers due to COVID-19 and potential future pandemics

Recommendations and protocols to prevent airborne virus transmission in school classrooms are leading to changes on occupants' actions. Until recently, the main drivers to window operation behaviour were environmental factors associated to thermal comfort requirements, such as indoor and outdoor air temperature (JIA et al., 2021; MICOLIER et al., 2019; MUN; KWAK; HUH, 2021; STAZI; NASPI; D'ORAZIO, 2017b). The current pandemic brought up the urgency in addressing IAQ related drivers, such as the indoor CO_2 concentration, with direct association to air renewal. Consequently, the decision to open or close a window, especially during the heating season, is followed by the trade-off between achieving thermal comfort or improving indoor air quality (ALONSO et al., 2021). Thus, the behavioural dimension is currently being affected by the COVID-19 response measures, including changes in energy-related behaviours, decision-making and daily routines (FELL et al., 2020). Also, the potential changes on actions' drivers may be different and not comparable between and within countries, since COVID-19 impacts and restrictions were different in each place (FELL et al., 2020). Therefore, it is essential to investigate the behaviour changes, their actions' drivers, their impact in the building environment, including energy and thermal performance, and whether they are durable or ephemeral (FELL et al., 2020). Hence, this research topic is also important in phases without a pandemic, since it focuses on human and especially children's health and long-term well-being.

Figure 2.4 represents a framework for OB modelling in naturally ventilated school classrooms, highlighting in red the potential impacts due to the COVID-19 pandemic. Occupants' interactions regarding the classroom ventilation system (window, door and fan operation) and the clothing adjustment (use of masks) were impacted by recent secure measures and protocols. However, to what extent the behaviours' changes will be durable is still unknown. Also, whilst there is an urgent need in increasing IAQ in classrooms to reduce virus airborne transmission, thermal comfort requirements could potentially be put in second plan, if a simultaneous multi-input and output parameters interaction is not taken into consideration. So far, all models developed and simulated during the COVID-19 pandemic regarding window and door operation and mechanical ventilation operation aimed to find the best scenario to reduce the infection risk (ARJMANDI et al., 2021; HOU; KATAL; WANG, 2021; OROSA; NEMATCHOUA; REITER, 2020; PARK et al., 2021; SCHIBUOLA; TAMBANI, 2021;

ZIVELONGHI; LAI, 2021) and do not necessarily reflect the real occupant behaviour or its potential changes.

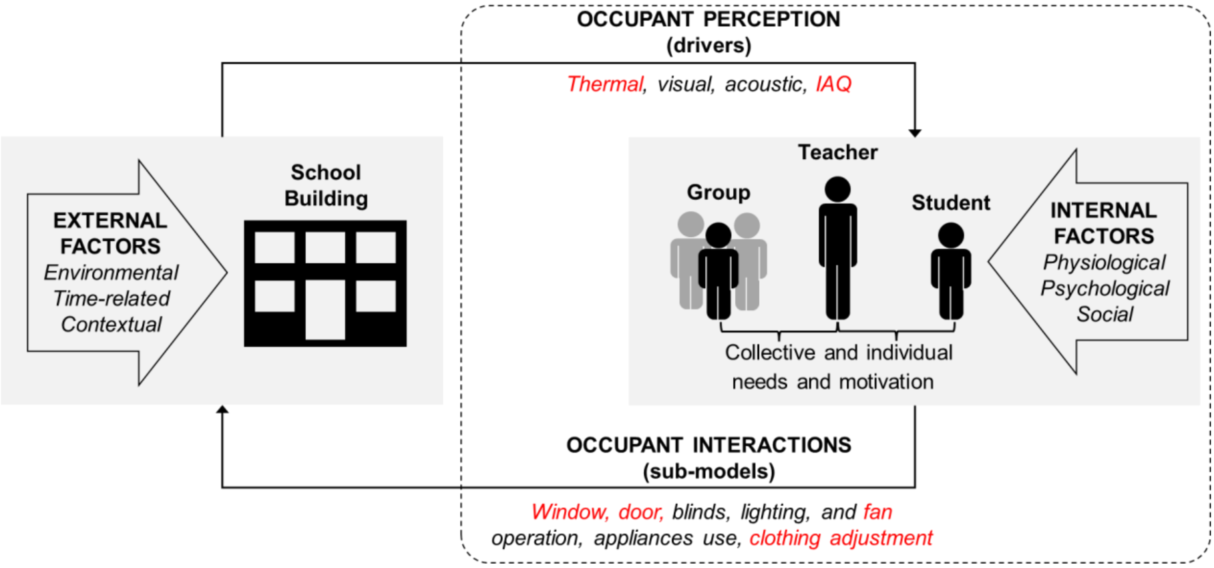

Figure 2.4 – Framework for OB in naturally ventilated classrooms

2.6 Conclusion: limitations and future perspectives

Occupant behaviour models have been developed to predict and represent human behaviour in building performance simulation, aiming at optimizing the building design and, therefore, reduce the performance gap. Occupants usually respond in different ways to the built environment, especially when comparing different building typologies and location. Nevertheless, the developed models focus on, mainly, office and residential contexts, whereas few publications address school buildings. Also, in locations where natural ventilation and mixed-mode are effective strategies for the cooling season, school classrooms usually provide manual operation of windows, which reinforces the occupant's role over the environment's performance. Therefore, this paper presents a comprehensive and critical review about occupant behaviour modelling for building performance simulation of naturally ventilated and mixed-mode school buildings.

We identified three main steps to represent the OB modelling approach in current literature, which refers to the data collection (pre-processing, step 1), the OB model development and evaluation (processing, step 2) and the OB model implementation (post-processing, step 3) in building performance simulation. Results from SLR 1 (mainly residential and office buildings, for instance) showed an implementation rate of 85% for step 1, 100% for step 2 and 56% for step 3. In contrast, the second and third steps were not fully considered in most of the research studies focused on school buildings (SLR 2), being present in only 46% (step 2) and 31% (step

3) of the reviewed studies, showing that OB modelling is still in an initial stage for school buildings, which is an important research gap. Nevertheless, the data collection (step 1) has been widely adopted as a research method in school buildings and can be identified in all the reviewed studies.

By comparing the data collection methods (step 1) adopted in SLR 1 and SLR 2, we identified similarities, such as the combination of both physical monitoring and occupant investigation methods. Nevertheless, a particularity of occupant investigation in school buildings is the identification of the teacher as the main active occupant regarding the environment adjustment, and the decision-making process relying mostly on collective needs and school rules. As to the model development (step 2), both SLR 1 and SLR 2 showed the environmental factors as the most investigated drivers, in special the indoor and outdoor air temperature. Although all the reviewed studies regarding school buildings considered, in their methodology, the correlation between occupant interaction (sub-models) and drivers, only 46% actually presented the resultant OB model. A comparison between SLR 1 and SLR 2 regarding the model implementation (step 3) showed that, from the few studies on school buildings that actually implemented the OB model, all of them adopted the 'direct input or control' implementation approach, by representing the studied environment through BPS tools. The co-simulation, a common approach adopted in the SLR 1 research studies, was not used in any of the reviewed studies from SLR 2.

Future research and OB model development and implementation are needed to address the following challenges, identified during this study:

- Almost half of the reviewed OB models focus on one single behaviour, however, in reality, occupant behaviours are connected. Therefore, to guarantee a more accurate representation, OB models should represent multiple behaviours simultaneously.

- External drivers, especially environmental factors (e.g., indoor and outdoor air temperature and CO_2 concentration), were more investigated in the reviewed studies than the internal drivers, since they are easier to measure and quantify. However, internal drivers, such as physiological and psychological factors, can also influence occupant behaviour and are essential to compare occupant behaviour in different typologies (e.g., schools' and offices' occupants have different preferences, ages, etc.).

- The OB model evaluation is essential to verify if the model is reliable and effective. However, it was little addressed in the literature and there is a lack of guidelines to properly develop this evaluation.

- As in some classrooms children have little or no freedom of action, teachers' behaviour and collective actions should be better investigated within the school buildings context.

- The OB investigation in school buildings usually focuses on a single scope, mainly energy consumption, IEQ, IAQ, thermal or visual comfort. However, OB can impact negatively and/or positively on different aspects of the building performance, so a simultaneous multi-input and output parameters interaction analysis should be taken into consideration. As an example, the urgent need to increase IAQ in classrooms to reduce COVID-19 airborne transmission might have, potentially, put thermal comfort requirements in second plan.

- The behavioural dimension in school buildings is currently being affected by the COVID-19 response measures, making it essential to investigate which are the behaviour changes, their actions' drivers and their impacts on the built environment. Also, to what extent the potential changes on actions' drivers due to COVID-19 pandemic in naturally ventilated classrooms will be durable or ephemeral is an important issue that impacts directly on children health, comfort and learning process and, therefore, should be better investigated.

3 School classrooms indoor conditions during the COVID-19 pandemic

This chapter is the transcription of the following paper:

> **Condições de conforto térmico e QAI em salas de aula naturalmente ventiladas durante a pandemia de Covid-19**
> Authored by Paula Brumer Franceschini, Iara Nogueira Liguori and Leticia Oliveira Neves
> Published in Ambiente Construído (ISSN: 1678-8621), volume 22, in 2022, and catalogued through the DOI: 10.1590/s1678-86212022000400637.

Resumo

Para a obtenção de boas condições de conforto térmico e qualidade do ar interior (QAI) em salas de aula naturalmente ventiladas, devem-se garantir taxas de renovação do ar adequadas. Em 2020, esta questão tornou-se especialmente relevante devido à pandemia de Covid-19, já que pode contribuir para a redução do potencial de transmissão de doenças respiratórias. O objetivo deste estudo é avaliar as condições de conforto térmico e QAI de uma sala de aula naturalmente ventilada a fim de identificar cenários que contribuam, simultaneamente, para a redução do risco de disseminação do vírus SARS-CoV-2 e para a manutenção do conforto térmico dos usuários. Variáveis climáticas foram monitoradas em uma sala de aula antes e durante a pandemia de Covid-19 e um modelo de simulação foi calibrado. Cenários variando o número de ocupantes e a taxa de renovação do ar foram simulados a fim de avaliar o impacto dessas variáveis na concentração de CO2, na probabilidade de infecção e na temperatura operativa interna. O melhor cenário apresentou uma redução de 42% na concentração de CO2 e 33% na probabilidade de infecção e um aumento de 60% nas horas ocupadas em conforto, se comparado ao pior cenário. No entanto, as estratégias adotadas devem ser analisadas para cada situação, assim como os riscos e os benefícios para os ocupantes da sala de aula.

Palavras-chave: Qualidade do Ar Interior (QAI). Conforto térmico. Ventilação natural. Edificação escolar.

Abstract

In order to achieve good thermal comfort and indoor air quality (IAQ) conditions in naturally ventilated classrooms, adequate air change rates must be ensured. In 2020, this issue became especially relevant due to the Covid-19 pandemic, since it may contribute to minimize the transmission potential of respiratory diseases. This study aims to evaluate the thermal comfort and IAQ conditions of a naturally ventilated classroom, in order to identify scenarios that contribute, simultaneously, to the reduction of the risk of dissemination of the SARS-CoV-2 virus and to the maintenance of thermal comfort for users. Environmental variables were monitored in a classroom before and during the Covid-19 pandemic and a simulation model was calibrated. Scenarios varying the number of occupants and the air change rate were simulated in order to assess the impact of these variables on the CO_2 concentration, on the infection probability and on the indoor operative temperature. The best scenario showed a reduction of 42% in the concentration of CO_2 and 33% in the infection probability and an increase of 60% in comfort hours, compared to the worst scenario. However, the strategies adopted must be analysed for each situation, as well as the risks and benefits for classroom occupants.

Keywords: Indoor air quality (IAQ). Thermal comfort. Natural ventilation. School building.

3.1 Introdução

As escolas são os locais em que as crianças passam a maior parte do tempo durante a infância (DENG; ZOU; LAU, 2021; KATAFYGIOTOU; SERGHIDES, 2014; STAZI; NASPI; D'ORAZIO, 2017b), o que reforça a importância da qualidade da arquitetura escolar, em amplo aspecto. As crianças são mais vulneráveis e sensíveis a influências do ambiente do que os adultos, pois:

(a) elas respiram mais rápido, uma vez que têm a taxa metabólica mais elevada, inalando mais ar (e mais poluentes) em relação ao peso do corpo;

(b) os seus órgãos estão ainda em desenvolvimento; e

(c) elas têm uma expectativa de vida maior e, portanto, têm mais tempo para manifestar qualquer doença associada (DENG; ZOU; LAU, 2021; WORLD HEALTH ORGANIZATION, 2018).

Além de influenciar a saúde e o bem-estar dos usuários, as condições de temperatura, umidade e qualidade do ar em salas de aula são fatores importantes no processo de aprendizagem dos alunos (DUTTON; SHAO, 2010; KATAFYGIOTOU; SERGHIDES, 2014). Uma pesquisa conduzida na Dinamarca mostrou que a falta de qualidade ambiental em escolas reflete em custos adicionais com professores e com cuidados médicos, devido ao absenteísmo por doenças, além de gerar impactos socioeconômicos (OLESEN, 2015). Nesse contexto, é importante melhorar as condições de conforto térmico e qualidade do ar interior (QAI) de salas de aula de edificações escolares para que as crianças tenham um desenvolvimento saudável e um melhor desempenho escolar.

Uma questão-chave para a obtenção de boas condições de conforto térmico e QAI em salas de aula é o uso de um sistema de ventilação apropriado, com taxas de renovação do ar adequadas (VAN DIJKEN, 2020). A avaliação da qualidade da ventilação de um ambiente pode ser monitorada pela concentração de dióxido de carbono (CO_2), pois, como os usuários exalam CO_2 ao respirar, a sua alta concentração pode indicar que a renovação do ar está inadequada (UMWELTBUNDESAMT, 2021). Esse é um ponto crítico para as edificações escolares, devido ao elevado índice de ocupação dos ambientes (HOU; KATAL; WANG, 2021) e, em especial, para os ambientes naturalmente ventilados – estratégia adotada em grande parte das escolas localizadas em climas tropical ou subtropical (WORLD HEALTH ORGANIZATION, 2015).

Em salas de aula naturalmente ventiladas, os níveis de ventilação recomendados frequentemente deixam de ser atendidos (DENG; ZOU; LAU, 2021; DUTTON; SHAO, 2010), uma vez que a ventilação natural depende das condições externas, que variam ao longo do tempo (VAN DIJKEN, 2020). Exemplo disso são os resultados obtidos por meio de medições contínuas das taxas de CO_2 em mais de 1.000 salas de aula na Dinamarca, na Suécia e na Noruega, que mostraram que apenas 44% das salas apresentavam níveis aceitáveis de concentração de CO_2 (de 385 a 1.000 ppm), sendo os piores resultados obtidos nos ambientes naturalmente ventilados (OLESEN, 2015).

Em 2020, as questões relacionadas à QAI em salas de aula tornaram-se especialmente relevantes devido à pandemia de Covid-19 (PULIMENO et al., 2020). O ambiente construído serve como potencial vetor de transmissão de doenças como a Covid-19, principalmente em ambientes fechados e com pouca ventilação, alta taxa de ocupação e grande período de exposição, como as escolas (BHAGAT et al., 2020; DIETZ et al., 2020). Evidências mostram que a taxa de contágio do SARS-CoV-2, ou seja, quantas pessoas saudáveis uma pessoa infectada contamina, é três a quatro vezes maior em ambientes internos do que em ambientes externos (DIETZ et al., 2020; QIAN et al., 2021), sendo a transmissão pelo ar a principal forma de contágio (HOU; KATAL; WANG, 2021).

Mesmo que muitos casos de transmissão do SARS-CoV-2 possam ser reduzidos por meio de medidas como o distanciamento social e o uso de máscaras, o ar interno necessita de soluções adequadas de ventilação para remover os contaminantes de forma segura (LIPINSKI et al., 2020). Assim, estratégias adequadas de ventilação em ambientes com alta taxa de ocupação, como salas de aula, podem contribuir para a redução do potencial de transmissão de doenças respiratórias (DIETZ et al., 2020).

Com o objetivo de manter as escolas abertas de forma segura, algumas publicações recentes trazem orientações para a ventilação adequada de salas de aula (ASHRAE, 2020a; CIBSE, 2020; VAN DIJKEN, 2020; WORLD HEALTH ORGANIZATION, 2020). A Agência Ambiental Federal da Alemanha sugere medidas relacionadas à abertura de janelas para garantir um mínimo de três trocas de ar por hora no ambiente (UMWELTBUNDESAMT, 2021). A ASHRAE, a Organização Mundial da Saúde (OMS) e o CIBSE recomendam a implementação de medidas para aumentar a ventilação natural, melhorar o sistema de filtragem do ar e purificar o ar interno (ASHRAE, 2020a; CIBSE, 2020; WORLD HEALTH ORGANIZATION, 2020). A REHVA ressalta que a ventilação natural não pode ser garantida o tempo todo, pois depende da diferença de temperatura entre os ambientes interno e externo e, portanto, a ventilação mecânica pode ser necessária para a obtenção de uma boa QAI (VAN DIJKEN, 2020).

Estudos recentes apontaram dados mais específicos sobre o risco de transmissão do vírus SARS-CoV-2 em salas de aula de escolas localizadas no Canadá (HOU; KATAL; WANG, 2021), na Itália (SCHIBUOLA; TAMBANI, 2021; ZIVELONGHI; LAI, 2021) e na Coreia do Sul (PARK et al., 2021), por meio do monitoramento da concentração de CO_2 no ambiente e do cálculo ou da simulação das taxas de renovação do ar. Para estimar a taxa de contágio, utilizou-se o modelo matemático de Wells-Riley, desenvolvido para prever a transmissão de doenças respiratórias em salas de aula (RILEY; MURPHY; RILEY, 1978) adaptado ao contexto da pandemia de Covid-19.

Hou, Katal e Wang (2021) identificaram valores recomendáveis para a taxa de renovação do ar ambiente, de $3h^{-1}$ a $8h^{-1}$, e para a concentração de CO_2, de aproximadamente 500 ppm, para prevenir a transmissão do vírus durante um dia letivo de até 8 horas de exposição para três escolas utilizadas como estudo de caso. Park et al. (2021) identificaram que uma taxa de renovação de ar de $6{,}5h^{-1}$ obtida por ventilação cruzada associada ao uso de máscaras seria medida adequada para proporcionar uma probabilidade de infecção abaixo de 1%, considerando-se um período de exposição de até 3 horas.

Os resultados de Schibuola e Tambani (2021) indicaram taxas de contágio variando entre valores abaixo de 1 (cenário com o uso de ventilação mecânica e com o uso de máscaras) a acima de 13 (cenário com ventilação natural e sem o uso de máscaras), concluindo que a ventilação mecânica e o uso de máscaras são estratégias efetivas para reduzir o risco de infecção em ambientes internos. Zivenlonghi e Lai (2021) identificaram que a abertura regular das janelas poderia reduzir pela metade a taxa de contágio nas salas de aula monitoradas e, quando associada ao uso de máscaras, poderia atingir níveis seguros de taxa de contágio.

O impacto da pandemia de Covid-19 no conforto térmico de salas de aula também tem sido abordado pela literatura recente (ALONSO et al., 2021; LOVEC; PREMROV; LESKOVAR, 2021; MONGE-BARRIO et al., 2022). Enquanto a pandemia evidenciou a importância da QAI em salas de aula, levando a mudanças significativas nos protocolos de ventilação, o conforto térmico, antes uma prioridade, passou para segundo plano (LOVEC; PREMROV; LESKOVAR, 2021). Diversos estudos mostraram uma piora nas condições de conforto térmico de salas de aula durante a pandemia, em especial em escolas naturalmente ventiladas e em períodos de temperatura externa muito baixa ou muito alta (ALONSO et al., 2021; MONGE-BARRIO et al., 2022).

Alonso et al. (2021), em um estudo conduzido em duas salas de aula no sul da Espanha, identificaram uma redução na média da concentração de CO_2 de 1.000 ppm antes da pandemia para 600-750 ppm durante a pandemia, mas um aumento das horas de desconforto térmico, de 50-60% para 80%. Monge-Barrio et al. (2022), ao monitorarem salas de aula antes e durante a pandemia, também na Espanha, identificaram uma redução na concentração de CO_2 e um aumento nas horas de desconforto, em especial no inverno, o que levou a um aumento do consumo de energia para aquecimento. Por outro lado, as condições de conforto térmico não se mostraram afetadas durante a pandemia em um estudo conduzido em salas de aula na Eslovênia, que mostrou, também, uma melhora de 30% na média diária da concentração de CO_2 interno em comparação com período anterior à pandemia (LOVEC; PREMROV; LESKOVAR, 2021).

No Brasil, o Ministério da Saúde publicou algumas orientações para a retomada das atividades escolares presenciais, porém a única recomendação em relação à ventilação das salas de aula é a de abrir as portas e as janelas para aumentar a circulação de ar no ambiente (BRASIL, 2020). No entanto, as condições climáticas e a arquitetura escolar brasileiras apresentam diferenças significativas em relação aos países mencionados nos estudos citados, sendo inadequado, portanto, importar as medidas sugeridas nos documentos internacionais já publicados (ASHRAE, 2020a; CIBSE, 2020; VAN DIJKEN, 2020; WORLD HEALTH ORGANIZATION, 2020).

As salas de aula de escolas públicas brasileiras e, em especial, das escolas públicas do estado de São Paulo, mantidas pela Fundação para o Desenvolvimento da Educação (FDE), funcionam, em sua maioria, com aberturas para ventilação natural e, em alguns casos, com ventilação mecânica proporcionada por ventiladores de teto ou parede. Nessas escolas, o ano de 2020 foi marcado pelo ensino a distância e por tentativas de volta às atividades em períodos de curta duração e com número reduzido de alunos.

Para que as escolas funcionem de forma mais segura, a QAI em salas de aula precisa ser avaliada, de forma a auxiliar na definição de estratégias que resultem em taxas de ventilação adequadas e, por consequência, que proporcionem um ambiente mais saudável e confortável aos usuários. Da mesma forma, aumentos na taxa de renovação do ar ambiente não devem acarretar uma piora nas condições de conforto térmico. Em vista disso, o objetivo deste estudo é avaliar as condições de conforto térmico e a QAI de salas de aula naturalmente ventiladas a fim de identificar cenários que contribuam, simultaneamente, para a redução do risco de disseminação do vírus SARS-CoV-2 e para a manutenção do conforto térmico dos usuários.

3.2 Método

O método adotado contemplou o monitoramento in loco de variáveis climáticas de uma sala de aula e simulações computacionais. As etapas de trabalho são detalhadas a seguir.

3.2.1 Monitoramento de variáveis climáticas em sala de aula

A coleta de dados foi realizada em uma escola estadual administrada pela Fundação para o Desenvolvimento da Educação, localizada em Campinas, São Paulo. A escola é de ensino médio, com alunos entre 14 e 17 anos. As salas de aula têm aproximadamente 49 m² e são distribuídas em três edificações térreas (Figura 3.1). A sala de aula selecionada para o estudo (Figura 3.2) tem a fachada com janela voltada para sudeste (ventilação unilateral, sendo o vento predominante em direção a sudeste). A obtenção de ventilação cruzada só é possível por meio da abertura da porta.

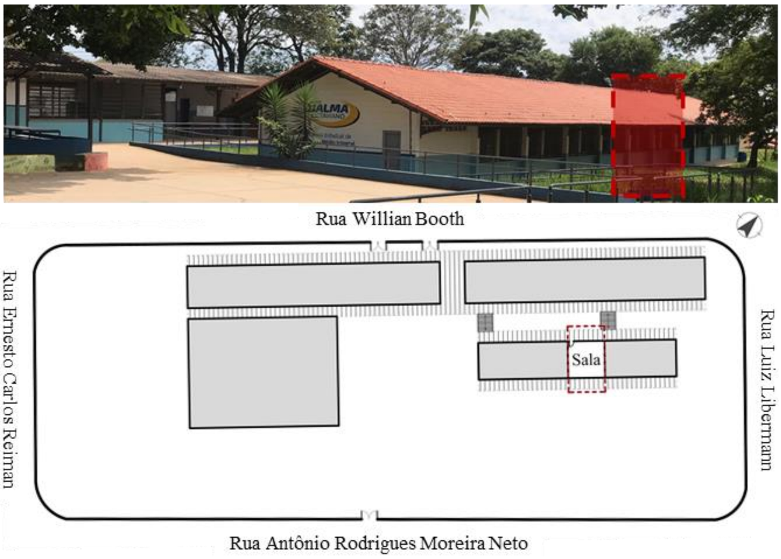

Figura 3.1 – Foto e planta da situação da escola, com a posição da sala de aula monitorada
Fonte: Liguori (2020).

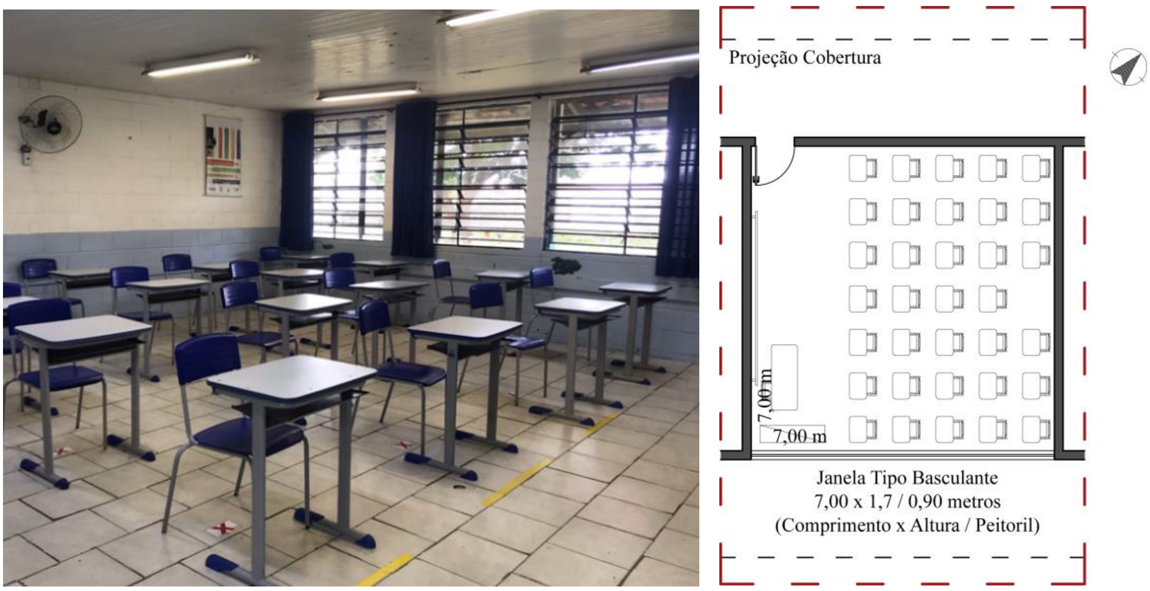

Figura 3.2 – Foto e planta baixa da sala de aula

O monitoramento foi realizado em dois períodos – antes e durante a pandemia de Covid-19 (Tabela 3.1). No período durante a pandemia, observaram-se mudanças no número de ocupantes e no período de ocupação devido às restrições impostas pelo Plano São Paulo (SÃO PAULO, 2021), elaborado para a pandemia de Covid-19, fase amarela. Adicionalmente, algumas estratégias foram recomendadas às escolas nesse período, como manter sempre as janelas e as portas abertas e não utilizar o ventilador.

As variáveis climáticas monitoradas incluíram: temperatura do ar (Ta), temperatura de globo (Tg) e umidade relativa (UR). Os equipamentos utilizados para a medição são apresentados na Tabela 3.2. O datalogger de temperatura do ar e de globo foi posicionado a uma altura de 1,5 m e a uma distância mínima de 40 cm da parede interna, em um tripé, para não atrapalhar o andamento da aula. Os dados foram registrados a cada 10 minutos. No período durante a pandemia, foram monitoradas também a concentração de CO_2 e a operação manual de janelas e ventiladores. O sensor de CO_2 foi posicionado na parede a uma altura de 1,1 m, referente à altura da cabeça de uma pessoa sentada (INTERNATIONAL STANDARD, 1998), afastado das janelas e próximo às mesas dos alunos.

Tabela 3.1 – Coleta de dados antes e durante a pandemia

Coleta	Período	Número de ocupantes	Período de ocupação
Antes da pandemia (5 dias, sendo 5 ocupados)	11/03 a 15/03/2019	40	7h30min às 12h30min e 13h30min às 16h30min
Durante a pandemia (7 dias, sendo 4 ocupados)	24/02 a 03/03/2021	20	8h às 11h30min

Tabela 3.2 – Especificações técnicas dos equipamentos utilizados para o monitoramento

Equipamento	Alcance	Precisão	Período
Datalogger temperatura/umidade, marca Testo, modelo 174H	-20 ºC a 70 ºC 0% a 100%	± 0,5 ºC ± 3%	Antes da pandemia
Datalogger temperatura/temperatura, marca Testo, modelo 175-T2	-35 ºC a 55 ºC	± 0,5 ºC	Antes e durante a pandemia
Sonda de esfera quente, marca Testo, modelos 0635 1549, 0635 1049 e 0613 1712	-25 ºC a 80 ºC	± 0,2 ºC	Antes e durante a pandemia
Datalogger Hobo de State/Pulse/Event/Runtime, marca ONSET (para o monitoramento da operação das janelas)	Frequência máxima 1 Hz	± 1 min	Durante a pandemia
Datalogger de temperatura e umidade, iButton Hygrochron (para o monitoramento da operação dos ventiladores e das variáveis externas)	-20 °C a 85 °C 0% a 100%	± 0,5 ºC ± 0,6%	Durante a pandemia
Datalogger wi-fi com *display* e sensores integrados de temperatura e umidade, CO_2 e pressão atmosférica, marca Testo, modelo 160 IAQ	0 ºC a 50 ºC 0% a 100% 0 a 5.000 ppm	± 0,5 ºC ± 2% ± (100 ppm + 3% do vm)	Durante a pandemia

As variáveis climáticas externas (temperatura do ar, umidade relativa, velocidade e direção do vento e índice de precipitação) de ambos os períodos (antes e durante a pandemia) foram disponibilizadas pelo Centro de Pesquisas Meteorológicas e Climáticas Aplicadas à Agricultura (Cepagri) da Unicamp, cuja estação meteorológica está localizada acerca de 10 km de distância da escola monitorada. Os dados foram convertidos para o formato EnergyPlus Weather File (epw) por meio do Weather Converter versão 8.1.0.005, um programa auxiliar do software EnergyPlus. No período antes da pandemia, as temperaturas de bulbo seco média, média máxima e média mínima registradas foram, respectivamente, 23,7 °C, 30,4 °C e 19,9 °C. No período durante a pandemia, foram de 23,2 °C, 30 °C e 18,7 °C, respectivamente.

3.2.2 Simulações computacionais

Um modelo de simulação da sala de aula monitorada foi calibrado com base nos dados coletados *in loco,* por meio do *software* EnergyPlus, versão 9.3. Na sequência, o modelo foi utilizado para a simulação de cenários, variando o número de ocupantes e a taxa de ventilação do ambiente, a fim de avaliar o impacto dessas variáveis na concentração de CO_2 e na temperatura operativa interna dos ambientes.

3.2.2.1 Elaboração do modelo

A sala de aula foi modelada como uma única zona térmica. As paredes laterais foram consideradas adiabáticas, pois são comuns a outras salas de aula da escola de condições térmicas similares, não incluídas no modelo (Figura 3.3). O modelo de temperaturas do solo não perturbadas Kusuda e Achenbach foi utilizado para simular as trocas de calor pelo solo (ELI et al., 2019). A sala de aula foi modelada sem obstruções no entorno imediato, tendo em vista que as edificações presentes no entorno da escola são de baixa altura e não bloqueiam a radiação solar incidente na edificação em estudo (Figura 3.4). Para o cálculo de ventilação natural, coeficientes de pressão para uma edificação de formato retangular e sem obstruções no entorno imediato foram considerados (SWAMI; CHANDRA, 1988), o que pode ser encarado como uma simplificação adotada neste estudo.

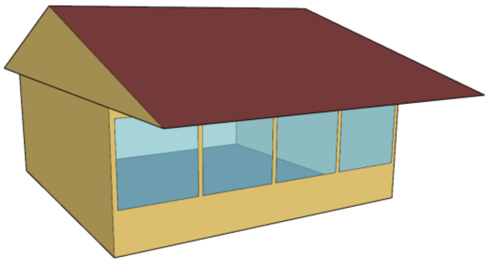

Figura 3.3 – Geometria da sala de aula

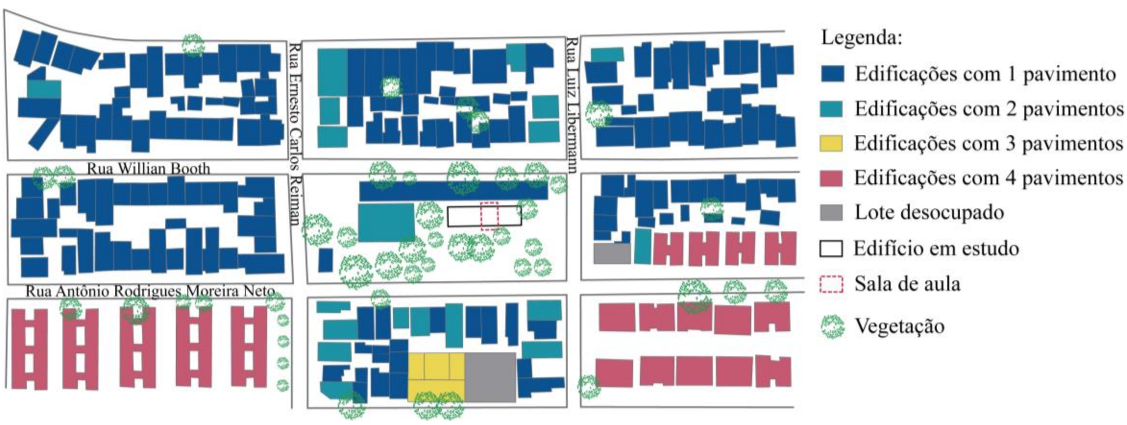

Figura 3.4 – Planta do entorno imediato da escola

As propriedades térmicas dos materiais que compõem a edificação (Tabela 3.3), as características das esquadrias (Tabela 3.4) e as cargas internas de ocupação, equipamentos e iluminação (Tabela 3.5), levantadas com base na leitura do projeto e na observação *in loco,* foram inseridas como dados de entrada. A ventilação natural foi modelada com o modelo AirFlow Network, utilizando como coeficiente de descarga o valor de 0,6 (FLOURENTZOU; VAN DER MAAS; ROULET, 1998) e as características das esquadrias apresentadas na Tabela 3.4.

Tabela 3.3 – Propriedades térmicas dos componentes construtivos

Componente	Descrição	Transmitância térmica – U (W/m². K)	Capacidade térmica – C (kJ/m². K)	Absortância solar da sup. externa – α	Fator solar – FS
Parede externa	Bloco de concreto 190x190x390 mm pintado	2,5	240	0,36	-
Janela	Vidro incolor 3 mm	5,7	-	-	0,87
Laje	Laje de concreto 150 mm	2,7	243	-	-
Piso	Argamassa de assentamento + piso cerâmico				
Forro	Forro de PVC	1,8	21	0,65	-
Cobertura	Telha cerâmica				

Tabela 3.4 – Características das esquadrias

Item	Descrição	Área efetiva de abertura para ventilação
Porta	Porta de giro – 90 cm x 210 cm	1
Janela	Janela com 12 folhas pivotantes e 6 fixas – 170 cm x 170 cm / peitoril 90 cm (4 unidades)	0,2

Tabela 3.5 – Cargas internas

Item	Descrição	Carga total
Ocupação	Taxa metabólica de uma pessoa sentada	108 W/pessoa
Equipamentos	2 ventiladores – 300 W 1 projetor – 260 W	560 W
Iluminação	6 luminárias, 2 lâmpadas fluorescentes cada – 40 W (unid.)	480 W

3.2.2.2 Calibração do modelo

O arquivo climático desenvolvido com base nos dados monitorados pela estação meteorológica do Cepagri/Unicamp durante o período da coleta de dados na escola foi utilizado para a calibração do modelo de simulação. Os dados coletados no período noturno (*i.e.*, sem influência da radiação solar e das cargas térmicas internas) foram utilizados na calibração, de forma a minimizar as incertezas. Nesse período, as condições internas são influenciadas prioritariamente pelas alterações advindas da temperatura externa, da transferência de calor por condução através da parede e da janela e da infiltração (NEVES et al., 2020). O erro médio absoluto (Mean Absolute Error – MAE) foi utilizado para avaliar a precisão do modelo de calibração, de forma a selecionar o modelo com valores de temperatura operativa interna mais próximos dos dados medidos.

Com o modelo físico da envoltória calibrado, as condições internas durante o dia foram calibradas inserindo o padrão de ocupação a partir dos dados coletados e observados nos dois períodos de medição. Para o período antes da pandemia, a simulação considerou:

(a) os ventiladores, a iluminação e o projetor ligados durante os períodos de aula (das 7h30min às 12h30min e das 13h30min às 16h30min);
(b) a ocupação em período integral com 40 pessoas (Tabela 3.1); e
(c) as janelas e a porta da sala abertas durante os períodos de aula.

Para o período durante a pandemia, a simulação considerou:

(a) os ventiladores desligados durante todo o tempo e a iluminação e o projetor ligados durante os períodos de aula (das 8h às 11h30min);
(b) a ocupação apenas no período da manhã com 20 pessoas (Tabela 3.1); e
(c) as janelas e a porta da sala abertas durante o dia todo (das 8h às 17h).

Para as duas simulações, o MAE foi calculado novamente para observar a diferença geral, sendo utilizados o erro médio normalizado (Normalised Mean Bias Error – NMBE) e o coeficiente de variação da raiz quadrada do erro médio (Coefficient of Variation of Root Mean Square Error – CV(RMSE)) para avaliar a precisão do modelo de calibração. Em ambos os modelos, o MAE ficou abaixo de 1 ºC e o NMBE e o CV(RMSE) ficaram abaixo dos valores de referência estabelecidos na ASHRAE *Guideline* 14 (ANSI/ASHRAE, 2002), que são de 10% e 30%, respectivamente (Tabela 3.6).

Tabela 3.6 – Precisão da calibração

Simulação	MAE (ºC)	NMBE (%)	CV(RMSE) (%)
Antes da pandemia	0,35	1,25	7,30
Durante a pandemia	0,85	-3,42	6,42

3.2.2.3 Cenários simulados

Dois parâmetros variáveis foram definidos para a elaboração dos cenários de simulação: a taxa de ocupação (número de ocupantes da sala de aula), tendo em vista que uma das estratégias utilizadas pelas escolas durante a pandemia foi a redução do número de alunos em sala de aula; e a taxa de renovação do ar ambiente (número de renovações de ar por hora) para analisar a necessidade de modificação do projeto de ventilação natural da sala de aula. Ambos os parâmetros têm por objetivo avaliar o impacto nos resultados da concentração de CO_2 e da temperatura operativa no ambiente interno. Para a simulação dos cenários, foi utilizado o modelo calibrado com o período de ocupação de aula integral, das 7h30min às 12h30min e das 13h30min às 16h30min.

Os cenários propostos para variação na taxa de ocupação (Tabela 3.7) foram definidos com base no Plano São Paulo (SÃO PAULO, 2021), que estabelece um percentual de ocupação das salas de aula para cada fase da pandemia: 35% na fase laranja (TO35), 70% na fase amarela (TO70) e 100% na fase verde (TO100), sendo a fase verde representativa da ocupação do ambiente antes da pandemia. A ocupação máxima (100%) considerou a turma completa de 45 alunos.

Os cenários propostos para variação na taxa de renovação do ar ambiente seguiram os níveis de ventilação recomendados pela NBR 16401-3 (ABNT, 2008) para salas de aula (Tabela 3.7), que estabelece a vazão mínima de ar exterior para promover a renovação do ar interior e manter a concentração de poluentes do ar em níveis aceitáveis. Apesar de a norma tratar de instalações de ar-condicionado, o uso dos valores propostos foi julgado adequado para o intuito deste estudo, uma vez que inexistem dados normativos brasileiros de taxa de renovação do ar para ambientes naturalmente ventilados.

A norma propõe três níveis de vazão eficaz de ar exterior: mínimo (N1), intermediário (N2) e superior (N3), em que existem evidências de redução de reclamações e manifestações alérgicas. Para a área útil ocupada pelas pessoas (Az), foi considerada a área da sala de aula de 49 m² em todos os cenários. Os valores de vazão foram introduzidos nas simulações por meio do grupo Zone Airflow do EnergyPlus.

Tabela 3.7 – Cenários propostos, variando a taxa de ocupação e a vazão eficaz de ar exterior (Vef)

Variáveis	**Cenários**								
	N1 TO35	**N1 TO70**	**N1 TO100**	**N2 TO35**	**N2 TO70**	**N2 TO100**	**N3 TO35**	**N3 TO70**	**N3 TO100**
F_p (L/s.pessoa)*		5 (N1)			6,3 (N2)			7,5 (N3)	
TO (%)**	35	70	100	35	70	100	35	70	100
P_z (pessoas)	16	31	45	16	31	45	16	31	45
F_a (L/s.m²)*		0,6 (N1)			0,8 (N2)			0,9 (N3)	
V_{ef} (L/s)	109,4	184,4	254,4	140	234,5	322,7	164,1	276,6	381,6

Nota: F_p = vazão por pessoa; TO = taxa de ocupação; P_z = número máximo de pessoas na zona; F_a = vazão por área útil ocupada; e V_{ef} = vazão eficaz de ar exterior.

*valores para salas de aula de acordo com a NBR 16401-3 (ABNT, 2008).

**valores propostos no Plano São Paulo (SÃO PAULO, 2021).

O arquivo climático da cidade de Campinas no formato Typical Meteorological Year (TMY) anos 2003-2017 (LABORATÓRIO..., 2018) foi utilizado para simular tanto os cenários propostos como o modelo calibrado com a ocupação de antes e durante a pandemia de Covid-19.

3.2.2.4 Análise de resultados

Os resultados das simulações foram analisados em termos de concentração de CO_2 (ppm), número de renovações do ar por hora (h^{-1}) e temperatura operativa interna (°C) do modelo de referência (calibração) e dos cenários propostos.

Uma avaliação do risco de disseminação do vírus SARS-CoV-2 foi realizada para cada cenário proposto, considerando a presença de uma pessoa infectada na sala de aula e o período final do dia letivo, ou seja, a pior situação, uma vez que a probabilidade de infecção aumenta ao longo do período de exposição. A probabilidade de infecção foi estimada utilizando a ferramenta on-line Covid-19 Aerosol Transmission Estimator, versão 3.5.8, de 10 de novembro de 2021 (JIMENEZ; PENG, 2021). Essa ferramenta é atualizada constantemente, uma vez que novas informações sobre a Covid-19 são descobertas a cada dia, e estima apenas a transmissão do vírus pelo ar com base no modelo de Wells-Riley, calibrado para o contexto da pandemia de Covid-19.

Como dado de entrada para a fração da população imune, foram consideradas a cobertura vacinal da população com faixa etária de 15 a 17 anos, de 28,8% no dia 29 de novembro de 2021 (CAMPINAS, 2021), e a eficácia da vacina Pfizer (vacina oferecida à população dessa faixa etária), de 95% na prevenção de infecções, resultando no valor de 27,4%. Para a taxa de emissão quanta, que varia conforme a atividade, foi utilizado o valor de 9,4 quanta/h (pessoa sentada e falando) (JIMENEZ; PENG, 2021). Ainda, para cada cenário, o número de pessoas variou de acordo com a ocupação proposta, e a temperatura operativa interna e a taxa de renovação do ar variaram de acordo com os resultados das simulações. Foi também estimada a probabilidade de infecção para cada cenário variando a filtragem da máscara: sem máscara (0%), com máscara de pano (30%) e com máscara N95/PFF2 (90%) (JIMENEZ; PENG, 2021).

Os valores de temperatura operativa interna obtidos nas simulações e de temperatura do ar externa obtidos do arquivo climático foram utilizados para analisar o conforto térmico dos ocupantes com base no modelo adaptativo da ASHRAE 55 (ASHRAE, 2020b), considerando os limites de aceitabilidade de 80%, por meio do cálculo do percentual de horas ocupadas em conforto térmico (PHOCT). Os resultados dessa análise foram comparados com a probabilidade de infecção a fim de identificar o cenário que contribui simultaneamente para a redução do risco de disseminação do vírus SARS-CoV-2 e para o conforto térmico dos usuários, proporcionando condições internas mais satisfatórias.

3.3 Resultados e discussão

Os resultados da concentração de CO_2 no ambiente estão apresentados para um dia letivo representativo. A simulação representativa das condições de medição antes da pandemia resultou em alta concentração de CO_2, atingindo valores muito próximos do máximo de 1.000 ppm recomendado pela Anvisa (2003) nos períodos de ocupação (Figura 3.5). No período durante a pandemia, com a redução do número de ocupantes em 45%, a concentração de CO_2 reduziu cerca de 30% em relação ao período anterior, atingindo picos de aproximadamente 700 ppm durante o período de ocupação (Figura 3.5).

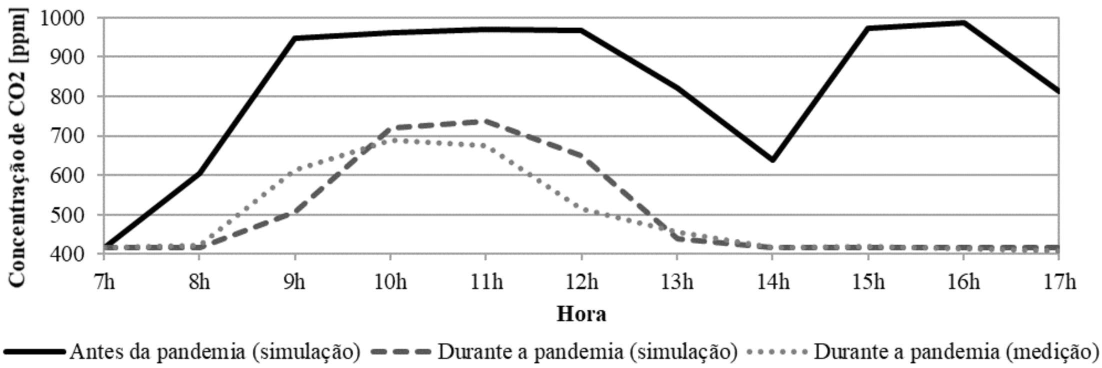

Figura 3.5 – Concentração de CO_2 durante um dia letivo representativo dos períodos de medição

Com relação aos cenários propostos, aqueles com vazão eficaz de ar exterior de acordo com o nível mínimo (N1) proposto pela NBR 16401-3 (ABNT, 2008) apresentaram concentração de CO_2 acima do nível recomendado de até 1.000 ppm (ANVISA, 2003). Ainda, a maioria dos cenários apresentou uma concentração de CO_2 elevada durante o período de ocupação, acima de 850 ppm, o que demonstra a necessidade de uma ventilação acima dos níveis indicados na NBR 16401-3 (ABNT, 2008) para manter níveis recomendáveis para o contexto da pandemia (HOU; KATAL; WANG, 2021) (Figura 3.6).

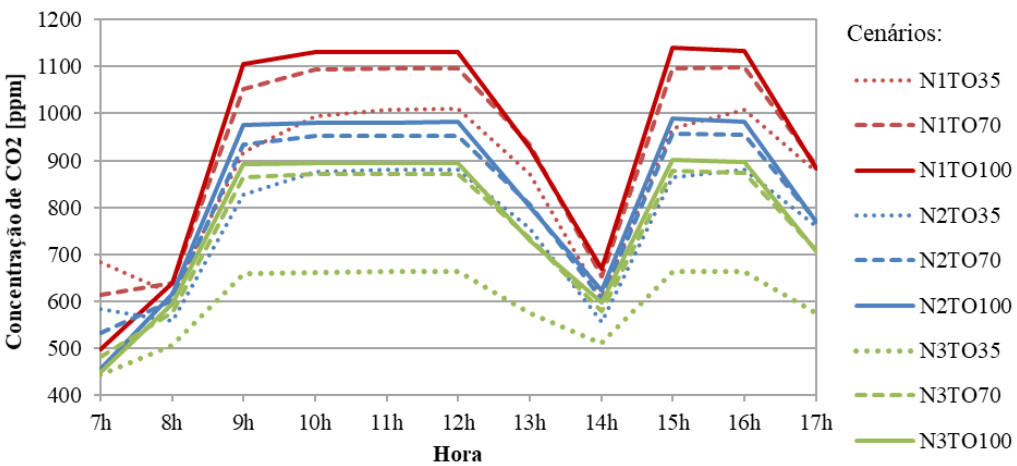

Figura 3.6 – Predição da concentração de CO_2 durante um dia letivo representativo nos cenários propostos

A mudança nos valores de vazão eficaz teve maior impacto nos resultados de concentração de CO_2 no ambiente do que na variação no número de ocupantes, sendo os resultados dos cenários do nível mínimo (N1) aproximadamente 13% superiores aos resultados dos cenários do nível intermediário (N2) e aproximadamente 20% superiores aos resultados dos cenários do nível superior (N3). O cenário N3 TO35 apresentou a maior redução da concentração de CO_2 em comparação com os outros cenários com a mesma taxa de ocupação: em relação ao cenário N1 TO35, a redução foi de aproximadamente 35% (350 ppm) e, em relação ao cenário N2 TO35, a redução foi de 25% (220 ppm).

A alteração na taxa de ocupação provocou uma diferença mais significativa entre os cenários com 35% e 70% de ocupação, principalmente para o nível superior (N3) de vazão eficaz, nos quais a redução do número de ocupantes resultou em mais de 25% de redução da concentração de CO_2 (210 ppm). A diferença na concentração de CO_2 foi menor entre os cenários com 70% e 100% de ocupação – os quais possuem uma taxa de variação de ocupação menor do que os cenários anteriores, de aproximadamente 3% (entre 25 ppm e 35 ppm).

Como nas simulações dos cenários hipotéticos considerou-se uma taxa fixa de renovação do ar (vazão eficaz) para cada cenário, a variação entre valores máximos e mínimos dentro de cada cenário foi pequena (Tabela 3.8). Maior flutuabilidade nos resultados ao longo do dia podem ser observados nas simulações representativas do monitoramento antes e durante a pandemia, o que reflete melhor a realidade (Tabela 3.8). Adicionalmente, a redução no número de ocupantes no período durante a pandemia resultou em valores de temperatura interna menores, diminuindo a diferença entre as temperaturas externa e interna e, consequentemente, a taxa de renovação de ar por efeito chaminé e a média da taxa de renovação de ar (dado de saída da simulação), quando comparada ao resultado do período anterior à pandemia (Tabela 3.8).

Tabela 3.8 – Predição da renovação de ar por hora no período de ocupação (h^{-1})

	N1 TO35	**N1 TO70**	**N1 TO100**	**N2 TO35**	**N2 TO70**	**N2 TO100**	**N3 TO35**	**N3 TO70**	**N3 TO100**	**Antes da pandemia**	**Durante a pandemia**
Média	2,76	4,64	6,40	3,52	5,89	8,10	6,60	6,94	9,57	7,07	5,15
Desvio padrão	0,02	0,03	0,04	0,02	0,03	0,04	0,03	0,04	0,05	1,21	1,27
Média máxima	2,78	4,68	6,46	3,55	5,94	8,17	6,65	6,99	9,65	8,12	6,96
Média mínima	2,74	4,61	6,35	3,50	5,85	8,05	6,57	6,89	9,50	5,26	3,70

Comparando os resultados de média máxima e mínima das condições de medição antes e durante a pandemia com os cenários propostos (Figuras 3.5 e 3.6 e Tabela 3.8), é possível observar que a sala analisada apresentou resultados equivalentes aos níveis intermediário (N2) ou superior (N3) na NBR 16401-3 (ABNT, 2008), já que o número de renovações de ar durante os períodos de medição, antes e durante a pandemia, se manteve próximo aos valores desses cenários. Os resultados do período anterior à pandemia se aproximaram aos do cenário N2 TO100, que tem aproximadamente a mesma ocupação do ambiente real. Já os resultados do período durante a pandemia apresentaram menor concentração de CO_2, próxima de 700 ppm, aproximando-se dos resultados do cenário N3 TO35, com número semelhante de ocupantes.

Os resultados demonstram que a sala de aula analisada está com valores médios de ventilação adequados, de acordo com os padrões propostos pela NBR 16401-3 (ABNT, 2008) para ambos os casos analisados, antes e durante a pandemia. No entanto, tanto o cenário antes da pandemia como todos os cenários hipotéticos com 70% e 100% de ocupação resultaram em taxas de concentração de CO_2 elevadas durante o período de ocupação da sala, o que indicaria a necessidade de aumento do valor de vazão de ar por pessoa, em relação ao indicado pela NBR 16401-3 (ABNT, 2008), de forma a auxiliar na obtenção de uma melhor qualidade do ar interior na sala de aula.

O cálculo da probabilidade de infecção mostra que as taxas de renovação de ar e a ocupação influenciam nos resultados quando os usuários estão sem máscara (6,2% de variação entre o melhor e o pior cenários) ou usando máscara de pano (2,28% de variação entre o melhor e o pior cenários) (Tabela 3.9). A probabilidade de infecção varia pouco entre os cenários com o uso da máscara N95/PFF2, ficando sempre abaixo de 1% – valor considerado satisfatório por estudos anteriores (PARK et al., 2021). Entretanto, considerando-se as observações realizadas in loco, sabe-se que a situação mais comum na sala de aula monitorada é o uso da máscara de pano. Neste caso, apenas o cenário N3 TO35 apresenta, ao final do período letivo, probabilidade de infecção próxima ao recomendável pela literatura.

Tabela 3.9 – Predição da probabilidade de infecção para cada cenário proposto ao final do dia letivo (maior período de exposição), considerando diferentes filtragens de máscaras

	N1 TO35	**N1 TO70**	**N1 TO100**	**N2 TO35**	**N2 TO70**	**N2 TO100**	**N3 TO35**	**N3 TO70**	**N3 TO100**
Sem máscara (0%)	6,23%	8,40%	9,43%	5,27%	6,98%	8,18%	3,23%	5,29%	5,86%
Máscara de pano (30%)	2,26%	3,06%	3,43%	1,90%	2,52%	2,97%	1,15%	1,90%	2,10%
N95/PFF2 (90%)	0,07%	0,09%	0,10%	0,06%	0,07%	0,09%	0,03%	0,05%	0,06%

Ainda considerando apenas o uso da máscara de pano, embora no início do período letivo todos os cenários apresentem probabilidade de infecção e concentração de CO_2 abaixo de 1% e de 700 ppm, respectivamente, ao longo do dia, a diferença entre os resultados dos cenários torna-se maior, evidenciando, em especial, o cenário N3 TO35 pelos baixos valores e, em oposição, os cenários N1 TO70 e N1 TO100 pelos valores acima de 1.000 ppm (Figura 3.7).

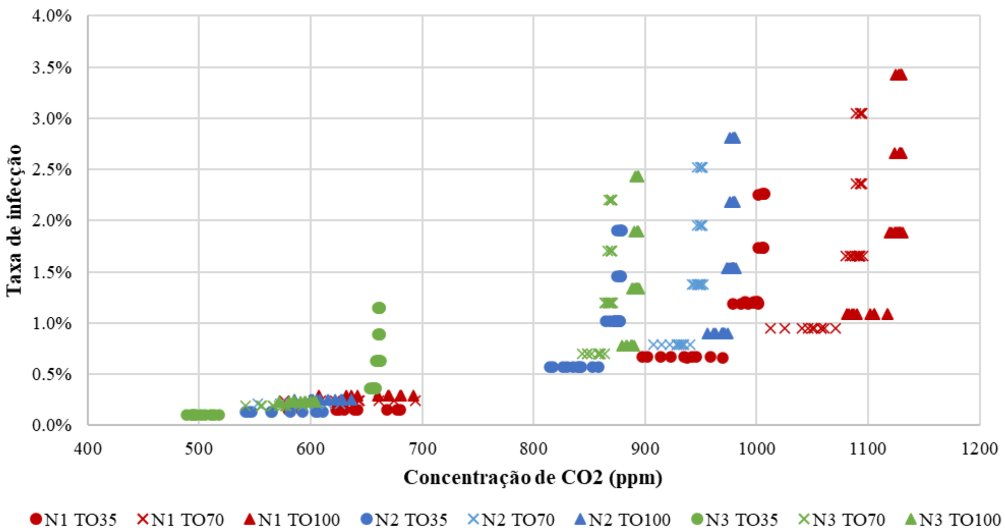

Figura 3.7 – Relação entre a probabilidade de infecção (máscara de pano) e a concentração de CO_2 nos cenários propostos

Em relação ao conforto térmico, os cenários com maiores concentrações de CO_2 (cenários N1 TO70 e N1 TO100) apresentam também maiores valores de temperatura operativa interna e, consequentemente, menos tempo em conforto térmico (PHOCT = 25%) (Figura 3.8). A mesma relação pode ser observada para o cenário com menor concentração de CO_2 (N3 TO35), que, apesar de cumprir os valores recomendados de concentração de CO2 (1.000 ppm, segundo a Anvisa (2003)) e, na maior parte do tempo, de probabilidade de infecção (abaixo de 1%, de acordo com Park et al. (2021)), ainda assim apresenta condições inadequadas de conforto térmico na maior parte do tempo (PHOCT = 40%, considerando-se apenas a semana representativa). Ainda, as concentrações de CO_2 menores em cada cenário (Figura 3.8) acontecem no início das aulas, às 8h e às 14h, e vão aumentando ao longo do período de ocupação, conforme mostra a Figura 3.8.

Na Figura 3.9, pode-se observar que a taxa de renovação de ar altera pouco os resultados de temperatura operativa interna, havendo uma redução de 1%, em média, do N1 para o N2 e do N2 para o N3. A taxa de ocupação, por sua vez, provocou alterações mais significativas nos resultados de temperatura operativa interna apenas se comparados os cenários de 35% de ocupação com os demais, sendo o cenário N3 TO35 o que apresenta os melhores resultados.

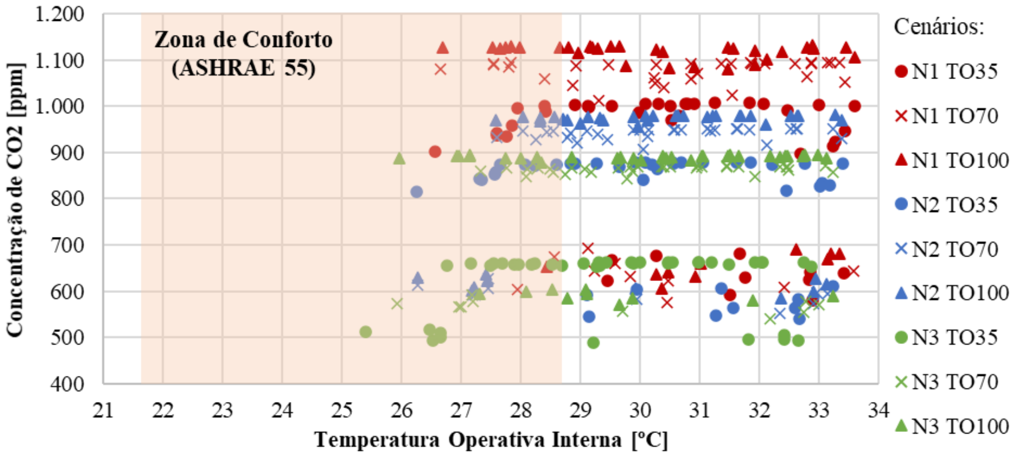

Figura 3.8 – Relação entre concentração de CO_2 e temperatura operativa interna para os cenários propostos (semana representativa – 24/02 a 03/03)

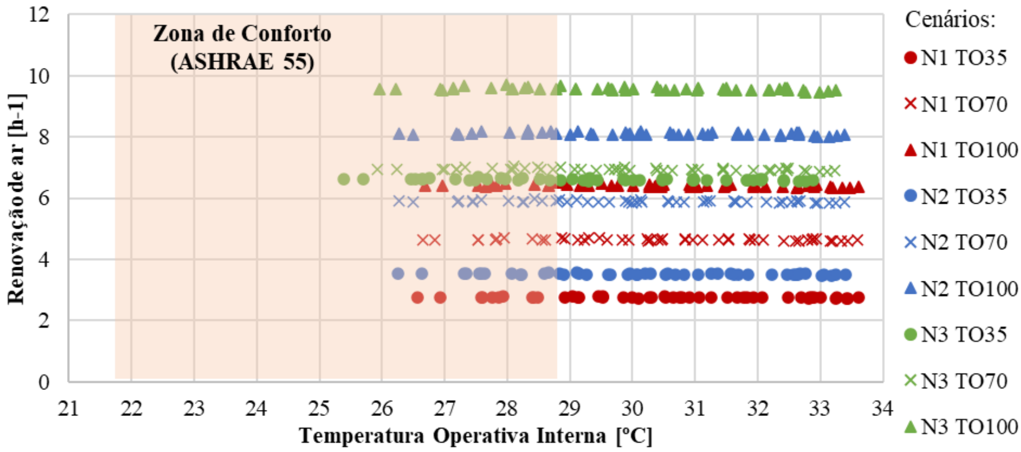

Figura 3.9 – Relação entre taxa de renovação de ar e temperatura operativa interna para os cenários propostos (semana representativa)

3.4 Conclusão

A pandemia de Covid-19 suscitou uma discussão mundial sobre as condições adequadas de QAI para o funcionamento de escolas, de forma a minimizar o risco de transmissão do vírus SARS-CoV-2 em ambientes fechados e com altas taxas de ocupação. As principais estratégias adotadas até o momento incluíram a redução do número de ocupantes, a redução do período letivo em sala de aula e estratégias para o aumento da renovação do ar ambiente, como manter sempre as portas e as janelas das salas de aula abertas.

Neste estudo, um modelo de simulação calibrado foi utilizado para simular nove cenários alterando as taxas de ar externo e de ocupação de uma sala de aula, a fim de verificar os impactos na QAI, em termos de concentração de CO_2 e probabilidade de infecção; e no conforto térmico, em termos de temperatura operativa interna. Como objeto de estudo, foi selecionada uma sala de aula de uma escola da FDE com dimensões, projeto de esquadrias e estratégia de ventilação (ventilação natural unilateral) representativas das escolas públicas do estado de São Paulo.

Dentre os cenários analisados, o cenário N3 TO35 apresentou os menores valores de taxa de concentração de CO_2, probabilidade de infecção e horas de desconforto térmico. Se comparado ao pior cenário (cenário N1 TO100), o cenário N3 TO35 apresentou redução de aproximadamente 42% na concentração de CO_2 ambiente e de 33% na probabilidade de infecção e um aumento no PHOCT de 60%, considerando o período analisado. Conclui-se que a redução no número de ocupantes associada a uma taxa adequada de renovação do ar são estratégias efetivas para a redução da concentração de CO_2 no ambiente interno e, consequentemente, para a redução do risco de transmissão de doenças respiratórias como a Covid-19.

Adicionalmente, os resultados das simulações dos cenários hipotéticos mostraram que as medidas implementadas durante a pandemia (abertura das janelas e das portas e redução do número de usuários) poderiam auxiliar na redução da concentração de CO_2 e da probabilidade de infecção, além de melhorar o conforto térmico da sala de aula analisada. A diferença desses resultados com os obtidos nos estudos conduzidos na Espanha (ALONSO et al., 2021; MONGE-BARRIO et al., 2022) indica, também, a necessidade de investigação desses parâmetros para cada clima e contexto específicos.

As medidas adotadas pelas escolas devem ser analisadas de forma a equilibrar potenciais benefícios e riscos aos ocupantes. A redução de 100% para 70% da ocupação, proposta na fase amarela do Plano São Paulo (SÃO PAULO, 2021), por exemplo, não trouxe grandes benefícios em relação à concentração de CO_2 e à probabilidade de infecção para o ambiente estudado, o que indica a provável necessidade de adoção de medidas mais eficazes de renovação do ar ambiente para possibilitar a manutenção de maior número de alunos em sala de aula, caso a máscara de pano seja adotada. Neste caso, as concentrações de CO_2 elevadas e a probabilidade de infecção maior do que 1% demonstram que, para manter uma QAI satisfatória, se faz necessária uma ventilação acima dos níveis indicados na NBR 16401-3 (ABNT, 2008), em especial com relação à taxa de vazão indicada por pessoa.

É importante ressaltar, no entanto, que a generalização deste estudo é limitada, visto que se trata de apenas um estudo de caso, considerando, portanto, apenas um clima, um projeto escolar com características arquitetônicas específicas e um cenário de taxa de infecção (uma pessoa infectada dentro da sala de aula em questão). O estudo aqui apresentado, contudo, pode ser utilizado como base metodológica para replicação a outras situações. Sugere-se, nesse sentido, a análise de possíveis implicações no projeto arquitetônico de salas de aula advindas de mudanças nas taxas de renovação de ar por pessoa e por área do ambiente, como dimensionamento e posicionamento de esquadrias para ventilação natural, dimensionamento das salas de aula (área de piso e pé-direito), entre outros fatores. Sugere-se, também, a análise de outros aspectos relacionados à QAI, como a presença de materiais particulados e de compostos orgânicos voláteis, além da investigação de estratégias que, associadas à ventilação natural, poderiam melhorar a QAI, como o uso de filtros e purificadores de ar.

4 Window operation behaviour: generalized linear models

This chapter is the transcription of the following paper:

Investigation of window operation behaviour in naturally ventilated classrooms during the COVID-19 pandemic
Authored by Paula Brumer Franceschini, Marcel Schweiker and Leticia Oliveira Neves
Published in the Proceedings of 18th Healthy Buildings Europe Conference and presented on 12th June 2023.

Abstract

The COVID-19 pandemic has once again emphasized indoor air quality (IAQ) as a fundamental path for preventing airborne virus transmission, especially in indoor environments with increased ventilation needs due to high occupancy and long exposure time, such as school classrooms. In naturally ventilated classrooms, thermal and IAQ conditions are mainly affected by window operation. Therefore, this study addresses the window operation behaviour, the thermal conditions and the perceived IAQ in naturally ventilated classrooms in a humid subtropical climate during the COVID-19 pandemic. Window operation and environmental variables of classrooms were monitored in three school buildings. Generalized linear models were developed to establish correlations between window status, indoor conditions and COVID-19 restrictive measures. Thermal conditions and IAQ were adequate most of the time in all classrooms. Indoor operative temperature, relative humidity, CO_2 concentration and COVID-19 restrictions were identified as drivers for window status in all schools. Yet, the results suggest that occupant behaviour is context dependent. Indeed, the school with the highest number of 'closed' status presented higher CO_2 concentrations and more differences in seasonal behaviour. The other two schools presented a behaviour pattern more correlated with the COVID-19 restrictions, a higher number of 'open' status and more cold discomfort hours.

4.1 Introduction

Occupant behaviour is defined as the interaction of occupants with building systems with the goal of achieving thermal, visual or acoustic comfort (DELZENDEH et al., 2017) or a sufficient indoor air quality (IAQ). If efficient, this interaction allows occupants to adapt the indoor environment to their needs (e.g., window, blinds, lighting and air-conditioning operation) or themselves to the environment (e.g., clothing adjustment and drinking hot or cold beverage). In naturally ventilated buildings with manually operable windows, the IAQ is mainly affected by occupant behaviour (YAN et al., 2017). In this context, the window fulfils a “multi-purpose function”, since the occupants’ decision to open or close the window depends on a balance between IAQ, thermal, visual and acoustic parameters (ZHANG; BARRETT, 2012).

To date, studies on occupant behaviour in naturally ventilated buildings have primarily been conducted in oceanic climates and in residential and office environments and, more recently, in school buildings. Assessing occupant behaviour in naturally ventilated school buildings can lead to guidelines towards improving IAQ and its influence on students’ health, well-being and learning process (BELAFI et al., 2018). Previous studies have demonstrated that naturally ventilated classrooms often fail to achieve recommended levels of ventilation, thus providing poor IAQ (DUTTON; SHAO, 2010). Therefore, the window operation has been the most investigated occupant behaviour parameter in the literature for naturally ventilated school buildings (BELAFI et al., 2018; HERACLEOUS; MICHAEL, 2019; KORSAVI; JONES; FUERTES, 2022b; STAZI; NASPI; D’ORAZIO, 2017a). Other behaviours addressed in schools included lighting (SIMANIC et al., 2020), blinds operation (PISTORE et al., 2019; SIMANIC et al., 2020) and clothing adjustment (PISTORE et al., 2019). The students were mainly identified as passive users towards discomfort, with the teacher being the main active occupant (PISTORE et al., 2019). Nevertheless, the results from previous research studies showed differences in behavioural triggers among school buildings and seasons. For example, Belafi et al. (2018) investigated window operation in two classrooms and identified habits and time-dependent actions as triggers for occupant behaviour in one classroom, while in the other classroom behaviour was driven by indoor and outdoor temperatures. These differences demonstrate that rules and habits can vary between and within different schools, climates and cultures and, therefore, occupant behaviour must be investigated for each situation (BELAFI et al., 2018).

The IAQ in school buildings became even more relevant in 2020, due to the COVID-19 pandemic. Recent studies highlighted the association between indoor environments, especially those with poor ventilation, high occupancy and high exposure time, such as school buildings; and risk of infection, showing that the SARS-CoV-2 reproduction rate (contagiousness) can increase three to four times in these spaces when compared to outdoor environments (HOU; KATAL; WANG, 2021).

Recent studies investigated the impact of the COVID-19 pandemic on classrooms' indoor environmental quality (IEQ) and on the infection risk regarding ventilation and occupancy rates, window opening behaviour and the use of masks (HOU; KATAL; WANG, 2021; PARK et al., 2021; ZIVELONGHI; LAI, 2021). It is well known that occupant behaviour and daily routine in schools have been affected by COVID-19 response measures (FELL et al., 2020). However, since COVID-19 impacts and restrictions were different in each place, the potential changes on actions' drivers may be different and not comparable between and within countries (FELL et al., 2020).

Most school buildings located in tropical and subtropical climates, including most of the Brazilian public school buildings, are fully or partially naturally ventilated (WORLD HEALTH ORGANIZATION, 2015). Publications regarding occupant behaviour in naturally ventilated school buildings are fare recent (from the last five years, mainly), confirming it as a relatively new subject. So far, few studies were conducted in tropical or subtropical climates and addressed the COVID-19 pandemic impact on occupant behaviour. Taking this research gap into consideration, this study addresses the window operation behaviour, the indoor thermal conditions and the perceived IAQ in naturally ventilated classrooms in a humid subtropical climate during the COVID-19 pandemic.

4.2 Methods

This paper is based on a case study and supported by field research and statistical analysis. The field research included physical monitoring and was performed on a set of classrooms of three public-school buildings located in the state of Sao Paulo, Brazil (Figure 4.1). The schools were selected from a database of 130 public-school buildings built in the state of Sao Paulo in the last fifteen years. All the schools in this database have a standardized design, with classrooms of same floor area and window design. Thus, the selection of schools for this study was based on their location and willingness to participate in this research, in order to enable the data collection. School A is an elementary school (ages 6-15) built in 2015 and located in the city of Campinas. Schools B and C are located in the city of Sao Paulo, the first is an elementary school (ages 6-11) built in 2014 and the latter is a high school (ages 15-18) built in 2012. Both cities are characterized by a humid subtropical climate – Cfa (Köppen climatic classification).

Figure 4.1 – Monitored classrooms

4.2.1 Field research

The physical monitoring was conducted during four rounds in each classroom at two-month intervals within the range of one year (from August 2021 to August 2022), in order to cover all seasons of the year.

Indoor environmental variables were monitored in a 10-minute time-step by dataloggers placed inside a typical classroom of each selected school. The dataloggers, Testo 175-T2 with hot sphere probe, used to monitor air temperature (T_{in}: range -35 °C to 55 °C ± 0.5 °C) and globe temperature (T_g: range -25 °C to 80 °C ± 0.2 °C), and Testo 160 IAQ, used to monitor relative humidity (RH: range 0 to 100% ±2%) and CO_2 concentration (range 0 to 5000 ppm ± 100 ppm + 3 % of reading), were placed away from the windows at about 1.1 m above the floor (seated person) according to ISO 7726 (International Organization for Standardization, 1998). The mean radiant temperature (T_{mr}) and the indoor operative temperature (T_{op}) were calculated using the air temperature and the globe temperature measurements. The number of occupants was monitored through the attendance list provided by each classroom's teacher. The manual operation of windows was monitored by using an Onset Hobo State with binary output (closed = 0/ open = 1). Outdoor environmental variables (air temperature – T_{out}, relative humidity – RH_{out}, precipitation, wind speed and wind direction) measurements were acquired from the nearest weather station (3.5 to 8 km distant), to enable comparisons between indoor and outdoor conditions.

During the physical monitoring, restrictive occupancy measures due to the COVID-19 pandemic were observed. Therefore, the monitoring period was divided into three restrictive measures levels (Table 4.1).

Table 4.1 – COVID-19 restrictive measures levels

Restrictive measures	**Levels**		
	High	**Intermediate**	**Low**
Reduced number of occupants	x		
Reduced exposure time	x		
Windows and doors opened during occupancy	x	x	
Mandatory use of masks	x	x	x

Questionnaires (Appendix A) were applied with the classroom teachers in order to describe the students' routine and behaviour related to the environmental comfort and sanitary protocols arising from the pandemic.

4.2.2 Dataset and statistical analysis

The data collected during the physical monitoring phase was merged into a common dataset, by associating window status (open/closed) with time of the day and environmental variables.

As a first step of analysis, the R programming language (R CORE TEAM, 2022) was used to create representative plots of the collected data. The indoor operative temperature acceptability limits (considering 80% of occupant satisfaction) was analysed according to the ASHRAE 55 adaptive model for naturally conditioned spaces (ASHRAE, 2020b), considering an interval between 21 °C and 28 °C. Also, relative humidity levels above 40% and below 60% were considered satisfactory (CIBSE, 2020). The Steady State CO_2 method (ALLEN et al., 2020) (Equation 1) was used to set IAQ thresholds to analyse the monitored indoor CO_2 concentration levels, according to target levels of outdoor air flow rate (air changes per hour – ACH) (Table 4.2). The calculation considered a classroom volume of 142.8 m³, an average number of occupants of 24 persons and a default outdoor CO_2 concentration level of 400 ppm.

Equation 4.1

$$C_{ss} = \frac{CO_{2\,gen.rate} + target\ vol.flow * CO_{2\,out} * 1 * 10^{-6}}{\frac{target\ vol.flow}{1 * 10^{-6}}}$$

Where:

C_{ss} = steady state CO_2 concentration (ppm)

CO_2 gen. rate = CO_2 generation rate (ppm)

target vol. flow = target volumetric flow (ACH)

CO_2 out = outdoor CO_2 concentration (ppm)

Table 4.2 – IAQ thresholds

IAQ level	Predicted outdoor air flow rate (ACH)	Corresponding CO_2 concentration range (ppm)
Ideal	≥ 6	< 823
Excellent	5 – < 6	823 – < 907
Good	4 – < 5	907 – < 1034
Bare minimum	3 – < 4	1034 – < 1245
Low	< 3	≥ 1245

The second step consisted of applying generalized linear models (logistic regression) to assess the influence of the recorded parameters on the window status, considering a binary operation state (all windows closed = 0/ at least one window open = 1). A specific window operation model was created for each school classroom, in order to compare the window operation drivers between them. Indoor operative temperature, relative humidity and CO_2

concentration were included as predictors, since they were pointed out as window operation triggers in previous studies (BELAFI et al., 2018; HERACLEOUS; MICHAEL, 2019; KORSAVI; JONES; FUERTES, 2022b; STAZI; NASPI; D'ORAZIO, 2017a). A categorical variable related to the COVID-19 restrictive measures levels (Table 4.1) was also included as a predictor, in order to analyse the impact of the protocols on the window operation behaviour. Reciprocal transformation was applied to the CO_2 concentration data in order to reduce skewness. The continuous variables were normalized and the imbalanced data was treated by using the random walk over-sampling approach, an oversampling technique that generates synthetic instances so that mean and deviation of numerical variables remain close to the original ones.

Goodness-of-fit (GOF) estimators (deviance, chi-square probability, area under the ROC curve – AUC) and R2 statistics (McFadden's and Nagelkerke's) were employed to evaluate the level of statistical significance of each parameter (at .05 significance level) and the strength of the correlations, respectively. The statistical analyses were carried out in software R version 4.2.2 (R CORE TEAM, 2022).

4.3 Results and Discussion

4.3.1 Dataset and questionnaire analysis

The three monitored school classrooms showed similar environmental conditions (Table 4.3), meeting the required values for indoor operative temperature (according to the ASHRAE 55 adaptive model) and CO_2 concentration (according to the Steady State CO_2 method), on average, 69% and 92.7% of the time, respectively.

Table 4.3 – Summary of recorded parameters during the occupied period.

Variable	School A (n = 1170)			School B (n = 1489)			School C (n = 1142)		
	Mean	SD	Range	Mean	SD	Range	Mean	SD	Range
T_{op} (°C)	24.5	4.1	14.1 – 32.1	23.7	3.4	16.4 – 31.1	24.0	2.4	16.3 – 29.1
T_{out} (°C)	23.0	5.9	6.8 – 33.0	22.2	5.0	10.9 – 33.4	25.2	4.9	10.4 – 35.6
CO_2 (ppm)	540	107	359 – 1162	595	112	362 – 975	676	186	333 – 1682
RH (%)	53.1	10.0	27.0 – 74.0	62.1	11.1	30.0 – 80.3	63.6	8.8	30.0 – 87.0
RH_{out} (%)	59.1	16.7	26.0 – 89.0	73.1	20.7	22.9 – 99.9	61.8	18.4	16.0 – 96.0

The indoor CO_2 concentration (Figure 4.2) was ideal (below 823 ppm) in 97.5%, 95.8% and 83.7% of the time in schools A, B and C, respectively, suggesting that the air change rate was adequate in the measured classrooms (above 6 ACH). Yet, there were few outliers in school C (0.02%) above 1245 ppm, which represents poor IAQ conditions (less than 3 ACH). Indeed, school C presented higher CO_2 concentration during all COVID-19 restrictive levels (Figure 4.3).

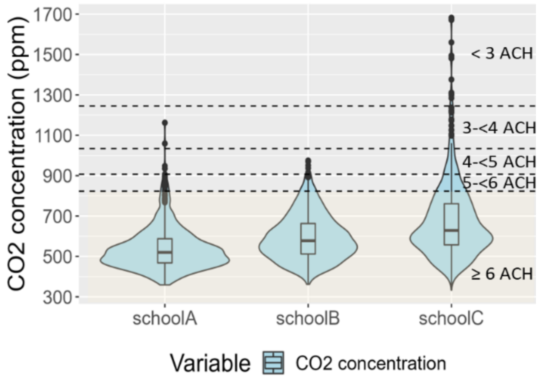

Figure 4.2 – Indoor CO_2 concentration during occupied period.

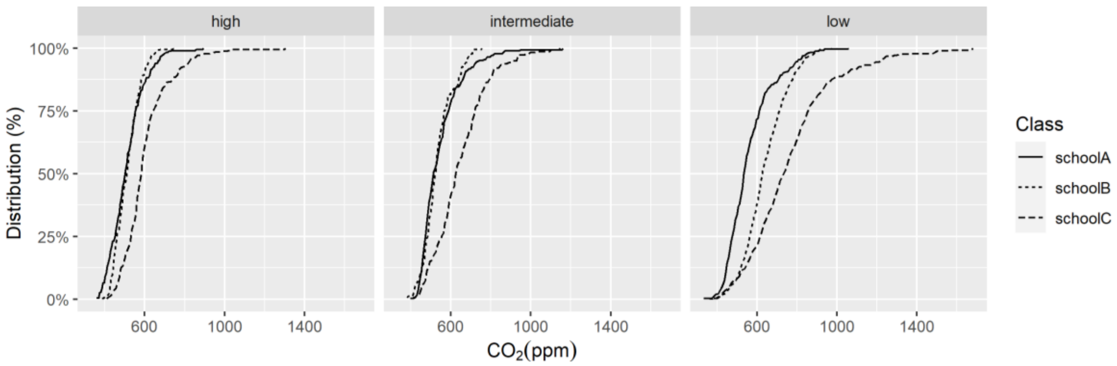

Figure 4.3 – Cumulative indoor CO_2 concentration during occupied period.

The indoor operative temperature interquartile range (Figure 4.4) was within the comfort zone limits for all schools, as the classrooms thermal conditions were adequate on 59%, 61.8% and 87.6% of the time in schools A, B and C, respectively. However, classrooms from schools A and B presented cold discomfort hours 20.1% and 25.2% of the time and hot discomfort hours 20.9% and 13% of the time, respectively. School C, despite having higher values of CO_2 concentration (which indicates lower values of ACH), presented better thermal conditions than the formers, especially during the period with high restrictive measures regarding the COVID-19 pandemic (Figure 4.5).

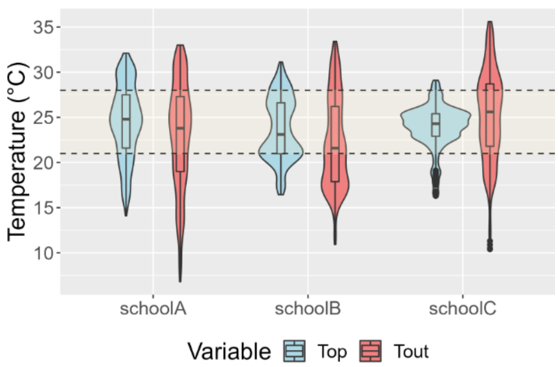

Figure 4.4 – Indoor operative temperature and outdoor air temperature during occupied period.

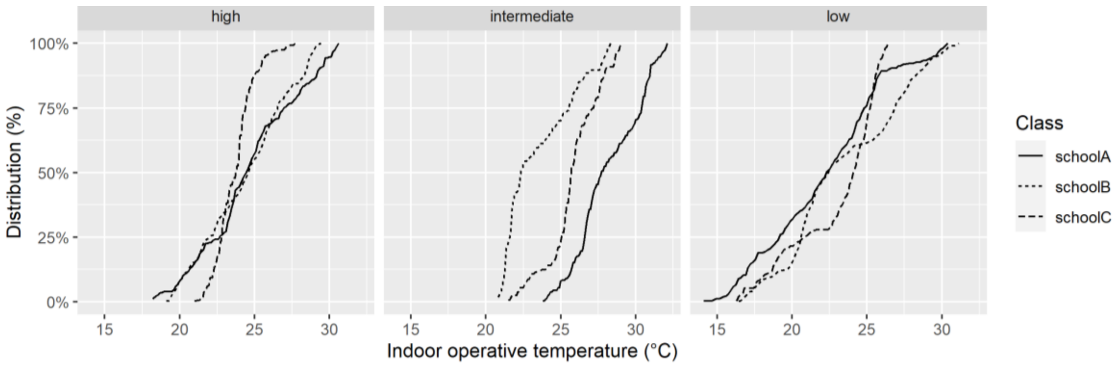

Figure 4.5 – Cumulative indoor operative temperature during occupied period.

The indoor relative humidity (Figure 4.6) was satisfactory 63.4%, 29.3% and 28.2% of the time in schools A, B and C, respectively. Schools B and C presented high humidity levels most of the time.

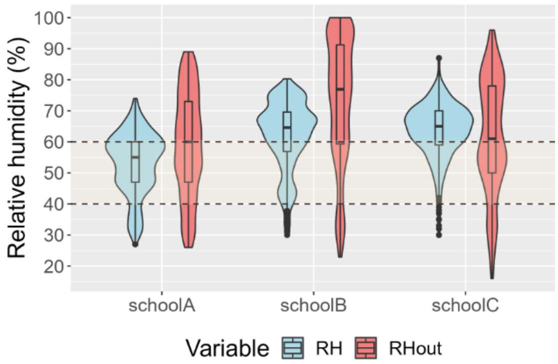

Figure 4.6 - Indoor and outdoor relative humidity during occupied period.

Figure 4.7 shows the frequencies of each window status (open/closed) during school days (excluding weekends and holidays), presented according to the levels of COVID-19 restrictive measures. The windows remained open in 71%, 98% and 76% of the time during the occupied periods in schools A, B and C, respectively. In schools A and C the window status during occupied periods varied between the restriction levels (especially between the high and intermediate levels), while in school B the windows remained open during most of the occupied period, for all restriction levels. A remarkable difference from school B, acknowledged through the questionnaires' responses, consists in the fact that only teachers and staff were allowed to operate the windows, whereas in schools A and C the students were also allowed to operate them. In school C the 'closed' status was more frequent in the higher restriction level, which could be associated to the lower indoor operative temperatures (Figure 4.3) and a possible breach of protocol by the students, which were the main active occupants in terms of window operation.

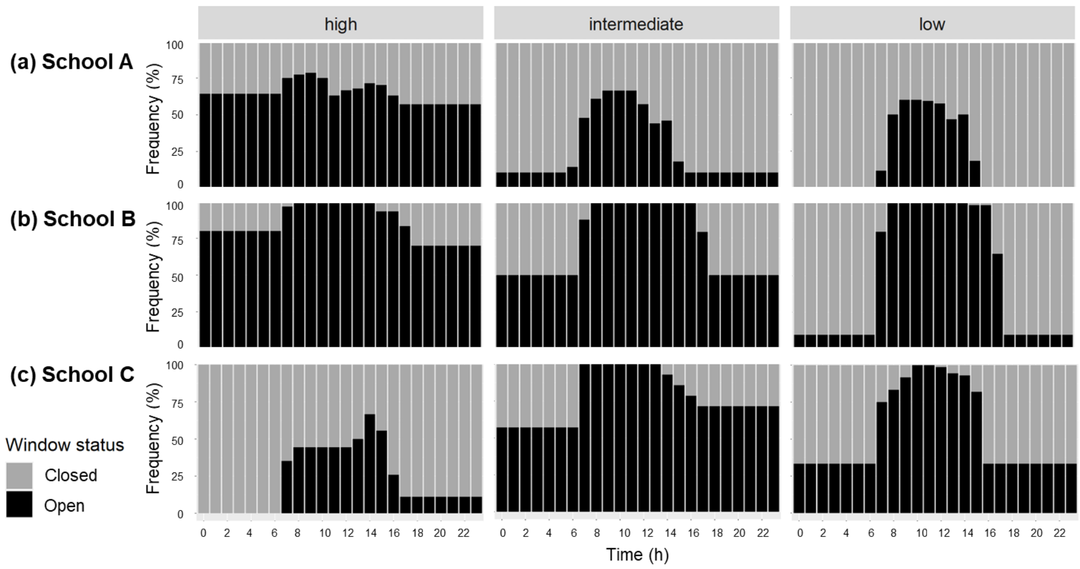

Figure 4.7 – Window status during school days and COVID-19 restrictive measures levels.

Additional analysis of the data revealed that differences in seasonal behaviour were more evident in school C, in which the highest frequency of ‘open’ status coincided with the hottest season of the year (‘intermediate’ restriction level) regardless of the established protocols. In opposition, the COVID-19 restrictive measures were strictly followed mainly by school B, regardless of the weather conditions. A higher number of observations of window ‘open’ status was observed as the COVID-19 restrictive measures were reduced. Windows remained closed for longer periods when the outdoor air temperature was lower. Indeed, the cold season coincided with the period with fewer restrictive measures.

4.3.2 Window status modelling results

Table 4.4 reports the outcomes from the generalized linear model of each school. The models were selected according to the lowest Akaike information criterion (AIC) value. The outcomes suggest that window status (open/closed) is related to the indoor environmental variables and is also highly influenced by the COVID-19 restrictive measures, however some drivers varied between schools. In schools A (model X^2 (18) = 443, $p < .001$) and C (model X^2 (16) = 821, $p < .001$) all single predictor variables included in the model were significant (p-value $< .05$), while in school B (model X^2 (19) = 1270, $p < .001$) the categorical variable COVID-19 restrictions intermediate level was not significant.

The area under ROC curve (AUC), used as goodness-of-fit (GOF) estimator, and R^2 statistics are provided in Table 4.5. Predictions of window status are significant in all models. Yet, GOF estimators and R^2 statistics for school C are of better statistical quality.

Table 4.4 – Regression parameters for logistic models.

Model	School A			School B			School C		
Correlations	**Estimate**	**SD**	**p-value**	**Estimate**	**SD**	**p-value**	**Estimate**	**SD**	**p-value**
Intercept	0.94	0.21	<.001*	4.85	0.95	<.001*	-1.00	0.12	<.001*
COVID-19 restrictions	-2.43/	0.64/	<.001*/	10.67/ -	6.10/	.080/	6.71/ 2.59	0.86/	<.001*/
(int./ low)	-0.89	0.25	<.001*	4.33	0.96	<.001*		0.23	<.001*
RH	-2.06	0.38	<.001*	2.68	1.09	.014*	-0.64	0.24	.008*
T_{op}	-4.60	0.63	<.001*	-0.49	0.07	<.001*	-0.63	0.15	<.001*
CO_2	1.44	0.23	<.001*	5.06	1.07	<.001*	0.47	0.12	<.001*
COVID-19 restrictions	3.41/ 2.86	0.56/	<.001*/	-26.70/ -	13.26/	.043*/	2.74/	0.52/	<.001*/
(int./ low):RH		0.41	<.001*	3.01	1.10	.006*	-0.36	0.33	.274
COVID-19 restrictions	5.57/ 5.74	0.78/	<.001*/	NI	NI	NI	NI	NI	NI
(int./ low):T_{op}		0.64	<.001*						
COVID-19 restrictions	-1.21/	0.31/	<.001*/	-17.18/ -	6.75/	.010*/	NI	NI	NI
(int./ low):CO_2	-2.50	0.27	<.001*	6.68	1.08	<.001*			
RH:T_{op}	-0.53	0.14	<.001*	-6.89	2.07	<.001*	-4.55	0.61	<.001*
RH:CO_2	-1.49	0.29	<.001*	5.00	1.33	<.001*	-2.16	0.35	<.001*
T_{op}:CO_2	NI	NI	NI	7.96	1.04	<.001*	NI	NI	NI
COVID-19 restrictions	NI	NI	NI	5.67/ 4.93	14.93/	.704/	3.73/ 3.84	0.65/	<.001*/
(int./ low):RH: T_{op}					2.08	.018*		0.65	<.001*
COVID-19 restrictions	1.47/ 2.49	0.41/	<.001*/	6.17/	11.78/	.600/	1.40/ 2.11	0.50/	<.001*/
(int./ low):RH:CO_2		0.35	<.001*	-3.49	1.35	.009*		0.37	.005*
COVID-19 restrictions	NI	NI	NI	-5.52/	7.10/	.437/	NI	NI	NI
(int./ low):T_{op}:CO_2				-7.59	1.05	<.001*			
RH:T_{op}:CO_2	1.43	0.31	<.001*	1.58	0.15	<.001*	-3.48	0.67	<.001*
COVID-19 restrictions	-2.01/	0.51/	<.001*/	NI	NI	NI	3.59/ 2.83	0.74/	<.001*/
(int./ low):RH:T_{op} :CO_2	-1.95	0.39	<.001*					0.69	<.001*

Caption: * statistically significant values; NI = interactions not included in the model.

Note: variables have been normalized before the statistical analysis

Table 4.5 – Goodness-of-fit (GOF) estimator and R^2 statistics for each model.

Model	AUC	McFadden's R^2	Nagelkerke's R^2
School A	0.80	0.25	0.39
School B	0.68	0.39	0.56
School C	0.92	0.42	0.59

The indoor operative temperature was a significant predictor for window status in all schools, which is in line with current literature (BELAFI et al., 2018; DUTTON; SHAO, 2010; STAZI; NASPI; D'ORAZIO, 2017a). The correlation between CO_2 concentration and window status was also statistically significant in all schools, which was observed in other studies (DUTTON; SHAO, 2010; HERACLEOUS; MICHAEL, 2019), but differs from the results found by Stazi et al. (2017a).

The interaction between the COVID-19 restrictive measures levels and indoor operative temperature was statistically relevant for school A only (Table 4.4). In fact, as shown in Figure 4.7, windows remained fully open mainly during the 'high' restriction level, and the operation during the other two levels was more affected by indoor operative temperature fluctuations. The interaction between restrictive measures levels and indoor CO_2 concentration was statistically relevant for schools A and B. For these schools, the withdrawal of the requirement to open windows at the 'low' restriction level led to an increase in the 'closed' window status and, consequently, an increase in the CO_2 concentration. School C did not show a behaviour pattern that correlates with the restrictive measures.

The differences among the schools, which was also observed by Belafi et. al. (2018), could be explained by differences in social behaviour, which were corroborated by the answers to the questionnaires given by the teachers. This result reinforces the need to investigate window operation behaviour in each context, considering rules and habits variations.

4.4 Conclusion

The aim of this study was to investigate the window operation behaviour, the indoor thermal conditions, and the perceived IAQ in naturally ventilated classrooms in a humid subtropical climate during the COVID-19 pandemic. Physical monitoring of environmental variables and occupant investigation were conducted in three Brazilian public-school buildings and generalized linear models were developed to assess the influence of the recorded parameters on window status (open/ closed).

Indoor operative temperature, relative humidity and CO_2 concentration were identified as triggers for window operation in all schools. Besides having similar indoor dimensions and layout, the differences between the school classrooms suggest that occupant behaviour is context dependent, being highly influenced by rules and habits, as confirmed by the outcomes from the generalized linear models and the questionnaires responses.

The reduced number of a closed status observed during this study show that the COVID-19 pandemic has influenced occupant behaviour through the protocols established in this period, mainly for schools A and B. Nevertheless, differences in seasonal behaviour were more evident in school C, regardless of the established protocols. These findings provide a first aid regarding the impacts of the pandemic on window operation behaviour of naturally ventilated school classrooms and, consequently, on its indoor environmental conditions.

Previous studies regarding window operation in school buildings were conducted before the COVID-19 pandemic (BELAFI et al., 2018; DUTTON; SHAO, 2010; HERACLEOUS; MICHAEL, 2019; STAZI; NASPI; D’ORAZIO, 2017a) and, thus, were not influenced by restrictive measures. Therefore, our results differ from previous research studies regarding the reduced number of ‘closed’ status observed during occupied periods, which is a consequence of the protocols imposed by the COVID-19 pandemic.

5 Occupant behaviour: generalized linear mixed models

This chapter is the transcription of the following paper:

> **Predictive modelling of multi-domain factors on window, door, and fan status in naturally ventilated school classrooms**
> Authored by Paula Brumer Franceschini, Marcel Schweiker and Leticia Oliveira Neves
> Published in Building and Environment (ISSN: 0360-1323), volume 264, in 2024, and catalogued through the DOI: 10.1016/j.buildenv.2024.111912.

Abstract

Most studies regarding the investigation of occupant behaviour (OB) in school classrooms addressed the environmental influence on window operation solely and were conducted in oceanic climates. This study aimed to identify and quantify the influence of multi-domain factors (including thermal, indoor air quality, contextual and multi-behaviour domains) on window, door, and fan status in naturally ventilated school classrooms in a humid subtropical climate, in order to predict OB. Environmental variables, manual operation of windows, doors and fans, and occupancy rate were monitored and questionnaires were applied in a set of classrooms of three public school buildings in the state of São Paulo, Brazil, during four rounds at two-month intervals, resulting in a comprehensive year-long study. During part of the physical monitoring, restrictive occupancy measures due to the COVID-19 pandemic were observed. Generalized Linear Mixed Models were applied to assess the influence of the recorded parameters on the window, door, and fan status and to generate OB predictive models. Results showed that indoor environmental variables influenced window, door, and fan status in school classrooms, with few exceptions. Yet, the models including school routines, social norms and teachers' behaviour as predictors led to the highest accuracy. This suggests that, while a more complex model with additional predictors can provide more accurate predictions of OB, it also becomes more context-dependent and less generalizable. The trade-off between model complexity and generalizability is an important consideration in this research study, and it

highlights the nuanced relationship between multi-domain factors affecting occupant behaviour in school buildings.

Keywords: occupant behaviour, school building, natural ventilation, multi-domain, field monitoring.

5.1 Introduction

Occupant behaviour (OB) largely impacts a building's performance across various aspects, including indoor conditions, usability, functionality and energy consumption (O'BRIEN; TAHMASEBI, 2023). Occupants interact with buildings' controls and interfaces, in order to adapt the environment to their needs (e.g., window, blinds, lighting and air-conditioning operation) or to adapt themselves to the environment (e.g., clothing adjustment and drinking hot or cold beverages), aiming to maintain their comfort and preferences (DELZENDEH et al., 2017; HONG et al., 2016b). They usually respond in different ways to the built environment, since there are many influential factors, such as external (environmental, time-related, contextual) and internal factors (physiological, psychological, social), to the decision-making process (SCHWEIKER et al., 2018; YAN et al., 2017).

Studying OB in buildings presents challenges due to its inherent complexity and dynamic nature, due to issues related to privacy that hinder data collection, and due to substantial costs associated with obtaining various sensors to monitor OB (DONG et al., 2022). As a result of OB uncertainty and unpredictability, this parameter is often oversimplified in building performance simulation (BPS), potentially contributing to a performance gap between predicted and actual building performance (MAHDAVI et al., 2021; SHI et al., 2019; WANG; HONG; JIA, 2018). Indeed, for a long time in BPS tools, OB representation was limited to occupants' presence in fixed and scheduled patterns, which do not reflect reality (DELZENDEH et al., 2017). In response to these challenges, occupant modelling has garnered attention from researchers and practitioners, driven by the potential to reduce the performance gap, the increasing interest in occupant well-being and the advancements in computational and simulation capabilities (O'BRIEN; TAHMASEBI, 2023).

Over the last decade, more than 500 papers have been published on OB, providing data on occupancy, including occupant presence and movement, as well as occupants' actions, such as window and door operation, blinds or solar shading adjustment, thermostat or air-conditioning setting (DONG et al., 2022). These studies have led to the development of OB models and aimed at predicting and representing human behaviour in BPS, optimizing building design, reducing the performance gap, enhancing comfort, identifying adaptive opportunities, and fostering strategies for healthier indoor spaces (O'BRIEN; TAHMASEBI, 2023). However, despite OB being influenced by many factors simultaneously, most studies in this area consider the influence of environmental factors on OB solely (SCHWEIKER et al., 2020). Schweiker et al. (2020) identified 97 records (64 publications) on behavioural multi-domain studies, most of them applying field studies approaches and being conducted in office and residential settings located in Europe (37 records), Asia (14 records), North America (8 records) and Oceania (2 records). No studies identified in this literature review were undertaken in school buildings and few were conducted in tropical or subtropical climates.

School buildings present unique challenges, distinct from offices, residential buildings, and other educational buildings like universities, since primary and secondary schools are occupied mainly by children, in specific periods of the year and with different daily timetables, more group rules and less freedom of action (BELAFI et al., 2018). We identified six studies in the literature which developed OB predictive models for school buildings, using linear or logistic regression analysis to assess the influence of the predictors on OB (Table 5.1). These studies were conducted mainly in oceanic climate (DUTTON; SHAO, 2010; HEEBØLL; WARGOCKI; TOFTUM, 2018; KORSAVI; JONES; FUERTES, 2022a, 2022b), according to the Köppen classification, and window operation was the most addressed OB. All mentioned studies investigated the physical domain, including thermal and/ or air quality variables as predictors. The contextual domain was represented only by the hour of the day in most of these studies and one study applied a multi-behavioural approach by analysing the blind status as a predictor for light operation (Table 5.1).

Table 5.1 – Predictors investigated in existing occupant behaviour models for school classrooms.

Occupant behaviour	Model	Predictors											
		T_{in}	T_{op}	RH	V	CO_2	P	R_s	A_s	T_{out}	RH_{out}	h	CB
Window operation	Dutton & Shao (2010)	•				•	•	•		•		•	
	Stazi et al. (2017a)	•				•				•		•	
	Belafi et al. (2018)	•				•				•		•	
	Heebøll et al. (2018)	•				•						•	
	Korsavi et al. (2022b)		•	•	•	•				•	•		
Door operation	Heebøll et al. (2018)	•				•						•	
Lights operation	Korsavi et al. (2022a)								•				•
Blinds adjustment	Korsavi et al. (2022a)		•					•	•	•			

Caption: T_{in} = Indoor air temperature (°C); T_{op} = Indoor operative temperature (°C); RH = relative humidity (%); V = wind speed (m/s); CO_2 = CO_2 concentration (ppm); P = vapour pressure (Hpa); R_s = solar radiation (W/m²); A_s = solar altitude (°); T_{out} = outdoor air temperature (°C); RH_{out} = outdoor relative humidity (%); h = Hour of the day (h); CB = closed blinds (%).

The results derived from the OB models identified in Table 5.1 reveal differences in behavioural triggers among school buildings and seasons. For instance, regarding window operation, Belafi et al. (2018) observed that habits and time-dependent actions were the main occupant behaviour drivers in one monitored classroom, whereas indoor and outdoor temperatures were the main drivers in another one – both classrooms from the same elementary school building. Similarly, Stazi et al. (2017) identified indoor and outdoor temperatures, daily routine and habits as primary triggers for window operation, with a weak relationship with CO_2 concentration. In contrast, Dutton and Shao (2010) found a significant correlation between window opening and CO_2 concentration. They also noted differences among seasons, such as indoor air temperature influencing window closing during unheated periods and outdoor temperature influencing window closing during heated periods. Korsavi et al. (2022b) discovered significant statistical differences in the median window opening area (WOA) between seasons, with higher WOA during summer (5 m²) and lower WOA during winter (0.8 m²). Heebøll et al. (2018) noted disparities in window and door operations based on different ventilation systems (mechanical ventilation system, automatic window opening and exhaust fan) in classrooms. Furthermore, Korsavi et al. (2022a) found differences in blind operation between seasons, influenced by contextual, occupant-related and building-related factors, with solar altitude and operative temperature affecting blind operation during non-heating seasons and solar altitude and solar radiation influencing blind operation during heating seasons. In the same research study, solar radiation and blind occlusion were identified as drivers for light operation (KORSAVI; JONES; FUERTES, 2022a).

As identified by Schweiker et al. (2020) and corroborated by the studies presented in Table 1 within the context of school buildings, there is a lack of behavioural multi-domain studies in tropical or subtropical climates. Most school buildings located in these climates are partially or fully naturally ventilated, with manually operable windows, which reinforces the occupant's role over their environment's performance (YAN et al., 2017). For example, in the state of São Paulo, Brazil, all public-school buildings maintained by the Foundation for Education Development (*Fundação para o Desenvolvimento da Educação*, FDE) have manually operable windows to provide natural ventilation, and most of them also have manually operable fans. Natural ventilation influences not only the classroom's thermal performance, but also impacts its indoor air quality (IAQ) (STABILE et al., 2017) and, consequently, on students' health and learning process (PEREIRA et al., 2017). The IAQ became particularly relevant in 2020, during the COVID-19 pandemic, due to its importance in helping prevent airborne virus transmission in indoor environments (FRANCO, 2020), especially in high occupancy environments, such as school buildings (LIPINSKI et al., 2020).

Given this scenario, this study aimed to identify and quantify the influence of multi-domain factors (including thermal, indoor air quality, contextual and multi-behaviour domains) on window, door, and fan status in naturally ventilated school classrooms in a humid subtropical climate, in order to improve the ability to predict occupant behaviour.

5.2 Method

The research method was based on a case study and supported by field research and statistical analysis. The method was developed in four main steps, which are presented in Figure 5.1.

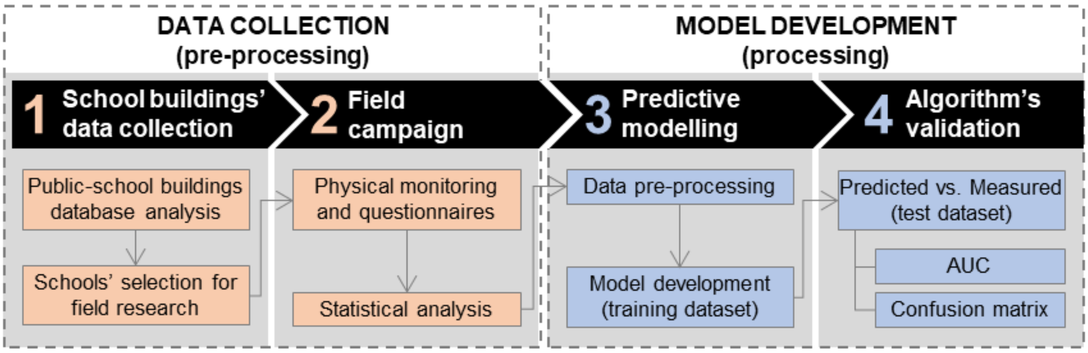

Figure 5.1 – Research framework.

5.2.1 School buildings' data collection

A comprehensive data collection was carried out, encompassing public schools built by the Foundation for Education Development (FDE) over the past fifteen years in the state of São Paulo, Brazil. This dataset[1] included information on 66 school buildings, effectively representing half of the public-school buildings constructed in the state of São Paulo within this time frame.

Envelope design and construction characteristics from the architectural design of the 66 school buildings were collected, organized and classified in five main groups: (i) building general information (Brazilian bioclimatic zone, construction year, built area, number of floors, number of classrooms, azimuth angle of long axis of building, ground floor shape plan, width-to-length ratio); (ii) classrooms characteristics (solar orientation, position in the building, floor-to-ceiling height, floor-to-floor height); (iii) external and internal walls and roof thermal properties (solar absorptance, U-factor, thermal capacity); (iv) classrooms' outdoor façade (glazing U-factor, glazing solar heat gain coefficient, natural ventilation strategy, window sill height, window frame height, percentage of operable window frame, window opening factor, window-to-wall

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[1] The dataset is available at https://doi.org/10.25824/redu/Z4BWFL

ratio); (v) shading device (type, material, perforation, horizontal distance between shading device and window, vertical shadow angle, horizontal shadow angle).

The number of classrooms from the schools' dataset varied between 6 and 27 in each school (mean = 13), and the number of floors varied between 2 and 5 (mean = 4). The classrooms' architectural design is standardized, with dimensions of 6.9 m x 6.9 m (floor area = 47.6 m²) and a floor-to-ceiling height varying between 2.75 m to 3.19 m (mean = 2.96 m). Most of the classrooms have large operable windows in the main façade and operable windows facing the corridor (except for two schools). The façade windows have a window-to-wall ratio (WWR) varying between 8% and 73% (mean = 67, standard deviation = 9) and an operable window frame (OWF) varying between 16% and 100% (mean = 63, standard deviation = 11), while the corridor windows have a WWR varying between 9% and 70% (mean = 22, standard deviation = 8) and an OWF varying between 25% and 100% (mean = 63, standard deviation = 25). The categorical variables statistical analysis is presented in Table 5.2.

Table 5.2 – Categorical variables analysis, based on the dataset of 66 FDE schools.

Variable	**Categories**	**Frequency**	**Selected school building**
Ground shape plan	Rectangular	91%	Schools A, B and C
	U-shape	5%	-
	H-shape	2%	-
	O-shape	2%	-
Classrooms solar orientation	N-S	35%	Schools A and C
	NW-SE	27%	-
	NE-SW	20%	-
	E-W	18%	School B
Classrooms' position in the building	Middle floor	38%	School C
	Middle and top floors	23%	School B
	Top floor	21%	School A
	Bottom and top floors	6%	-
	Bottom, middle, and top floors	2%	-
Natural ventilation strategy	Single sided ventilation	85%	Schools B and C
	Cross ventilation	15%	School A

Three schools were thoughtfully chosen from the dataset for the monitoring phase. The selection criteria ensured that the chosen school buildings were comparable to one another and representative of the broader dataset (Table 2). Furthermore, the school location and the willingness to participate in the research study were also considered.

5.2.2 Field campaign

The physical monitoring was conducted in a set of classrooms within three public school buildings chosen from the dataset, which are situated in the cities of Campinas and São Paulo (Table 5.3). These cities share a common humid subtropical climate (Cfa), as per the Köppen classification, characterized by hot summers and mild winters. The physical monitoring spanned four rounds, each taking place at two-month intervals, resulting in a comprehensive year-long study period from August 2021 to August 2022 (Table 5.4). Although the measurement periods are not the same for all schools, the total measured time frame ensured coverage of all seasons throughout the year.

Table 5.3 – Monitored school buildings.

Variable		School A	School B	School C
School general information	Location	Campinas, Brazil	São Paulo, Brazil	São Paulo, Brazil
	Construction year	2015	2014	2012
	Built area (m²)	3201	4945	2742
	Number of classrooms	10	27	12
	Students' age (years old)	6 – 15	6 – 11	15 – 18
Monitored classroom	Students' age (years old)	10 – 15	9 – 11	15 – 18
	Position in the building	Top floor	Middle floor and top floor	Middle floor
	Natural ventilation strategy	Cross ventilation	Single-sided ventilation	Single-sided ventilation
	Solar orientation	North	East	South

Table 5.4 – Monitoring period.

	Aug/21	**Sep/21**	**Oct/21**	**Nov/21**	**Dec/21**	**Jan/22**	**Feb/22**	**Mar/22**	**Apr/22**	**May/22**	**Jun/22**	**Jul/22**	**Aug/22**
School A	•				SB*	SB*	•			•		WB*	
School B		•		•	SB*	SB*		•			•	WB*	
School C			•	•	SB*	SB*			•			WB*	•

*SB = Summer break; WB = Winter break.

The school classrooms are naturally ventilated, with manually operable windows and fans. The fans, windows and door locations in each classroom are presented in the classrooms' perspectives (Figures 5.2 to 5.4), with the operable frames from the windows marked in red. The selection of the monitored classrooms considered the occupancy (i.e., classrooms occupied during a large period of the day), the teachers' availability to participate in the research and the students' capacity to complete questionnaires, taking into account their reading and interpretation skills. The selected classrooms were occupied during the morning and afternoon with one short break in each period plus a lunch break. The classrooms from schools A and B were occupied by one group during the morning and another group during the afternoon. The classrooms from School C were occupied by multiple groups during both periods.

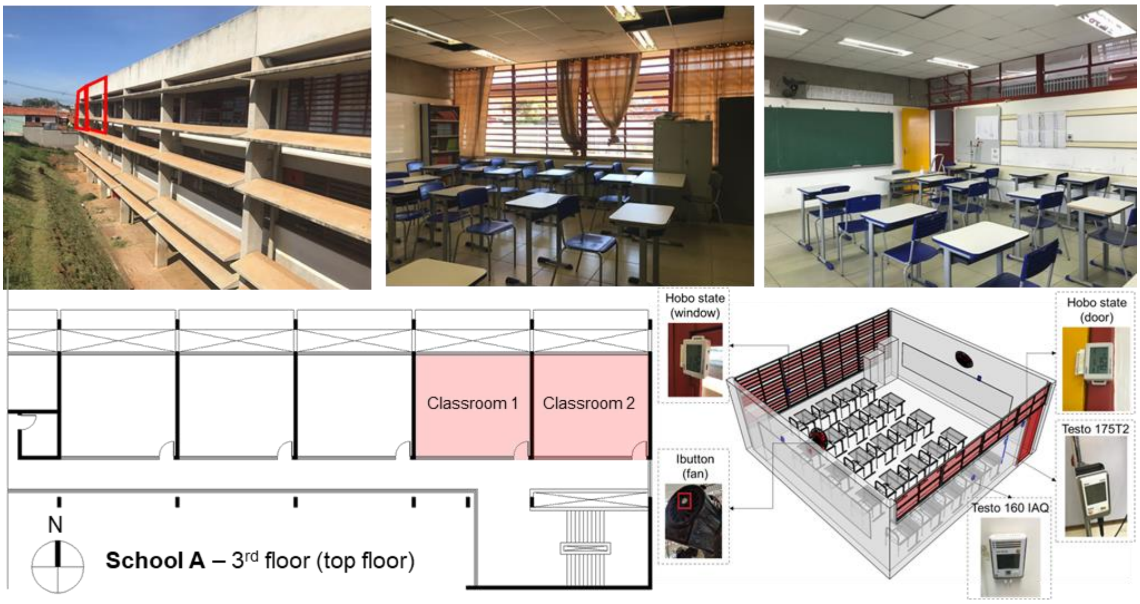


Figure 5.2 – Pictures of the school and the monitored classroom, floor plan and classroom perspective (School A).

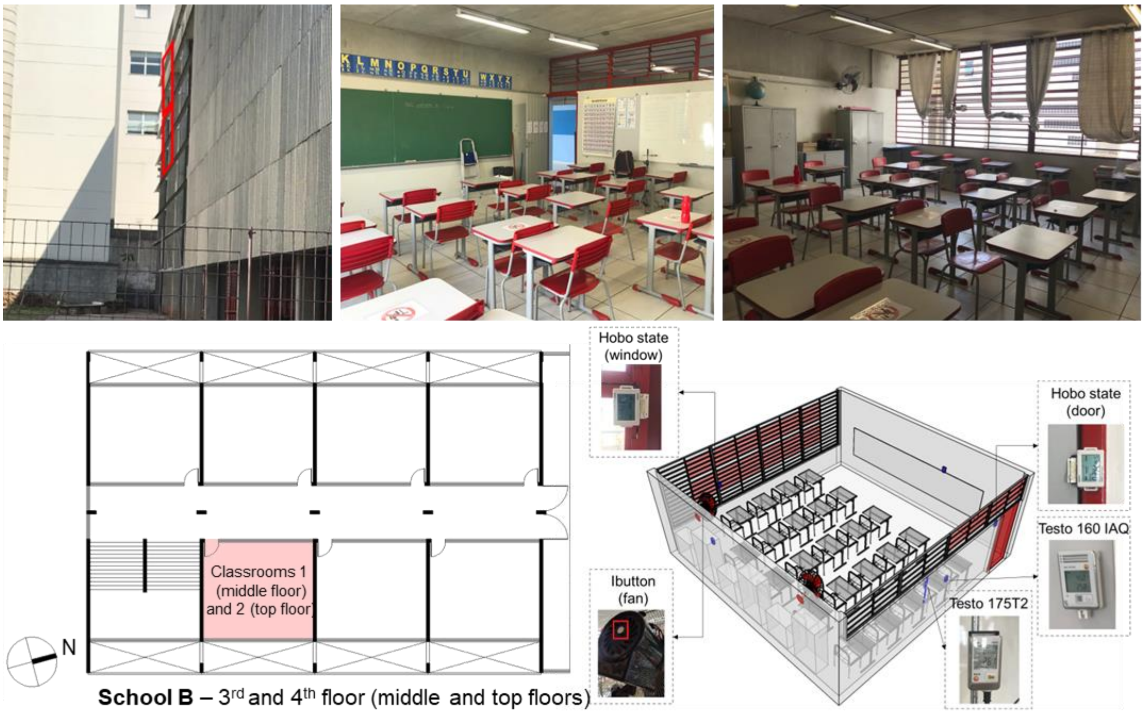


Figure 5.3 – Pictures of the school and the monitored classroom, floor plan and classroom perspective (School B).

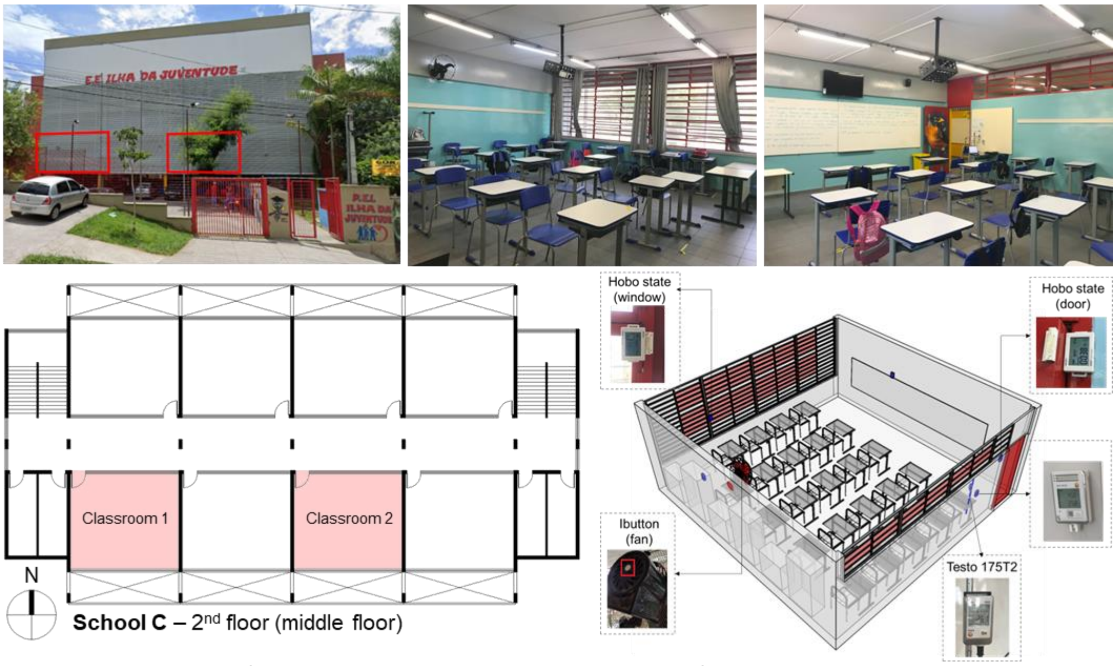


Figure 5.4 – Pictures of the school and the monitored classroom, floor plan and classroom perspective (School C).

Indoor environmental variables (air temperature, globe temperature, relative humidity, CO_2 concentration) were monitored in a 10-minute time-step by dataloggers placed inside the selected classrooms. The dataloggers were placed away from the windows at a height of 1.1 meters. The status of windows and doors (open/ closed) and fans (on/ off) was also monitored by using binary state sensors. Since there is more than one operable window in each classroom, a binary approach was adopted, marking 0 when all windows were closed and 1 when at least one window was open. The number of occupants was monitored through the attendance list provided by each classroom's teacher. Outdoor environmental variables measurements (air temperature, relative humidity, precipitation, wind speed and wind direction) were acquired from the nearest weather station (3.5 to 8 km distant), to enable comparisons between indoor and outdoor conditions.

During part of the physical monitoring – from August 2021 to February 2022 – restrictive occupancy measures due to the COVID-19 pandemic were observed, such as a reduced number of occupants, reduced occupancy period, mandatory use of masks and the necessity to keep windows and doors open and the fan off during occupancy (Table 5.5). As a result, a binary variable was incorporated into the data collection, distinguishing between periods with and without COVID-19 restrictive measures. The schools in Brazil reopened after the COVID-19 vaccines were made available for adults (starting in January 2021) and for children above 12 years old (starting in June 2021). The vaccination in children below 12 years old began in January 2022, coinciding with the removal of COVID-19 restrictive measures in schools.

Table 5.5 – COVID-19 restrictive measures.

	Number of occupants		Occupancy period	
	With COVID-19 restrictions (08/21 to 02/22)	**Without COVID-19 restrictions (03/22 to 08/22)**	**With COVID-19 restrictions - reduced period - (08/21 to 02/22)**	**Without COVID-19 restrictions - regular period - (03/22 to 08/22)**
School A	3 – 28	26 – 31	7 h – 9:20h/ 13 h – 15:20 h	7 h – 11:20 h/ 12:20 h – 16 h
School B	7 – 28	24 – 36	7 h – 11 h/ 13:30h – 17:30 h	7 h – 11:50 h/ 13h – 17:50 h
School C	14 – 31	11 – 36	7:00 h – 11:30 h/ 13:00h – 16:30 h*	

*School C maintained the regular period also during the period with COVID-19 restrictions.

Questionnaires were applied to students to analyse occupant satisfaction levels related to environmental comfort, clothing and building design (Appendix B). In addition, questionnaires were applied to teachers in order to describe the students' routine and behaviour related to the environmental comfort and sanitary protocols arising from the pandemic (Appendix A). A total of 113 students, aged between 9 and 18 years old (comprising 23% from School A, 73% from School B, and 4% from School C), participated in the questionnaire surveys. Responses were also obtained from three teachers, with one teacher representing each of the three schools in the study.

5.2.3 Predictive modelling

The questions raised through the analysis of the collected data provided support for the development of predictive models. The models were developed using the R programming language, version 4.3.1 (R Core Team, 2023). Data pre-processing included the following:

- CO_2 concentration data was subjected to a reciprocal transformation to reduce skewness (see Appendix C in supplementary material).
- Continuous variables were normalized.
- The dataset was randomly split into 80% (training dataset) and 20% (test dataset) in order to perform cross-validation of the developed models, by assessing their accuracy across different samples (FIELD; MILES; FIELD, 2012).
- The imbalanced data regarding window, door, and fan status was balanced by using the random walk over-sampling approach. This technique generates synthetic instances, ensuring that the mean and standard deviation of numerical variables remain close to the original data (MARKOVIC, 2020).

In order to assess the behavioural diversity and considering the monitored schools as a variable of a random nature, the logistic regression was applied in the training dataset by using the Generalized Linear Mixed Model function. Therefore, occupant behaviour prediction was assessed through the investigation of the influence of the recorded parameters on the window, door, and fan status, considering a binary operation state (closed/ off = 0 or open/ on = 1)

The models were developed based on four hypotheses, which were formulated in light of previous research findings (Table 5.6). The variables included as predictors represented the indoor environmental variables (indoor operative temperature, relative humidity and CO_2 concentration), the school routine (weekday, hours of the day and occupancy period), teacher behaviour, window, door, and fan status and the restrictions imposed due to the COVID-19 pandemic (occupancy rate and periods with and without COVID-19 restrictions). One model was developed for each system (window, door, and fan) and each hypothesis, resulting in a total of 12 models (4 models per system). Also, a fifth model was developed for each system (windows, door and fans) including all the significant predictors from models 1 to 4, resulting in a total of 15 models (5 models per system) (Table 5.6).

Table 5.6 – Proposed models and predictors.

Model	Hypothesis	Research context	Domains	Predictors
1	Indoor environmental conditions influence window, door, and fan status in school classrooms.	Previous studies investigated indoor environmental variables as predictors for window and door status (Table 1). This hypothesis aims to confirm or refute the published results, with a focus on our case study.	Physical (thermal and IAQ)	Indoor operative temperature, relative humidity, CO_2 concentration
2	The school routine and the teacher's behaviour had a greater influence than the indoor thermal conditions on window, door, and fan status in school classrooms.	During the monitoring period, we identified differences in window, door, and fan status related to school routine and teachers' behaviour.	Physical (thermal and IAQ) and contextual	Model 1 + weekday, hour of the day, occupancy period, teacher
3	In school classrooms, window, door, and fan status are predictor variables for each other.	The data collected during the monitoring period suggests that windows, doors, and fans status impact each other.	Physical (thermal and IAQ) and multi-behavioural	Model 1 + window, door, and/or fan status
4	The restrictions imposed by the pandemic (social norms) had a greater influence than the indoor thermal conditions on window, door, and fan status in school classrooms.	The teachers demonstrated awareness of and compliance with COVID-19 pandemic restrictions.	Physical (thermal and IAQ) and contextual	Model 1 + occupancy rate + COVID-19 restrictions
5	Indoor environmental conditions, school routine and the restrictions imposed by the pandemic (multi-domain factors) are predictors of window, door, and fan status in school classrooms.	Creating a general model based on merging the previous models.	Physical (thermal and IAQ), contextual and multi-behavioural	Models 1 + 2 + 3 + 4

A base model included all the predictors listed in Table 5.6. Subsequently, the dredge function was applied to categorize the models based on Akaike's information criterion (AIC), selecting the models with smaller AIC values, as they represent a better fit of the data. The selected models were analysed considering the predictors' standardized coefficients, which indicate their individual contribution to the model (i.e., to what degree each predictor affects the outcome and if the relationship is positive or negative); their confidence intervals, which indicate to what extent these values would vary across different samples; and their p-values, which indicate whether the predictor is making a significant contribution to the model or not, considering a .05 significance level (FIELD; MILES; FIELD, 2012). As the standardized coefficients were all measured in standard deviation units and, thus, not dependent on the units of measurement of the variables, they are directly comparable, providing better insight into the importance, also called effect size, of a predictor in the model (FIELD; MILES; FIELD, 2012) (see Appendix D in supplementary material). The Akaike's information criterion (AIC) was employed to compare the models, considering a difference in AIC, Δ_{AIC}, greater than 2 as a good improvement of the model.

5.2.4 Algorithm's validation

The validation procedure for each model was conducted using the test dataset to generate confusion matrices, showing the relationship between predicted and actual results (GERALDI, 2021; MO et al., 2019). The confusion matrix consists of true positive (TP), true negative (TN), false positive (FP) and false negative (FN) values. These values were used to calculate the model's prediction accuracy, which indicates the proportion of correct predictions and is defined as (TP + TN)/ (TP + FP + TN + FN); the model's precision (or positive predictive value), which is related to the positively predicted outcomes and all the positively predicted results and is calculated by TP / (TP + FP); the model's recall (or sensitivity), which is the proportion of predicted true positive results and all true positive results and is defined as TP / (TP + FN); and the model's F1-score, which is the harmonic mean between the precision and the recall and makes the models more comparable, being defined as 2TP / (2TP + FP + TN + FN) (Li et al., 2019; Mo et al., 2019). The Area Under the Receiver Operating Characteristic curve (AUROC Curve, or AUC) was also calculated, which graphically represents the TP and the FP rates at various threshold settings obtained from the predictions on real data (BELAFI et al., 2018). Its index ranges between 0.5 (no correlation at all) and 1 (exact predictions), but values above 0.7 are generally considered satisfactory (HALDI; ROBINSON, 2009).

5.3 Results

5.3.1 Descriptive statistics of environmental conditions and operational states

Table 5.7 shows descriptive statistics of the indoor and outdoor variables during the whole occupied period, when the windows and door were closed and the fan was off (window, door, and fan (WDF) status = 0) and when the windows and door were open and the fan was on (WDF status = 1). The indoor conditions during other scenarios are presented in the supplementary material (Appendix E). The indoor conditions were satisfactory most of the time in all classrooms, meeting the required values for indoor operative temperature according to the ASHRAE 55 adaptive thermal comfort model (80% acceptability) (ASHRAE, 2020b) on average 69% of the time. The adaptive comfort temperature range varied depending on the month and school location (São Paulo or Campinas). The lower temperature range considered in this study was between 19.8 ºC and 26.8 °C and the upper range was between 21.8º C and 28.8 ºC. The indoor CO_2 concentration met ideal levels on average 92.7% of the time, according to the limits suggested by Allen et al. (2020). Periods of WDF status = 1 had in comparison to periods with WDF status = 0 on average higher outdoor and indoor operative temperatures, indoor relative humidity and CO_2 concentration.

Table 5.7 – Descriptive statistics of indoor and outdoor conditions during the occupied period.

Variable	**All occupied period (n = 3800)**			**WDF* status = 0 (n = 68)**			**WDF status = 1 (n = 503)**		
	Mean	**SD**	**Range**	**Mean**	**SD**	**Range**	**Mean**	**SD**	**Range**
T_{op} (°C)	24.0	3.4	14.1 – 32.1	22.9	4.5	15.8 – 31.7	23.8	4.3	16.4 – 32.1
T_{out} (°C)	23.4	5.4	6.8 – 35.6	21.2	6.1	8.5 – 31.8	24.4	5.3	10.4 – 35.5
RH (%)	59.8	11.1	27.0 – 87.0	57.6	7.9	32.0 – 72.0	62.1	9.0	37.0 – 87.0
RH_{out} (%)	65.4	19.9	16.0 – 100.0	64.5	15.6	32.0 – 99.0	63.4	15.9	20.3 – 99.9
CO_2 (ppm)	602.3	147.1	333.0 – 1682.0	580.3	127.4	393.0 – 948.0	633.7	156.8	333 – 1682

*WDF = Window, door, and fan

Table 5.8 shows the frequency of window, door, and fan status during the occupied period. The most prevalent scenario observed was both the windows and door open while the fan remained off. In contrast, the less common situation involved both the windows and door closed, with the fan turned on. In addition, some associations were observed. For instance, the fan was on predominantly when the window was open, probably due to higher outdoor temperatures (Figure D1 in Appendix E). In this context, the temperature could be a trigger for occupants to use all available resources (i.e., window and fan) aiming to reduce thermal discomfort due to heat. These results suggest that one status can influence the others and these correlations should be further investigated.

Table 5.8 – Window, door, and fan (WDF) status frequency.

		Fan			
		Off (0)	**On (1)**		
Window	**Closed (0)**	68 (2%)	27 (1%)	**Closed (0)**	**Door**
		466 (12%)	80 (2%)	**Open (1)**	
	Open (1)	287 (8%)	171 (5%)	**Closed (0)**	
		2198 (58%)	503 (13%)	**Open (1)**	

Figure 5.5 illustrates the frequency of open/on or closed/off status for windows, doors, and fans, according to each teacher. Results show different behaviours, especially for windows and fans. The difference was less evident for the door operation since the door remained open most of the time during all lessons. This prompts the question of the extent to which teachers exert influence over the status of windows, doors and fans, and whether this influence holds greater significance compared to indoor environmental conditions.

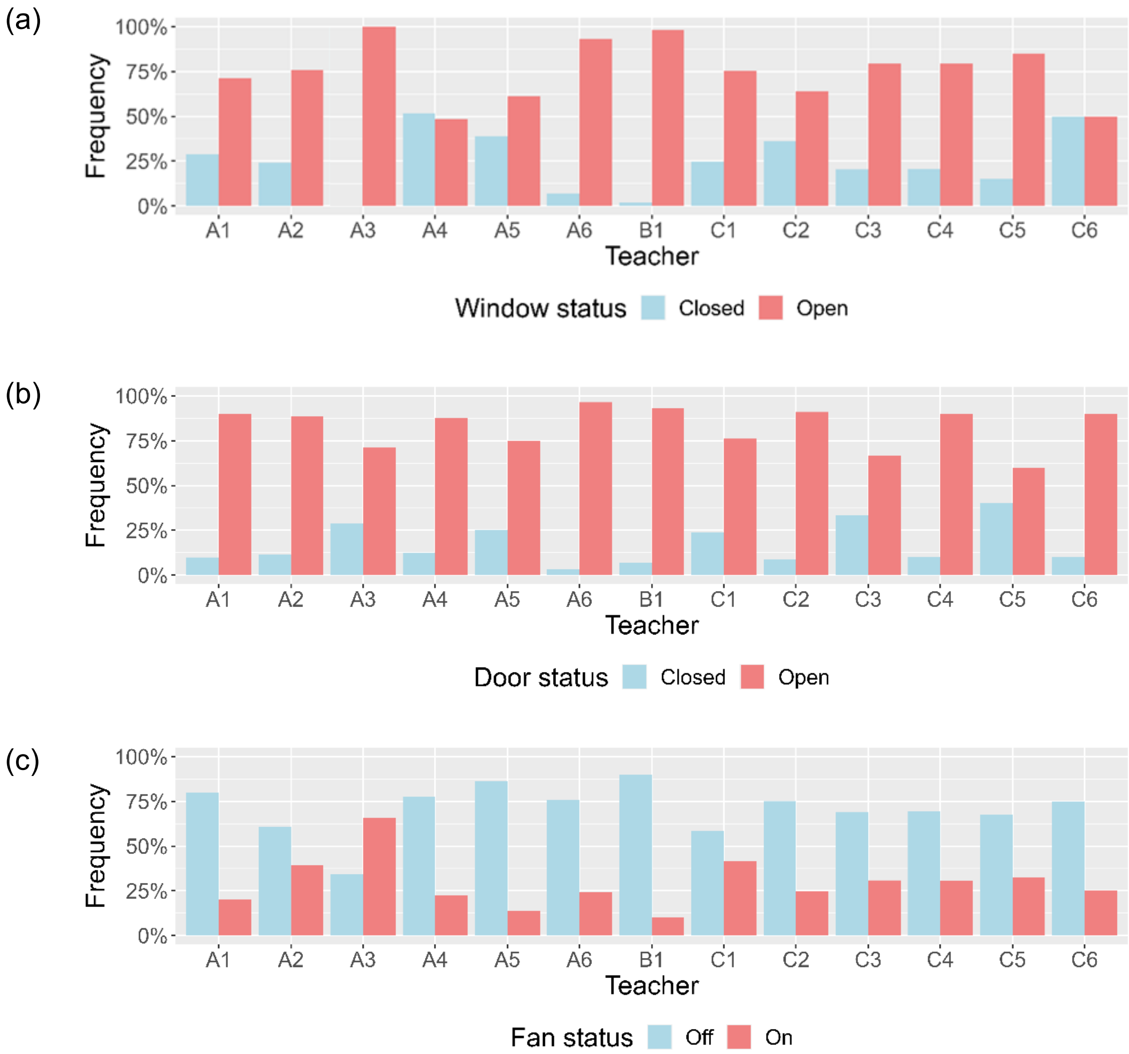


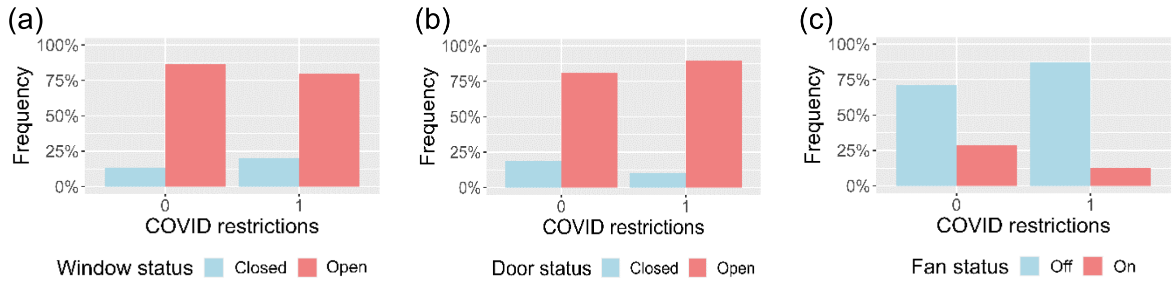
Figure 5.5 – Teachers and (a) window, (b) door, and (c) fan status during the occupied period.

The answers to the questionnaires showed that 46% of the participants were satisfied with the classroom thermal conditions, with a mean indoor operative temperature of 26.2 ºC, while 42% reported feeling hot, with a mean indoor operative temperature of 27.8 ºC, and 12% reported feeling cold, with a mean indoor operative temperature of 23.6 ºC.

When questioned about window operation, 80% of the students declared that they did not open or close the window during the day that the questionnaire was applied. Those who did operate the windows cited indoor thermal conditions as their primary motivation, such as ventilating the classroom or addressing discomfort due to heat. The hour of the day they declared as most usual to open the windows was upon arriving in the classroom. In addition, the students that operated the windows on that day were predominantly from schools A and C, which is explained by the teachers' responses to the questionnaires: in school B, only teachers and staff were allowed to operate the windows, whereas in schools A and C – where classrooms are occupied by older students than the monitored classrooms from school B – the students were also allowed to operate them.

A small percentage of students (2%) reported operating the fans during the days that the questionnaires were applied, and their main motivation was also the indoor thermal conditions. All students who reported operating the fans were from schools A and C, which strengthens the notion that teacher behaviour or students' age may influence occupant behaviour in this regard. In the case of the fan operation, the accessibility could also be an obstacle for the students, since they could not reach the switches without the use of a ladder or chair. All teachers reported that they often turn on the fans upon students' request, as well as other times of the day, based on their own decisions. This behaviour contrasts with students' approach to the windows, as they can reach and operate the windows themselves. This could explain the limited use of fans, as shown in Figure 5c. These findings reinforce the necessity of exploring predictors beyond environmental variables for determining window, door, and fan status, such as teachers' behaviour and school routine.

All teachers reported being conscious of and adhering to the COVID-19 pandemic restrictions during the initial phase of the monitoring period. This observation is partly supported by the collected data (Figure 5.6), particularly concerning door and fan status. During the occupied period with restrictions, the door was open 90% of the occupied time and the fan was off 87% of the time, suggesting that most of the time the guidelines were followed in these classrooms, whereas during the period without restrictions, the door was open 81% of the occupied time and the fan was off 71% of the time. The window remained open for longer periods during the occupied period without restrictions (86%) than during the occupied period with restrictions (80%), indicating a potential impact from other factors, such as indoor thermal conditions. Yet, the window, door and fan status in both periods were similar, with a predominance of open status for windows and doors and off status for fans. This suggests that, just after the COVID-19 restrictions were lifted, occupant behaviour changed very little. However, it is important to highlight that the habits and concerns raised during the pandemic may have continued even after restrictions were lifted.



Notes: COVID restrictions 0 (without restrictions) and 1 (with restrictions).

Figure 5.6 – COVID-19 restrictions and (a) window, (b) door, and (c) fan status during the occupied period.

5.3.2 Predictive modelling

- *Hypothesis 1: Indoor conditions influence window, door, and fan status in school classrooms.*

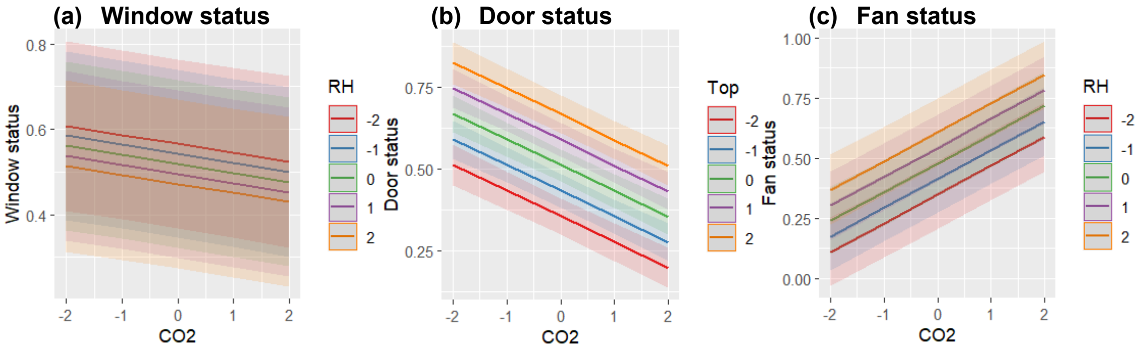
Environmental variables were, so far, the most investigated predictors for occupant behaviour in school buildings, as presented in Table 5.1. Our models from hypothesis 1 (Table 5.9) reveal that indoor operative temperature, relative humidity and CO_2 concentration are significant predictors of the status of windows and doors, confirming that indoor conditions influence their status in school classrooms. The fan status, though, was influenced only by relative humidity and CO_2 concentration, since indoor operative temperature presented a small effect on the AIC and, therefore, was not included in this model.

Relative humidity and CO_2 concentration presented a negative relationship with window status, indicating that as relative humidity and CO_2 concentration increase, the likelihood of the window being open decreases. The same pattern is observed between CO_2 concentration and door status. The other predictors exhibit a positive correlation with window, door, and fan status. The relative humidity has a stronger influence over the window status than the other predictors, as indicated by the standardized coefficients, but still similar to CO_2 concentration and indoor operative temperature, while the CO_2 concentration has a stronger influence over the door and fan status. The two predictors with stronger influence in each model are represented in Figure 5.7, which also shows the positive or negative correlations.

Table 5.9 – Models for window, door, and fan status – hypothesis 1.

	Window (AIC = 6670.7)			Door (AIC = 7210.8)			Fan (AIC = 6468.4)		
	Std. Coef.	**95% CI**	**p-value**	**Std. Coef.**	**95% CI**	**p-value**	**Std. Coef.**	**95% CI**	**p-value**
T_{op}	0.04	[0.01, 0.07]	0.00*	0.16	[0.13, 0.19]	0.00*	NI	NI	NI
RH	-0.05	[-0.08, -0.01]	0.01*	0.07	[0.04, 0.10]	0.00*	0.12	[0.09, 0.15]	0.00*
CO_2	-0.04	[-0.07, -0.02]	0.00*	-0.17	[-0.20, -0.14]	0.00*	0.25	[0.22, 0.28]	0.00*

Caption: * statistically significant values; NI = interactions not included in the model; AIC = Akaike's information criterion.



Note: scale -2 to 2 represents normalized values. Actual ranges: Top 14.1 ºC – 32.1 ºC; RH 27% - 87%; CO_2 333 ppm – 1682 ppm.

Figure 5.7 – Models' prediction based on environmental variables, showing the predictors with higher effect size.

- *Hypothesis 2: The school routine and the teacher's behaviour had a greater influence than the indoor thermal conditions on window, door, and fan status in school classrooms.*

Consistent with the findings from hypothesis 1, the indoor environmental variables were also identified as significant predictors for window, door, and fan status in models from hypothesis 2, except for CO_2 concentration for window status and indoor operative temperature for fan status (Table 5.10). The negative and positive relationships between these predictors and window, door, and fan status remained consistent with the previous models. However, it is important to note that the effect sizes of these predictors changed with the inclusion of other variables in the models. In models from hypothesis 2, the indoor operative temperature had a stronger influence on window and door status, while relative humidity had a stronger impact on fan status.

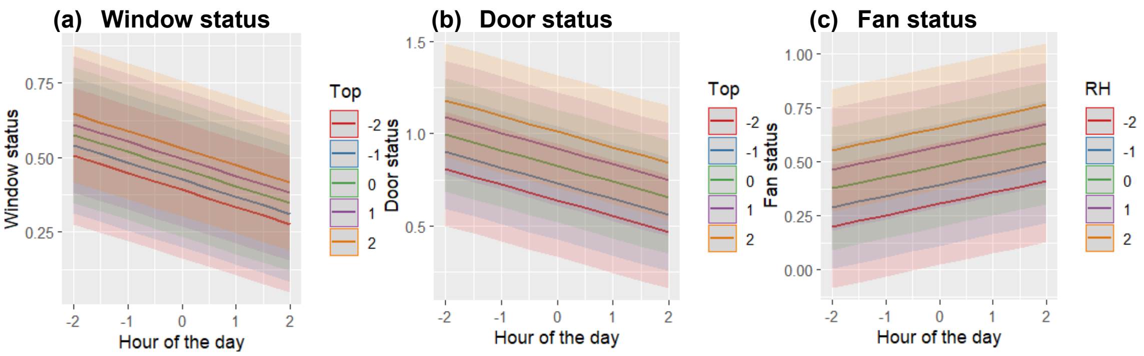
Based on the collected data, we reinforce here the influence of the teacher, particularly on window and fan status. Indeed, most of the teachers were identified as significant predictors (Table 5.10). The variables weekday and hour of the day, which represent the school routine, were also identified as significant predictors in all models. The occupancy period, though, was not included in the window model due to its small effect on the AIC. The hour of the day exhibited a negative correlation with window and door status, suggesting that the likelihood of the window and door being open decreases with time (Figure 5.8). This could be related to the school routine, since windows and doors tend to be opened mainly during arrival times and closed mainly during departure times, regardless of the environmental conditions. In contrast, the hour of the day exhibited a positive correlation with fan status, indicating that the fan was more frequently operated during the afternoon.

Table 5.10 – Models for window, door, and fan status – hypothesis 2.

	Window (AIC = 5557.5)			Door (AIC = 5757.6)			Fan (AIC = 5174.3)		
	Std. Coef.	95% CI	p-value	Std. Coef.	95% CI	p-value	Std. Coef.	95% CI	p-value
T_{op}	0.07	[0.05, 0.10]	0.00*	0.19	[0.16, 0.21]	0.00*	0.02	[-0.01, 0.05]	0.13
RH	-0.05	[-0.08, -0.02]	0.00*	0.04	[0.01, 0.07]	0.00*	0.17	[0.14, 0.20]	0.00*
CO_2	-0.02	[-0.05, 0.00]	0.10	-0.12	[-0.15, -0.10]	0.00*	0.16	[0.13, 0.19]	0.00*
TeacherA2	-0.10	[-0.24, 0.04]	0.15	-0.23	[-0.39, -0.07]	0.01*	0.08	[-0.07, 0.23]	0.32
Teacher A3	-0.11	[-0.29, 0.06]	0.21	-0.63	[-0.84, -0.43]	0.00*	0.41	[0.23, 0.59]	0.00*
TeacherA4	-0.43	[-0.56, -0.30]	0.00*	-0.31	[-0.47, -0.16]	0.00*	0.03	[-0.13, 0.19]	0.71
TeacherA5	-0.06	[-0.21, 0.09]	0.41	-0.51	[-0.66, -0.36]	0.00*	0.05	[-0.12, 0.22]	0.55
TeacherA6	-0.27	[-0.49, -0.05]	0.02*	-1.33	[-1.46, -1.19]	0.00*	0.80	[0.64, 0.95]	0.00*
TeacherB1	0.77	[0.53, 1.00]	0.00*	-0.34	[-0.48, -0.19]	0.00*	0.06	[-0.09, 0.21]	0.46
TeacherC1	-0.57	[-0.82, -0.32]	0.00*	-1.25	[-1.42, -1.07]	0.00*	0.75	[0.57, 0.93]	0.00*
TeacherC2	-0.77	[-1.03, -0.52]	0.00*	-1.54	[-1.72, -1.37]	0.00*	1.14	[0.96, 1.32]	0.00*
TeacherC3	-0.42	[-0.68, -0.17]	0.00*	-1.55	[-1.72, -1.38]	0.00*	0.88	[0.70, 1.06]	0.00*
TeacherC4	-0.78	[-1.07, -0.50]	0.00*	-1.94	[-2.13, -1.76]	0.00*	1.52	[1.32, 1.73]	0.00*
TeacherC5	-0.15	[-0.42, 0.11]	0.26	-1.70	[-1.88, -1.52]	0.00*	1.12	[0.93, 1.31]	0.00*
TeacherC6	-1.22	[-1.60, -0.84]	0.00*	-1.79	[-2.08, -1.49]	0.00*	1.24	[0.86, 1.62]	0.00*
Tuesday	0.35	[0.27, 0.42]	0.00*	0.24	[0.16, 0.31]	0.00*	-0.35	[-0.42, -0.28]	0.00*
Wednesday	0.22	[0.14, 0.29]	0.00*	0.23	[0.15, 0.31]	0.00*	-0.62	[-0.70, -0.54]	0.00*
Thursday	0.05	[-0.02, 0.13]	0.17	0.26	[0.19, 0.34]	0.00*	-0.77	[-0.85, -0.69]	0.00*
Friday	0.18	[0.09, 0.26]	0.00*	0.38	[0.30, 0.47]	0.00*	-0.90	[-0.98, -0.81]	0.00*
Hour of the day	-0.12	[-0.15, -0.09]	0.00*	-0.17	[-0.19, -0.14]	0.00*	0.10	[0.07, 0.13]	0.00*
Occupancy period	NI	NI	NI	0.06	[0.04, 0.09]	0.00*	-0.04	[-0.07, -0.02]	0.00*

Caption: *statistically significant values; NI = interactions not included in the model; AIC = Akaike's information criterion.

The variables representing school routine and teacher behaviour had a more significant influence on window, door, and fan status, in terms of effect size, if compared to the indoor thermal conditions. However, there were exceptions to this trend. For instance, the hour of the day was less influential on the fan status than the relative humidity and the CO_2 concentration. Additionally, specific teachers had either less importance or no influence at all on window and fan status, when compared to indoor thermal conditions.



Note: scale -2 to 2 represents normalized values. Actual ranges: Top 14.1 ºC – 32.1 ºC; RH 27% - 87%; Hour of the day 7 h – 17:50 h.

Figure 5.8 – Models' prediction based on the hour of the day and environmental variables, showing the predictors with higher effect size.

- *Hypothesis 3: In school classrooms, window, door, and fan status are predictor variables for each other.*

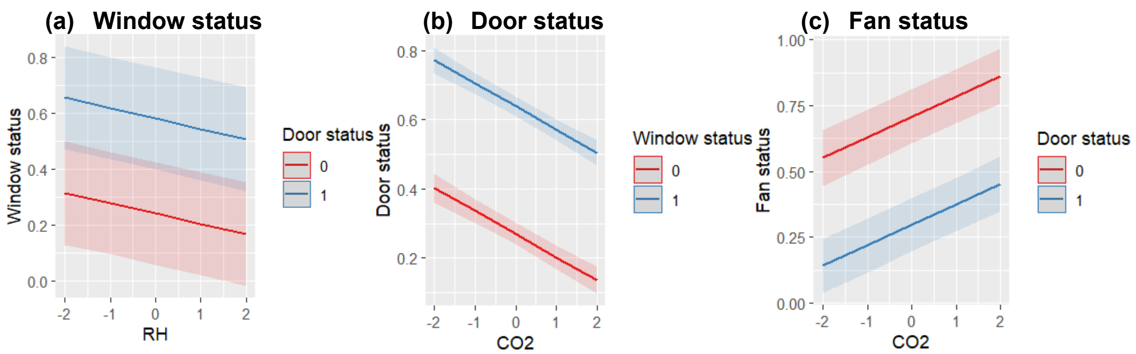
By including window, door or fan status as predictors, the indoor operative temperature for window status and the relative humidity for door status did not present a notable impact on occupant behaviour (Table 5.11), unlike the models from hypotheses 1 and 2. The negative correlation between relative humidity, CO_2 concentration and window status, as well as between CO_2 concentration and door status, remained consistent, as observed in the previous models.

The door and fan status were significant predictors for the window status, as well as the window and door for the fan status. The window status was the only significant predictor for the door status. These correlations were positive for the window and door status models (Figure 5.9), indicating that the probability of the window being open was higher when the door was open and the fan was on and the probability of the door being open was higher when the window was open. On the contrary, the correlations between window and door status with fan status were negative. This implies that the likelihood of the fan being on when the door and window were closed was higher than when they were open.

Table 5.11 – Models for window, door, and fan status – hypothesis 3.

	Window (AIC = 5882.5)			Door (AIC = 6538.6)			Fan (AIC = 5342.6)		
	Std. Coef.	95% CI	p-value	Std. Coef.	95% CI	p-value	Std. Coef.	95% CI	p-value
T_{op}	NI	NI	NI	0.14	[0.11, 0.17]	0.00*	0.02	[-0.21, 0.19]	0.00*
RH	-0.07	[-0.10, -0.04]	0.00*	0.07	[0.04, 0.10]	0.12	0.12	[0.09, 0.15]	0.00*
CO_2	-0.04	[-0.07, -0.02]	0.00*	-0.15	[-0.18, -0.12]	0.00*	0.16	[0.13, 0.19]	0.00*
Window status	NI	NI	NI	0.35	[0.32, 0.37]	0.00*	-0.16	[-0.19, -0.14]	0.00*
Door status	0.32	[0.29, 0.34]	0.00*	NI	NI	NI	-0.39	[-0.41, -0.36]	0.00*
Fan status	0.19	[0.16, 0.21]	0.00*	-0.02	[-0.05, 0.00]	0.06	NI	NI	NI

Caption: *statistically significant values; NI = interactions not included in the model; AIC = Akaike's information criterion.



Notes: scale -2 to 2 represents normalized values. Actual ranges: RH 27% - 87%; CO_2 333 ppm – 1682 ppm. Window, door, and fan status 0 (closed/ off) and 1 (open/ on).

Figure 5. 9 – Models' prediction based on window, door or fan status and environmental variables, showing the predictors with higher effect size.

- *Hypothesis 4: The restrictions imposed by the pandemic (social norms) had a greater influence than the indoor thermal conditions on window, door, and fan status in school classrooms.*

The addition of COVID-19 restrictions as predictor variables resulted in the indoor operative temperature not being a significant predictor for the window status and the relative humidity not being a significant predictor for the door status (Table 5.12). The other environmental variables remained significant predictors for window, door, and fan status, maintaining the same positive or negative correlations as before.

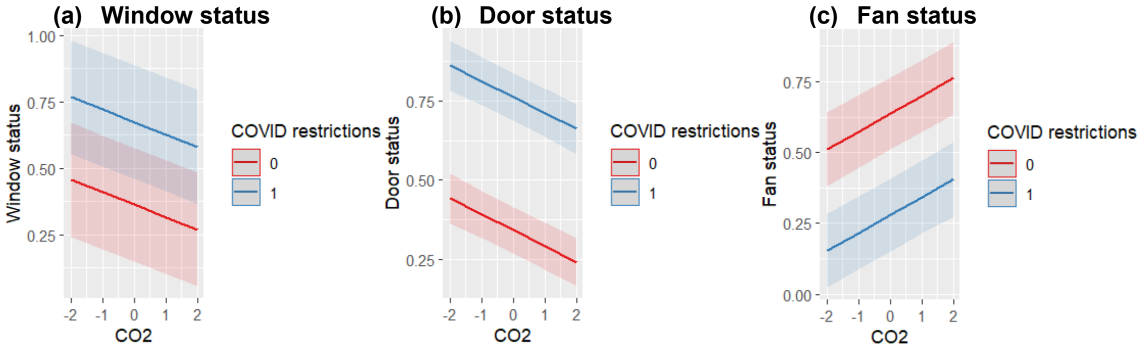
Given that part of the data was collected during the COVID-19 pandemic (Table 5.4), the inclusion of these predictors (variations in occupancy rate and COVID-19 restrictions, which were mandatory use of masks and the necessity to keep windows and doors open and fans off during occupancy) in the models is a unique and novel aspect, compared to studies conducted prior to the pandemic. The impacts of the restrictions imposed by the pandemic on the window, door, and fan status appeared to be of a greater influence than indoor thermal conditions. Therefore, these variables emerged as significant predictors in all models, as expected, since it includes general recommendations that the users were adhering to, except for the interaction between CO_2 concentration and occupancy rate in the door status model.

The COVID-19 restrictions exhibited a positive correlation with window and door status, indicating that, during the period with restrictions, the likelihood of the window and door being open was higher (Figure 5.10). The fan status showed an opposite trend: during the period with restrictions, the likelihood of the fan being on was lower. These findings are in line with the analysis of the collected data (Figure 5.6) and the protocols imposed by the COVID-19 pandemic, as they suggest that during the period with restrictions, windows and doors should remain open, while the fan should remain off.

Table 5.12 – Models for window, door, and fan status – hypothesis 4.

	Window (AIC = 5824.6)			**Door (AIC = 6586.9)**			**Fan (AIC = 5809.3)**		
	Std. Coef.	**95% CI**	**p-value**	**Std. Coef.**	**95% CI**	**p-value**	**Std. Coef.**	**95% CI**	**p-value**
T_{op}	NI	NI	NI	0.05	[0.02, 0.08]	0.00*	0.06	[0.04, 0.09]	0.00*
RH	-0.08	[-0.11, -0.05]	0.00*	0.11	[0.08, 0.14]	0.10	0.05	[0.02, 0.08]	0.00*
CO_2	-0.10	[-0.13, -0.07]	0.00*	-0.11	[-0.14, -0.08]	0.00*	0.13	[0.10, 0.16]	0.00*
COVID restrictions	0.62	[0.56, 0.68]	0.00*	0.84	[0.78, 0.91]	0.00*	-0.72	[-0.78, -0.65]	0.00*
Occupancy rate	0.42	[0.17, 0.22]	0.00*	0.11	[0.08, 0.14]	0.00*	0.05	[0.01, 0.08]	0.00*
CO_2:Occupancy**	0.19	[0.17, 0.22]	0.00*	NI	NI	NI	-0.03	[-0.06, -0.01]	0.02*

Caption: *statistically significant values; **the use of colon between predictors refers to an interaction between two variables; NI = interactions not included in the model; AIC = Akaike's information criterion.



Notes: scale -2 to 2 represents normalized values. Actual range: CO_2 333 ppm – 1682 ppm. COVID restrictions 0 (without restrictions) and 1 (with restrictions).

Figure 5.10 – Models' prediction based on COVID-19 restrictions and environmental variables, showing the predictors with higher effect size.

- *Hypothesis 5: indoor environmental conditions, school routine and the restrictions imposed by the pandemic are predictors of window, door, and fan status in school classrooms.*

A fifth model was created for window, door, and fan status including all significant variables from the previous models, in order to predict occupant behaviour more accurately in school classrooms (Table 5.13), given the current research scenario (naturally ventilated school classrooms situated in a humid subtropical climate).

The predictive model for window status revealed that the variables relative humidity, CO_2 concentration, COVID-19 restrictions, teacher behaviour, school routine and door and fan status are significant predictors, corroborating the results of the previous models. The variables relative humidity, CO_2 concentration and hour of the day presented a negative correlation with window status, indicating that, as their values increased, the likelihood of the window being open decreased (Figure 5.11a). The other significant predictors had a positive correlation with the window status, suggesting that the period with the restrictions imposed by the COVID-19 pandemic, a higher number of occupants, the door open and the fan on increase the chance of the window being open (Figure 5.11b). In contrast, the variables indoor operative temperature and occupancy period were not identified as significant predictors for window status.

Table 5.13 – Models for window, door, and fan status – hypothesis 5.

	Window (AIC = 4483.5)			Door (AIC = 4927.7)			Fan (AIC = 4119.4)		
	Std. Coef.	**95% CI**	**p-value**	**Std. Coef.**	**95% CI**	**p-value**	**Std. Coef.**	**95% CI**	**p-value**
T_{op}	NI	NI	NI	0.08	[0.06, 0.11]	0.00*	0.10	[0.08, 0.13]	0.00*
RH	-0.09	[-0.12, -0.07]	0.00*	0.10	[0.07, 0.13]	0.00*	0.09	[0.06, 0.11]	0.00*
CO_2	-0.05	[-0.08, -0.03]	0.00*	-0.05	[-0.08, -0.02]	0.00*	0.03	[0.00, 0.06]	0.02*
COVID restrictions	0.43	[0.38, 0.49]	0.00*	0.60	[0.54, 0.65]	0.00*	-0.42	[-0.48, -0.37]	0.00*
Occupancy rate	0.26	[0.23, 0.29]	0.00*	0.00	[-0.02, 0.04]	0.37	0.07	[0.05, 0.10]	0.00*
CO_2:Occupancy**	0.12	[0.10, 0.14]	0.00*	-0.07	[-0.09, -0.05]	0.00*	NI	NI	NI
TeacherA2	-0.06	[-0.18, 0.07]	0.36	-0.14	[-0.29, 0.01]	0.06	-0.05	[-0.19, 0.08]	0.44
TeacherA3	-0.13	[-0.29, 0.03]	0.12	-0.53	[-0.71, -0.34]	0.00*	0.26	[0.10, 0.42]	0.00*
TeacherA4	-0.43	[-0.54, -0.31]	0.00*	-0.04	[-0.19, 0.10]	0.58	-0.16	[-0.30, -0.02]	0.03*
TeacherA5	-0.11	[-0.24, 0.03]	0.12	-0.38	[-0.53, -0.24]	0.00*	-0.15	[-0.30, 0.00]	0.06
TeacherA6	-0.23	[-0.42, -0.03]	0.02*	-1.17	[-1.29, -1.04]	0.00*	0.63	[0.49, 0.77]	0.00*
TeacherB1	0.57	[0.36, 0.79]	0.00*	-0.34	[-0.48, -0.21]	0.00*	0.09	[-0.04, 0.23]	0.19
TeacherC1	-0.47	[-0.70, -0.25]	0.00*	-1.14	[-1.30, -0.97]	0.00*	0.59	[0.43, 0.75]	0.00*
TeacherC2	-0.54	[-0.77, -0.31]	0.00*	-1.34	[-1.50, -1.18]	0.00*	0.85	[0.69, 1.02]	0.00*
TeacherC3	-0.23	[-0.46, 0.00]	0.05	-1.38	[-1.54, -1.23]	0.00*	0.64	[0.48, 0.80]	0.00*
TeacherC4	-0.56	[-0.81, -0.30]	0.00*	-1.64	[-1.81, -1.47]	0.00*	1.02	[0.84, 1.20]	0.00*
TeacherC5	-0.04	[-0.28, 0.20]	0.76	-1.56	[-1.72, -1.40]	0.00*	0.77	[0.60, 0.94]	0.00*
TeacherC6	-0.94	[-1.28, -0.60]	0.00*	-1.53	[-1.80, -1.26]	0.00*	0.94	[0.60, 1.28]	0.00*
Tuesday	0.22	[0.15, 0.29]	0.00*	0.17	[0.10, 0.24]	0.00*	-0.27	[-0.34, -0.21]	0.00*
Wednesday	0.20	[0.13, 0.26]	0.00*	0.14	[0.07, 0.21]	0.00*	-0.45	[-0.52, -0.38]	0.00*
Thursday	0.08	[0.01, 0.15]	0.03*	0.19	[0.12, 0.26]	0.00*	-0.60	[-0.67, -0.53]	0.00*
Friday	0.16	[0.08, 0.24]	0.00*	0.31	[0.23, 0.39]	0.00*	-0.70	[-0.78, -0.62]	0.00*
Hour of the day	-0.11	[-0.13, -0.08]	0.00*	-0.08	[-0.11, -0.05]	0.00*	NI	NI	NI
Occupancy period	NI	NI	NI	0.03	[0.01, 0.05]	0.01*	NI	NI	NI
Window status	NI	NI	NI	0.22	[0.20, 0.24]	0.00*	-0.11	[-0.13, -0.09]	0.00*
Door status	0.21	[0.19, 0.23]	0.00*	NI	NI	NI	-0.26	[-0.28, 0.23]	0.00*
Fan status	0.17	[0.15, 0.20]	0.00*	0.04	[0.02, 0.06]	0.00*	NI	NI	NI

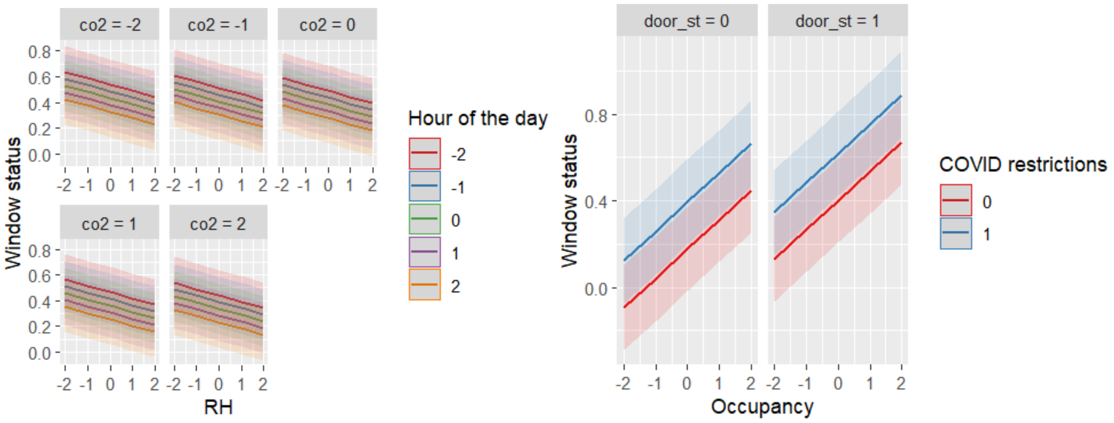
Caption: *statistically significant values; **the use of colon between predictors refers to an interaction between two variables; NI = interactions not included in the model; AIC = Akaike's information criterion.

The predictive model for door status showed that the indoor environmental variables, the COVID-19 restrictions, the teachers' behaviour, the school routine and the window and fan status were significant predictors. This differs from the results of the predictive models for door status from hypotheses 1 to 4, where relative humidity and fan status did not emerge as significant predictors and, specifically for hypothesis 4, occupancy rate emerged as a significant predictor. This suggests that other factors in the model may be playing a more dominant role in influencing the door status. Similar to the predictive model for window status, the CO_2 concentration, the hour of the day and the teachers' behaviour had a negative correlation with door status, while the correlations between indoor operative temperature, relative humidity, COVID-19 restrictions, weekdays, window and fan status were positive (Figure 5.12).

The predictive model for fan status had similar significant predictors as the model for window status, except for the hour of the day. Nevertheless, the correlations between predictors and fan status were opposite to what was observed in the predictive models for window and door

(Figure 5.13). This suggests that, as the indoor environmental variables' values increase, the probability of the fan being on also increases. On the other hand, the COVID-19 restrictions and the open door and windows decrease the probability of the fan being on.

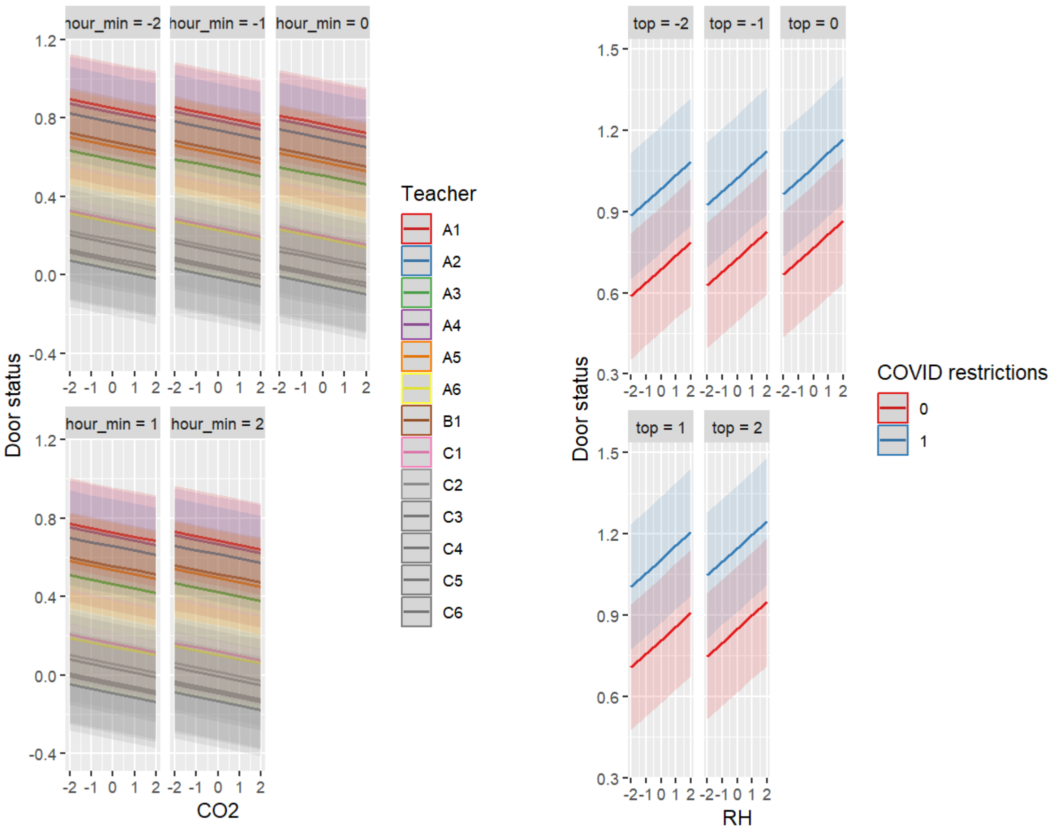
(a) Significant predictor with a negative correlation with window status **(b) Significant predictor with a positive correlation with window status**



Notes: scale -2 to 2 represents normalized values. Actual ranges: RH 27% - 87%; CO_2 333 ppm – 1682 ppm; Hour of the day 7 h – 17:50 h; Occupancy 3 – 36 occupants. Window, door, and fan status 0 (closed/ off) and 1 (open/ on). COVID restrictions 0 (without restrictions) and 1 (with restrictions).

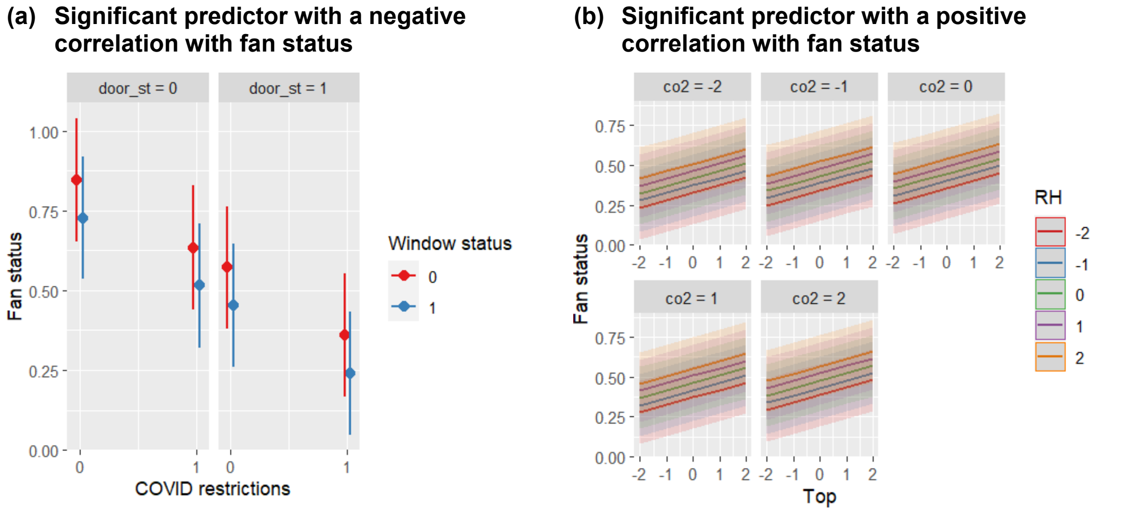
Figure 5.11 – Window status models' prediction, showing the predictors with higher effect size

(a) Significant predictor with a negative correlation with door status **(b) Significant predictor with a positive correlation with door status**



Notes: scale -2 to 2 represents normalized values. Actual ranges: Top 14.1 ºC – 32.1 ºC; RH 27% - 87%; Hour of the day (hour_min) 7 h – 17:50 h. COVID restrictions 0 (without restrictions) and 1 (with restrictions).

Figure 5.12 – Door status models' prediction, showing the predictors with higher effect size.



Notes: scale -2 to 2 represents normalized values. Actual ranges: Top 14.1 ºC – 32.1 ºC; RH 27% - 87%; CO_2 333 ppm – 1682 ppm. Window, door, and fan status 0 (closed/ off) and 1 (open/ on). COVID restrictions 0 (without restrictions) and 1 (with restrictions).

Figure 5.13 – Fan status models' prediction, showing the predictors with higher effect size.

5.3.3 Algorithm's validation

The models for window and door status predicted more open (1) than closed status (0) (Tables 5.14 and 5.15), while the models for fan status predicted more off (0) than on status (1) (Table 5.16), with an accuracy greater than 0.5 for all models. This means that more than 50% of the predictions were correct in all models – specifically 72%, 79% and 74% for window, door, and fan models of hypothesis 5, which is a positive outcome for assessing occupant behaviour. The F1-score, which incorporates both precision and recall in its calculation, demonstrated satisfactory values for window and door models. However, the F1-score for the fan status models was lower, below 0.3 for all models. This occurred because these three indexes (F1-score, precision and recall) consider the true positive values, and these models predicted more negative values, or off status (0).

Most window and fan status models presented values for AUC above 0.7, which is considered satisfactory. Despite only the model for door status from hypothesis 2 presenting an AUC of 0.7, models from hypotheses 4 and 5 came very close to this threshold. In general, models from hypothesis 5 presented higher values of AUC, followed by models from hypotheses 2 and 4, which reinforces the importance of school routine, teachers' behaviour and social norms (COVID-19 restrictions) as predictors for window, door, and fan status.

The comparison between the models from hypothesis 1, which include fewer predictors (only environmental variables), and the models from hypothesis 5, which include all significant predictors from the other models (multi-domain variables), reveals that window, door and fan models from hypothesis 1 are less accurate, with less than 70% of correct predictions. This result suggests that by including variables from multiple domains to the models, they better describe the obtained data from reality, but also became more context-dependent. Thus, the models get less generalizable, especially if we consider the contextual domain, such as school routine and teachers' behaviour. Therefore, the trade-off between a more accurate or a more general model should be further investigated, in order to evaluate the models' applicability.

Table 5.14 – Prediction performance and AUC for window models.

Models	Confusion Matrix						AUC
	Pred. (0)	Pred. (1)	Precision	Recall	Accuracy	F1-score	
Model 1	268	515	0.89	0.69	0.67	0.74	0.71
Model 2	331	452	0.94	0.65	0.67	0.70	0.75
Model 3	244	539	0.87	0.71	0.67	0.75	0.69
Model 4	281	502	0.90	0.69	0.67	0.73	0.72
Model 5	231	552	0.90	0.75	**0.72**	**0.78**	**0.76**

Table 5.15 – Prediction performance and AUC for door models.

Models	Confusion Matrix						AUC
	Pred. (0)	Pred. (1)	Precision	Recall	Accuracy	F1-score	
Model 1	335	448	0.92	0.61	0.62	0.69	0.66
Model 2	229	554	0.92	0.76	0.74	0.79	**0.70**
Model 3	173	610	0.88	0.79	0.73	0.81	0.63
Model 4	333	450	0.91	0.61	0.62	0.69	0.68
Model 5	165	618	0.91	0.83	**0.79**	**0.83**	0.69

Table 5.16 – Prediction performance and AUC for fan models.

Models	Confusion Matrix						AUC
	Pred. (0)	Pred. (1)	Precision	Recall	Accuracy	F1-score	
Model 1	434	349	0.33	0.67	0.63	**0.25**	0.69
Model 2	566	217	0.41	0.52	0.73	0.20	0.72
Model 3	625	158	0.35	0.32	0.72	0.13	0.67
Model 4	427	356	0.29	0.61	0.59	0.23	0.72
Model 5	613	170	0.41	0.41	**0.74**	0.16	**0.76**

The metrics analysed during the algorithm's validation were compared to those of existing models (Table 5.17), showing that the values from the models in this study, particularly from model 5, are satisfactory and similar to literature.

Table 5.17 – Comparison of prediction performance and AUC of existing models in the literature.

Reference	Context	Model	Accuracy	F1-score	AUC
Present study	School	Window	0.67 – 0.72	0.70 – 0.78	0.69 – 0.76
		Door	0.62 – 0.79	0.69 – 0.83	0.63 – 0.70
		Fan	0.59 – 0.74	0.13 – 0.25	0.69 – 0.76
Stazi et al. (2017a)	School	Window	-	-	0.51 – 0.72
Belafi et al. (2018)	School	Window	-	-	0.50 – 0.68
Markovic et al. (2018)	Office	Window	0.86 – 0.89	0.53 – 0.65	-
Mo et al. (2019)	Residential	Window	0.59 – 0.82	0.55 – 0.82	-
Jia et al. (2019)	Office	Window	0.77	0.49	-
		Door	0.81	0.87	-
		Blinds	0.74	0.83	-
Grassi et al. (2022)	Office	Window	0.72	0.13	0.78
		Air-Conditioning	0.83	0.23	0.84

5.4 Discussion

Environmental variables (physical domain) were the most investigated predictors in literature for occupant behaviour in school buildings. Taking this into account, the findings from the first and second models are aligned with prior research studies, indicating that indoor operative temperature serves as a predictor for window status (BELAFI et al., 2018; DUTTON; SHAO, 2010; KORSAVI; JONES; FUERTES, 2022b; STAZI; NASPI; D'ORAZIO, 2017a). Yet, when other domains were included in models 3, 4 and 5, this association was not maintained. Korsavi et al. (2022b) identified a negative correlation between relative humidity and window status, which is in line with our results, showing that high indoor humidity indicates that windows are closed. The association between CO_2 concentration and window status, identified in almost all models of this study, with exception of model 2, was significant in only one study from current literature (DUTTON; SHAO, 2010), with weak correlations reported in other studies (KORSAVI; JONES; FUERTES, 2022b; STAZI; NASPI; D'ORAZIO, 2017a). We identified a negative correlation between CO_2 concentration and window status in our models, suggesting that, as for relative humidity, high CO_2 concentration indicates that windows are closed. No correlation was found between indoor environmental variables and door status in the study conducted by Heebøll et al. (2018), which differs from our results.

Time-dependent actions, daily routines and teacher behaviour (contextual domain) were identified as predictors for window and door status in previous studies in school classrooms (BELAFI et al., 2018; HEEBØLL; WARGOCKI; TOFTUM, 2018; KORSAVI; JONES; FUERTES, 2022b; STAZI; NASPI; D'ORAZIO, 2017a), aligning with the outcomes of this study. The hour of the day, especially the arrival and departure periods, was identified as a predictor for window status in three studies (BELAFI et al., 2018; KORSAVI; JONES; FUERTES, 2022b; STAZI; NASPI; D'ORAZIO, 2017a). These findings align with the results of the present study, which observed a negative correlation between the hour of the day and window status, suggesting that as the hour increases (i.e., approaching departure time), the likelihood of the window being open decreases. This might be because occupants closed the windows before leaving the classroom. Heebøll et al. (2018) also identified the hour of the day as a trigger for door status and, despite not including teacher behaviour as a predictor in their model, they suggest that the differences found in door status between classrooms could be due to a particular teacher behaviour.

No studies regarding the relation between variables related to the school routine and fan status were identified in the literature. Yet, our study revealed a positive correlation between hour of the day and fan status, suggesting that the fan was more operated during the afternoon. This finding could be also related to the indoor operative temperature, that also presented a positive correlation with fan status, as temperatures tend to be higher in the afternoon. In addition, fan status presented a positive correlation with CO_2 concentration in all models (i.e., an increase in CO_2 concentration can lead to increased use of fans), which could be related to the sensation of stale air, that might trigger occupants to turn on the fan. Yet, it should be further investigated in future studies.

Our results suggest that one status can impact others (multi-behavioural domain). However, the actions could be often taken at the same time, influenced by the same environmental predictor, requiring further investigation to confirm our findings. Nevertheless, no research studies were found correlating window, door, and fan status in the context of school classrooms, which is a novelty of this study.

The inclusion of predictors related to the COVID-19 pandemic (variations in occupancy rate and COVID-19 restrictions) in the models (contextual domain) is also a unique and novel aspect, compared to studies conducted prior to the pandemic. No studies including restrictions or other social norms as predictor variables for occupant behaviour in school classrooms were found in literature, as presented in Table 5.1. These findings reinforce the importance of social norms in indoor environments with high density, such as school classrooms. Indeed, scenarios such as the COVID-19 pandemic, in which such norms became more pronounced, require a review of predictive models since they can effectively change occupant behaviour, impacting on indoor conditions. In addition, cultural factors also play a significant role on occupant behaviour, for example, in the context of the COVID-19 pandemic, on how much people adhere or not to the imposed restrictions, thus requiring further investigation considering other locations.

The models from hypothesis 5 presented improved predictions of occupant behaviour, as confirmed by the algorithm validation, by including multi-domain factors as predictors for window, door and fan status. These models could be applied in future studies as reference models. Yet, while more complex models with additional predictors can provide more accurate predictions of occupant behaviour, they also become more context-dependent and less generalizable. Given the significant influence of school routine, teachers' behaviour and social norms (COVID-19 restrictions) on window, door, and fan status, further research is warranted. Expanding the scope to include more case studies would contribute to a more comprehensive understanding of these dynamics.

5.4.1 Limitations

This study has some limitations primarily associated with the field campaign phase, which is a common challenge in studies involving monitoring campaigns. These limitations include:

(i) Sample size: the restricted number of monitoring equipment required a limited number of monitored classrooms, resulting in a sample of three schools. Larger sample sizes are often preferred to develop more precise models, as they provide more data to train the models effectively.

(ii) Measurement lengths: due to equipment constraints, classrooms were not monitored simultaneously. Instead, the monitoring campaign was split into four rounds to cover all the seasons in each classroom (Table 5.4). This sequential monitoring may introduce variability based on time of the year.

(iii) Occupancy data: the absence of equipment to monitor occupancy required the use of attendance lists provided by each teacher, which may not be as reliable as data obtained from dedicated occupancy monitoring equipment, potentially introducing some level of uncertainty into the analysis.

(iv) Internal factors: the study did not consider internal factors such as psychological and physiological variables that could potentially be included as predictors in the models. This omission was due to the complexity of monitoring these factors.

(v) Lack of measured data on OB before the COVID-19 pandemic: since we do not have data from these schools before the restrictions, we could not analyse the changes in OB by comparing it before and after the pandemic.

Despite these limitations, the study offers valuable insights and a foundation for future research in the field of occupant behaviour and its impact on school buildings' performance.

5.5 Conclusions

This study aimed to identify and quantify the influence of multi-domain factors (including thermal, indoor air quality, contextual and multi-behaviour domains) on window, door, and fan status in naturally ventilated school classrooms in a humid subtropical climate, in order to predict occupant behaviour. The novelties of this research study were the investigation of door and fan together with the window status, which can significantly influence indoor environmental conditions; the inclusion of time-related and contextual factors as predictor variables, which were less explored in previous studies; and the comparison between periods with and without restrictions imposed by the COVID-19 pandemic, which highlighted the interference of social norms on occupant behaviour.

In general, the indoor environmental variables (indoor operative temperature, relative humidity and CO_2 concentration) influenced window, door, and fan operation in school classrooms, confirming findings from previous studies (BELAFI et al., 2018; DUTTON; SHAO, 2010; STAZI; NASPI; D'ORAZIO, 2017a). Yet, we showed that other predictors could have a greater influence on occupant behaviour, such as the teachers' behaviour and the COVID-19 restrictions, indicating the relevance of investigating the contextual domain in behavioural studies. Indeed, the models including school routines, social norms and teachers' behaviour as predictors were the ones with better results during the validation phase. This suggests that, while more complex models with additional predictors can provide more accurate predictions of occupant behaviour, they also become more context-dependent and less generalizable. Also, the inclusion or exclusion of variables in the models led to some differences in the significance of predictors. The trade-off between model complexity and generalizability is an important consideration in this research study, and it highlights the nuanced relationship between various factors affecting occupant behaviour in school buildings.

This study provides a more comprehensive understanding of occupant behaviour from a multi-domain approach and its impact on environmental conditions in school classrooms. The presented results hold the potential to advance our understanding of occupant behaviour in school buildings and its implications for building performance. Future studies could further enhance the sample size by collecting data from other school classrooms, investigating teachers' and students' behaviour in different contexts (e.g., different climates, types of classrooms, students of different ages). This could lead to the development of more generalizable predictive models, as well as suggestions and recommendations for performance-based design and operation of classrooms.

6 Model implementation

This chapter is part of a paper currently in development in collaboration with Prof. Dr. Leticia Oliveira Neves and Prof. Dr. Marcel Schweiker. It presents preliminary results of the implementation of a window status predictive model on building performance simulation.

Thermal comfort and perceived indoor air quality optimization with respect to occupant behaviour in naturally ventilated school buildings

Abstract

School classrooms often present poor indoor air quality (IAQ) conditions, especially if naturally ventilated, when the building's thermal and IAQ performance is directly associated to the occupant behaviour regarding window operation. Therefore, research efforts have been directed at understanding which parameters are the main triggers for occupants' actions towards window operation, pointing out thermal comfort parameters as the main action triggers, while IAQ (CO_2 concentration) remains a secondary restriction. Since March 2020, the COVID-19 pandemic not just renewed but also emphasized the interest and urgency on investigating deficient IAQ and thermal comfort conditions in classrooms. Yet, most of the published research studies have been carried out considering isolated objectives. Giving this scenario, this paper aims at filling this research gap, regarding the need to develop a comprehensive study of the relationship between thermal comfort and perceived IAQ and their association with occupant behaviour, considering a simultaneous multi-input and output parameters interaction. Therefore, we analysed potential conflicts between thermal comfort and IAQ, with regard to triggers for manual operation of windows in naturally ventilated classrooms, and identified optimal situations of balance between both drivers. The methodological approach included statistical analysis, development of an occupant behaviour predictive model, building performance simulation and multi-objective optimization. The findings reveal variations of up to 42.5% in CO_2 levels and 9% in discomfort hours between actual and optimized occupant behaviours. This suggests that adjusting occupant behaviour can significantly improve indoor conditions, leading to enhanced thermal comfort and air

quality. The results also indicate that optimal window operation and occupancy strategies differ among schools, highlighting the need for context-specific analyses. Tailoring these strategies to each setting is crucial for improving classroom design and operational efficiency.

Keywords: occupant behaviour, school building, thermal comfort, indoor air quality, multi-objective optimization.

6.1 Introduction

Occupant behaviour (OB) is defined as the actions building users may (or may not) take to modify the indoor environment (HOES et al., 2009). The prediction accuracy of building performance simulations (BPS) has been greatly associated to occupant behaviour modelling, which led to an increasing attention to the topic specially in the last ten years (AHMED et al., 2023). Researchers have been developing behavioural models with the aim of accurately predicting human behaviour in BPS (BELAFI et al., 2018; CHATZIDIAKOU; MUMOVIC; SUMMERFIELD, 2015; MADUREIRA et al., 2016; STAZI; NASPI; D'ORAZIO, 2017a). Deterministic models with fixed rules and, more recently, stochastic dynamic models have both been adopted in the abovementioned studies, aiming to estimate the human behaviour in a more realistic way. Logistic regression is one of the most adopted methods, since it provides good approximations with occupants' behaviours (BELAFI et al., 2018).

The main building typologies under investigation are, usually, offices and residential buildings, while research studies concerning school buildings are less frequent and more recent (BELAFI et al., 2018; HEEBØLL; WARGOCKI; TOFTUM, 2018; KORSAVI; JONES; FUERTES, 2022b; LOURENÇO; PINHEIRO; HEITOR, 2014; MADUREIRA et al., 2016; STAZI; NASPI; D'ORAZIO, 2017a). Nevertheless, this typology has its particularities, such as the classroom's management, which is often dictated by the teacher, its high occupation density and excessive internal gains, with direct implications on occupants' health and well-being. In addition, classrooms usually present poor thermal comfort and indoor air quality[2] (IAQ) conditions, in special if naturally ventilated (De Giuli et al., 2012; Pereira et al., 2014), which emphasizes the relevance of this research topic. Thus, one of the key behaviour types investigated in the current literature is related to the ventilation strategy (mechanical and/or natural ventilation), since it impacts directly on thermal comfort, IAQ and energy consumption.

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[2] According to EPA (2021): "Indoor Air Quality (IAQ) refers to the air quality within and around buildings and structures, especially as it relates to the health and comfort of building occupants."

In regions where natural ventilation is an effective strategy for the cooling season, such as Brazil and Southern European countries, for example, classrooms are usually naturally ventilated, with manual operation of windows (DUARTE; GLÓRIA GOMES; MORET RODRIGUES, 2017). In this case, the building's thermal and IAQ performance is directly associated to the outdoor environmental conditions; to the architectural design, especially the building envelope; and to the occupant behaviour regarding window and door operation, which can represent up to 87% of the total air change rates (Iwashita and Akasaka, 1997). Natural ventilation can be an effective strategy to reduce energy consumption and improve IAQ (HERACLEOUS; MICHAEL, 2019) provided that, among other factors, an optimal operation of windows is achieved.

Research efforts have been directed at understanding which parameters are the main triggers for occupants' actions towards window operation. Results from several field studies and surveys regarding occupant behaviour models for naturally ventilated school buildings point out thermal comfort parameters as the main action triggers regarding window operation, while IAQ (CO_2 concentrations) remains as a secondary restriction (Stazi et al., 2017a; Stazi et al., 2017b). Indeed, correlations between occupant behaviour and CO_2 concentrations were proven to be weak, which means that users' actions are not driven by this stimulus because of their unawareness of indoor CO_2 concentrations (STAZI; NASPI; D'ORAZIO, 2017a). Research studies also point out noise problems (Madureira et al., 2016), improper direct solar radiation on seated users (BERNARDI; KOWALTOWSKI, 2006) and daily routine, such as arrivals and breaks (BELAFI et al., 2018; STAZI; NASPI; D'ORAZIO, 2017a) as triggers for window operation. In fact, in terms of occupant behaviour, in school environments nonphysical behavioural patterns should also be investigated, since social rules and habits can override thermal stimuli (BELAFI et al., 2018; STAZI; NASPI; D'ORAZIO, 2017a). Suggestions for future studies include analysing occupant behaviour in different seasons and climates to support building use practices (BELAFI et al., 2018) and further investigating health risks (MADUREIRA et al., 2016).

Still, the IAQ is an important problem in school classrooms, since high indoor CO_2 levels and other pollutants might impact human health and well-being (BELAFI et al., 2018; STAZI et al., 2017; STAZI; NASPI; D'ORAZIO, 2017a). The IAQ is a globally relevant issue in school classrooms, since several research studies reported poor indoor ventilation rates and high CO_2 levels, in special in naturally ventilated rooms (Mendell and Heath, 2005; Stazi et al., 2017b). Since March 2020, the COVID-19 pandemic not just renewed but also emphasized the interest and urgency on investigating deficient IAQ and thermal comfort conditions in school classrooms (ALONSO et al., 2021). Research studies have confirmed airborne transmission (respiratory droplets and aerosols) as one of the major transmission routes of SARS-CoV-2, which increases the possibility of transmission of COVID-19 in indoor environments with high occupancy rates, such as classrooms (MORAWSKA et al., 2020; NOORIMOTLAGH et al., 2021). The problem can become even more serious in naturally ventilated classrooms that rely only on occupants to achieve good IAQ conditions through manual operation of windows (ALONSO et al., 2021).

Several research studies have shown the importance of air renewal to dilute contaminants and, consequently, to reduce airborne infection risks, both in naturally and mechanically ventilated environments (PARK et al., 2021; QIAN et al., 2021). The indoor CO_2 levels may be used as an index to estimate the ventilation rate and, therefore, the airborne transmission of diseases (BHAGAT et al., 2020; HOU; KATAL; WANG, 2021). Hence, its concentration rate is widely used as an indicator of IAQ (CHATZIDIAKOU; MUMOVIC; SUMMERFIELD, 2015). As a result, the current pandemic brought into discussion which CO_2 levels and ventilation rates thresholds would be adequate to reduce the probability of infection in school classrooms, since recommendations from standards could not be enough to prevent airborne transmission (HOU; KATAL; WANG, 2021). Yet, there are no generic conclusions when the subject is the adequate ventilation rate threshold to prevent the airborne transmission of COVID-19, since it depends on several parameters such as occupancy density, room size, exposure time/duration, indoor heat sources, humidity, etc. (ASCIONE et al., 2021; HOU; KATAL; WANG, 2021; SUN; ZHAI, 2020; ZIVELONGHI; LAI, 2021). In the case of fully naturally ventilated environments, the performance is also associated to the local climate, the building design (opening sizes and relative positions) and the occupant behaviour (PARK et al., 2021; QIAN et al., 2021). Seasonal variation is also an important variable, since occupants tend to leave windows closed when outdoor temperatures are low (DENG; ZOU; LAU, 2021; ZIVELONGHI; LAI, 2021). Yet, most of the published research studies have been carried out considering isolated objectives solely (ARJMANDI et al., 2021).

Giving this scenario, this research study aims to analyse potential conflicts between thermal comfort and perceived indoor air quality, with regard to triggers for manual operation of windows in naturally ventilated classrooms, and to identify optimal situations of balance between both drivers to support building use practices focused on occupant-centric building operation.

6.2 Method

This research method is based on a case study and supported by field research, statistical analysis, and building performance simulation. The method was developed in three main steps, which are presented in Figure 6.1.

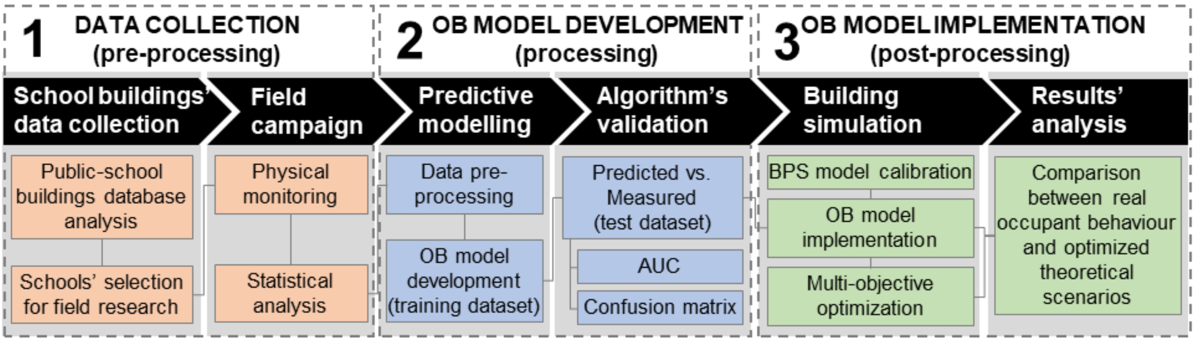

Figure 6.1 – Research method.

6.2.1 Data collection (pre-processing)

- *School buildings' data collection*

A comprehensive data collection was carried out, encompassing public schools built by the Foundation for Education Development (FDE) over the past fifteen years in the state of São Paulo, Brazil. This dataset[3] included information on 66 school buildings, effectively representing half of the public-school buildings constructed in the state of São Paulo within this time frame. All the schools in this database have a standardized design, with classrooms of the same floor area and window design. The school classrooms are naturally ventilated, with large operable windows in the main façade and operable windows facing the corridor.

- *Field campaign*

The physical monitoring was performed on a set of classrooms of three public-school buildings thoughtfully chosen from the dataset (Figure 6.2). The selection criteria ensured that the selected school buildings were comparable to one another and representative of the broader dataset. Furthermore, the school location and the willingness to participate in the research study were also considered. School A is an elementary school (ages 6-15) built in 2015 and located in the city of Campinas. Schools B and C are in the city of Sao Paulo, the first is an

[3] The dataset is available at https://doi.org/10.25824/redu/Z4BWFL

elementary school (ages 6-11) built in 2014 and the latter is a high school (ages 15-18) built in 2012. Both cities are characterized by a humid subtropical climate – Cfa (Köppen climatic classification). The selected classrooms are occupied during the morning and afternoon with one short break in each period plus a lunch break.

Figure 6.2 – Monitored classrooms.

The physical monitoring was conducted during four rounds in each classroom at two-month intervals within the range of one year (from August 2021 to August 2022). Besides the measurement periods not being the same for all schools, the total measured time frame ensured coverage of all seasons throughout the year. Indoor environmental variables were monitored in a 10-minute time-step by dataloggers placed inside a typical classroom of each selected school. The dataloggers, Testo 175-T2 with hot sphere probe, used to monitor air temperature (Tin: range -35 °C to 55 °C ± 0.5 °C) and globe temperature (Tg: range -25 °C to 80 °C ± 0.2 °C), and Testo 160 IAQ, used to monitor relative humidity (RH: range 0 to 100% ±2%) and CO_2 concentration (range 0 to 5000 ppm ± 100 ppm + 3 % of reading), were placed away from the windows at about 1.1 m above the floor (seated person) according to ISO 7726 (International Organization for Standardization, 1998). The mean radiant temperature (Tmr) and the indoor operative temperature (Top) were calculated using the air temperature and the globe temperature measurements. The number of occupants was monitored through the attendance list provided by each classroom's teacher. The manual operation of windows was monitored by using an Onset Hobo State with binary output (closed = 0/ open = 1). Outdoor environmental variables (air temperature – Tout, relative humidity – RHout, precipitation, wind speed and wind direction) measurements were acquired from the nearest weather station (3.5 to 8 km distant), to enable comparisons between indoor and outdoor conditions.

During part of the physical monitoring – from August 2021 to February 2022, restrictive occupancy measures due to the COVID-19 pandemic were observed. Therefore, the monitoring period was divided into two sets – with and without restrictive measures. The restrictive measures consisted of reduced number of occupants in the classroom, reduced occupancy period, necessity to keep windows and doors opened during the whole occupancy period, mandatory use of masks.

6.2.2 OB model development (processing)

- *Predictive modelling*

The data collected during the physical monitoring phase was merged into a common dataset, by associating window status (open/closed) with time of the day and environmental variables. The R programming language (R Core Team, 2022) was used to create representative plots of the collected data and to develop a predictive model of window status. The dataset was randomly split into two subsets: one to generate the models, using 80% of the dataset (train dataset), and another one to evaluate the models, using 20% of the dataset (test dataset).

Binary logistic regression was chosen as the statistical method to analyse the sample and to create the model, since it is a stochastic model widely used to estimate window operation behaviour, by assuming a probabilistic relationship with previously selected predictor variables (CARLUCCI et al., 2020). A window status predictive model was developed by applying the generalized linear mixed model (GLMM) function in the training dataset, considering the monitored schools as a variable of random nature, to assess the influence of the recorded parameters on the window status, which was defined as a binary operation state (all windows closed = 0, at least one window open = 1).

Indoor operative temperature, indoor relative humidity, indoor CO_2 concentration and number of occupants were tested as possible predictor variables. The outdoor weather variables air temperature, relative humidity and CO_2 concentration were not considered to avoid multicollinearity, which may bias the regression model. Also, a categorical variable related to the COVID-19 restrictive measures was included as a predictor variable, in order to analyse the impact of the protocols on the window status, considering two COVID-19 restriction categories: “yes” when windows and doors should remain open during occupancy) and “no” (when windows and doors could be freely operated). In addition, the interaction between the environmental variables (indoor operative temperature, indoor relative humidity and indoor CO_2 concentration) and the interaction between occupancy and COVID-19 restrictions were tested as predictors in the model. The variables and interactions that were not significant as predictors for window status (p-value > 0.05) were excluded from the model.

- *Algorithms’ validation*

The model was evaluated by using the test dataset to generate a confusion matrix, showing the relationship between predicted and actual results. The confusion matrix consists of true positive, true negative, false positive and false negative values. The Area Under the Receiver

Operating Characteristic curve (AUROC Curve, or AUC) was generated through the comparison between the train and the test datasets and was used to analyse the performance of the model. Its index ranges between 0.5 (no correlation at all) and 1 (exact predictions), but values above 0.7 are generally considered satisfactory (HALDI; ROBINSON, 2009).

6.2.3 OB model implementation (post-processing)

- *BPS model calibration*

The schools' geometries and their surroundings were modelled in the plug-in Euclid (Figure 6.3). Information from field measurements, *in situ* observation and the architectural design documentation were used as input data in the software EnergyPlus for envelope (Tables 6.1 and 6.2), internal heat gains (Table 6.3) and operation schedules. The Kusuda Achenbach correlation was used to calculate undisturbed ground temperatures, in order to simulate heat transfer through the ground (ELI et al., 2019). The multizone AirflowNetwork (AFN) model was used to model natural ventilation. The discharge coefficient (Cd) was set to the standard value of 0.6 (Flourentzou, Van Der Maas & Roulet, 1998). The CpSimulator tool, which is based on computational fluid dynamic (CFD), was used to predict the wind pressure coefficients, in order to correctly predict the surroundings interference over the building's natural ventilation performance. The CpSimulator tool uses OpenFOAM as the background software to solve steady Reynolds-averaged Navier–Stokes (RANS) equations using turbulence models for specific atmospheric boundary layer (ABL) applications (BRE; GIMENEZ, 2022). The boundary conditions of the ABL log-law profile were set as: reference aerodynamic roughness length (zref) equal to 450 m; aerodynamic roughness length of the building's terrain (z0) equal to 0.25 m; reference mean wind velocity at building height (Vref) equal to 40 m/s; mean wind velocity (V) equal to 21.14 m/s. The wind pressure coefficients were calculated according to Equation 6.1.

$$C_P = \frac{p - p_0}{0.5. V_{ref}{}^2} \qquad \text{Eq. 6.1}$$

Where: p_0 = 0 m^2/s^2

(a) School A model (b) School B model (c) School C model

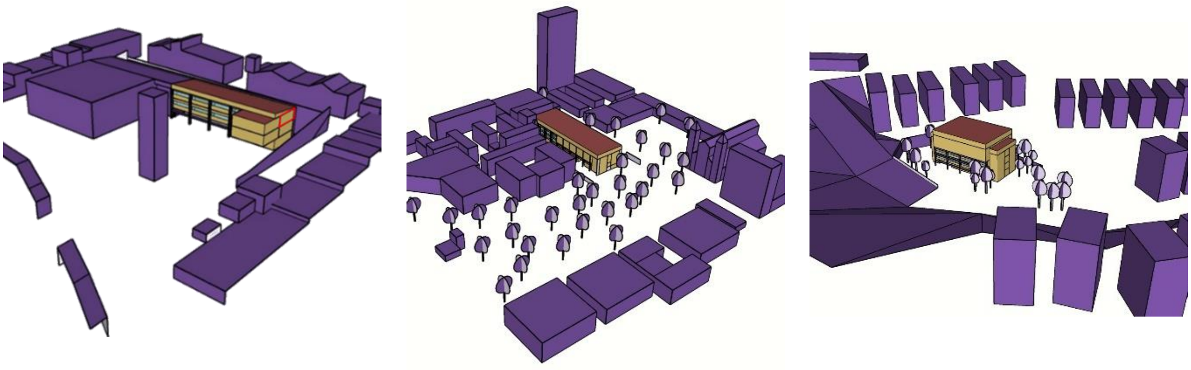

Figure 6.3 – Building simulation models geometry.

Table 6.1 – Thermal properties of envelope construction.

School	Item	Description	U-factor (W/m². K)	Thermal capacity (kJ/m². K)	Solar absorptance (α)	Solar heat gain coefficient (SHGC)
School A	Walls	Concrete block 190x190x390 mm	1.6	202	0.19	-
	Windows	Clear glazing 3 mm	5.7	-	-	0.87
	Floor	Concrete slab 150 mm + plaster + ceramic tiles	2.7	243	-	-
	Roof	Galvanized steel roofing + air chamber + concrete capping + concrete slab 150 mm+ air chamber + mineral acoustic ceiling	1.1	164	0.25	-
School B	Walls	Concrete block 190x190x390 mm	2.2	202	0.65	-
	Windows	Clear glazing 3 mm	6.3	-	-	0.87
	Floor	Concrete slab 150 mm + plaster + ceramic tiles	2.7	243	-	-
	Roof	Galvanized steel roofing + air chamber + concrete capping + concrete slab 150 mm	1.7	140	0.25	-
School C	Walls	Concrete block 190x190x390 mm	2.2	202	0.27	-
	Windows	Clear glazing 3 mm	6.3	-	-	0.87
	Floor	Concrete slab 150 mm + plaster + ceramic tiles	2.7	243	-	-
	Roof	Sandwich roofing + air chamber + concrete slab 210 mm + air chamber + mineral acoustic ceiling	0.6	515	0.25	-

Table 6.2 – Window and door frames.

School	Item	Description	Window opening factor
School A	Door	90 cm x 210 cm	1.0
	Façade window	20 pivot windows and 8 fixed glazing windows – 180 cm x 210 cm / window sill 80 cm (4 units)	0.4
	Hallway window	4 pivot windows – 180 cm x 80 cm / window sill 220 cm (4 units)	0.6
Schools B and C	Door	90 cm x 210 cm	1.0
	Façade window	20 pivot windows and 8 fixed glazing windows – 180 cm x 210 cm / window sill 80 cm (4 units)	0.4
	Hallway window	6 pivot windows and 4 fixed glazing windows– 180 cm x 80 cm / window sill 220 cm (4 units)	0.4

Table 6.3 – Internal loads.

Item	Description	Total loads
Occupancy	1.7 m²/person during school period (7 h to 16 h)	108 W/person
Equipment	2 fans – 150 W/unit	300 W
Electric lights	6 lamps with 2 fluorescent bulbs each– 40 W/unit	480 W

The BPS models were calibrated through the software EnergyPlus using measured indoor air temperature and mean radiant temperature data from the field measurements. Data collected at night (i.e. without the influence of solar radiation and internal thermal loads) was used in the calibration to minimise uncertainties. During this period, internal conditions are primarily influenced by changes in outdoor air temperatures, through conduction heat transfer through the wall, the window and the infiltration (NEVES et al., 2020). Outdoor variables (air temperature, relative humidity, wind speed and direction and precipitation index) for the same measurement period were obtained from the nearest weather station (3.5 to 8 km distant). Data were converted to EnergyPlus Weather File (epw) format using Weather Converter version 8.1.0, an EnergyPlus auxiliary program.

The Mean Absolute Error (MAE), the Normalised Mean Bias Error (NMBE) and the Coefficient Variation of Root Mean Square Error (CV RMSE) were used to verify the accuracy of the models, according to ASHRAE guideline 14 (ASHRAE, 2002). In all models, the MAE was below 1 ºC and the NMBE and the CV RMSE were below the ASHRAE 14 thresholds, which are 10% and 30%, respectively (Table 6.4).

Table 6.4 – Calibration results.

Model	MAE (ºC)	NMBE (%)	CV RMSE (%)
School A	0.95	-3.06	5.31
School B	0.84	-2.82	5.52
School C	0.85	-3.62	3.60

- *OB model implementation in BPS*

The occupant behaviour predictive model regarding window operation was implemented in EnergyPlus, in order to reproduce the real occupant behaviour, i.e., perform an annual simulation considering the window operation schedule based on real occupant behaviour. The occupant behaviour model implementation was based on the methodology provided by Gunay, O'Brien and Beausoleil-Morrison (2016), which is based on an EnergyPlus Energy Management System (EMS) script. In the beginning of each runtime, the inputs from the behaviour models are generated from a normal distribution, based on values of mean ± standard deviation. Then, the adaptive state for the window status (open/ closed) is computed via the logistic function previously developed (Equation 6.2), generating a random number sampled from a uniform distribution (0 = closed, 1 = open). This number is then compared to the likelihood estimated from Equation 2.

$$P(Y) = \frac{\mathrm{e}^{(\log odds)}}{1 + \mathrm{e}^{(log\ odds)}} = \frac{e^{(b_0 + b_1 X_{1i} + b_2 X_{2i} + \ldots b_n X_{ni})}}{1 + e^{(b_0 + b_1 X_{1i} + b_2 X_{2i} + \ldots b_n X_{ni})}} \qquad \text{Eq. 6.2}$$

Where: P(Y) is the probability of Y occurring, b0 is the Y intercept, bn is the regression coefficient, Xn is the value of the predictor variable, e is the base of natural logarithms.

The implementation of the occupant behaviour models was divided into two simulation sets, according to the COVID restrictive measures categorical variable (“yes” when windows and doors should remain open during occupancy and “no” when windows and doors could be freely operated), since they characterize variations in the logistic regression function.

- *Multi-objective optimization*

The multi-objective optimization (MOO) was chosen as the method to create optimized solutions in terms of thermal comfort and IAQ, since it is an interesting method to deal with conflicting design criteria, as an approach to realistic scenarios (NGUYEN; REITER; RIGO, 2014). The Non-Dominated Sorting Genetic Algorithm (NSGA-II) was chosen to develop this research study, since it is the most common algorithm implemented to solve multi-objective problems (EVINS, 2013) and it has been successfully implemented in similar studies (MOKHTARI; JAHANGIR, 2021). The NSGA-II is based on the evolution of a population of individuals (chromosomes) through genetic-inspired operations (such as crossover, mutation and selection), each representing a solution for the optimization problem (AMASYALI; EL-GOHARY, 2021).

The MOO problem intends to simultaneously maximize the thermal comfort conditions inside the classroom, in accordance with the adaptive model of ASHRAE 55-2020, and also maximize IAQ inside the classroom, in accordance with satisfactory levels of CO_2 concentration. Therefore, we selected, as objective functions, minimizing the number of exceedance hours per year (calculated according to year the ASHRAE 55-2020 adaptive thermal comfort model) and minimizing the average annual indoor CO_2 concentration. Both objective functions were configured in EnergyPlus through the Output: Table: Annual and Output: Table: Summary Reports objects.

The deterministic scenarios were created based on a combination of the number of occupants inside the classroom and the window state (open/ closed) and considering the goal of optimizing thermal comfort and IAQ conditions in the classroom. For the number of occupants, minimum and maximum values were defined, as well as a range of variation. For the window state, deterministic rules were set based on optimized thermal comfort conditions (based on the adaptive thermal comfort limits for naturally ventilated spaces from ASHRAE 55-2020) or optimized IAQ conditions (based on the reference values of CO_2 concentration for school buildings set by guidelines and protocols published during the pandemic (REHVA, 2021; CIBSE, 2021; UBA, 2021)). The EMS application was used to set the window state scenarios. For the scenarios regarding CO_2 concentration, a hysteresis operation was adopted as a control strategy, i.e., a deadband of 100 ppm was set so the window state would not change when CO_2 concentration levels fall within it. The deterministic scenarios are presented on Table 6.5.

Table 6.5 – Deterministic scenarios for multi-objective optimization.

Decision variables	**Deterministic scenarios**
Number of occupants	Minimum = 6 (5 students + teacher) Maximum = 31 (30 students + teacher, which represents current reality) Range of variation = 5
Window state	Always open during occupancy
	Always open during occupancy + Night time ventilation during weekdays
	Open during occupancy AND when Top > adaptive comfort 80% minimum acceptability limit (ASHRAE 55-2020)
	Open during occupancy AND when Top > adaptive comfort 80% minimum acceptability limit (ASHRAE 55-2020) + Night time ventilation during weekdays
	Open during occupancy AND when Top > adaptive comfort 90% minimum acceptability limit (ASHRAE 55-2020)
	Open during occupancy AND when Top > adaptive comfort 90% minimum acceptability limit (ASHRAE 55-2020) + Night time ventilation during weekdays
	Open during occupancy AND when CO_2 levels are above 700 ppm + deadband 100 ppm (REHVA, 2021; CIBSE, 2021; UBA, 2021)
	Open during occupancy AND when CO_2 levels are above 700 ppm + deadband 100 ppm (REHVA, 2021; CIBSE, 2021; UBA, 2021) + Night time ventilation during weekdays
	Open during occupancy AND when CO_2 levels are above 800 ppm + deadband 100 ppm (REHVA, 2021; CIBSE, 2021; UBA, 2021)
	Open during occupancy AND when CO_2 levels are above 800 ppm + deadband 100 ppm (REHVA, 2021; CIBSE, 2021; UBA, 2021) + Night time ventilation during weekdays

The optimization procedure was developed within the software R, through the packages eplusr and epluspar. The former establishes the communication between R and EnergyPlus, conducting data-driven analytics by using EnergyPlus as the background simulation engine (JIA; CHONG, 2021). The latter is an extension of the eplusr package that conducts specific parametric analyses on EnergyPlus models, including MOO using the NSGA-II algorithm (JIA; CHONG, 2021). The simulation job was set to run and evaluate one hundred generations containing 20 individuals per generation, resulting in a total of 2000 annual energy simulations. Then, the Pareto set was extracted and the Pareto front of discomfort hours and total carbon emissions was generated.

- *Comparison between real occupant behaviour and optimized theoretical scenarios*

Results from occupant behaviour predictive model implementation in BPS were compared against optimized scenarios, created through a deterministic approach, aiming to find out if occupants are operating windows near optimal conditions, considering thermal comfort and IAQ; and also how could window operation be improved, considering the classrooms' current architectural design.

6.3 Preliminary results and discussion

6.3.1 Field research descriptive statistics

The summary of the environmental conditions monitored during the occupied period in the school classrooms is presented in Table 6.6. The indoor CO_2 concentration presented similar values in schools A and B, while school C presented higher CO_2 concentration during all monitoring period (Figure 6.4a). The indoor relative humidity was between 40% and 60% (CIBSE, 2020) 63.4%, 29.3% and 28.2% of the time in schools A, B and C, respectively. Indeed, Schools B and C presented high humidity levels most of the time (Figure 6.4b). The indoor operative temperature was adequate on 59%, 61.8% and 87.6% of the time in schools A, B and C, respectively, according to the adaptive model of ASHRAE 55-2020 (Figure 6.4c). However, classrooms from schools A and B presented cold discomfort hours 20.1% and 25.2% of the time and hot discomfort hours 20.9% and 13% of the time, respectively. School C, despite having higher values of CO_2 concentration, presented better thermal conditions than the formers.

Table 6.6 – Summary of recorded parameters during the occupied period.

Variable	School A (n = 1170)			School B (n = 1489)			School C (n = 1142)		
	Mean	SD	Range	Mean	SD	Range	Mean	SD	Range
T_{op} (°C)	24.5	4.1	14.1 – 32.1	23.7	3.4	16.4 – 31.1	24.0	2.4	16.3 – 29.1
T_{out} (°C)	23.0	5.9	6.8 – 33.0	22.2	5.0	10.9 – 33.4	25.2	4.9	10.4 – 35.6
CO_2 (ppm)	540	107	359 – 1162	595	112	362 – 975	676	186	333 – 1682
RH (%)	53.1	10.0	27.0 – 74.0	62.1	11.1	30.0 – 80.3	63.6	8.8	30.0 – 87.0
RH_{out} (%)	59.1	16.7	26.0 – 89.0	73.1	20.7	22.9 – 99.9	61.8	18.4	16.0 – 96.0

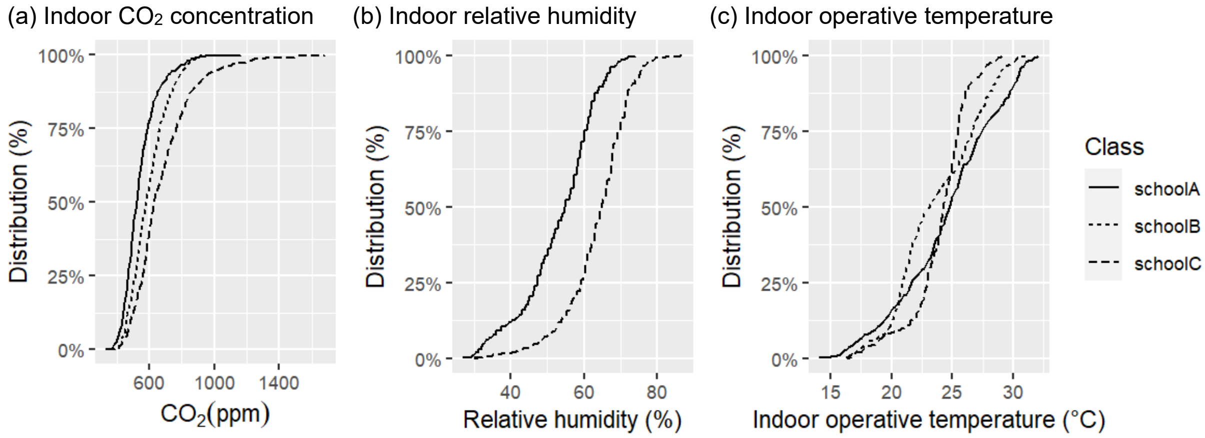

Figure 6.4 – Cumulative indoor environmental variables during occupied period.

The window remained open most of the time in all schools during the periods with and without COVID-19 restrictive measures (Figure 6.5). Yet, in School C, unlike in Schools A and B, the window remained open longer during the period without restrictions. This suggests that, in this school, the window status was influenced more by environmental factors than by the restrictions. In School B, the windows remained opened almost all the time, with little difference between both periods.

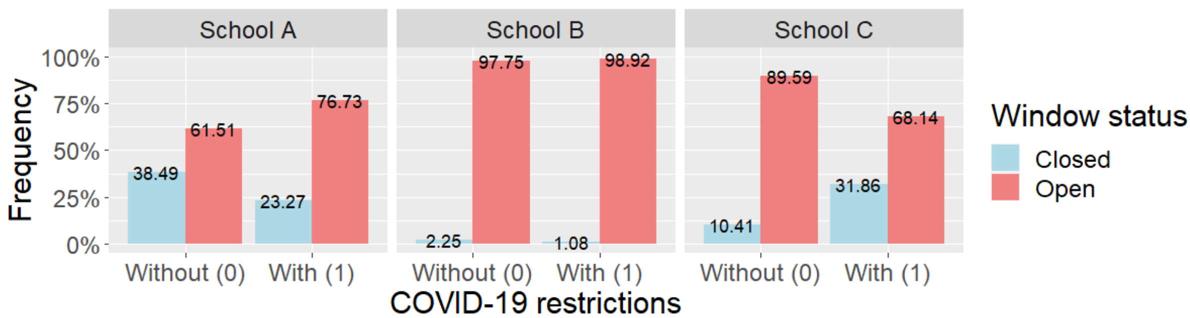

Figure 6.5 – Window status during occupied period with and without COVID-19 restrictions (field campaign results).

Figures 6.6 to 6.8 present the frequency of window status throughout the day. In School A, the windows were mostly open during the morning, particularly in the middle of the period, indicating that occupants tended to operate the windows more when arriving at or leaving the classroom. In the afternoon, the windows were primarily open during the first half and in the end of the period. In School B, the windows remained open throughout the day, except at the end of the afternoon, suggesting that occupants closed the windows when leaving the classroom. In School C, the windows remained open most of the day, particularly at the end of the morning and afternoon periods, suggesting that the windows were likely left open during unoccupied times to ventilate the classroom.

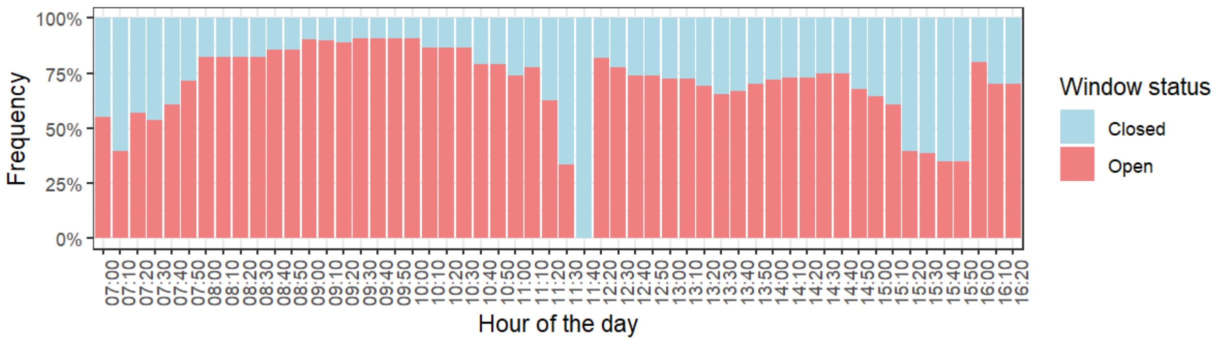

Figure 6.6 – Window status during the day – School A.

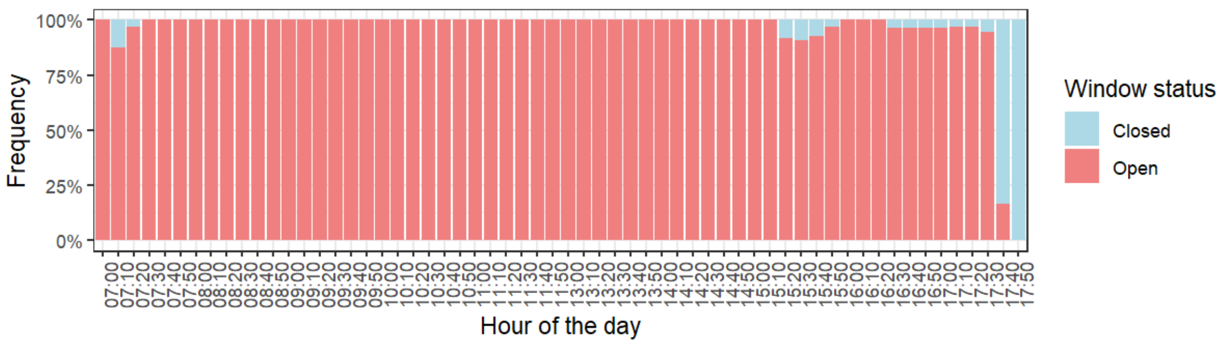

Figure 6.7 – Window status during the day – School B.

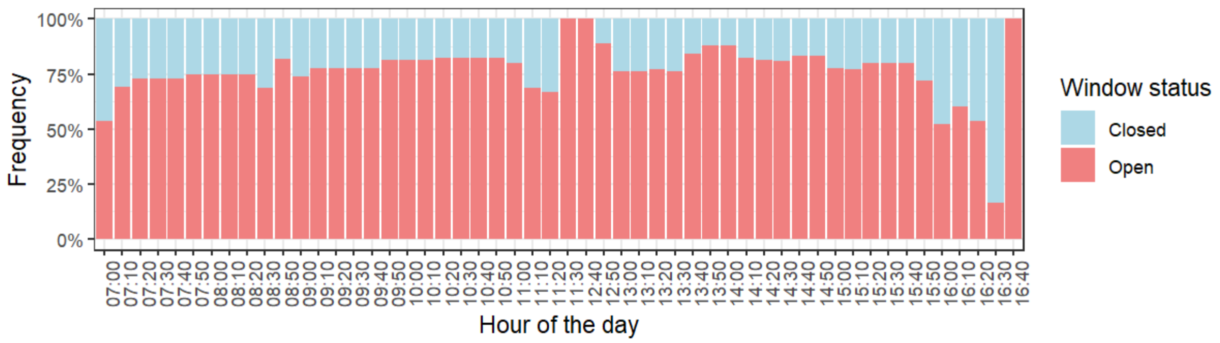

Figure 6.8 – Window status during the day – School C.

6.3.2 Occupant behaviour predictive model

Table 6.7 reports the outcomes from the window status model. The model presents a negative correlation between CO_2 concentration and window status, suggesting that higher CO_2 levels are associated with closed windows. This finding aligns with a study by Dutton and Shao (2010), but contrasts with other studies (KORSAVI; JONES; FUERTES, 2022b; STAZI; NASPI; D'ORAZIO, 2017a). Indoor operative temperature and relative humidity were not significant for window status and, consequently, were excluded from the model. This results differs from current literature, which found these variables significant predictors for window status in school classrooms (BELAFI et al., 2018; DUTTON; SHAO, 2010; KORSAVI; JONES; FUERTES, 2022b; STAZI; NASPI; D'ORAZIO, 2017a). Yet, while indoor operative temperature and relative humidity alone were not significant, their interactions with CO_2 concentration were found to be significant predictors for window status. COVID-19 restrictions exhibited a negative correlation with window status, suggesting that windows were less likely to be open during periods of restrictions. Despite the fact that this finding aligns with results from window status in School C, it is surprising, as it contrasts with the protocols implemented during the COVID-19 pandemic. Occupancy and its interaction with COVID-19 restrictions were not significant predictors for window status and were therefore excluded from the model.

Table 6.7 – Regression parameters for window status model.

	Estimate	Standard Error	p-value
Intercept	0.9041588	0.07650470	0.0000*
CO_2	-0.0032530	0.00047187	0.0000*
COVID-19 restrictions	-0.0359068	0.01555586	0.0211*
CO_2:Top **	0.0001233	0.00001772	0.0000*
CO_2:RH **	0.0000480	0.00000722	0.0000*
CO_2:Top:RH **	-0.0000019	0.00000029	0.0000*

Caption: * statistically significant values; **the use of colon between predictors refers to an interaction between variables.

The model value for AUC resulted in 0.75, which is considered satisfactory. Additionally, the confusion matrix results showed that the model predicted more open (n = 667) than closed status (n = 116), with 85% of correct predictions.

6.3.3 Model's implementation

The model's implementation in the building performance simulation (BPS) was conducted for an entire year, utilizing a treated weather file specific to each city. As a result, the simulation outcomes cannot be directly compared to the results from the field research, which focused on shorter periods of the year and relied on environmental data collected without statistical treatment.

Despite the window status being influenced by the COVID-19 restrictions, the results for window status with and without restrictions were very similar in all schools (Figures 6.9). This suggests that COVID-19 restrictions had a lower impact on window status compared to other factors included in the model. Furthermore, the simulation indicated a higher frequency of open windows during the period without restrictions, which was expected based on the model's negative correlation between COVID-19 restrictions and window status. The simulation results also showed very similar window status outcomes for all schools.

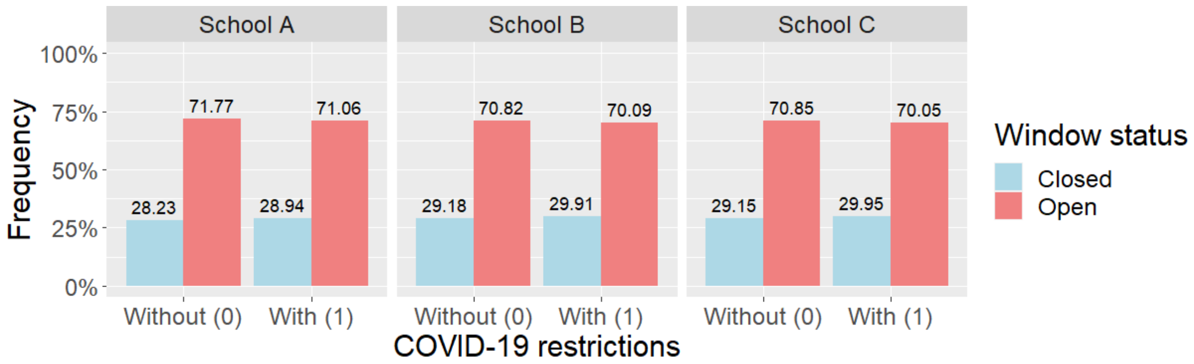

Figure 6.9 – Results for window status during occupied period with and without COVID-19 restrictions (BPS implementation results).

School A presented lower CO_2 concentration compared to the other schools (Figure 6.10a). Schools B and C had similar CO_2 concentration results, with School C exceeding 2000 ppm. School A presented lower indoor operative temperature most of the time when compared to the other schools, but at times it reached higher temperatures (Figure 6.10b). Schools B and C also presented similar results for indoor operative temperature. The similar results for Schools B and C could be related to the use of the same weather file in the simulation, as both schools are located in the same city. This could be seen as a limitation of the study, since outdoor variables can vary significantly across different areas, especially in large cities like São Paulo.

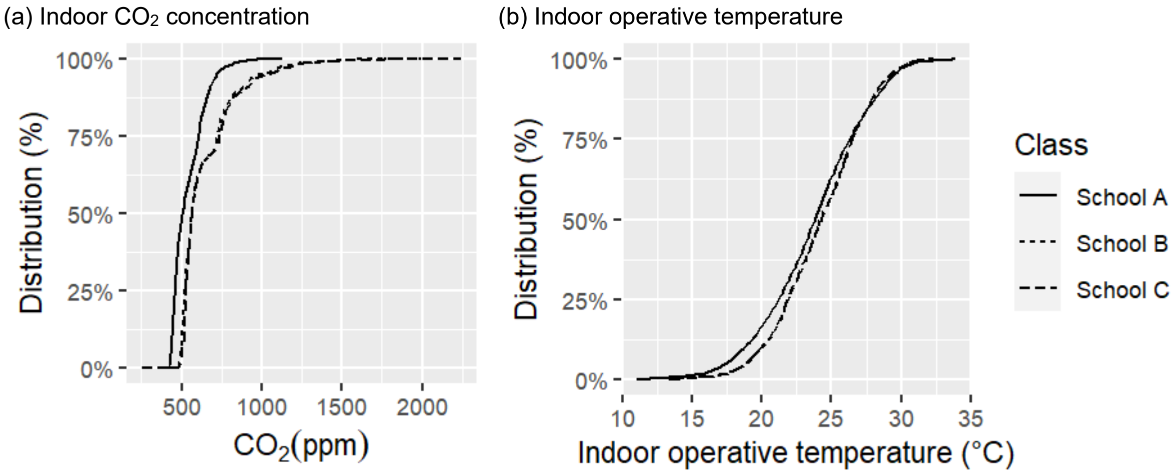

Figure 6.10 – Cumulative indoor environmental variables during occupied period.

The results from the model implementation suggest that the OB model predicts window status in a generalized manner, using data collected from all schools. This approach could be useful for designing new school buildings by factoring in occupant behaviour to improve predictions of building performance. Yet, for building renovations, it is recommended to use data from the specific existing school to develop a tailored model for more accurate predictions of building performance, highlighting the relevance of contextual factors.

6.3.4 Comparison between real occupant behaviour and optimized theoretical scenarios

Figures 6.11 to 6.13 show the results for discomfort time (ASHRAE, 2020b) and levels of CO_2 concentration, comparing optimized theoretical scenarios with real occupant behaviour across the three school buildings. The mustard yellow points represent the population, or candidate solutions, based on the deterministic scenarios outlined in Table 6.5. The blue points indicate the Pareto front, which comprises a set of optimal trade-off solutions, considering our objective functions: minimizing the number of exceedance hours per year and minimizing the average annual indoor CO_2 concentration. The red and green points represent the real occupant behaviour with and without the COVID-19 restrictive measures, respectively.

As expected, the real occupant behaviour under COVID-19 restrictive measures (red point) and without such restrictions (green point) presented similar results in each school, as the window status was also very similar, as shown in Figure 6.9.

The Pareto front for School A (Figure 6.11) indicates that the scenario achieving the optimal balance between both objective functions was the one with minimal occupancy (6 persons) and windows open during occupancy when the indoor operative temperature exceeded the adaptive comfort 80% minimum acceptability limit (resulting in CO_2 levels of 452 ppm and 973 hours of discomfort). In comparison, real occupant behaviour resulted in CO_2 levels that were approximately 21% higher and 9% more hours of discomfort.

In School B (Figure 6.12), the optimal scenario also involved minimal occupancy (6 persons) with windows always open during occupancy, resulting in CO_2 levels of 450 ppm and 1,091 hours of discomfort. Compared to this optimized scenario, real occupant behaviour led to CO_2 levels that were 19% higher and 4.5% more hours of discomfort.

In School C (Figure 6.13), the optimal solution involved an occupancy of 11 persons with windows always open during occupancy, resulting in CO_2 levels of 469 ppm and 1,030 hours of discomfort. In comparison to this optimized scenario, real occupant behaviour led to CO_2 levels that were 42.5% higher and 6% more hours of discomfort.

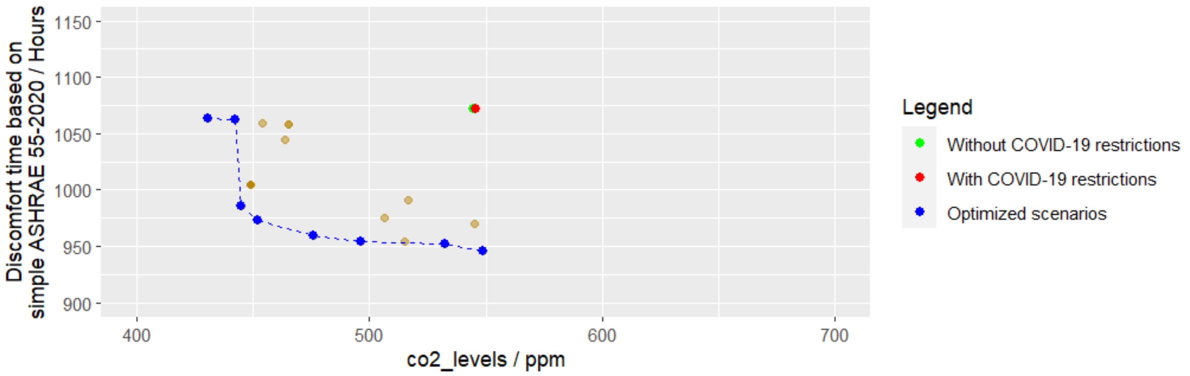

Figure 6.11 – Optimized theoretical scenarios and real occupant behaviour for School A.

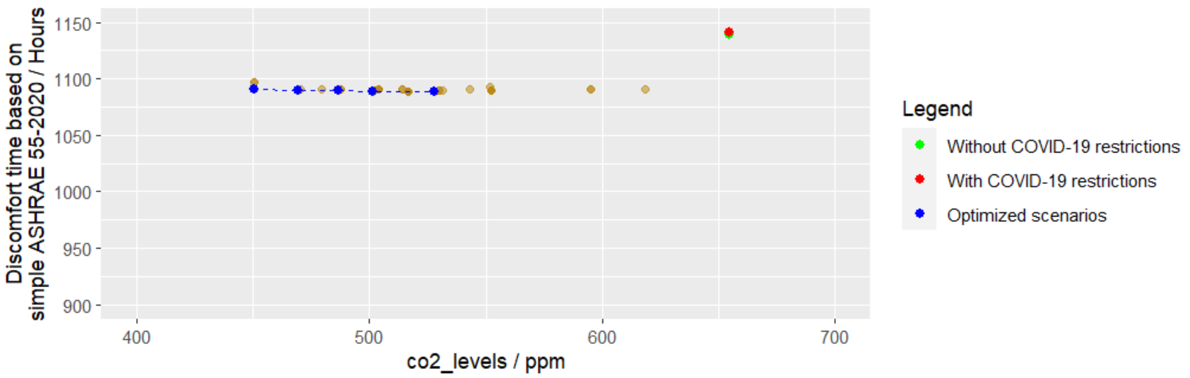

Figure 6.12 – Optimized theoretical scenarios and real occupant behaviour for School B.

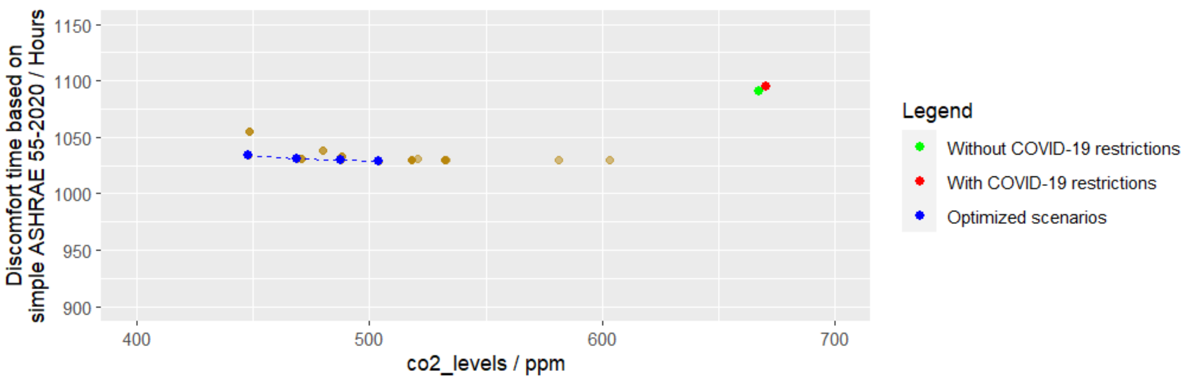

Figure 6.13 – Optimized theoretical scenarios and real occupant behaviour for School C.

Therefore, regarding window status, the optimized scenario for School A suggests that windows should be opened based on the indoor operative temperature thresholds. In contrast, for Schools B and C, the windows should remain open during occupancy. As for occupancy, the optimized solutions for Schools A and B involved a minimum occupancy of 6 persons, while in School C, the best scenario indicated an occupancy of 11 persons. These findings highlight an important consideration for managing indoor environments, especially in the context of future pandemics.

When comparing these optimized scenarios with actual occupant behaviour, the real behaviour resulted in less favourable indoor conditions, especially concerning CO_2 levels – although satisfactory CO_2 levels and discomfort times under 1150 hours were achieved. This indicates that window operation and occupant density significantly influence classroom health, suggesting that adjustments in occupant behaviour could further improve indoor conditions, enhancing both thermal comfort and perceived air quality.

6.4 Conclusions

This study aimed to analyse potential conflicts between thermal comfort and perceived indoor air quality, with regard to triggers for manual operation of windows in naturally ventilated classrooms, and to identify optimal situations of balance between both drivers to support building use practices focused on occupant-centric building operation. The data collected in three school buildings was used to develop a window status predictive model and to calibrate one BPS model for each school. The window status predictive model was implemented in the simulation, reproducing the real occupant behaviour for the entire year. Multi-objective optimization was applied to identify optimal situations of balance between thermal comfort and perceived indoor air quality. Results from the simulations considering the real occupant behaviour and the multi-objective optimization were compared to find out if occupants are operating windows near optimal conditions and to identify how could window operation be improved, considering the classrooms' current architectural design.

CO_2 concentration and its interactions with indoor operative temperature and relative humidity in addition to the COVID-19 restrictions were identified as significant predictors in our model. The results from the model implementation suggest that the OB model predicts window status in a generalized manner, utilizing data collected from all schools. While this generalized approach may be useful for designing new school buildings by incorporating occupant behaviour into performance predictions, it is recommended that renovations rely on data specific to the existing school to develop a tailored model, ensuring more accurate predictions of building performance.

The results from the multi-objective optimization reveal that the optimal strategies vary by school. For window operation, School A benefits from adjusting window openings based on indoor temperature thresholds, while Schools B and C perform better with windows consistently open during occupancy. In terms of occupancy, the recommendation is a minimum of 6 persons in Schools A and B, and 11 persons in School C. These strategies underscore a critical consideration for managing indoor environments, particularly in the context of future pandemics, where the relationship between classroom size and occupant density and the recommendations for window operation should be carefully reviewed. It is worth highlighting that, since the optimal strategies varied between schools, the recommendations should be evaluated according to each specific context.

The real occupant behaviour resulted in worse outcomes compared to the optimized scenarios, with significant differences in CO_2 levels, especially in School C (42.5% higher), and discomfort times, particularly in School A (9% higher). This suggests that occupant behaviour concerning window operation and occupancy directly impacts thermal comfort and perceived indoor air quality. Additionally, there is an opportunity to enhance indoor conditions by modifying occupant behaviour.

This study provides valuable insights into how occupant behaviour regarding window operation and occupancy affects indoor conditions in school classrooms. The findings highlight significant variations in indoor air quality (CO_2 levels) and thermal comfort (discomfort hours) between real and optimized occupant behaviours, suggesting that adjusting occupant behaviour could improve indoor conditions. Additionally, the optimized scenarios offer practical recommendations for enhancing classroom design and operational strategies. Future research should explore other behaviours in school classrooms, such as door and fan operation, to identify optimal strategies for these elements as well, further improving indoor environmental conditions.

7 General Discussion

Occupant behaviour (OB) models have been developed to predict and represent human actions in building performance simulations, to optimize building design and reduce the performance gap. Three main steps to represent the OB modelling approach were identified in the literature, which were used to structure this research: the data collection (pre-processing, step 1), the OB model development and evaluation (processing, step 2) and the OB model implementation in building performance simulation (post-processing, step 3). While data collection (step 1) is widely adopted as a research method in school buildings, the second and third steps have been less thoroughly explored in studies conducted in this context. This indicates that OB modelling is still in its early stages for school buildings, representing an important research gap. Table 7.1 summarizes the objectives addressed, the methods employed, and the main contributions of each chapter in this thesis.

The literature review, presented in **Chapter 2**, highlights several key aspects of occupant behaviour in school buildings. Teachers were identified as the primary active occupants responsible for making environmental adjustments, with decision-making processes largely driven by collective needs and school rules. Environmental factors, particularly indoor and outdoor air temperatures, were the most frequently studied drivers in this context. Additionally, most studies tend to focus on a single behaviour, such as window or light operation, and a specific scope, such as energy consumption, indoor environmental quality, indoor air quality, or thermal and visual comfort. However, in practice, occupant behaviours are interconnected and can have both positive and negative impacts on various aspects of building performance. Furthermore, the COVID-19 pandemic introduced restrictive measures in school buildings (e.g., opening windows and doors and reducing the number of occupants), directly affecting occupant behaviour, making it essential to investigate which are the behaviour changes, their actions' drivers and their impacts on the built environment.

In this context, a first analysis of the impact of the restrictions implemented during the COVID-19 pandemic on the built environment is presented in **Chapter 3**. The results suggest that the restrictive measures can help to reduce the CO_2 concentration and the probability of infection, in addition to improving the thermal comfort of the analysed classroom. Yet, the measures adopted by schools must be analysed for each specific climate and context in order to balance potential benefits and risks to occupants. Due to their impact on the built environment, COVID-19 restrictive measures were included as a predictor variable in the models developed in this research aiming to investigate their influence on occupant behaviour.

The OB modelling approach was applied in **Chapters 4, 5 and 6**. To address the research gaps identified in the literature, the data collected in three school buildings included multi-domain factors, considering not only environmental variables (such as thermal and indoor air quality factors) but also contextual and multi-behaviour domains. Data collection (step 1), particularly related to occupant investigation, usually presents challenges due to OB complexity and uncertainty, ethical issues, and the requirement of specific monitoring equipment, as identified in the literature review and described in this research as limitations.

The data collected was used to develop OB predictive models (step 2), with different objectives in each chapter. In **Chapter 4**, three window status predictive models, one for each school, were developed using the generalized linear model (GLM) to analyse the differences in behaviour between schools. Indoor operative temperature, relative humidity, CO_2 concentration and COVID-19 restrictions were identified as triggers for window operation in all schools. Yet, the outcomes indicate that occupant behaviour varies between schools, suggesting that behaviour is context-dependent and strongly influenced by rules and habits, as confirmed by the questionnaire responses.

In **Chapter 5**, window, door and fan status predictive models were developed using the generalized linear mixed model (GLMM), considering the monitored schools as a variable of a random nature and testing multi-domain variables as possible predictors. The analysis identified indoor environmental variables, such as operative temperature, relative humidity, and CO_2 concentration, as significant predictors for window, door, and fan status in almost all models. However, other factors like teachers' behaviour and COVID-19 restrictions emerged as potentially more influential on occupant behaviour and the models that included these predictors demonstrated better performance during the validation phase, underscoring the importance of considering the contextual domain in behavioural studies.

In **Chapter 6**, one window status predictive model was developed using the generalized linear mixed model (GLMM), considering the monitored schools as a variable of a random nature, aiming to represent OB in the BPS through an entire year to analyse potential conflicts between thermal comfort and perceived indoor air quality. Indoor environmental variables (CO_2 concentration, indoor operative temperature and relative humidity) were tested as predictors for window status in addition to the COVID-19 restrictions. CO_2 concentration and its interactions with indoor operative temperature and relative humidity, and the COVID-19 restrictions were identified as significant predictors in this model.

Overall, the OB predictive models indicated that context-related factors (e.g., teachers' behaviour and COVID-19 restrictions) had a greater influence on window, door, and fan status than environmental variables in school classrooms. This finding is likely unique to school buildings, where decision-making processes are primarily driven by collective needs and school rules, differing from other contexts such as office and residential buildings. However, the inclusion or exclusion of certain variables in the models resulted in differences in the significance of predictors, raising questions about which variables should be included when developing an OB model. While models with additional predictors offered more accurate predictions, they also became more context-dependent and less generalizable. Therefore, the inclusion of predictors should consider the objective of the research. This trade-off between model complexity and generalizability is a key consideration in this research, highlighting the nuanced relationship between various factors influencing occupant behaviour in school buildings.

Chapter 6 also presents the OB model implementation (step 3). The window status predictive model was implemented in building performance simulations to predict occupant behaviour related to window operation throughout the entire year in each school. The implementation results suggest that the OB model predicts window status in a generalized manner, as the outcomes were similar across the three schools. This similarity arises because a single model was developed using data collected from all schools. An alternative approach would be to develop one model for each school by applying the Generalized Linear Model (GLM). While this generalized approach can be valuable for designing new school buildings by incorporating occupant behaviour into performance predictions, it is recommended that renovations utilize data specific to the existing school to develop a tailored model, ensuring more accurate predictions of building performance. However, it is important to note that such a tailored model would benefit only the specific school for which it was developed. Therefore, once more the research's objective should be considered when choosing the approach to develop OB models.

Results from real occupant behaviour regarding thermal comfort (discomfort hours) and perceived indoor air quality (CO_2 levels), extracted from the building performance simulations, were compared to optimized scenarios in **Chapter 6**. The parameters analysed in the multi-objective optimization included those considered in the COVID-19 restrictive measures:

window operation and occupancy. The optimal strategies varied between schools. For window operation, school A benefits from adjusting window openings based on indoor temperature thresholds, while schools B and C perform better with windows consistently open during occupancy. In terms of occupancy, the recommendation is a minimum of 6 persons in schools A and B, and 11 persons in school C. The real occupant behaviour resulted in worse outcomes compared to the optimized scenarios, with significant differences in CO_2 levels, especially in school C (42.5% higher), and discomfort times, particularly in school A (9% higher).

This study highlights the significant influence of occupant behaviour on thermal comfort and indoor air quality within school environments. By comparing real occupant behaviour with optimized scenarios, it is evident that targeted adjustments to window operation and occupancy levels can substantially improve indoor conditions. The variation in optimal strategies across different schools emphasizes the need for context-specific approaches when designing and managing classroom environments.

Furthermore, these findings are particularly relevant in the context of future pandemics, where maintaining healthy indoor air quality and comfortable thermal conditions is crucial. The optimized scenarios not only offer actionable recommendations for enhancing classroom design and operation but also underscore the importance of revisiting occupant behaviour and building strategies to ensure the well-being of occupants. Ultimately, this research provides valuable insights that can inform both new school designs and renovations, helping to create safer and more comfortable learning environments.

Table 7.1 – Summary of analyses across chapters.

Chapter	Main objective of the paper	Thesis objectives addressed in each chapter*					Methods	OB modelling approach			Main contributions
		MO	SO1	SO2	SO3	SO4		Data collection (step 1)	Model development (step 2)	Model implementation (step 3)	
2	Addressing the knowledge gap on occupant behaviour modelling for naturally ventilated school buildings and understanding the potential changes on actions' drivers due to the COVID-19 pandemic.		●	●			Systematic literature review				Identification of knowledge and research gaps.
3	Evaluating the thermal comfort and IAQ conditions of a naturally ventilated classroom, in order to identify scenarios that contribute, simultaneously, to the reduction of the risk of dissemination of the SARS-CoV-2 virus and to the maintenance of thermal comfort for users.			●		●	Field research and building performance simulation (BPS)	●			Analysis of the impact of the COVID-19 restrictive measures on the risk of dissemination of the virus and on thermal comfort.
4	Addressing the window operation behaviour, the thermal conditions and the perceived IAQ in naturally ventilated classrooms in a humid subtropical climate during the COVID-19 pandemic.	●		●	●		Field research and statistical analysis (generalized linear models - GLM)	●	●		Identification of predictors for window status and differences in occupant behaviour between schools.
5	Identifying and quantifying the influence of multi-domain factors (including thermal, indoor air quality, contextual and multi-behaviour domains) on window, door, and fan status in naturally ventilated school classrooms in a humid subtropical climate, in order to predict occupant behaviour.	●		●	●		Field research and statistical analysis (generalized linear mixed models - GLMM)	●	●		Identification of predictors for window, door and fan status, considering multi-domain factors.
6	Analysing potential conflicts between thermal comfort and perceived indoor air quality, with regard to triggers for manual operation of windows in naturally ventilated classrooms, and identifying optimal situations of balance between both drivers to support building use practices focused on occupant-centric building operation.	●		●	●	●	Field research, statistical analysis (GLMM), BPS and multi-objective optimization	●	●	●	Recommendations for window operation and occupancy for school classrooms based on optimal situations of balance between thermal comfort and perceived indoor air quality.

***Main objective (MO):** Identify and quantify the influence of multi-domain factors (including thermal, indoor air quality, contextual and multi-behaviour domains) on window, door, and fan status in naturally ventilated school classrooms in a humid subtropical climate, in order to improve the ability to predict occupant behaviour.
Specific objective 1 (SO1): Identifying and analysing existing occupant behaviour models for naturally ventilated and mixed-mode school buildings.
Specific objective 2 (SO2): Investigating potential impacts on occupant behaviour due to restrictions implemented during the COVID-19 pandemic in school buildings.
Specific objective 3 (SO3): Developing predictive occupant behaviour models based on the collected data.
Specific objective 4 (SO4): Analysing potential conflicts between thermal comfort and indoor air quality and identifying optimal situations of balance between both drivers.

8 Conclusion

The **main objective** of this thesis was to identify and quantify the influence of multi-domain factors (including thermal, indoor air quality, contextual and multi-behaviour domains) on window, door, and fan status in naturally ventilated school classrooms in a humid subtropical climate, in order to improve the ability to predict occupant behaviour (OB). The thesis is structured into five main chapters, each addressing specific objectives as well as the main objective. This research confirms the hypothesis that including multi-domain factors in OB models can enhance the prediction of occupant behaviour in building performance simulations (BPS) of school classrooms. However, the results also suggest that more complex models with additional predictors become more context-dependent and less generalizable. The trade-off between model complexity and generalizability is an important consideration in this thesis.

The **first specific objective (SO1)** – identifying and analysing existing occupant behaviour models for naturally ventilated and mixed-mode school buildings – is addressed in Chapter 2. A unique aspect of occupant investigation in school buildings is recognizing the teacher as the primary active occupant responsible for environmental adjustments, with decision-making processes largely based on collective needs and school rules. Despite this, environmental factors, particularly indoor and outdoor air temperatures, remain the most studied drivers. This finding underscores the need to investigate additional domains beyond the physical (environmental factors) that influence occupant behaviour in school buildings, especially the contextual domain, such as teachers' behaviour and collective actions, thus supporting the main objective of this thesis.

Furthermore, although all the reviewed studies on school buildings considered the correlation between occupant behaviour and drivers in their methodology, only 46% actually presented the resultant OB model, and few studies implemented the OB model in BPS tools. These studies typically focus on a single aspect, such as energy consumption, indoor environmental quality, indoor air quality (IAQ), or thermal or visual comfort. However, occupant behaviour can impact various aspects of building performance both negatively and positively, needing a simultaneous analysis of multi-input and output parameters interaction.

The **second specific objective (SO2)** – investigating potential impacts on occupant behaviour due to restrictions implemented during the COVID-19 pandemic in school buildings – is addressed in chapters 2 to 6. The outcomes from the literature review, presented in Chapter 2, support the need to investigate the behaviour changes, their actions' drivers and their impacts on the built environment due to the restrictions implemented during the COVID-19 pandemic. The restrictions, which are related to occupant behaviour (opening windows and doors and reducing the number of occupants), can help to reduce the CO_2 concentration and the probability of infection, in addition to improving the thermal comfort in naturally ventilated school classrooms, as shown in Chapter 3. Yet, the measures adopted by schools must be analysed for each specific climate and context in order to balance potential benefits and risks to occupants.

In this context, the restrictions implemented during the COVID-19 pandemic were included as a predictor in the occupant behaviour predictive models developed in Chapters 4, 5 and 6. These restrictions showed statistical significance for the status of windows, doors, and fans in all models, indicating their impact on occupant behaviour. Yet, the results from the real occupant behaviour, simulated over a year in Chapter 6, revealed little variance when comparing the periods with and without the COVID-19 restrictions. This suggests that, although the restrictive measures were identified as a predictor of occupant behaviour, the actual changes in behaviour might not be as significant as anticipated.

The **third specific objective (SO3)** – developing predictive occupant behaviour models based on the collected data – is addressed in chapters 4, 5 and 6. In Chapter 4, that presents one window status predictive model for each school, indoor operative temperature, relative humidity, CO_2 concentration and the restrictions imposed during the COVID-19 pandemic were identified as triggers for window operation in all schools. In addition, the differences between the school classrooms suggest that occupant behaviour is context dependent, being highly influenced by rules and habits.

The results presented in Chapter 5 highlighted that predictors such as the teachers' behaviour and the COVID-19 restrictions could have a greater influence on occupant behaviour than environmental variables, indicating the relevance of investigating other domains in behavioural studies. Also, the models including additional predictors were the ones with better results during the validation phase, suggesting that, while more complex models can provide more accurate predictions of occupant behaviour, they also become more context-dependent and less generalizable.

The model implementation, in Chapter 6, indicates that the developed OB model predicts window status in a generalized manner, as the outcomes were similar across the three schools. This generalized approach can be valuable for designing new school buildings by incorporating occupant behaviour into performance predictions. Yet, for building renovations a specific model using only data specific to the existing school should ensure more accurate predictions of building performance.

The **fourth specific objective (SO4)** – analysing potential conflicts between thermal comfort and indoor air quality – is addressed in chapters 3 and 6. Chapter 6 also identifies optimal situations of balance between both drivers. The indoor conditions were analysed considering occupant behaviours related to the restrictions imposed during the COVID-19 pandemic: window operation and occupancy. The results from both chapters confirm that occupant behaviour impacts significantly thermal and indoor air quality conditions. In Chapter 3, a comparison between the best and the worst simulated scenarios revealed a reduction of 42% in the concentration of CO_2 and 33% in the infection probability and an increase of 60% in comfort hours. In Chapter 6, the findings highlight variations of up to 42.5% in CO_2 levels and up to 9% discomfort hours between real and optimized occupant behaviours. These significant differences between scenarios indicate the opportunity to enhance indoor conditions by adjusting occupant behaviour.

The optimal situations of balance between thermal comfort and indoor air quality, presented in Chapter 6, indicate that the optimal strategies vary by school, highlighting the need for recommendations to be evaluated according to each specific context. The optimized scenarios provide practical recommendations for improving classroom design and operational strategies. These findings underscore a critical consideration for managing indoor environments, particularly in the context of future pandemics, where the relationship between classroom size and occupant density and the recommendations for window operation should be reviewed.

8.1 Main contributions to science and society

This thesis addresses a significant gap in the literature by providing data on occupant behaviour in naturally ventilated school classrooms situated in a humid subtropical climate. The findings underscore the complexity of occupant behaviour, which is influenced by multiple factors and presents many challenges for investigation. Consequently, the results contribute to the debate on the uncertainty of addressing occupancy models in building performance simulations, allowing standards for integrating occupant models in building design to better reflect reality.

Furthermore, occupant behaviour has a direct impact on indoor environmental conditions, particularly in buildings where occupants can interact with the building systems, such as those with manually operable windows. The results of this research offer insights for designers and architects on how to design school buildings that promote the interaction between occupants and buildings' systems to contribute to a comfortable and healthy environment. In this context, the data provided by this research supports the development of more occupant-friendly spaces, emphasizing systems that are accessible and easy to interact with.

The outcomes also benefit the schools that participated in this research by providing them with reports on the collected data, key findings regarding the developed occupant behaviour models and suggestions for operating windows, doors and fans. In addition, a general report provided to the Foundation for Education Development (FDE) will contribute to the design and operation of public-school buildings in the state of Sao Paulo.

8.2 Limitations and future research

The limitations of this study include:

(i) Monitoring equipment – Due to the restricted number of monitoring equipment, the schools were not monitored simultaneously. Instead, the monitoring campaign was split into four rounds to cover all the seasons in each classroom. This sequential monitoring may introduce variability based on time of the year. Also, the absence of equipment to monitor occupancy required the use of attendance lists provided by each teacher, which may not be as reliable as data obtained from dedicated occupancy monitoring equipment, potentially introducing some level of uncertainty into the analysis.

(ii) Sample size – Also due to the restricted number of equipment, the sample was limited to three schools. Larger sample sizes are often preferred to develop more precise models, as they provide more data to train the models effectively.

(iii) Internal factors – The study did not consider internal factors such as psychological and physiological variables that could potentially be included as predictors in the models. This omission was due to the complexity of investigating and monitoring these factors.

Future studies could further enhance the sample size by collecting data from other school classrooms in different contexts (e.g., different climates, types of classrooms, students of different ages) and investigate a broader range of factors that can influence occupant behaviour, such as internal (e.g., psychological and physiological variables) and contextual (e.g., school routine and rules) factors.

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APPENDICES

Appendix A: Teachers' questionnaire (Appendix of Chapters 4 and 5)

QUESTIONÁRIO

Turno(s) em que dá aula: □ Manhã □ Tarde **Data:** ____/____/____ **Hora:**______

1. O que você está vestindo hoje?

□ Short/ Bermuda □ Camiseta manga curta □ Sandália/ Chinelo
□ Saia □ Camiseta manga longa □ Tênis
□ Calça comprida □ Malha/ jaqueta □ Sapato/ Bota

2. Neste momento, a sala está:

□ Muito quente □ Nem quente nem fria □ Muito fria
□ Pouco quente □ Pouco fria

3. Neste momento, como você gostaria que a sua sala estivesse?

□ Mais quente □ Como já está □ Mais fria

4. Neste momento, o vento que está entrando pela janela na sala:

□ Está agradável □ A janela está fechada
□ Não incomoda □ Incomoda

5. Neste momento, em relação ao quadro negro, o sol/ a claridade que está entrando pela janela:

□ Está agradável □ Atrapalha
□ Não atrapalha □ Não está entrando sol/claridade

6. Em geral, quem opera as janelas, as persianas/cortinas (se houver) e os ventiladores dentro da sala de aula?

□ Apenas os professores ou outros funcionários
□ Apenas os alunos
□ Quase sempre os professores ou outros funcionários
□ Quase sempre os alunos
□ Qualquer pessoa (professores ou alunos)

7. Os alunos costumam solicitar para abrir ou fechar a janela?

□ Sim, com muita frequência □ Sim, raramente
□ Sim, às vezes □ Não

8. Os alunos costumam solicitar para ligar ou desligar o ventilador?

□ Sim, com muita frequência □ Sim, raramente
□ Sim, às vezes □ Não

9. Os alunos costumam solicitar para ligar ou desligar a luz?

☐ Sim, com muita frequência ☐ Sim, raramente
☐ Sim, às vezes ☐ Não

10. Os alunos costumam solicitar para abrir ou fechar a persiana/cortina?

☐ Sim, com muita frequência ☐ Sim, raramente
☐ Sim, às vezes ☐ Não
☐ Não há persiana/cortina na sala de aula

11. Quanto tempo a janela da sala permaneceu aberta hoje, durante a aula?

☐ Apenas no início da aula
☐ Apenas no fim da aula
☐ Durante todo o horário de aula
☐ A janela permaneceu fechada durante toda a aula

12. Quem abriu a janela da sala hoje?

☐ Eu
☐ Outro funcionário
☐ Aluno
☐ Não sei, a janela já estava aberta quando eu cheguei
☐ A janela não foi aberta hoje

13. Quem fechou a janela da sala hoje?

☐ Eu
☐ Outro funcionário
☐ Aluno
☐ A janela não foi fechada (está aberta)
☐ A janela permaneceu fechada durante toda a aula

14. No caso de você ter aberto ou fechado a janela da sala hoje, qual foi a motivação?
(Apenas responder se respondeu EU nas questões 12 e/ou 13)

☐ Porque tinha cheiro ruim
☐ Para ventilar a sala de aula
☐ Por causa da chuva
☐ Porque estava muito quente
☐ Porque estava muito frio
☐ Outro motivo: ___________________________

15. Quem ligou o ventilador da sala hoje?

☐ Eu
☐ Outro funcionário
☐ Aluno
☐ Não sei, já estava ligado quando eu cheguei
☐ O ventilador não foi ligado hoje

16. Quem desligou o ventilador da sala hoje?

□ Eu
□ Outro funcionário
□ Aluno
□ O ventilador não foi desligado ainda (está ligado)
□ O ventilador permaneceu desligado durante toda a aula

17. No caso de você ter ligado ou desligado o ventilador da sala hoje, qual foi a motivação? (Apenas responder se respondeu EU nas questões 15 e/ou 16)
□ Para ventilar a sala de aula
□ Porque estava muito quente
□ Porque estava muito frio
□ Outro motivo: ____________________________

18. Quem ligou a luz da sala hoje?
□ Eu
□ Outro funcionário
□ Aluno
□ Não sei, a luz já estava ligada quando cheguei
□ A luz não foi ligada hoje

19. Quem desligou a luz da sala hoje?
□ Eu
□ Outro funcionário
□ Aluno
□ A luz não foi desligada ainda (está ligada)
□ A luz permaneceu desligada durante toda a aula

20. No caso de você ter ligado ou desligado a luz da sala hoje, qual foi a motivação? (Apenas responder se respondeu EU nas questões 18 e/ou 19)
□ Para enxergar melhor o quadro negro
□ Para enxergar melhor a minha mesa
□ Outro motivo: ____________________________

Caso haja persiana/ cortina na sala de aula:

21. Quem abriu a persiana/ cortina da sala hoje?
□ Eu
□ Outro funcionário
□ Aluno
□ Não sei, a persiana/ cortina já estava aberta quando cheguei
□ A persiana/ cortina não foi aberta hoje

22. Quem fechou a persiana/ cortina da sala hoje?
□ Eu
□ Outro funcionário
□ Aluno
□ A persiana/ cortina não foi fechada hoje (está aberta)
□ A persiana/ cortina permaneceu fechada durante toda a aula

23. No caso de você ter aberto ou fechado a persiana da sala hoje, qual foi a motivação?
(Apenas responder se respondeu EU nas questões 21 e/ou 22)

☐ Para enxergar melhor o quadro negro

☐ Para enxergar melhor a minha mesa

☐ Outro motivo: ____________________________

Em relação às mudanças na escola devido à pandemia do COVID-19:

24. Quais as recomendações da escola para o uso de máscara?

☐ É obrigatório em todos os ambientes fechados

☐ É obrigatório em todos os ambientes da escola (fechados e abertos)

☐ É obrigatório apenas na sala de aula

☐ Não é obrigatório

☐ Outra: _________________________

☐ Não fizeram nenhuma recomendação

25. Quais as estratégias adotadas por você (ou recomendadas pela direção da escola) para uso da sala de aula, em função da pandemia? (pode marcar mais de uma alternativa)

☐ Deixar a janela sempre aberta ☐ Não abrir a janela

☐ Deixar a porta sempre aberta ☐ Não deixar a porta aberta

☐ Deixar o ventilador sempre ligado ☐ Não ligar o ventilador

☐ Outra: ____

☐ A direção da escola não fez nenhuma recomendação

☐ Não mudei de comportamento em relação a antes da pandemia

26. O número de alunos em sala de aula:

☐ Diminuiu ☐ Permaneceu o mesmo ☐ Aumentou

27. O tempo de permanência dos alunos em sala de aula:

☐ Diminuiu ☐ Permaneceu o mesmo ☐ Aumentou

28. Caso o tempo em sala de aula tenha reduzido, qual a alternativa para suprir o número de aulas necessárias?

☐ Uso de espaços ao ar livre dentro da escola

☐ Atividades remotas

☐ Outro: ____

29. A posição dos móveis em sala de aula:

☐ Mudou ☐ Permaneceu igual

30. Você notou alguma mudança no comportamento dos alunos em relação ao ambiente da sala de aula?

____

____

31. Por favor, descreva outras mudanças que você notou e não foram mencionadas:

Appendix B: Students' questionnaire (Appendix of Chapter 5)

QUESTIONÁRIO

NOME: ________________________ **IDADE:** ____ **SEXO:** □ FEMININO □ MASCULINO
DATA: ____/____/____ **HORA:**______ **TURMA:**________**TURNO:** □ MANHÃ □ TARDE

1. O QUE VOCÊ ESTÁ VESTINDO HOJE?

□ SHORT/ BERMUDA □ CAMISETA MANGA CURTA □ SANDÁLIA/ CHINELO
□ SAIA □ CAMISETA MANGA LONGA □ TÊNIS
□ CALÇA COMPRIDA □ MALHA/ JAQUETA □ SAPATO/ BOTA

2. NESTE MOMENTO, A SUA SALA ESTÁ:

□ MUITO QUENTE □ NEM QUENTE, NEM FRIA □ MUITO FRIA
□ POUCO QUENTE □ POUCO FRIA

3. NESTE MOMENTO, COMO VOCÊ GOSTARIA QUE A SUA SALA ESTIVESSE?

□ MAIS QUENTE □ COMO JÁ ESTÁ □ MAIS FRIA

4. NESTE MOMENTO, O VENTO QUE ESTÁ ENTRANDO PELA JANELA NA SALA:

□ ESTÁ AGRADÁVEL □ A JANELA ESTÁ FECHADA
□ NÃO ATRAPALHA □ ATRAPALHA

5. NESTE MOMENTO, EM RELAÇÃO À SUA MESA, O SOL/ A CLARIDADE QUE ESTÁ ENTRANDO PELA JANELA:

□ ESTÁ AGRADÁVEL □ NÃO ESTÁ ENTRANDO SOL/CLARIDADE
□ NÃO ATRAPALHA □ ATRAPALHA

6. NESTE MOMENTO, EM RELAÇÃO AO QUADRO/ LOUSA, O SOL/ A CLARIDADE QUE ESTÁ ENTRANDO PELA JANELA:

□ ESTÁ AGRADÁVEL □ NÃO ESTÁ ENTRANDO SOL/CLARIDADE
□ NÃO ATRAPALHA □ ATRAPALHA

7. <u>VOCÊ</u> ABRIU A JANELA DA SALA DE AULA HOJE?

□ SIM, QUANDO EU CHEGUEI NA SALA □ SIM, DURANTE A AULA
□ SIM, QUANDO EU SAÍ DA SALA □ NÃO

8. <u>VOCÊ</u> FECHOU A JANELA DA SALA DE AULA HOJE?

□ SIM, QUANDO EU CHEGUEI NA SALA □ SIM, DURANTE A AULA
□ SIM, QUANDO EU SAÍ DA SALA □ NÃO

9. POR QUE VOCÊ ABRIU/ FECHOU A JANELA DA SALA DE AULA HOJE?
(APENAS RESPONDER SE RESPONDEU <u>SIM</u> NAS QUESTÕES 7 E/ OU 8)

□ PORQUE TINHA CHEIRO RUIM
□ PARA VENTILAR A SALA DE AULA
□ POR CAUSA DA CHUVA
□ PORQUE ESTAVA MUITO QUENTE
□ PORQUE ESTAVA MUITO FRIO

□ OUTRO MOTIVO: ___________________________

10. VOCÊ LIGOU O VENTILADOR DA SALA DE AULA HOJE?

□ SIM, QUANDO EU CHEGUEI NA SALA □ SIM, DURANTE A AULA

□ SIM, QUANDO EU SAÍ DA SALA □ NÃO

11. VOCÊ DESLIGOU O VENTILADOR DA SALA DE AULA HOJE?

□ SIM, QUANDO EU CHEGUEI NA SALA □ SIM, DURANTE A AULA

□ SIM, QUANDO EU SAÍ DA SALA □ NÃO

12. POR QUE VOCÊ LIGOU/ DESLIGOU O VENTILADOR DA SALA DE AULA HOJE?
(APENAS RESPONDER SE RESPONDEU SIM NAS QUESTÕES 10 E/ OU 11)

□ PARA VENTILAR A SALA DE AULA

□ PORQUE ESTAVA MUITO QUENTE

□ PORQUE ESTAVA MUITO FRIO

□ OUTRO MOTIVO: ___________________________

13. VOCÊ LIGOU A LUZ DA SALA DE AULA HOJE?

□ SIM, QUANDO EU CHEGUEI NA SALA □ SIM, DURANTE A AULA

□ SIM, QUANDO EU SAÍ DA SALA □ NÃO

14. VOCÊ DESLIGOU A LUZ DA SALA DE AULA HOJE?

□ SIM, QUANDO EU CHEGUEI NA SALA □ SIM, DURANTE A AULA

□ SIM, QUANDO EU SAÍ DA SALA □ NÃO

15. POR QUE VOCÊ LIGOU/ DESLIGOU A LUZ DA SALA DE AULA HOJE?
(APENAS RESPONDER SE RESPONDEU SIM NAS QUESTÕES 13 E/ OU 14)

□ PARA ENXERGAR MELHOR O QUADRO/ LOUSA

□ PARA ENXERGAR MELHOR A MINHA MESA

□ OUTRO MOTIVO: ___________________________

CASO HAJA PERSIANA/ CORTINA NA SALA DE AULA:

16. VOCÊ ABRIU A PERSIANA/ CORTINA DA SALA DE AULA HOJE?

□ SIM, QUANDO EU CHEGUEI NA SALA □ SIM, DURANTE A AULA

□ SIM, QUANDO EU SAÍ DA SALA □ NÃO

17. VOCÊ FECHOU A PERSIANA/ CORTINA DA SALA DE AULA HOJE?

□ SIM, QUANDO EU CHEGUEI NA SALA □ SIM, DURANTE A AULA

□ SIM, QUANDO EU SAÍ DA SALA □ NÃO

18. POR QUE VOCÊ ABRIU/ FECHOU A PERSIANA/CORTINA DA SALA DE AULA HOJE?
(APENAS RESPONDER SE RESPONDEU SIM NAS QUESTÕES 16 E/ OU 17)

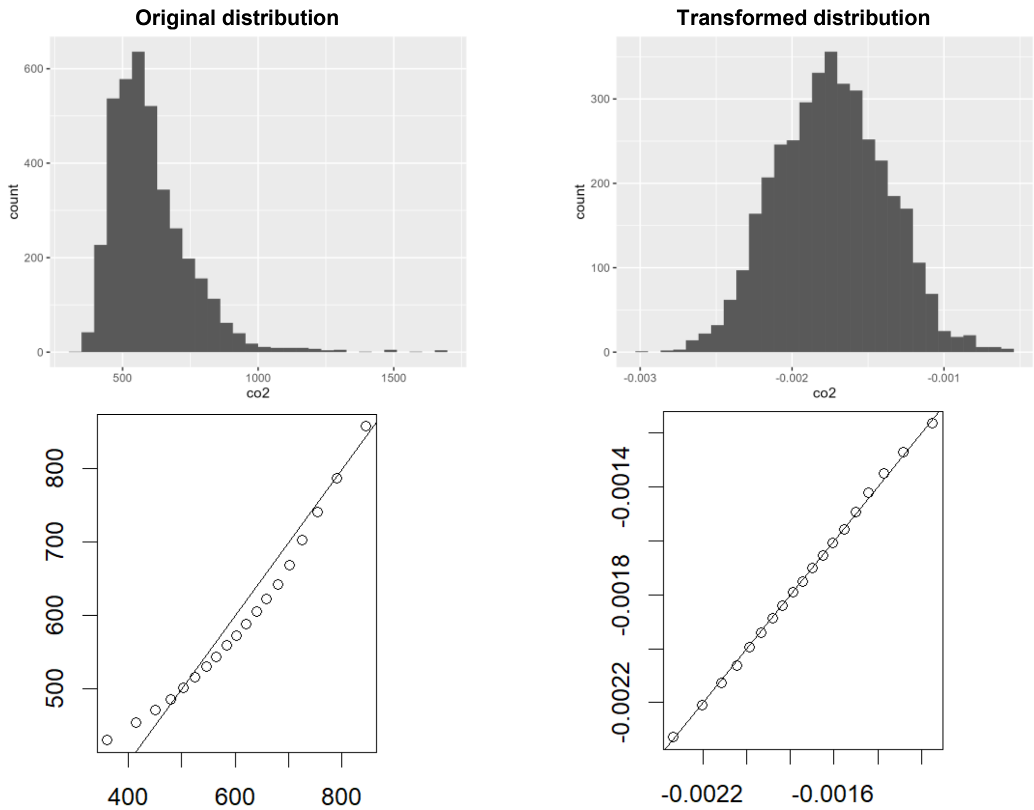
□ PARA ENXERGAR MELHOR O QUADRO/ LOUSA

□ PARA ENXERGAR MELHOR A MINHA MESA

□ OUTRO MOTIVO: ___________________________

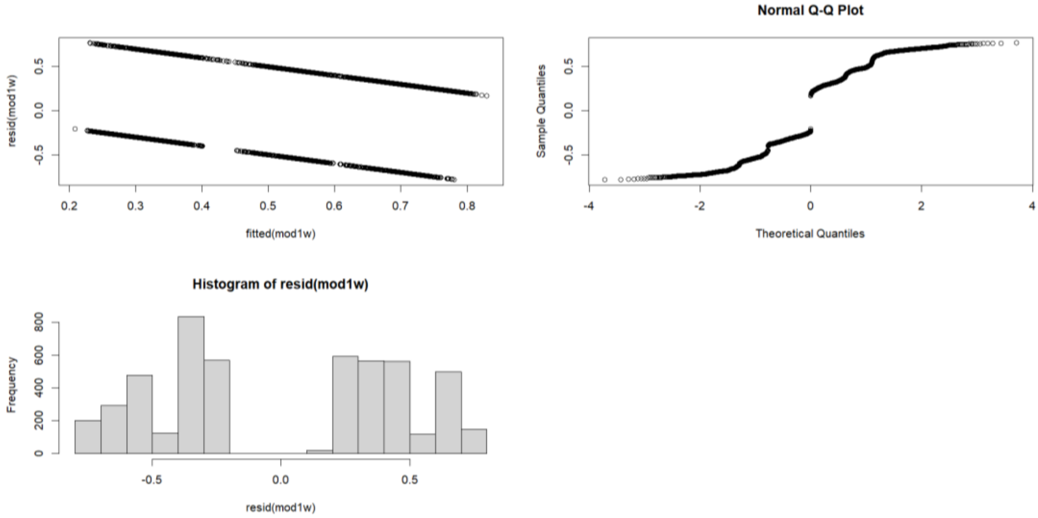
Appendix C: CO_2 concentration transformation (Appendix of Chapter 5)

CO_2 concentration data was subjected to a reciprocal transformation to reduce skewness.

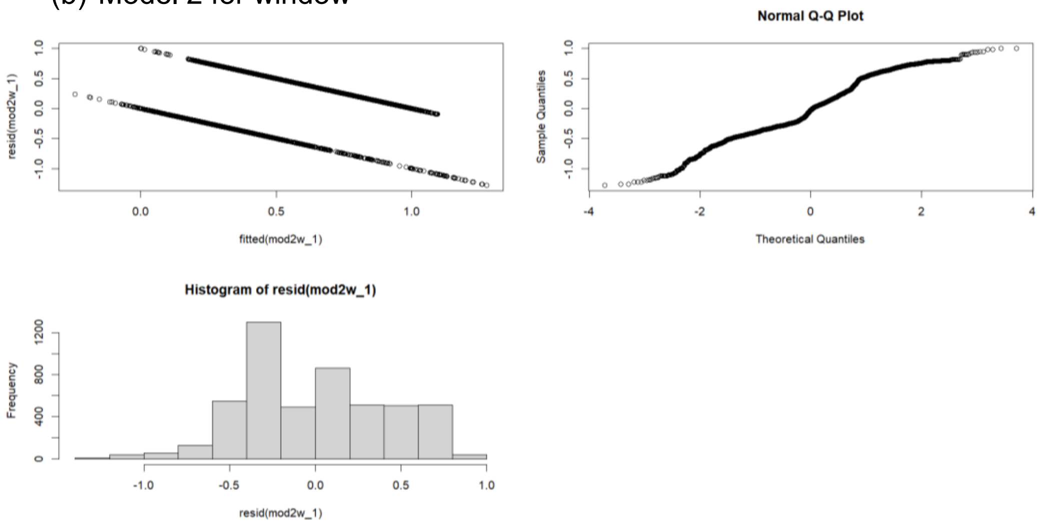


Appendix D: Models' residual analysis (Appendix of Chapter 5)

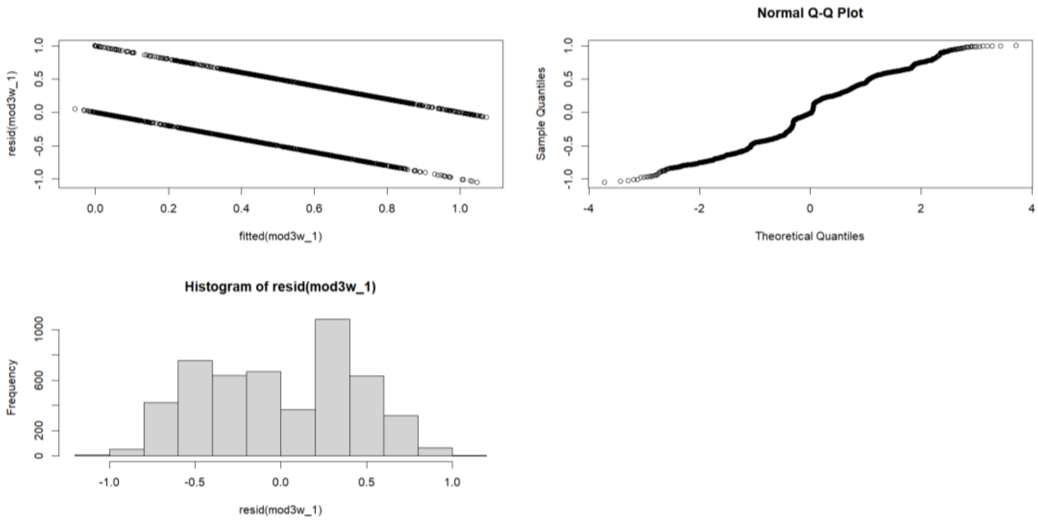
(a) Model 1 for window



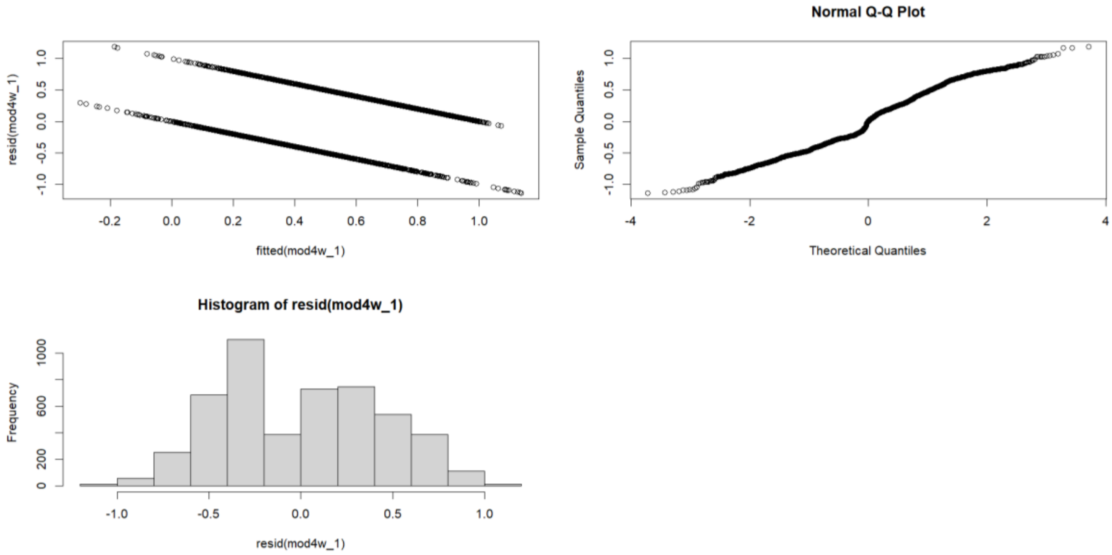
(b) Model 2 for window



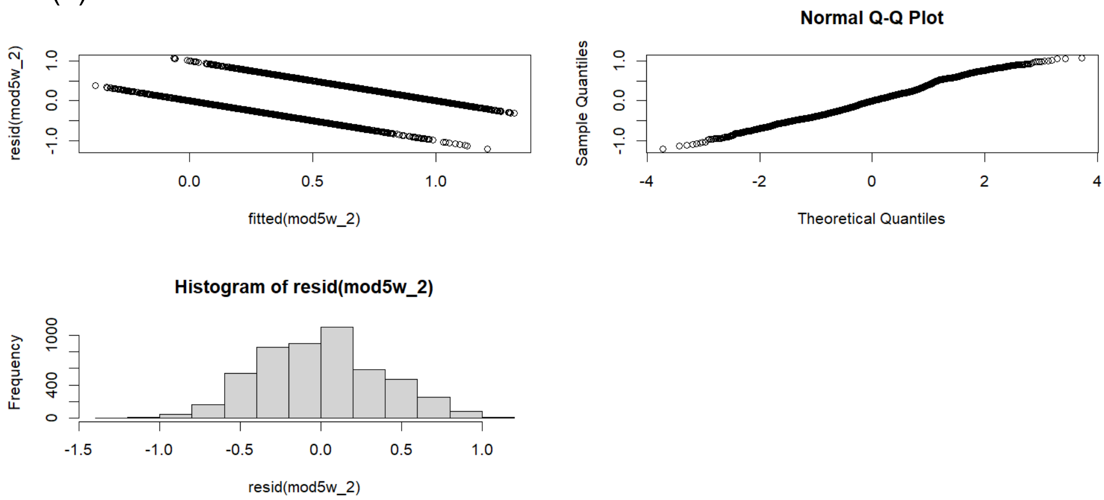
(c) Model 3 for window



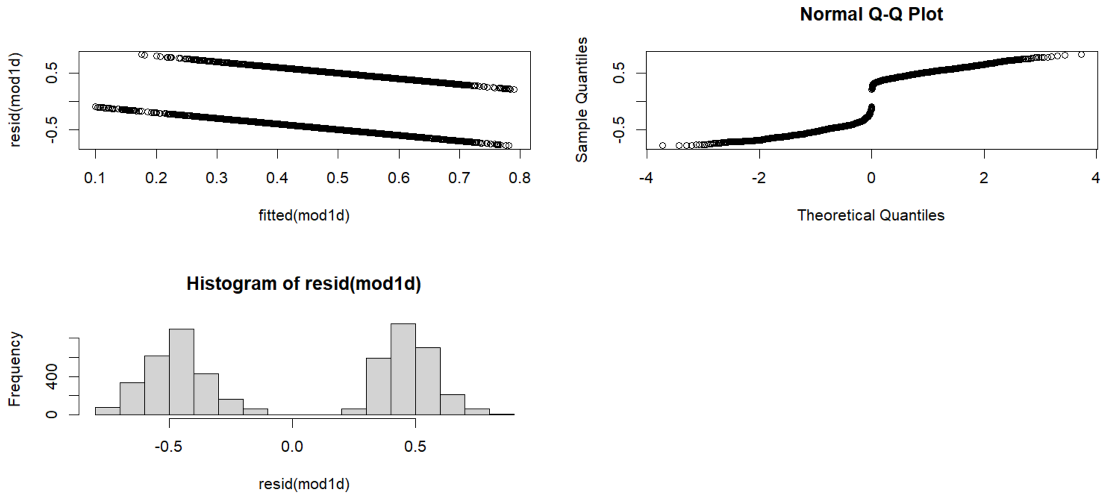
(d) Model 4 for window



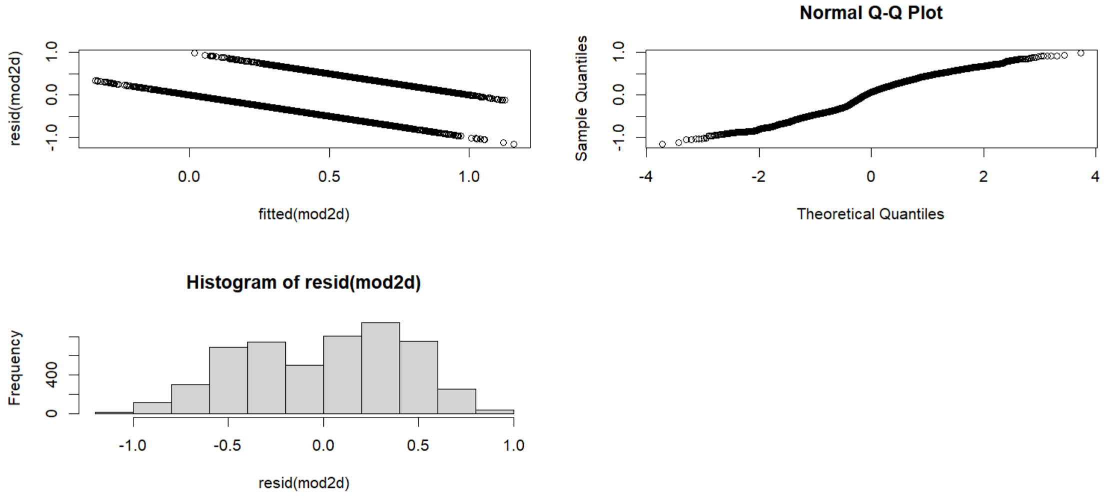
(e) Model 5 for window



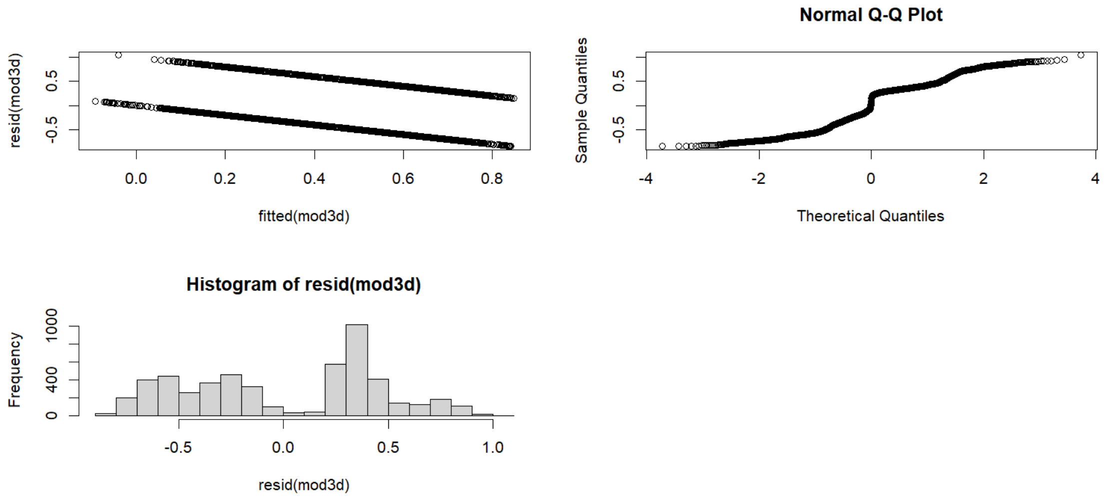
(f) Model 1 for door



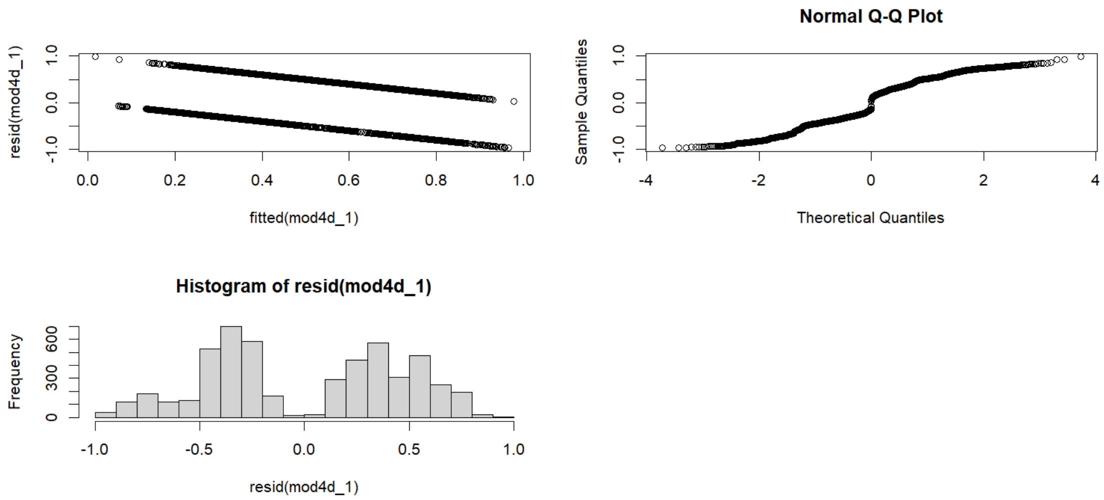
(g) Model 2 for door



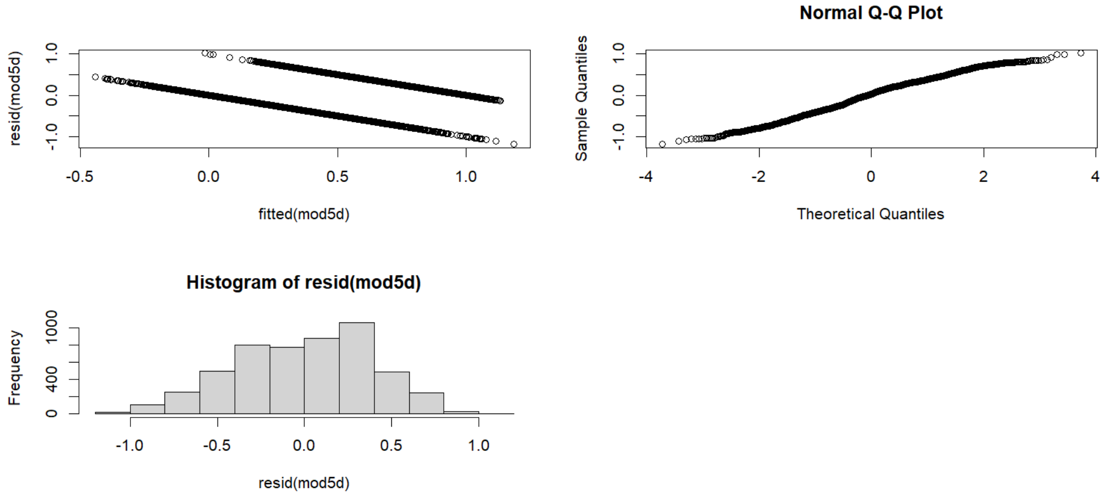
(h) Model 3 for door



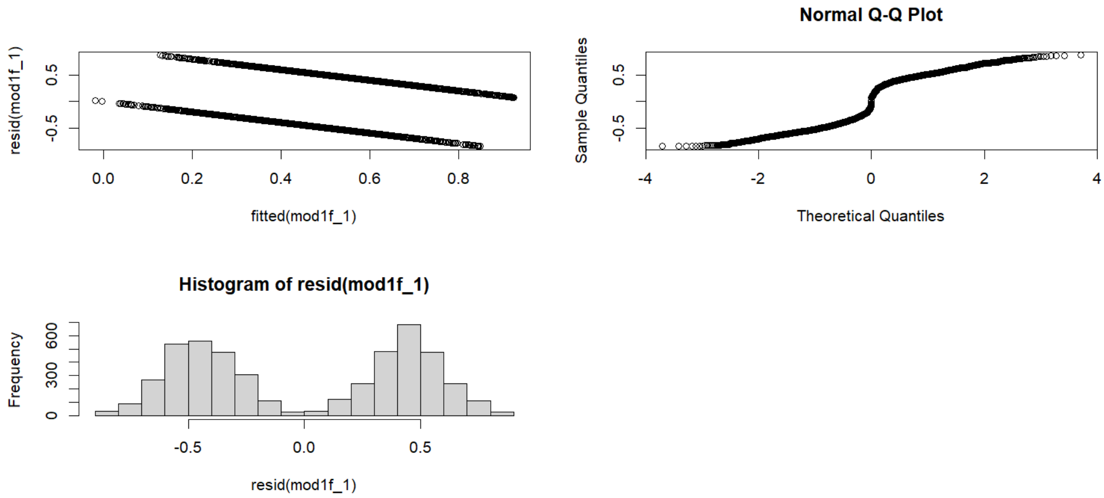
(i) Model 4 for door



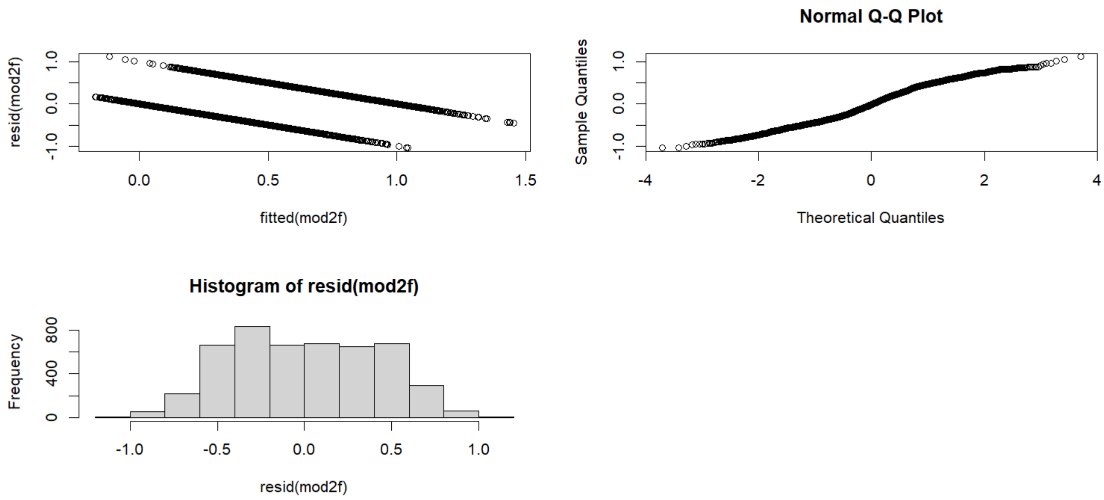
(j) Model 5 for door



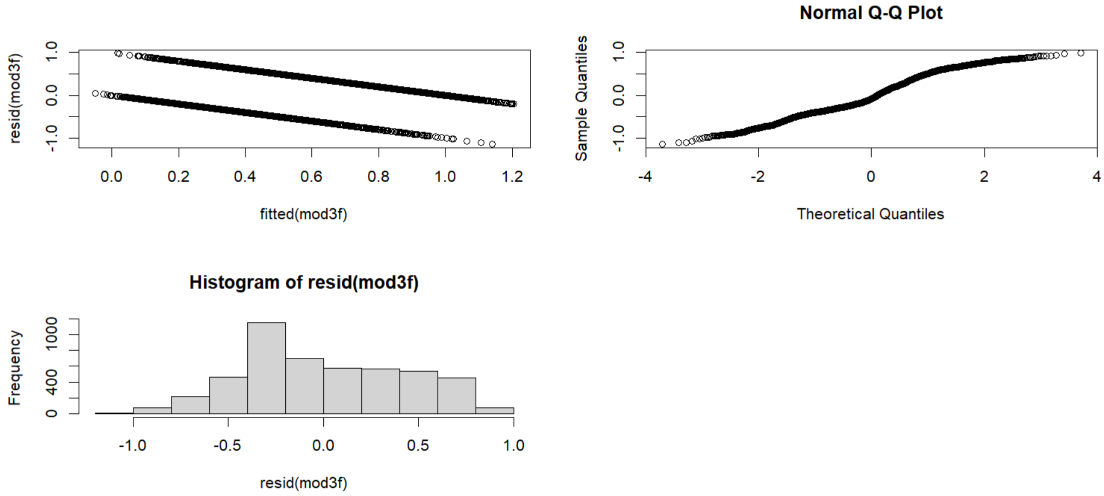
(k) Model 1 for fan



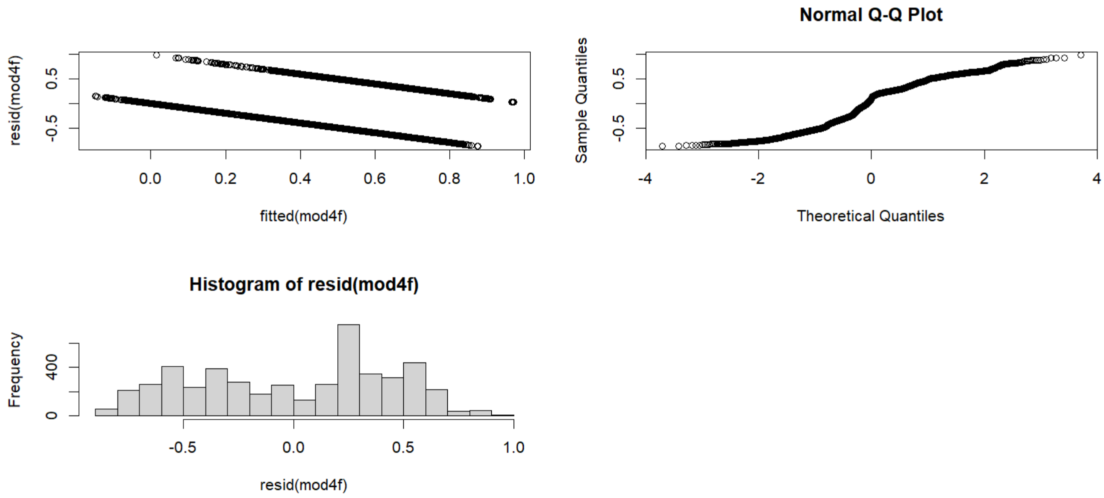
(l) Model 2 for fan



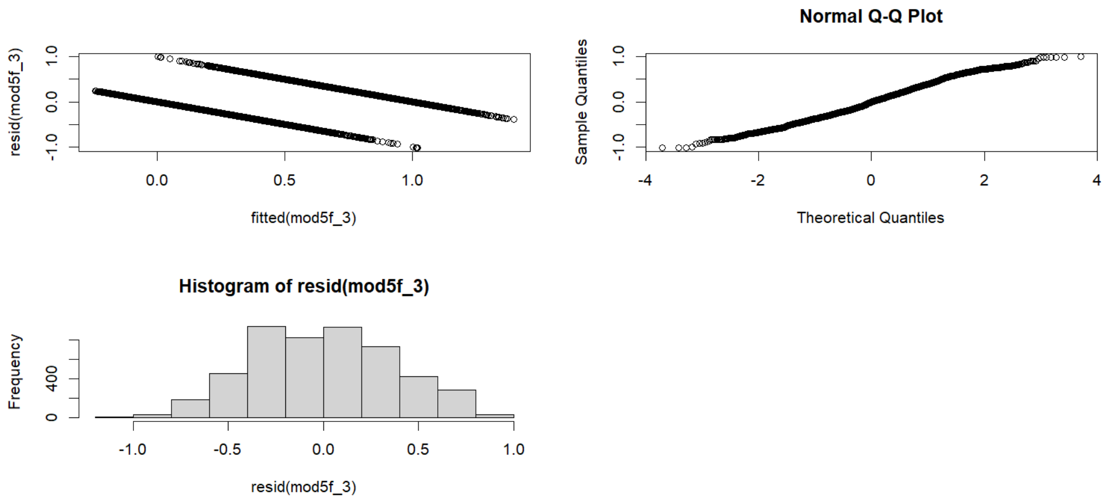
(m) Model 3 for fan



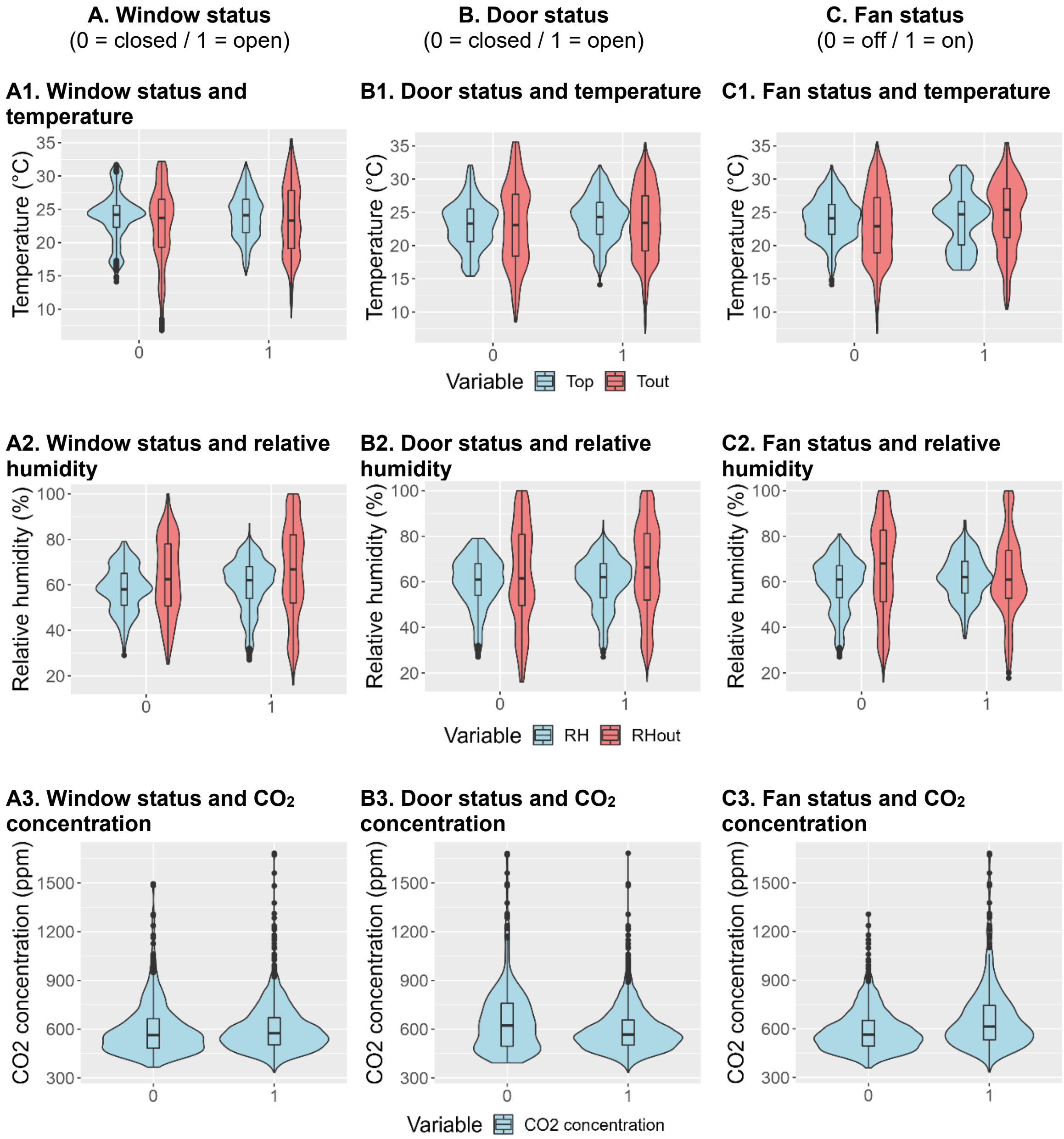
(n) Model 4 for fan



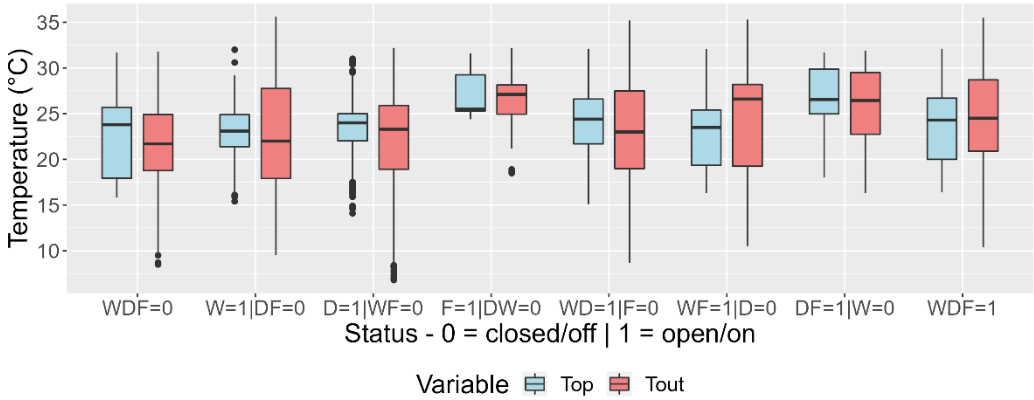
(o) Model 5 for fan



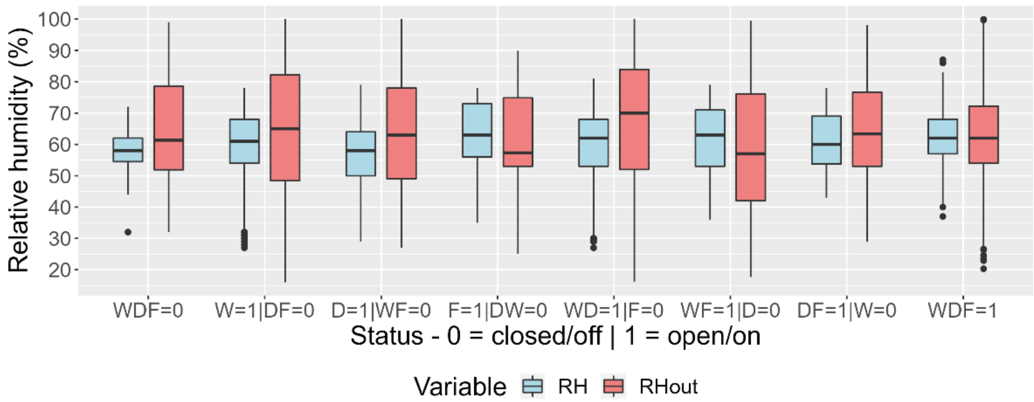
Appendix E: Indoor conditions, window, door and fan status during occupied period (Appendix of Chapter 5)



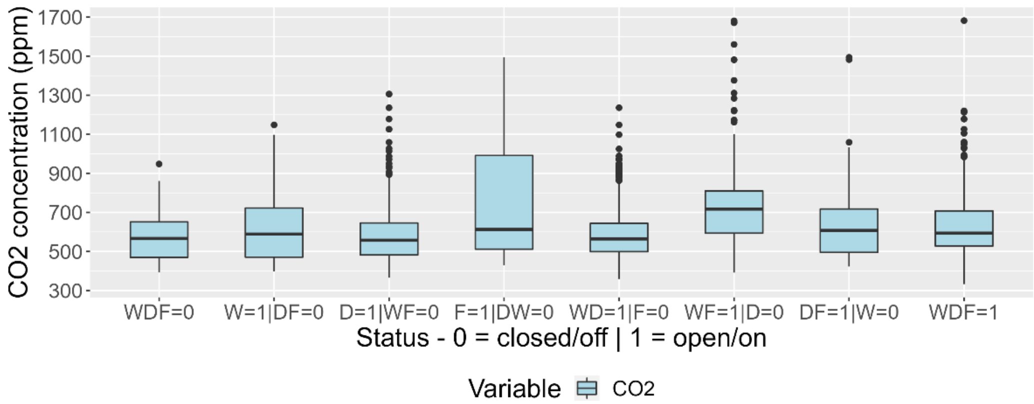
D1. Window (W)/ Door (D)/ Fan (F) status and temperature



D2. Window (W)/ Door (D)/ Fan (F) status and relative humidity



D3. Window (W)/ Door (D)/ Fan (F) status and CO_2 concentration



Appendix F: Permission for published journal papers (Chapters 2 and 5)

Chapters 2 and 5 have been formally published via Elsevier (journals Energy and Buildings and Building and Environment). Elsevier permits the inclusion of published papers in an author's thesis, as outlined in their guidelines:

"Authors are allowed to incorporate their articles, either in full or in part, within a thesis or dissertation for non-commercial purposes."

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ANNEX

Annex A: Permission for published journal paper (Chapter 3)

AMBIENTE CONSTRUÍDO
Revista da Associação Nacional de Tecnologia do Ambiente Construído

Porto Alegre, 06 de julho de 2023.

Permissão

Como autores do artigo "**Condições de conforto térmico e QAI em salas de aula naturalmente ventiladas durante a pandemia de Covid-19"** publicado na revista Ambiente Construído (v. 22, n. 4, 2022), **Paula Brumer Franceschini**, **Iara Nogueira Liguori** e **Iara Nogueira Liguori**, podem incluir este trabalho em dissertação ou tese desde que feita a citação da Revista como fonte original.

Ercília Hitomi Hirota
Editora-chefe

Associação Nacional de Tecnologia do Ambiente Construído - ANTAC
Av. Osvaldo Aranha, 99 - 3º andar - Centro
Porto Alegre - RS - Brasil
CEP 90035-190
Tel.: (51) 3308-4084 | 3308-3518 Fax: (51) 3308-4054
E-mail: ambienteconstruido@ufrgs.br
www.seer.ufrgs.br/ambienteconstruido

Annex B: Ethical Committee approval

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PARECER CONSUBSTANCIADO DO CEP

DADOS DA EMENDA

Título da Pesquisa: Avaliação do impacto do comportamento do usuário no desempenho termoenergético de edificações escolares com certificação AQUA-HQE

Pesquisador: PAULA BRUMER FRANCESCHINI KAGAN

Área Temática:

Versão: 4

CAAE: 31809020.0.0000.8142

Instituição Proponente: Faculdade de Engenharia Civil, Arquitetura e Urbanismo

Patrocinador Principal: Financiamento Próprio

DADOS DO PARECER

Número do Parecer: 4.484.150

Apresentação do Projeto:

INFORMAÇÕES FORNECIDAS PELO PESQUISADOR VIA PLATAFORMA BRASIL

O setor da construção civil é responsável por 36% do consumo global de energia. Além dos sistemas de iluminação, climatização e outros equipamentos, o comportamento do usuário também influencia no consumo de energia da edificação. Os estudos existentes relacionados ao consumo de energia em edificações focam, principalmente, no edifício e nos seus sistemas e nos contextos residenciais e comerciais. Este estudo objetiva avaliar o impacto do comportamento dos usuários no desempenho termoenergético de salas de aula de edificações escolares administradas pela Fundação para o Desenvolvimento da Educação (FDE) do Estado de São Paulo, Brasil, e com a certificação AQUA-HQE, a fim de fornecer diretrizes para o projeto e a operação de edificações centradas no usuário. Primeiro, uma revisão sistemática da literatura será realizada para coletar informações sobre modelos existentes de comportamento do usuário e conforto térmico em edificações escolares. Após, será realizada uma coleta de dados sobre as 20 escolas da FDE com certificação AQUA-HQE para agrupá-las de acordo com as suas características e analisa-las em conjunto. Na etapa seguinte, serão monitorados o comportamento do usuário e as variáveis climáticas em salas de aula de três escolas selecionadas e aplicados questionários com os usuários das escolas. Um modelo de simulação energética da edificação será calibrado a partir dos dados coletados in loco para explorar diferentes cenários de operação dos sistemas (ar condicionado, ventiladores e/ou ventilação natural). O conhecimento adquirido a partir da análise dos estudos de caso será testado no modelo calibrado em relação às suas consequências no desempenho da edificação. Por último, serão desenvolvidas diretrizes baseadas no comportamento dos usuários para auxiliar profissionais a escolher o modelo de ocupação mais adequado para cada edificação.

Hipótese:
O estudo do comportamento do usuário em escolas e a organização destas informações na forma de diretrizes poderá auxiliar profissionais no projeto de edificações com maior eficiência energética.

Critério de Inclusão:
Serão incluídos na amostra, os alunos e professores das escolas estaduais da FDE selecionadas que aceitarem participar da pesquisa, através da entrega dos Termos de Assentimento e de Consentimento Livre e Esclarecido assinados.

Objetivo da Pesquisa:
INFORMAÇÕES FORNECIDAS PELO PESQUISADOR VIA PLATAFORMA BRASIL

Este estudo objetiva avaliar o impacto do comportamento dos usuários no desempenho termoenergético de salas de aula de edificações escolares administradas pela Fundação para o Desenvolvimento da Educação (FDE) do estado de São Paulo, Brasil, e com a certificação AQUA-HQE, a fim de fornecer diretrizes para o projeto e a operação de edificações centradas no usuário.

Avaliação dos Riscos e Benefícios:
Segundo os pesquisadores "Riscos mínimos (risco existente em atividades habituais como estudar, conversar, ver TV, etc.) e que envolve o preenchimento de questionário e uso de infraestrutura convencional de edifícios (ligar e desligar o ventilador e/ou o ar condicionado, abrir e fechar as janelas, etc.)."

Quanto aos benefícios, é informado que "O participante poderá ter uma ampliação da consciência ambiental e da compreensão de problemas ambientais associados ao seu comportamento."

Comentários e Considerações sobre a Pesquisa:
Emenda a protocolo já aprovado.

Justificativa para emenda:
"Devido à pandemia do COVID-19, foi proposta uma emenda a esse projeto de pesquisa, que visa incluir questões relevantes sobre mudanças no comportamento dos usuários em função da pandemia e sua consequente interferência na taxa de ventilação e qualidade do ar de ambientes escolares. Espera-se, dessa forma, que os dados coletados sejam válidos e representativos para o período de pandemia, além de comparáveis com dados de outras pesquisas, coletados anteriormente à pandemia. As modificações estão destacadas em azul no projeto de pesquisa e incluem a medição de mais uma variável (concentração de CO2) na coleta de dados e a adição de algumas questões nos questionários para alunos e professores."

Considerações sobre os Termos de apresentação obrigatória:
ver "Considerações sobre os Termos de apresentação obrigatória"

Conclusões ou Pendências e Lista de Inadequações:
O protocolo foi considerado aprovado neste CEP e, caso não tenha autorizações institucionais pendentes ou centros co-participantes, pode ser iniciado.

Não estão sob o escopo deste parecer
- Eventuais alterações documentais realizadas sem aviso prévio e/ou não solicitadas pelo CEP em forma de pendência ou de recomendação;
- Dados coletados em data anterior a este parecer;
- Caso, eventualmente, os dados sejam coletados com autorizações institucionais pendentes (se necessário);
- Caso, eventualmente, os dados sejam coletados sem a aprovação/autorização do centro co-participante (se necessário).
- Relatório final deve ser apresentado ao CEP via notificação ao término do estudo.

Considerações Finais a critério do CEP:
- Vale lembrar que a interação com os participantes de pesquisa só pode ser iniciada a partir da aprovação desse protocolo no CEP. Os cronogramas de geração/coleta de dados deve acompanhar

o relatório final de pesquisa

- Cabe enfatizar que, segundo a Resolução CNS 510/16, Art.28 Inciso IV, o pesquisador é responsável por "(...) manter os dados da pesquisa em arquivo, físico ou digital, sob sua guarda e responsabilidade, por um período mínimo de 5 (cinco) anos após o término da pesquisa".

- O participante da pesquisa tem a liberdade de recusar-se a participar ou de retirar seu consentimento em qualquer fase da pesquisa, sem penalização alguma e sem prejuízo ao seu cuidado. (Res.510/16, Cap.III, Art.9, inciso II)

- A responsabilidade de obtenção de registro de consentimento, bem como o de sua guarda, é de inteira responsabilidade da equipe de pesquisa. Tais documentos podem ser solicitados a qualquer momento pelo sistema CEP-CONEP para fins de auditoria, bem como servem de proteção para os próprios pesquisadores em caso de eventuais denúncias por parte dos participantes.

- Eventuais modificações ou emendas ao protocolo devem ser apresentadas ao CEP de forma clara e sucinta, identificando a parte do protocolo a ser modificada e suas justificativas e aguardando a aprovação do CEP para continuidade da pesquisa.

- Relatório final deve ser apresentado ao CEP via notificação ao término do estudo.

- Caso a pesquisa seja realizada ou dependa de dados a serem observados/coletados em uma instituição (ex. empresas, escolas, ONGs, entre outros), essa aprovação não dispensa a autorização dos responsáveis. Caso não conste no protocolo no momento desta aprovação, estas autorizações devem ser submetidas ao CEP em forma de notificação antes do início da pesquisa.

- Vale também ressaltar o Art. 3o, inciso VIII da Resolução 510/16:
"São princípios éticos das pesquisas em Ciências Humanas e Sociais:
VIII - garantia da não utilização, por parte do pesquisador, das informações obtidas em pesquisa em prejuízo dos seus participantes;"

- O papel do CEP é proteger e garantir os direitos do participante de pesquisa. Está além das funções e das capacidades técnicas do CEP a validação jurídica de documentos como termos de cessão de uso/reprodução de imagem e voz e demais tipos de autorizações.

- As declarações feitas na Plataforma Brasil são feitas sob pena da incidência nos artigos 297-299 do Código Penal Brasileiro sobre a falsificação de documento público e falsidade ideológica, respectivamente.

Este parecer foi elaborado baseado nos documentos abaixo relacionados:

Tipo Documento	Arquivo	Postagem	Autor	Situação
Informações Básicas do Projeto	PB_INFORMAÇÕES_BÁSICAS_1651658_E1.pdf	16/12/2020 22:52:23		Aceito
TCLE / Termos de Assentimento / Justificativa de Ausência	TALE_Alunos_16dez20.pdf	16/12/2020 22:51:26	PAULA BRUMER FRANCESCHINI KAGAN	Aceito
TCLE / Termos de Assentimento / Justificativa de Ausência	TCLE_Resp_16dez20.pdf	16/12/2020 22:51:14	PAULA BRUMER FRANCESCHINI KAGAN	Aceito
TCLE / Termos de Assentimento / Justificativa de Ausência	TCLE_Professores_16dez20.pdf	16/12/2020 22:51:00	PAULA BRUMER FRANCESCHINI KAGAN	Aceito
Projeto Detalhado / Brochura Investigador	projeto_16dez20.pdf	16/12/2020 22:50:20	PAULA BRUMER FRANCESCHINI KAGAN	Aceito
Outros	CartaResposta2_Parecer4467427_E1_17dez2020.pdf	16/12/2020 22:40:02	PAULA BRUMER FRANCESCHINI KAGAN	Aceito
Outros	AutorizacaoEscola1.pdf	23/07/2020 20:29:43	PAULA BRUMER FRANCESCHINI	Aceito
Outros	CartaResposta1_Parecer4155288_23jul2020.pdf	23/07/2020 20:27:46	PAULA BRUMER FRANCESCHINI	Aceito
Outros	AtestadoMatricula_2020.pdf	10/05/2020 16:14:03	PAULA BRUMER FRANCESCHINI	Aceito
Folha de Rosto	folhaDeRosto_assinada.pdf	13/04/2020 11:16:48	PAULA BRUMER FRANCESCHINI	Aceito

Situação do Parecer:
Aprovado

Necessita Apreciação da CONEP:

Não

CAMPINAS, 23 de Dezembro de 2020

Assinado por:
Thiago Motta Sampaio
(Coordenador(a))