THESIS

IN-HOME ENVIRONMENTAL QUALITY: INDICES OF INDOOR AIR POLLUTION AND INDOOR DISCOMFORT AND THEIR PATTERNS IN COLORADO HOMES

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ABSTRACT

IN-HOME ENVIRONMENTAL QUALITY: INDICES OF INDOOR AIR POLLUTION AND INDOOR DISCOMFORT AND THEIR PATTERNS IN COLORADO HOMES

Understanding the indoor residential environment is important for the health and well-being of occupants. The data used for this thesis included homes from the IEQ Study, which was conducted in partnership with an energy efficiency program of the City of Fort Collins (Epic Homes). Using an index that combines indoor air pollution and indoor thermal comfort, the indoor environmental index (IEI), served as a tool to quantify indoor environmental quality (IEQ) of twenty-eight homes. Daily averages of continuous measurements of $PM_{2.5}$, CO_2, TVOC, T, and RH were used to estimate a daily IEI. The median IEI of homes in the study ranged from 3.8 to 6.3 out of 10 (the lower score indicating a better IEQ). This study undertook a unique approach to estimating some in-home activities by categorizing disaggregated energy data in time spent cooking, cleaning, and temperature control. The Spearman correlation coefficient was used to relate various behavior, home, and outdoor factors to IEQ. Daily time spent cooking was correlated with IEI, as well as outdoor $PM_{2.5}$, year built, estimated volume, and type of cooking fuel. A multivariate linear regression model was constructed to understand the predictive factors from a combination of outdoor continuous measurements, continuous energy use data as a proxy for occupant behavior, categorical occupant behavior, and categorical home characteristics. Smoking was the only significant factor in estimating IEI. The IEI was comprised of two subindices, the indoor air pollution index (IAPI) and the indoor discomfort index (IDI), which underwent the same process of multivariate linear regression modeling, and also showed limited predictive utility.

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CHAPTER 1: INTRODUCTION

Multiple lines of evidence demonstrate that the general U.S. population spends most of their time indoors – the National Human Activity Pattern Survey conducted among a representative sample of the U.S. population indicated that, on average, Americans spends about 90% of their time indoors (Klepeis et al., 2001). Not only do Americans spend a large portion of time inside buildings, time spent in homes is on the rise. The American Time Use Survey (ATUS) found that in 2020, 62% of waking time was spent at home, compared to 50% in 2019 (U.S. Bureau of Labor Statistics, 2021). In the United States, the combination of urban growth (Patino & Siegel, 2018), an aging population (Joint Center for Housing Studies of Harvard University, 2014), a global pandemic (Eslaid & Ahmed, 2021), and climate change (Institute of Medicine [IOM], 2011) has made understanding housing conditions particularly important. A model of Colorado's Front Range from 2005 -2050 describes climate-driven fire regime change as the greatest contributing factor to increasing wildfire risks (Liu et al., 2015), perhaps further increasing time spent indoors. In addition, the COVID-19 outbreak in late 2019 and early 2020 shifted many activities from various indoor spaces, such as schools and workplaces, to homes. Furthermore, the World Health Organization (WHO) Housing and health guidelines states that housing conditions are related to occupant health and quality of life (WHO, 2018). Therefore, understanding our indoor residential environment is increasingly paramount for the benefit of individuals and society.

There are two important terms when discussing the indoor environment: indoor air quality (IAQ) and indoor environmental quality (IEQ). IAQ refers to the quality and composition of the air we breathe while inside a structure. Typically, agents that can degrade indoor air quality are chemical and biological pollutants that originate from both anthropogenic (e.g., cigarettes, paints, hairspray) and non-anthropogenic sources (e.g., wildfires, soil). Some examples of chemical pollutants include formaldehyde, fine particulate matter ($PM_{2.5}$), and nitrogen dioxide (NO_2). Some examples of biological contaminants include bacteria, molds, viruses, pollen, dust mites, and cockroaches. IEQ is more comprehensive than IAQ and refers to the quality of a building's environment as it is influenced by many factors, including lighting, air quality, and damp conditions. Often, IEQ is discussed in relation to the health and well-being of the occupants, encompassing IAQ in addition to other physical and psychological aspects of the indoor environment such as thermal comfort.

The residential sector consumes 22% of the nation's total electricity use (U.S. Energy Information Administration [EIA], 2021), prompting stakeholders, including local and state governments, as well as residents and property managers, to pursue residential energy efficiency policies and programs with the intent to reduce energy consumption and address climate-related emission reduction goals. A home's energy use and consumption is influenced by the outdoor environment, the building structure and envelope, as well as the activities and behaviors of occupants inside a home. These same factors also influence a home's IEQ. Fort Collins Utilities recognized the overlap between energy efficiency and IEQ, creating an IEQ Study in partnership with Colorado State University as a component of their residential energy efficiency program, Epic Homes. The overall objective of the IEQ Study is to understand the relationship between energy efficiency upgrades and indoor environmental quality, and in particular, as they relate to potential downstream impacts on health and well-being of residents.

This thesis uses data from the IEQ Study and seeks to answer the following questions:

(1) How does IEQ change temporally within a home and vary between homes in Fort Collins?

(2) What are the benefits and limitations of using electrical energy consumption data as proxies for in-home activities that also have the potential to impact IEQ?

(3) What patterns of home characteristics and energy activities are observed and to what extent do these factors explain variability in residential IEQ?

CHAPTER 2: LITERATURE REVIEW

2.1 Indoor Environmental Quality (IEQ)

Indoor environmental quality (IEQ) refers to the conditions within a building or structure. IEQ encompasses many factors including indoor air quality (IAQ), thermal comfort, noise, and lighting. There is mounting evidence that IEQ causes and/or exacerbates morbidity and mortality (Gabel et al., 2019; Wu et al., 2007; Sundell, 2004; IOM, 2000). Research and guidelines on IEQ began with the modern hygienic revolution around 1850 with industrial workspaces as the focal point. Around 1960, the focus of environmental quality shifted to ambient air quality, which some attribute to Rachel L. Carson's book, *Silent Spring*. At the turn of the 21^{st} century, IEQ research began expanding to non-industrial indoor environments such as office spaces and public spaces (schools, hospitals, libraries, museums, churches, and temples). This research is solely focused on IEQ in residential environments.

There are various ways to determine the IEQ of a home. Many studies use questionnaires, asking residents to comment on their perception of the environment, or how they feel. For example, numerous studies of office spaces have evaluated IEQ based on the perception of thermal comfort, air quality, lighting, and acoustics (Tang et al., 2022; Liang et al., 2014; Kim et al., 2013; Kim & de Dear, 2012; Huizenga et al., 2006). Although this subjective approach gleans important information, such as resident satisfaction and comfort, there may be aspects of the indoor environment that, unbeknownst to residents, adversely impacts their health and quality of life. In addition, there are no standard IEQ surveys, making comparisons between studies difficult to interpret. In contrast, other studies strictly recorded measurements to estimate IEQ (Mujan et al., 2021; Wei et al., 2016). This objective method requires entering a participant's home multiple times to install and maintain devices. The IEQ Study data used in this thesis involved a combination of the above-mentioned methods; questionnaires were administered, and air quality sensors were employed to analyze how IEQ changes within a home over time and among different homes.

There are many factors that impact IEQ, ranging from building age and proximity to major roads, to the presence of physical, biological, and chemical factors. Studies tend to investigate between three and twelve factors, selecting based on the specific goals of their study (Wei, 2016). There are a variety of ways to characterize IEQ from a set of measured parameters. The first option is to use one or a set of proxy variables. A proxy in the context of IEQ would be something measurable in the indoor environment that is intended to reflect, or partially represent, some meaningful aspect of overall IEQ. One example of a common IEQ proxy is a measure of total volatile organic compounds (TVOC). TVOC has been used as a proxy for ventilation (Mølhave et al., 1997), indoor sources of construction material (Burman, 2019), and to index indoor air quality (Hori, 2020). Although some IEQ studies may rely heavily on a single proxy measure, others use a suite of proxy measures (Goldin et al., 2014; Hui et al., 2012). Another set of parameters that may be used to provide insight on IEQ include constructed parameters from the measured data, such as a ratio of indoor to outdoor concentrations for a given air pollutant (Tang et al., 2018; Chen & Zhao, 2011), an estimate of indoor infiltration for a given pollutant (Hossain et al., 2021; Wallace & Williams, 2005), or a measure of ventilation such as an effective air change rate determined from a decay regression of a measured pollutant (Dias Carrilho et al., 2015; Sherman, 1990). Finally, IEQ may also be characterized through the development of an index comprised of the measured factors, blending multiple factors into a single output (Saad et al., 2017; Moschandreas & Sofuoglu, 2004; Barbiroli et al., 1992; Ott, 1978).

This study selected the index approach because it is an effective tool for communicating IEQ with scholars of neighboring fields, as well as with non-academic stakeholders. It is well understood that a limitation to an index is that it reduces the complexity of a variety of IEQ parameters into a single value. Yet, an index for IEQ may have greater utility and value in broader conversations on health, building standards, energy efficiency, housing inequality, among other examples.

The most well-known index for air quality is the ambient air quality index (AQI). Per the Environmental Protection Agency (EPA), daily AQI is reported for cities with more than 35,000 people (EPA, n.d. -a). The AQI is calculated using the "worst operator" method as originally proposed by Ott (1978). Multiple factors of outdoor air quality are considered and an AQI score between 0-500 (best to worst) is calculated for each parameter. The reported AQI value is the highest parameter AQI value, and that parameter is listed as the responsible pollutant. A substantial downside of the "worst operator" approach is that it masks all other pollutants and the potential of aggregate harm. Barbiroli et al. (1992) recognizes three additional aggregate environmental index approaches, each with unique disadvantages: linear sum function, arithmetic means, and geometric means. In response, Barbiroli et al. (1992) proposes a new index method known as a "hierarchical tree structure." This synthetic index is constructed through intermediate indices of various levels, allowing the analysis of individual variables and the whole – a compromise with those who say an index oversimplifies a complex and diverse environment and those who say an index is necessary for rapid comparisons. This type of index is the first environmental index to allow for different degrees of aggregation, which may be modified to fit the of needs of individual studies.

An application of the hierarchical tree structure index is the Indoor Air Pollution Index (IAPI), which was developed by Sofuoglu & Moschandreas (2003). The IAPI model was developed using data from the Building Assessment Survey and Evaluation (BASE) study, conducted between 1994 – 1998. A year later, the Indoor Environmental Index (IEI), which was comprised from the IAPI and the Indoor Discomfort Index (IDI) was developed, also using data from the BASE study (Moschandreas & Sofuoglu, 2004). A major advantage of the IEI is that its aggregated tree structure allows for interrogating the contributing subindices of IEQ from various grouping levels. The flexibility of the tree structure, as proposed by Barbiroli et al. (1992), did not constrain our study to use the exact same parameters as Moschandreas & Sofuoglu (2004). Instead, we could use the parameters we measured and apply them using the methodology and framework.

2.2 IEQ Parameters

In this thesis, five measured parameters for indoor environmental quality were investigated: fine particulate matter ($PM_{2.5}$), carbon dioxide (CO_2), total volatile organic compounds (TVOC), temperature (T), and relative humidity (RH). The following sections (2.3.1 – 2.3.5) define each pollutant, the importance to indoor environmental quality, and existing agency standards.

2.2.1 Fine Particulate Matter ($PM_{2.5}$)

Particulate Matter (PM) is particles or droplets, often composed of a mixture of elements. The classification of PM is based on the size of the particles, where fine particulate matter, $PM_{2.5}$, has a diameter of 2.5 μm or less. $PM_{2.5}$ is of health concern because the particles are so small, they can penetrate our airways, making their way into our lungs and even blood (EPA, n.d. -d). Not only can the presence of $PM_{2.5}$ impair lung function, inhalation of high $PM_{2.5}$ concentrations or chronic exposure can lead to systemic inflammation, which can cascade to other organs, posing a risk factor for a variety of diseases (Tamayo-Ortiz et al., 2021; Ostro et al., 2014).

There are both national and global guidelines for outdoor $PM_{2.5}$. In 1997, the EPA set a $PM_{2.5}$ 24-hour standard of 60 μg/m^3 (EPA, 2016). Since 2006, the Environmental Protection Agency (EPA) established a $PM_{2.5}$ 24-hour standard of 35 μg/m3, which was retained in the 2012 and 2020 reviews (EPA, 2016). In 2021, the World Health Organization (WHO) updated the air quality guideline (AQG) level for $PM_{2.5}$ to 15 μg/m3 over 24-hours (World Health Organization [WHO], 2021). Annual average guideline values tend to be lower (as they are intended to address long-term exposures) with the US EPA annual average standard for PM2.5 being 12 μg/m^3, while the WHO recently issued an annual average of 5 μg/m^3 (WHO, 2021; EPA, 2016)

2.2.2 Carbon Dioxide (CO_2)

Federal policy regulating carbon dioxide (CO_2) is focused on reducing CO_2 emissions that contribute significantly to global warming, such as CO_2 emissions from gasoline and diesel vehicles, electricity, and industrial processes (EPA, n.d. -c). No indoor air standard for CO_2 exists. Some state health departments, such as Wisconsin and Minnesota, have published a recommendation that indoor CO_2 remain below 1,000 ppm (Wisconsin Department of Health and Services, 2021; Wisconsin Department of Health, n.d.). Occupational Safety and Health Administration (OSHA) has a Permissible Exposure Limit (PEL) of 5,000 ppm, while the

American Society of Heating, Refrigerating and Air Conditioning Engineers (ASHRAE) recommends CO_2 levels do not exceed 700 ppm above ambient concentration, yet in practice people are effectively using 1,000 ppm as the threshold (ASHRAE, 2016 -a; North Carolina State Energy Office, 2016). In agreement with the state recommendations and ASHRAE, in 2021, the Government of Canada published a Residential Indoor Air Quality Guidelines (RIAQG), in which CO_2 exposure limit is set at 1000 ppm on a 24-hour average (Gouvernement du Canada, 2021). Canada's RIAQG proposed exposure limits are explained to protect vulnerable populations and at CO_2 levels below this limit adverse health effects are unlikely to occur. Along with Canada, Germany, Portugal, Norway, France, Japan, and Korea have established guidelines for CO_2 between 600 - 1,000 ppm (Gouvernement du Canada, 2021).

2.2.3 Total Volatile Organic Compounds (TVOC)

A plethora of volatile organic compounds (VOC) agents are present in indoor air. There is a not a standard for what defines a contaminant as a VOC, but generally they have a boiling point of 50 °C – 100 °C, making them highly volatile in indoor environments. VOCs are emitted as gases and are present in many household products, such as paints, varnishes, adhesives, cleaning products, disinfection products, and cosmetic products. The summation of VOCs is known as Total VOC or TVOC. There is not an agreement on the procedure or compounds included to generate the TVOC value. The lack of a standard makes comparisons amongst studies difficult to interpret, and more pertinent for our research, it has made defining a guideline for an indoor residential TVOC concentration challenging.

The lack of a universal definition for VOC and TVOC limits the ability to form a guideline. It is also difficult to set a guideline or standard value for TVOC concentrations indoors because evidence that elevated TVOC concentrations are associated with poor or adverse health outcomes is inconclusive. TVOC concentrations above 3 mg/m3 are associated with odor detection, and TVOC concentrations above 25 mg/m3 have been associated with measures of sensory irritation (Molhave, et al., 1997). Still, there is a poor and limited evidence base for a causal relationship between TVOC and adverse health effects (Moschandreas & Sofuoglu, 2004; Nielsen, et al., 2007). However, there is some evidence to suggest that higher concentrations of TVOC may be indicative of underlying indoor conditions that contribute to health burden and disease (Herbarth et al., 2006; Sherriff et al., 2005; Andersson et al., 1997).

Despite limited understanding of the relationship between TVOC levels indoors and health, TVOC can still provide some potential insights on IEQ. First, VOCs are often associated with human activities – either from humans themselves (cite studies of human emissions) or from the products we use. Indoor environments with humans present tend to have higher levels of TVOC than indoor environments without humans present. For example, in occupied indoor environments, the indoor concentration of TVOC can be two to five times higher than the outdoor concentration (Hormigos-Jimenez et al., 2017; Y. M. Kim et al., 2001; European Collaborative Action [ECA], 1997; EPA, n.d. -e). Second, high TVOC levels may be indicative of poor ventilation as VOCs emitted in an indoor environment or room would accumulate over time if the ventilation rates to that space were low relative to the emission rates of VOCs. Lastly, there is evidence relationships may exist between TVOC levels and measures of discomfort, productivity, irritation, and sick building syndrome (Public Health England, 2019; Adebayo et al., 2018; Sarigiannis et al., 2011; Wolkoff, 2003; Andersson et al., 1997; Molhave et al., 1997). Thus, TVOC levels, even if they are not causally related to discomfort, productivity, sensory irritation, and symptoms associated with sick building syndrome, may be an indicator (or proxy) for the underlying conditions that are associated with those adverse outcomes.

The United States, like many countries, has not published a guideline for indoor TVOC, even though the EPA regulates the emissions of many VOCs to the outdoors in prevention of ozone (EPA, n.d. -e). The Occupational Safety and Health Administration (OSHA) set a permissible exposure limit (PEL) for formaldehyde, a single VOC, in indoor workspaces at 0.75 ppm, with a caveat that many PELs are outdated and inadequate (OSHA, n.d.). Globally, the WHO does not comment on a target TVOC level in their indoor air quality standards.

In 1990, Mølhave published a four-tier chart based on a literature review of field studies and controlled experiments, concluding TVOC < 200 ppb is necessary for comfortable non-industrial, indoor environments (Molhave, 1990). In the same year, Seifert conducted a field study in German homes, concluding that TVOC < 300 ppb should be the standard (Seifert, 1992). Several countries, such as Japan, Germany, Finland, China, and Korea have published guidelines for TVOC in indoor spaces with varying thresholds from 0.2 mg/m3 to 0.6 mg/m3 (Higashi et al., 2005). New VOCs are produced each year, further exacerbating efforts to develop a meaningful TVOC threshold. Thus, TVOC below 0.2 mg/m3 may be a good starting point, with the goal of the indoor TVOC level as low as possible to decrease risk (Hori, 2020).

2.2.4 Temperature (T)

Thermal perception varies on an individual basis due to physiological, psychological, and context related variables (Schweiker et al., 2018). In a comprehensive literature review on the diversity of human thermal perception, Schweiker et. al., found that body composition, metabolic rate, adaptation, and perceived control showed clear contribution to thermal perception, whereas the influence of age and sex remained uncertain (Schweiker, 2018). In addition, residential thermal comfort can become even more complex when acceptability range changes depending on activity level and clothing value, often depending on the rooms. For example, the bathroom critical lower limit is defined by a nude and wet person, versus a bedroom where someone is sleeping under covers, compared to a living room where someone is reclined (Peeters et al., 2009). The variability in reported thermal comfort makes it difficult to select an "optimum" thermal comfort value for all occupants, especially in a residential environment.

The WHO Housing and Health Guidelines published in 2018 focus on the health impacts of too cold or too hot housing, rather than the reported occupant thermal comfort. There is evidence that cold indoor temperatures contribute to adverse health, including outcomes such as increased blood pressure, asthma, and poor mental health (WHO, 2018). The WHO conducted a systematic review of indoor cold and health outcomes and proposed a strong recommendation for indoor temperatures to remain above 18 °C to prevent adverse health effects from the cold. It is noted that for vulnerable populations, a minimum indoor temperature above 18°C may be necessary. The WHO also conducted a systematic review of the effect of high indoor temperatures on health outcomes. Of the studies reviewed, none provided evidence of a minimal risk temperature upper limit. Therefore, WHO conditionally recommends that indoor temperature stays below 24 °C, pending further research.

2.2.5 Relative Humidity (RH)

Relative humidity (RH) is a measurement of the ratio of water vapor in the air to the total possible amount of water vapor the air could hold for the present temperature. RH is expressed as a percent and varies depending on temperature, weather, and location. When indoor RH is too high or too low, it provides an environment for common allergy or asthma triggers to thrive.

There are no federal standards for indoor relative humidity levels. In 2009, the WHO published an indoor air quality guide stating that high RH is a common denominator in excess moisture in buildings, which leads to microbial growth, increased dust mite levels, and mold – all of which may lead to adverse health effects (WHO, 2009, pg. 61). The WHO expresses concern for low RH, stating that it may provoke skin symptoms, nasal dryness, and congestion (WHO, 2009, pg. 42). Although the WHO recognizes that indoor RH has an acceptability range to manage health effects and illness, the actual boundary limits are not clearly defined.

ASHRAE states that RH should remain between 35% -55% to meet the recommended HVAC systems and equipment design (ASHRAE, 2016 -b). For health, ASHRAE provides a guideline that RH remains below 65% to reduce conditions that lead to microbial growth (ASHRAE Standard 62.1, 2016). However, ASHRAE does not recommend a lower bound for RH even though they acknowledge that lower RH levels may lead to dry skin, dry eyes, and irritation of mucus membranes (ASHRAE, 2017).

Although there is not a standard or guideline for relative humidity, many sources converge around similar values, in the range of 30% - 60%. Various HVAC companies post blog articles that state in-home comfortable levels for relative humidity are 30% - 60%, 40%-60%, or 40%-50% (Carnahan, 2022; Therma-Stor, 2020; Unsdorfer, 2021; Laury, 2019). The Mayo Clinic states that home humidity levels should be between 30% and 50% (Mayo Clinic Staff, 2021). The EPA recommends RH below 60%, and ideally between 30 and 50 percent (EPA, n.d. -b). In conclusion, indoor RH should not fall below 30% or exceed 60%.

2.3 Energy and IEQ

Energy efficiency is a priority for many homeowners and renters. There are federal and local programs devoted to promoting and funding energy efficiency retrofits, often with house-specific assessments and recommendations. Examples of such programs are the U.S. Department of Energy's Weatherization Assistance Program and Healthy Homes in Fort Collins, Colorado. When homes undergo energy efficiency upgrades, there is a unique opportunity to deliberately consider Non-Energy Impacts (NEIs) such as IEQ. In Vermont Energy Investment Corporation's (VEIC) Energy-Plus-Health Playbook, many energy upgrade projects are described to directly benefit a home's IEQ (Levin et al., 2019). Examples include insulation providing warmer and drier air with improved indoor T and RH, while ventilation reduces moisture, mold, particles, and allergens (Levin et al., 2019). Through an exhaustive literature review, the National Center for Healthy Housing (NCHH) found that different types of energy upgrades had varying positive effects on health-related outcomes (Wilson et al., 2016). The most well documented positive health outcome from energy upgrades was improved respiratory health (Wilson et al., 2016).

Although NCHH makes a strong case for how energy efficiency measures may improve occupant health, NCHH asks for more research to build upon the limited studies that exist. Existing research often jumps from energy upgrades to health outcomes, lacking a holistic understanding of the relationship between energy efficiency performance measurements and indoor environmental quality measurements. Pedersen et al. (2021) interviewed focus groups as part of the People-Environment-Indoor-Renovation-Energy (PEIRE) project, and the result of asking tenants if there was a connection between energy and IEQ was scarce discourse. Professionals may use a tool such as the Life-Cycle Cost Analysis (LCCA) in their decision-making process of any capital investment (Fuller, 2016). The LCCA accounts for many physical factors of the building operation, costs, and energy usage, however IEQ is not a factor. Not only have scientists and professionals lacked a holistic framework that considers both IEQ and energy, occupants and consumers are also unaware of the possible connection. To the best of our knowledge, energy use measurements and IEQ measurements have not before been used in tandem. Furthermore, categorizing disaggregated energy use as a surrogate for occupants' behavior is a novel technique this research employs. Together, these two methods allow for a unique analysis of energy efficiency performance and IEQ.

CHAPTER 3: METHODS

3.1 IEQ Study: Site Description and Population

Fort Collins, Colorado, is a city of ~170,000 residents along the front range of the Rocky Mountains, about 65 miles north of Denver, CO (Fort Collins, 2020). Fort Collins is a semi-arid climate, located in ASHRAE climate zone 5 (Pacific Northwest National Laboratory, 2015), and sits at an elevation of about 5,000 ft. The temperature typically varies from 19 °F to 87 °F, and the average annual precipitation is 14.5 in. (Fort Collins, 2020).

Fort Collins homes were the subject of this study. Of the 170,000 residents in Fort Collins, 88% identify as white, 11.6% as Hispanic or Latino, 4.0% as two or more races, 3.5% as Asian alone, and 1.6% Black or African American alone (U.S. Census Bureau, 2020). In 2020, it was estimated that there were 70,429 housing units with 53% owner occupied and 47% renter occupied (U.S. Census Bureau, 2020). The recent census also documented that the median property value of homes was $367,900 and the median household income was $65,866 (U.S. Census Bureau, 2020). A sample of houses drawn from the city of Fort Collins were selected for the Indoor Environmental Quality (IEQ) Study. The homes selected completed an energy assessment through the City of Fort Collins Utility Services and responded to a request to participate. In addition, all homes met the following eligibility criteria: access to wireless internet, heated by natural gas, and served by Fort Collins Utilities. Both homeowner and renter occupied residents voluntarily consented to participate in our study, most participating for 6-12 months. The IEQ Study is ongoing with rolling enrollment – this thesis selected data from the first twenty-eight participants with enrollment between July 20, 2020, and March 14, 2022 (Figure 1).

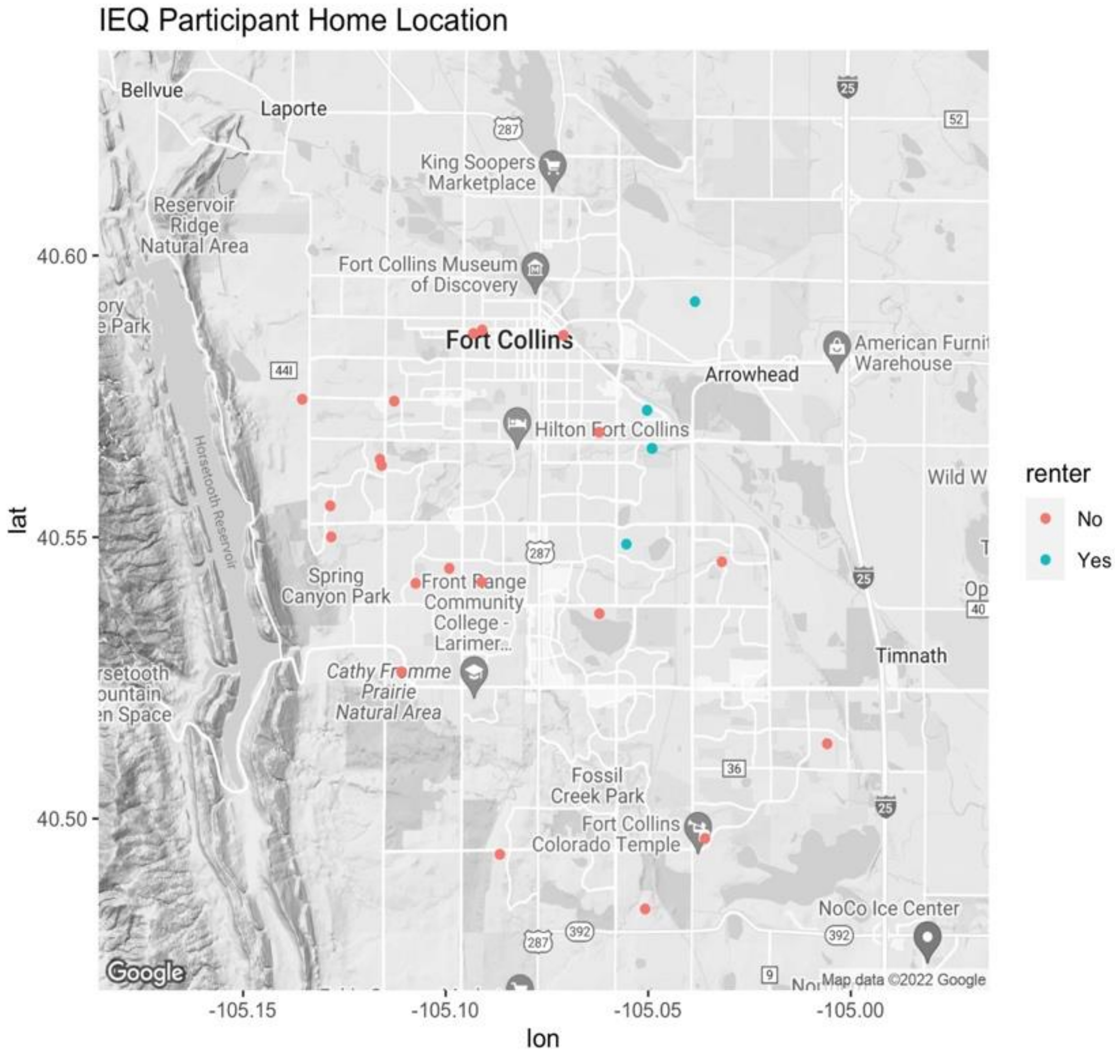

Figure 1: IEQ Study Participant Home Locations – 28 participants over 24 unique homes in Fort Collins

3.2 Data Collection

The IEQ Study is comprised of a series of visits to install several air monitoring devices, an energy monitoring device, and the administration of questionnaires. The air monitoring devices used in this study included an OMNI and UPAS. The OMNI is a commercial IAQ monitor from AWAIR that is accredited by RESET, a standard given to IAQ monitors that meet accuracy requirements (RESET, 2022). The OMNI continuously measures and records temperature (°C), humidity (%), CO_2 (ppm), TVOCs (ppb), $PM_{2.5}$ (µg/m3), light (lx), and noise (dBA). Five OMNI devices are installed at each home in the following locations: living room, kitchen, bedroom, garage, and outside. The second type of air sampler is an Ultrasonic Personal Air Sampler (UPAS), which is a size-selective device designed for collection of a time-integrated, filter-based sample of fine particulate matter (i.e., $PM_{2.5}$). The UPAS sampled air at a constant flow rate of 2 L/min. About two to three times during a home's participation, UPAS devices are installed in the living room, garage, and outside for one week at a time. The UPAS monitor is deployed to primarily serve as a calibration for the OMNI $PM_{2.5}$ measurements. To monitor participants' energy use, the Sense home energy monitor is installed at the onset of participation and detects individual devices by understanding the unique behavior associated with each device (Sense, 2016). Questionnaires about home characteristics, appliances, and behaviors – developed by using questions from previously validated surveys – were approved by the Institutional Review Board of Colorado State University and administered during initial and follow-up home visits.

3.3 Data Analysis

3.3.1 Data Cleaning and Preparation for Analysis

The OMNI data were organized by participant's home ID (to remove personal information from the data), location, time stamp, and recorded measurements. Based on our prior work (Purgiel et al., *in preparation*), we observed that the indoor air pollutant concentrations measured in the living room and kitchen were highly correlated (e.g., Spearman correlation coefficients > 0.7). Therefore, to obtain a single measure representative of the homes' common areas for this analysis, we averaged the living room and kitchen measurements to obtain a daily in-home measurement. The analysis was restricted to days with at least twenty-two hours of data, which accounted for 98% of days across all homes. The Sense energy data recorded individual appliance usage at one-minute resolution. Appliances were categorized by energy-related behavior: cooking, cleaning, and temperature control (see section 3.3.3 for more details). The daily summation of each energy-related behavior was calculated as the total time (minutes) of activity. The OMNI and Sense datasets were joined by home ID and date.

3.3.2 Indoor Environmental Index (IEI)

The Indoor Environmental Index (IEI) is a unitless value determined to represent indoor environmental quality from 0 (best indoor quality) to 10 (worst indoor quality). The IEI is an aggregate index, composed of two sub-indices, the Indoor Air Pollution Index (IAPI) and the Indoor Discomfort Index (IDI), through the arithmetic mean (eq 1).

$$IEI = \frac{IAPI + IDI}{2} \tag{1}$$

The Indoor Air Pollution Index (IAPI) is composed of several pollutant agents. In this thesis, the IAPI is composed of three agents: $PM_{2.5}$, carbon dioxide, and TVOC. Using a linear function, each agent corresponds to a subindex, which is aggregated using the arithmetic mean in conjunction with a tree-structure (Figure 1).

$$IAPI = \frac{1}{J}\sum_{j=1}^{J}\frac{1}{K}\sum_{k=1}^{K} 10\left[\frac{C_{j,k}^{max} - C_{j,k}^{obs}}{C_{j,k}^{max} - C_{j,k}^{min}}\left(\frac{C_{j,k}^{dmc} - C_{j,k}^{obs}}{C_{j,k}^{dmc}}\right)\right] \tag{2}$$

for $C^{max} > C^{obs}$ and $C^{dmc} > C^{obs} < C^{min}$

where *J* is the number of level-2 groups, *K* is number of level-1 groups, *max* is the 95th percentile from the entire dataset, *min* is the 5th percentile from the entire dataset, *obs* is the measured concentration in the subject building, *dmc* is the demarcation concentration value for the given pollutant, and *C* is the pollutant concentration.

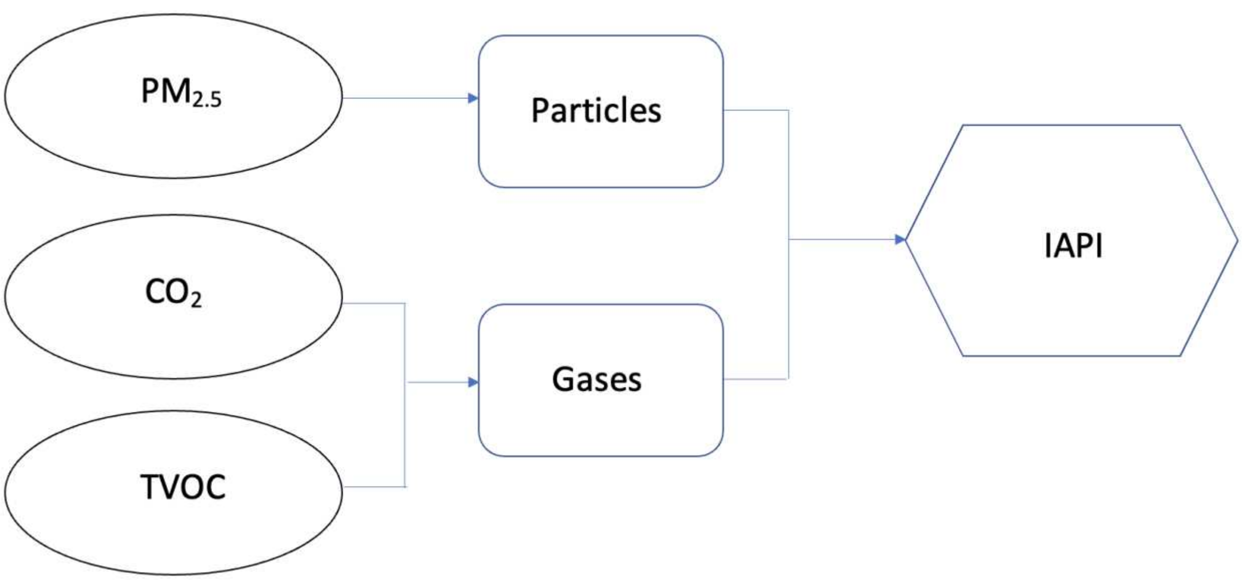

Figure 2: Tree structure for the IAPI

The IAPI is a single, unitless number between 0 (lowest pollution level and best indoor air quality) and 10 (highest pollution level and worst indoor air quality). The IAPI equation (eq 2) is comprised of three terms followed by aggregation throughout the tree structure: the location term $[C_{j,k}^{max} - C_{j,k}^{obs}]$; the normalization term $[C_{j,k}^{max} - C_{j,k}^{min}]$; and the weight term $[(C_{j,k}^{dmc} - C_{j,k}^{obs})/C_{j,k}^{dmc}]$. To meet the constraints of equation 2, at times the C^{obs} value must be altered using the following conditional statements:

(1) $if\ C^{obs} > C^{max},\ then\ in\ the\ location\ term\ C^{obs} = C^{max}$

$and\ in\ the\ weight\ term\ C^{obs} = C^{dmc}$

(2) $if\ C^{obs} > C^{dmc}\ and\ C^{obs} < C^{max},\ then\ C^{obs} = C^{dmc}$

(3) $if\ C^{obs} < C^{min},\ then\ C^{obs} = C^{min}$

The demarcation values represent standards or guidelines of pollutant concentrations informed by the risks they pose for public health. For this thesis, the demarcation values in Table 1 were selected based on our interpretation of current literature and guidelines for indoor residential air quality (WHO, 2021; Candada, 2021; Molhave, 1990).

Table 1. Demarcation values for pollutant variables

Pollutant	**Demarcation**	**Source**
PM2.5	15 µg/m3	WHO (2021)
CO2	1,000 ppm	Canada (2021)
TVOC	200 µg/m3	Molhave (1990)

The IAPI minimum and maximum values are the 5th and 95th quantiles of the dataset for each parameter. If possible, using a theoretical distribution that is visually and statistically the best-fit for each parameter will reduce the influence of outliers and measurement error. There is not a standard distribution applicable for all indoor air pollutants; thus, for each dataset the theoretical distribution for each pollutant must be investigated. In this thesis, we performed the Kolmogorov-Smirnov goodness-of-fit test to many theoretical distributions: normal, lognormal, gamma, and Weibull. For all assumed distributions, the p-value was less than our statistical significance level of 0.05, thus it was concluded that our data could not accurately be represented by any of these theoretical distributions. Therefore, the 5th and 95th percentile was calculated using linear interpolation of the empirical non-exceedance probability.

The Indoor Discomfort Index (IDI) is calculated using two indoor comfort agents, temperature (T) and relative humidity (RH). The IDI represents the absolute distance of an observed measurement from the defined optimal (Figure 2).

$$IDI = \frac{1}{L}\sum_{l=1}^{L} 10\ \frac{|CA_i^{opt} - CA_i^{obs}|}{CA_i^{ucl} - CA_i^{lcl}} \tag{3}$$

$$for\ 30 > \ CA^{obs} > 60\ for\ RH, and\ 15 < \ CA^{obs} < 27\ for\ T$$

where CA is the comfort agent, L is the number of comfort agents, *opt* is optimum comfort value, *ucl* is upper comfort level, *lcl* is lower comfort level, and *obs* is measured comfort agent value in subject building.

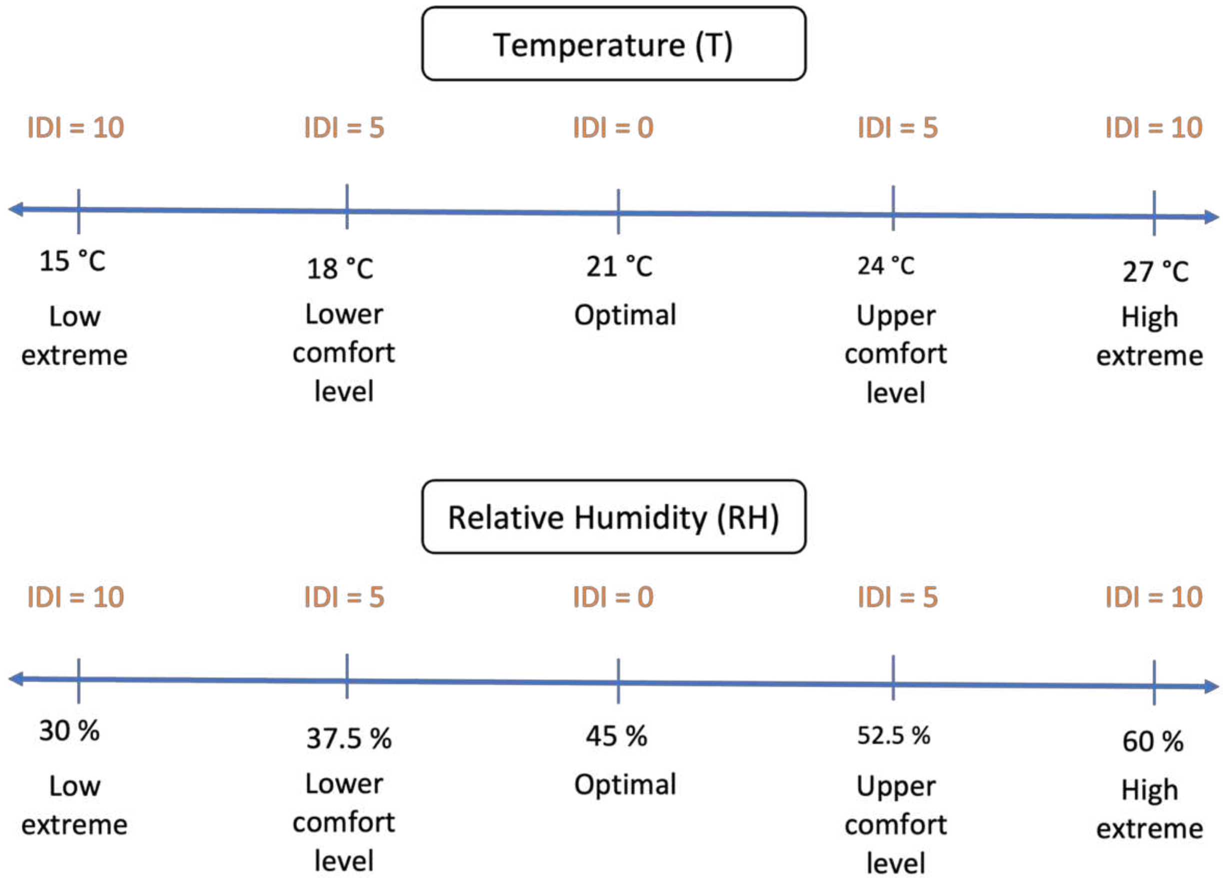

Figure 3: Indoor Discomfort Index (IDI) Schematic

IDI is a single, unitless number between 0 (best indoor thermal comfort) and 10 (worst indoor thermal comfort). The absolute value of the observed measurement to the defined optimum value is used to estimate the IDI. To meet the constraints of eq 3, at times the CA^{obs} value must be altered using the following conditional statements:

(1) $if\ CA_{RH}^{obs} > 60, then\ CA_{RH}^{obs} = 60$

(2) $if\ CA_{RH}^{obs} < 30, then\ CA_{RH}^{obs} = 30$

(3) $if\ CA_{T}^{obs} > 27, then\ CA_{T}^{obs} = 27$

(4) $if\ CA_{T}^{obs} < 15, then\ CA_{T}^{obs} = 15$

The basis for determining the comfort agent values were guidelines for lower and upper comfort level for T and suggestions on extreme values for RH (Table 2). These guidelines were laid out by the World Health Organization Housing and health guidelines (2018).

Table 2: Comfort agent values – values recommended by WHO Housing and Health Guidelines (2018)

	Temperature (°C)	***Relative Humidity (%)***
extreme low value	*15*	*30*
lower comfort level (lcl)	*18*	*37.5*
optimum comfort value (opt)	*21*	*45*
upper comfort level (ucl)	*24*	*52.5*
extreme high value	*27*	*60*

3.3.3 Evaluate in-home behavior using energy use

In the interest of understanding in-home behaviors, appliances and devices identified by the Sense were grouped based on three distinct in-home energy behaviors: cooking, cleaning, and temperature control (Table 3). The total daily time (minutes) allocated for each energy-related activity was calculated from the Sense energy monitoring data.

Table 3: Energy device and associated activity

Activity	Device Types
Cooking	oven, stove top, microwave, toaster oven, toaster, coffee maker, electric tea kettle, blender
Cleaning	garbage disposal, dishwasher, clothes washer, clothes dryer, vacuum
Temperature Control	furnace, space heater, other heat, mystery heat*, fan, air conditioning

*Mystery heat indicates that the Sense monitor cannot determine the device that is using heat

3.3.4 Home Energy Assessments and Questionnaires

In partnership with the city of Fort Collins, Efficiency Works™ conducts energy assessments. The energy assessment includes a blower door test, which is a diagnostic tool to determine a home's airtightness. Efficiency Works™ collects additional information relating to the home such as year built, floors above grade, surface areas, and conditioned area. Our research seeks additional qualitative data from the administration of questionnaires. Three questionnaires were developed using questions from previously validated surveys. Each questionnaire was approved by the International Review Board at Colorado State University. During the initial visit to a participant's home, the home and appliance questionnaire are administered. The home questionnaire investigates self-reported behaviors such as the use of cooling and heating appliances, in-home products, smoking, and cleaning habits. The appliance questionnaire collects data on the following household appliances: stove, oven, refrigerator, separate freezer, dishwasher, washer, dryer, and rechargeable appliances, as well as behaviors associated with each appliance. Lastly, a follow-up survey is administered during a participant's enrollment to note if any energy efficiency upgrades occurred in the home since the initial visit.

3.3.5 Model IEQ versus Energy Use

Multivariate linear regression (MVLR) models were developed to evaluate indoor environmental quality (eq 4). Separate models were developed for each dependent variable (IEI, IAPI, and IDI) was constructed. The independent variable candidates included data from the home assessments, questionnaires, and energy proxies for behavior. To investigate which candidate variables to include in the final model, a series of analysis were performed. First, univariate descriptions of each candidate variable (Table 4 in Results). Those that exhibited a distribution of values (i.e., varied) were then evaluated using a bi-variate analysis that assesses the monotonic relationship between each pair of variables. The visual tool for the bi-variate analysis was a heatmap of Spearman's correlation coefficients (Figures 12 & 13 in Results). Variables with correlation coefficients greater than the absolute value of 0.1, for at least one of proposed dependent variables (i.e., IEI, IAPI, IDI), were retained for inclusion as independent variables in the multivariate linear regression models. If two independent variables had a correlation value greater than the absolute value of 0.6, then only one of the variables was selected, to reduce multicollinearity in the final full models. In addition, variables used in the calculation of the indices (e.g., indoor pollutant concentrations, indoor temperature) are not included as independent variables in the model.

$$Index = b + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_i x_i + \cdots \quad (4)$$

where Index is either IEI, IAPI, or IDI; b is the y-intercept; x is the selected independent variable; and β is the coefficient for each independent variable.

After the independent variables are selected for each index's model (eq 5 in Results), a MVLR model was constructed in R (R Core Team. R, 2021, version 1.4.1106) using the lm function from the stats package (R Core Team. R, 2017). The explanatory power of each independent variable is understood by analyzing the associated p-value. A p-value less than 0.05 indicates that the independent variable contributes to explaining variability in the dependent variable at a statistically significant level. The overall performance of the model was evaluated by the R^2 value; an R^2 value closer to 0 indicates that the model is poor at explaining variability in the dependent variable (limited explanatory power), and an R^2 value closer to 1 indicates that the model explains more of the variability in the dependent variable.

CHAPTER 4: RESULTS

4.1 Home Energy Assessment and Questionnaire Data

A summary of the twenty-eight IEQ Study participants' homes and characteristics are presented in Table 4. The decile in which homes were built ranges from 1900s – 2010s, with a majority of homes built between 1970 - 1990 (N = 18, 64%). Most homes were owner occupied (N = 20, 71%) and had two occupants in residence (N = 13, 46%). The length of time residents had been living in their home ranged from 1 month to 182 months. Nearly three-fourths of study participants had been living in their home for three years (36 months) or less. Over the study period, residents tended to be home more on the weekend than during the week, with 88% of homes reporting that most to all residents were home during the weekend days (Saturday and Sunday) and only 44% of homes reporting that most to all residents were home during the weekdays (Monday through Friday). Estimated home value (e.g., market value) and size (e.g., conditioned area) were typical of Fort Collins homes. The average market value of homes in this study was \$562,235, compared to a municipality-wide average of \$557,048. Similarly, the average conditioned area of homes in this study was 2,037 ft^2, compared to a municipality-wide average of 2,380 ft^2. Homes exhibited a wide range of air changes per hour at 50 pascals of pressure differential (ACH_{50}), in which a low value (typically < 3) means the building's envelope is tightly sealed and a higher value (typically > 9) signifies a leaky building envelope. The arithmetic mean (and standard deviation) and median ACH_{50} in this study were 5.7 (2.9) and 5.6, respectively, while the highest and lowest values were 2.2 and 14.4. The number of energy star rated large appliances (main refrigerator, dishwasher, clothes washer, and clothes dryer) ranged from 0 (none are energy star rated) to 4 (all are energy star rated), with more than 80% of homes having at least one energy star appliance and slightly more than 20% of homes having four energy star appliances.

Table 4: Summary IEQ Study from energy assessment and questionnaires

Variable	Number of Homes	Percent of Homes
Decile Built		
1900	2	7%
1910	1	4%
1920	0	0%
1930	0	0%
1940	0	0%
1950	1	4%
1960	2	7%
1970	8	29%
1980	5	18%
1990	5	18%
2000	2	7%
2010	2	7%
2020	0	0%
Census Block Median Annual Household Income		
\$20,000 - \$49,999	1	4%
\$50,000 - \$89,999	11	39%
\$90,000 - \$119,999	13	46%
>\$120,000	3	11%
Market Value		
\$300,000 to \$399,999	1	4%
\$400,000 to \$499,999	7	27%
\$500,000 to \$599,999	10	38%
\$600,000 to \$699,999	5	19%
\$700,000 to \$799,999	2	8%
> \$800,000	1	4%
Owner or Renter Occupied		
Owner	20	71%
Renter	8	29%
Total Number of Occupants		
1	0	0%

2	13	46%
3	6	21%
4	6	21%
5	3	11%
Percent of Occupants at Home During the Day Mon. – Fri.		
0 – 25%	2	8%
26 – 50%	9	33%
51 – 75%	4	15%
76 – 100%	12	44%
Percent of Occupants at Home During the Day Sat. – Sun.		
0 – 25%	1	4%
26 – 50%	1	4%
51 – 75%	1	4%
76 – 100%	24	88%
Months At Current Residence		
0 to 12	9	33%
13 to 24	5	19%
25 to 36	5	19%
37 to 48	2	7%
49 to 60	2	7%
61 to 72	1	4%
73 to 84	0	0%
85 to 96	2	7%
>96	1	4%
Number of Floors (excluding basement)		
1	10	36%
2	15	54%
3	3	11%
Estimated Conditioned Area (ft^2)		
< 1499	9	32%
1500 - 2499	8	29%
2500 - 3499	9	32%
> 3500	2	7%
Estimated Volume (ft^3)		
5000 to 15000	8	30%
15000 to 25000	9	33%
25000 t0 35000	8	30%
35000 to 45000	2	7%

ACH_{50}		
≤ 3.0	4	14%
3.1 to 6.0	12	43%
6.1 to 9.0	9	32%
> 9.0	3	11%
Number of Energy Star Rated Appliances (main refrigerator, dishwasher, clothes washer, clothes dryer)		
0 appliances (0/4)	5	18%
1 appliance (1/4)	4	14%
2 appliances (2/4)	5	18%
3 appliances (3/4)	8	29%
4 appliances (4/4)	6	21%
Primary Stove Fuel		
electric	17	61%
natural gas	11	39%
Primary Heating Fuel		
electric	17	61%
gas	11	39%
Smoking		
0	26	92%
1	1	4%
2	1	4%
Pets		
0	5	19%
1	2	7%
2	5	19%
3	8	30%
4	7	26%

4.2 Indices for Indoor Environmental Quality, Indoor Air Quality, and Indoor Discomfort

Table 5 presents the descriptive statistics, the central tendency and variability, for the measured input variables. The 5th and 95th percentiles are specifically included in Table 5 because these values are used as C^{min} and C^{max}, respectively, in the calculation of the indoor air pollution index

(IAPI). Table 6 presents the resultant indices: Indoor Environmental Index (IEI); Indoor Air Pollution Index (IAPI); and Indoor Discomfort Index (IDI).

Table 5: Indoor Environmental Factors: Descriptive Statistics (N = 7384 days, over 28 homes)

	$PM_{2.5}$ (µg/m^3)	**CO_2 (ppm)**	**TVOC (ppb)**	**T (°C)**	**RH (%)**
mean (SD*)	9.9 (17.5)	687 (195)	459 (414)	20.6 (2.2)	37.5 (8.7)
median	4.7	642	334	20.5	38.3
minimum	0	400	20	10.2	9.3
maximum	238	2514	9248	29.3	65.1
5th percentile	1.0	461	107	17.1	22.4
95th percentile	33.5	1075	1206	24.2	50.5

*standard deviation

Table 6: Indices: Descriptive Statistics (N = 7384 days, over 28 homes)

	IEI	**IAPI**	**IDI**
mean (SD*)	5.1 (1.1)	6.7 (1.9)	3.6 (1.7)
median	5.1	6.3	3.4
minimum	2.2	2.8	0.0
maximum	8.7	10	9.8

*standard deviation

Table 7 presents the statistics of the measured outdoor factors, which are later included in the indoor environmental quality model.

Table 7: Outdoor Factors: Descriptive Statistics (N = 6107 days, over 28 homes)

	$PM_{2.5}$ (µg/m^3)	**T (°C)**	**RH (%)**
Mean (SD*)	9.1 (13.0)	9.7 (10.1)	54.4 (15.0)

median	5.2	8.5	51.9
minimum	0.0	-20.9	14.4
maximum	217	30.9	99.0

*standard deviation

4.2.1 Indoor Environmental Index (IEI)

Daily indoor environmental quality (IEQ) was estimated using the indoor environmental index (IEI). Figure 4 presents boxplots of each home's daily IEI. Not all homes participated for the same number of days, and at times the OMNI devices turned off, further reducing the sample size of a home. The number of recorded days is listed below the home's ID on the x-axis. The median home IEI score ranged from 3.8 (Home 6) to 6.3 (Home 22).

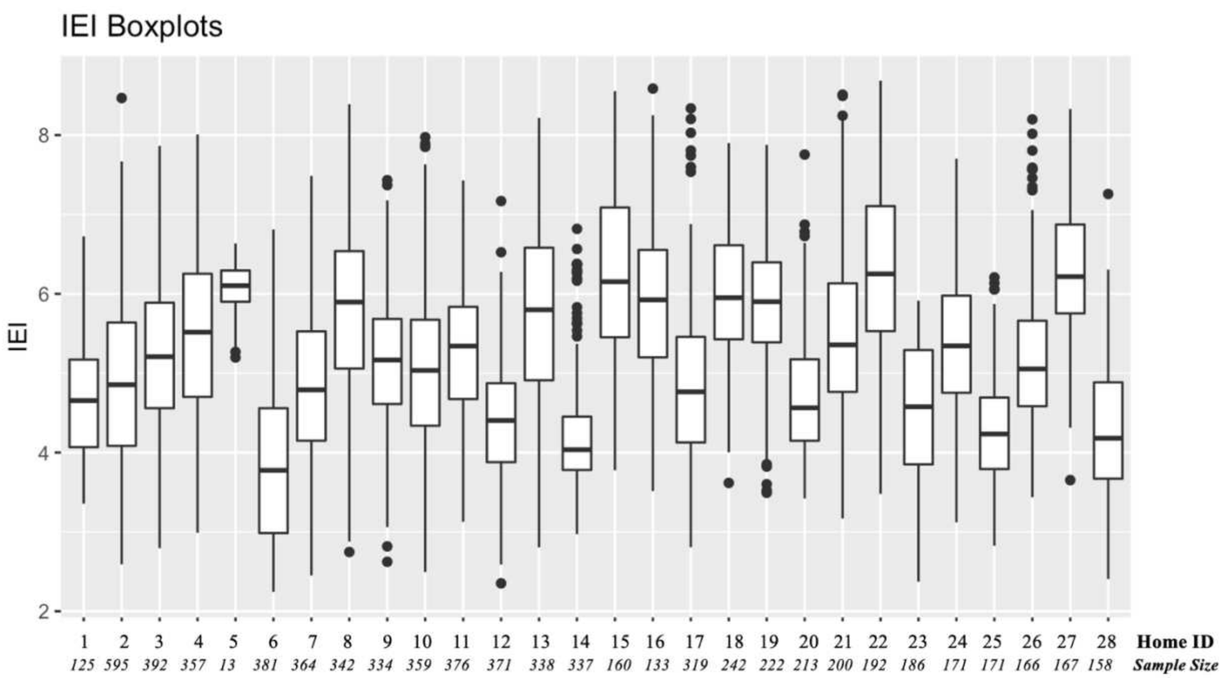

Figure 4: Daily Indoor Environmental Index (IEI) - The IEI is an index score that combines data on pollution and thermal comfort to quantify indoor environmental quality (high IEI relates to poor indoor environmental quality). The daily IEI of twenty-eight homes from the IEQ Study are presented above. The sample size is included below the Home ID because the length of participation varied and at times devices turned off.

A temporal heat map of all homes' IEI is another visual tool to display the within-home and between-home variance (Figure 5). For most of the time, fluctuation of IEI within a home appears to be unrelated to another home's fluctuation of IEI. However, there are small sections of days where all homes seem to experience similar indoor environmental quality, such as the days leading up to July 2021 and the middle of July 2021.

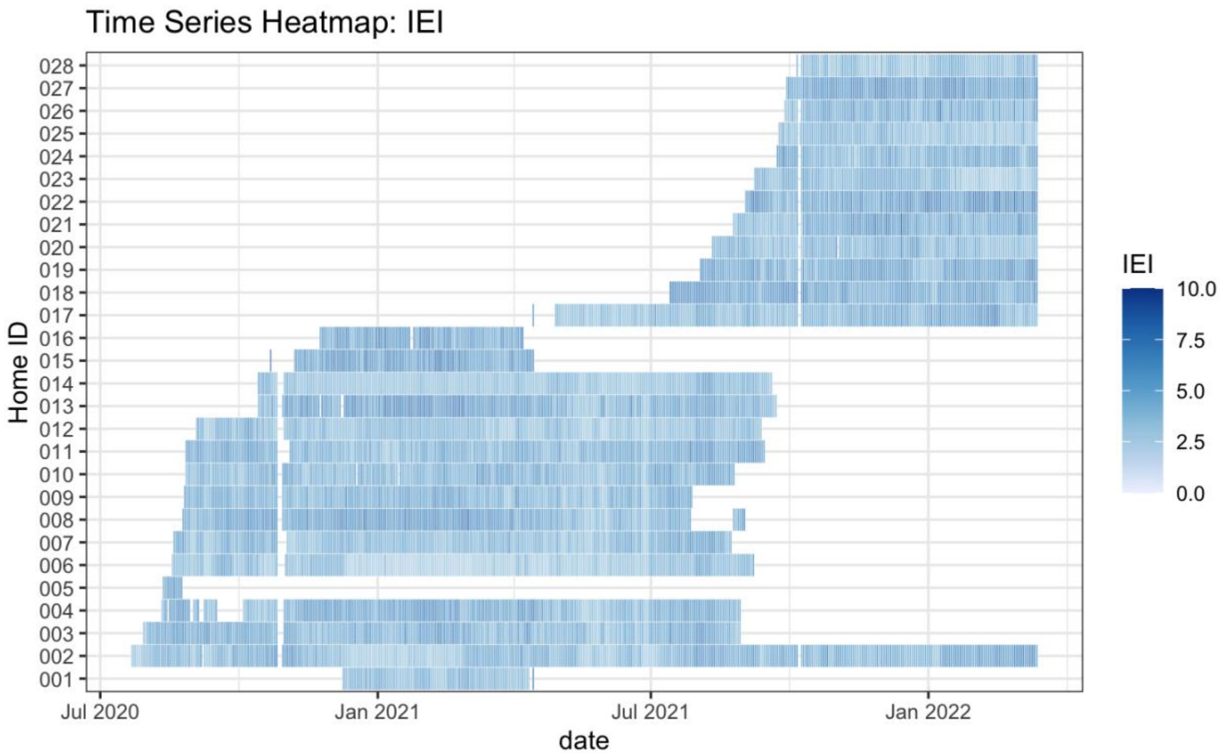

Figure 5: Time Series Heatmap of Indoor Environmental Index (IEI) - The temporal with-in home and between-home variance is demonstrated. A high IEI score indicates poor indoor environmental quality with respect to air pollution and thermal comfort.

The IEI is composed of two sub-indices that estimate the air pollution (IAPI) and thermal discomfort (IDI). Figure 6 presents a timeseries of IEI as an aggregation of the IAPI and IDI from example homes. The selected example homes are 6, 2, and 13, which represent the range of low, medium, and high IEI levels, respectfully (Figure 4). The remaining results will continue to use these three homes as example homes when evaluating the subindices of the IEI. It is evident in Figure 6 that throughout time, the IAPI score remains higher than the IDI score.

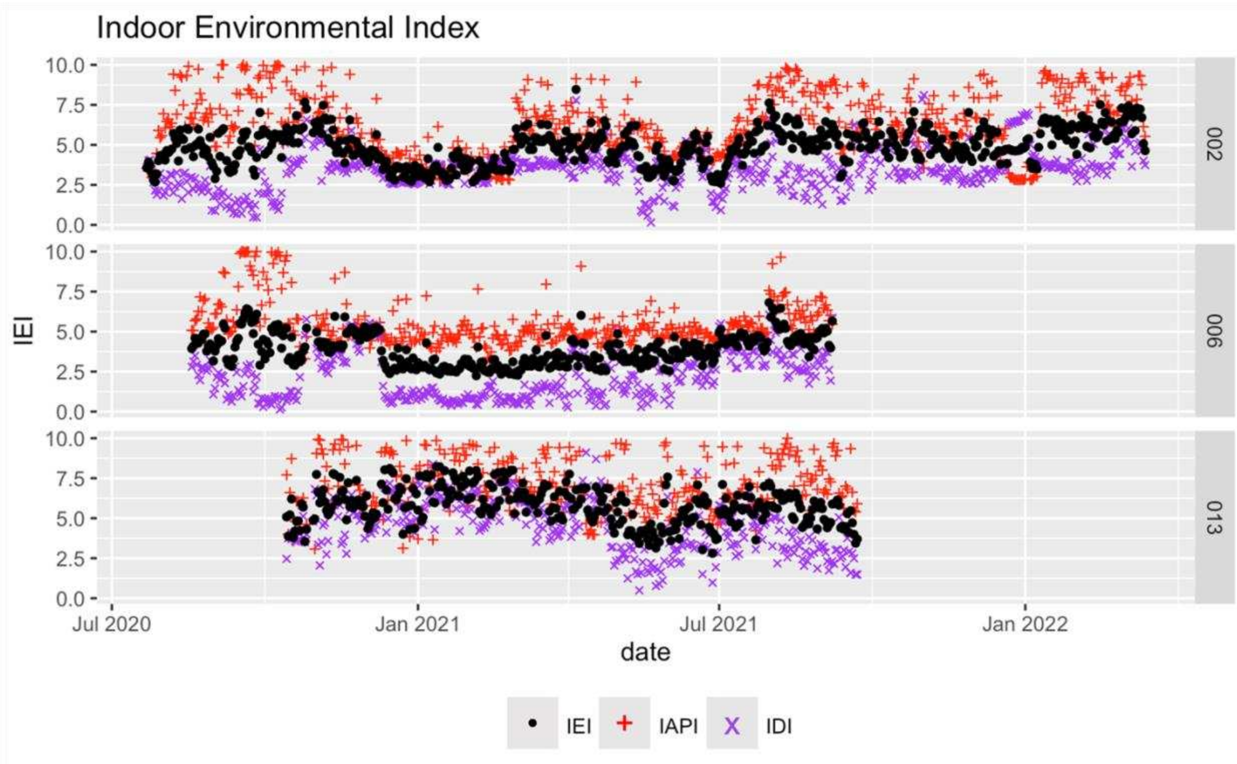

Figure 6: The composition of the Indoor Environmental Index (IEI) – The Indoor Air Pollution Index (IAPI) and the Indoor Discomfort Index (IDI) are aggregated to estimate the Indoor Environmental Index (IEI). Values closer to 0 indicate "good" indoor environmental quality and values closer to 10 indicate "poor" indoor environmental quality. Homes 2, 6, and 13 (as indicated in vertical text on the far-right hand side of the plots) were selected as example homes to demonstrate the within-home temporal changes of the three indices because they cover the range of low, medium, and high IEI (Figure 4).

4.2.2 Indoor Air Pollution Index (IAPI)

Daily indoor air quality (IAQ) was estimated using the indoor air pollution index (IAPI). Figure 7 presents boxplots of each home's daily IAPI. There was not a single day any home experienced an IAPI score lower than 2 (the lower IAPI score indicates better IAQ). Several homes experienced many days of an IAPI score of 10 (worst IAQ). Excluding home 5 due to small sample size, the median home IAPI score ranged from 4.9 (Home 12) to 9.3 (Home 18).

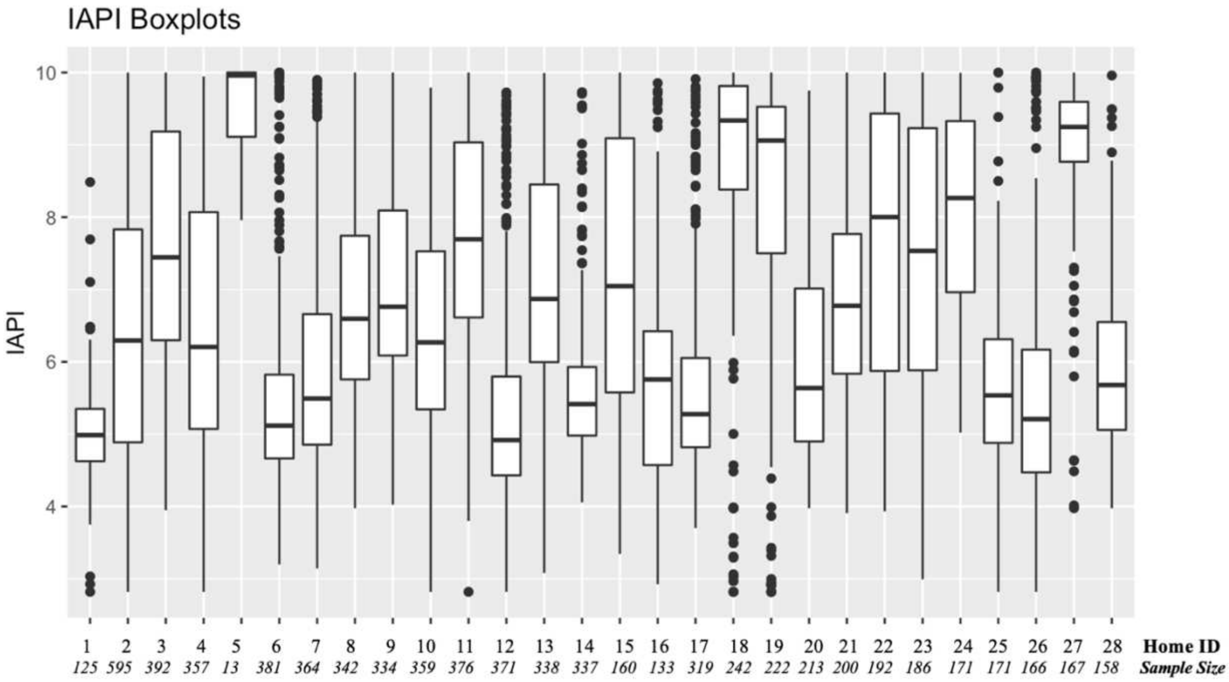

Figure 7: Daily Indoor Air Pollution Index (IAPI) - Concentration data of fine particulate matter ($PM_{2.5}$), carbon dioxide (CO_2), and total volatile organic compounds (TVOC), is used to estimate the IAPI (high IAPI relates to poor indoor air quality). The daily IAPI of twenty-eight homes from the IEQ Study are presented above. The sample size is included below the Home ID because the length of participation varied and at times devices turned off.

The IAPI score is estimated by the subindex scores of fine particulate matter ($PM_{2.5}$), carbon dioxide (CO_2), and total volatile organic compounds (TVOC). Figure 8 presents a timeseries of IAPI as an aggregation of these agents from the three example homes. It is evident in Figure 8 that throughout most of the time, the TVOC index remains at 10 (high in-home TVOC concentration).

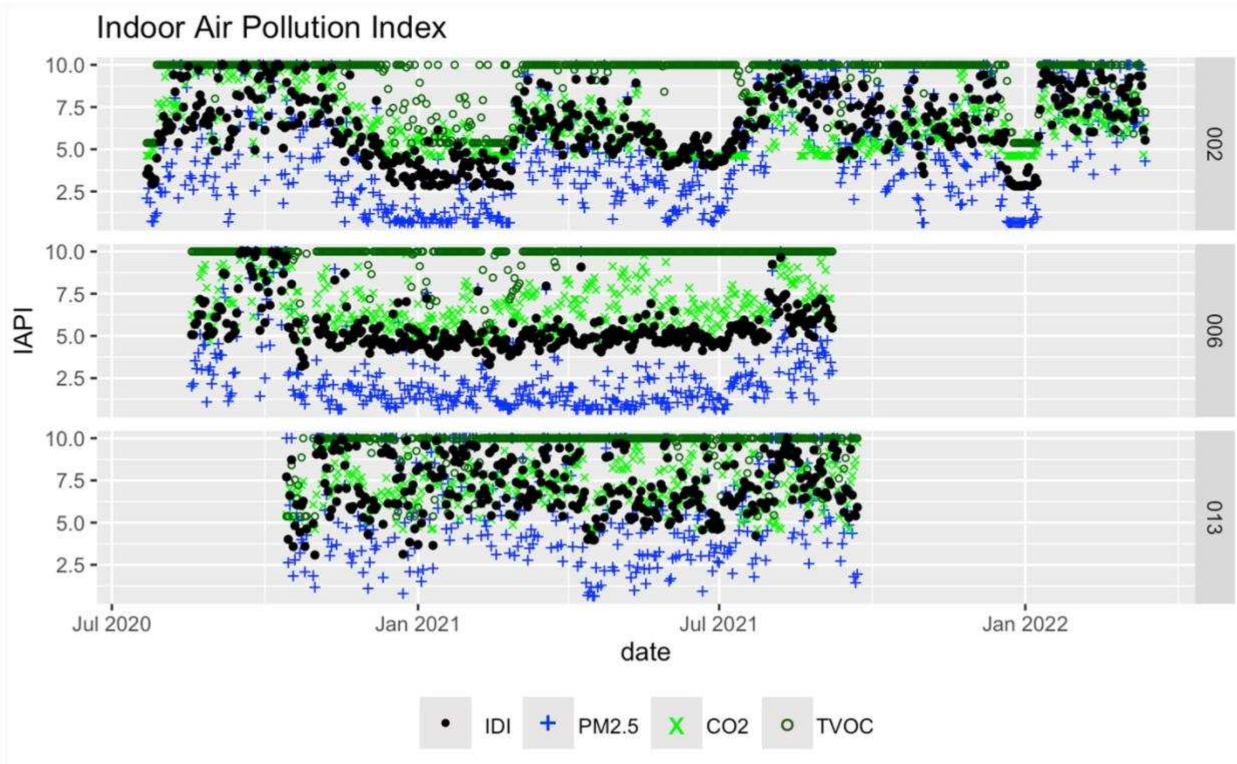

Figure 8: The composition of the Indoor Air Pollution Index (IAPI) – Fine particulate matter ($PM_{2.5}$), carbon dioxide (CO_2), and total volatile organic compounds (TVOC) are aggregated in a tree structure to estimate the Indoor Air Pollution Index (IAPI). Values closer to 0 indicate "good" indoor air quality and values closer to 10 indicate "poor" indoor air quality. Homes 2, 6, and 13 (as indicated in vertical text on the far-right hand side of the plots) were selected as example homes due to their range of overall indoor environmental quality (Figure 4).

4.2.3 Indoor Discomfort Index (IDI)

Daily indoor thermal comfort was estimated using the indoor discomfort index (IDI). Figure 9 presents boxplots of each home's daily IDI. No homes experienced a single day IDI of 10 (highest thermal discomfort), and several experienced IDI days close to 0 (lowest thermal discomfort). Most homes averaged an IDI score below 5, with the median home IDI score ranging from 1.5 (Home 23) to 6.3 (Home 16).

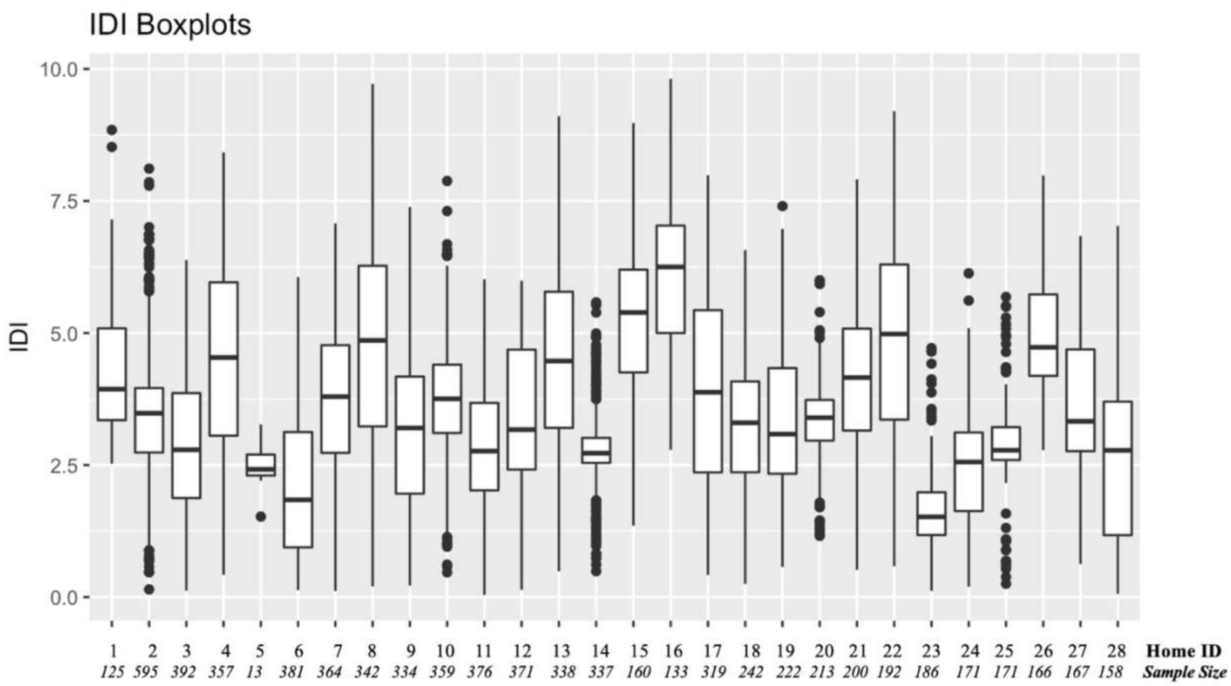

Figure 9: Daily Indoor Discomfort Index (IDI) – The daily average of temperature and relative humidity are used to estimate the IDI (high IDI relates to high thermal discomfort). The daily IDI of twenty-eight homes from the IEQ Study are presented above. The sample size is included below the Home ID because the length of participation varied and at times devices turned off.

The IDI score is estimated by the subindex score of daily temperatures (T) and relative humidity (RH). Figure 10 presents a timeseries of IDI as an aggregation of these agents from the three example homes. It is evident in Figure 10 that all three homes struggled with high relative humidity discomfort more than high thermal discomfort.

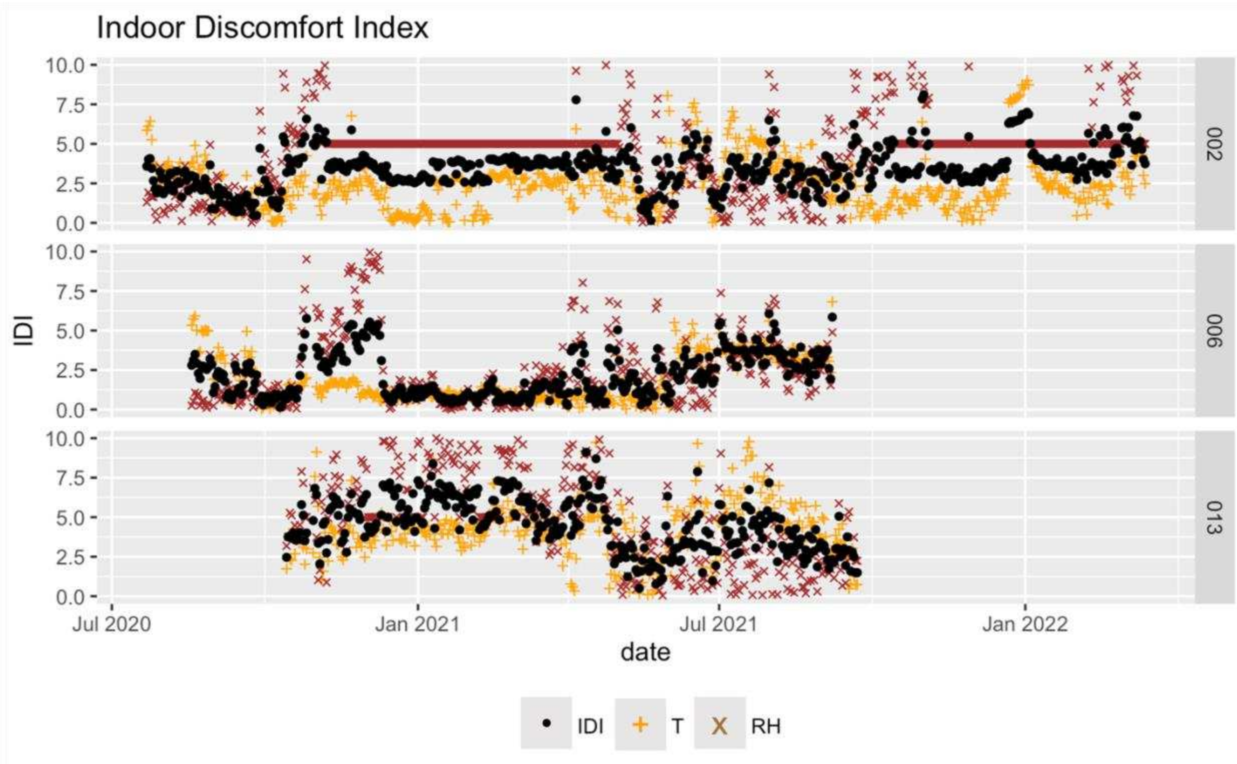

Figure 10: The composition of the Indoor Discomfort Index (IDI) – Temperature (T) and relative humidity (RH) are aggregated to estimate the Indoor Air Pollution Index (IAPI). Values closer to 0 indicate less thermal discomfort, and values closer to 10 indicate higher thermal discomfort. Homes 2, 6, and 13 (as indicated in vertical text on the far-right hand side of the plots) were selected as example homes due to their range of overall indoor environmental quality (Figure 4).

4.3 Energy use for in-home behavior

Each home's average daily electrical use by category (time spent cooking, time spent cleaning, and time spent on temperature control) are presented in Figure 11.

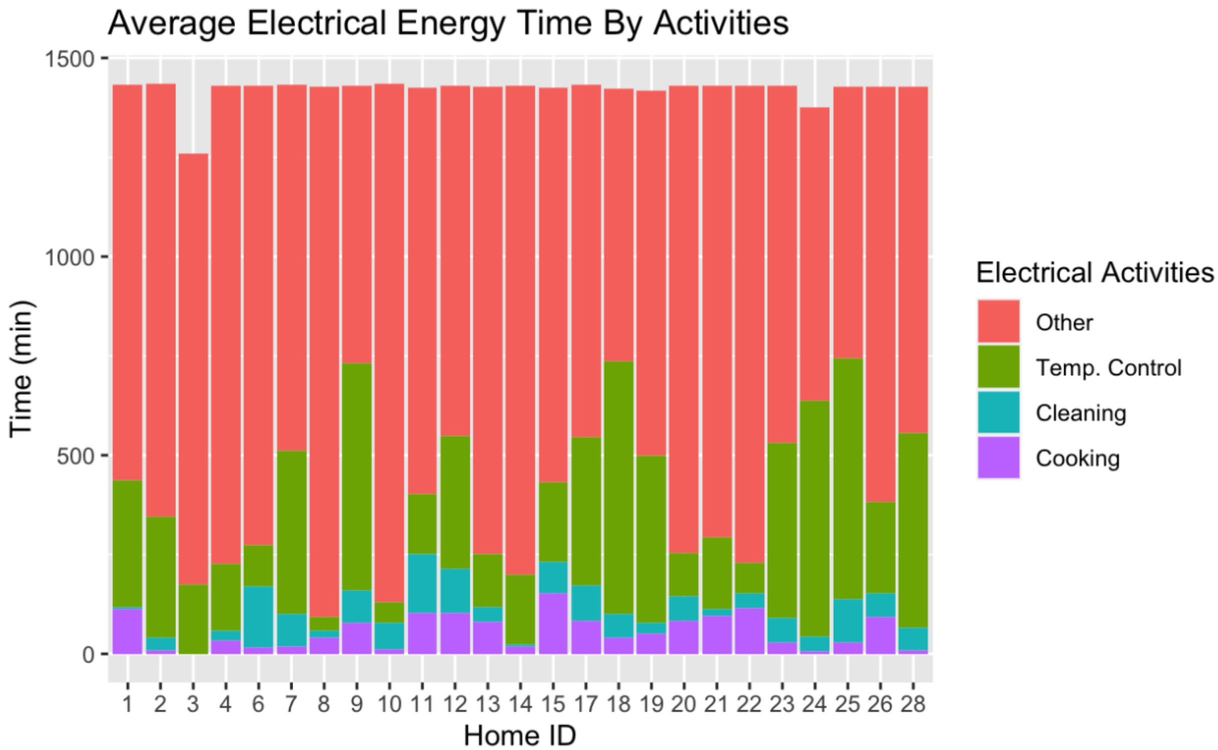

Figure 11: Categorical Daily Average Electrical Energy Time – The average daily minutes spent on four categorical electrical activities (cooking, cleaning, temperature control, and other) are graphed. Electrical cleaning activities included times when the following devices were using electricity: oven, stove top, microwave, toaster oven, toaster, coffee maker, electric tea kettle, and blender. Electrical cleaning activities included times when the following devices were using electricity: vacuum, clothes washer, clothes dryer, dishwasher, and garbage disposal. Temperature control activities included times when the following devices were using electricity: furnace, space heater, air conditioning, and fan. Other activities included the minutes spent using electrical devices previously unnamed, such as lights, water heater, always on, garage door, etc.…

4.4 Model

4.4.1 Heat Map: Spearman Correlation Between Dependent and Independent Variables

Heat maps that demonstrate the Spearman correlation between the dependent indices and candidate independent variables were constructed. Two heat maps are presented based on the type of independent variable: continuous (Figure 12) and categorical (Figure 13). The continuous heat map used daily data (N = 6, 107). The categorical heat map averaged each home's IEI, IAPI, and IDI and fixed characteristics of the home (N = 28).

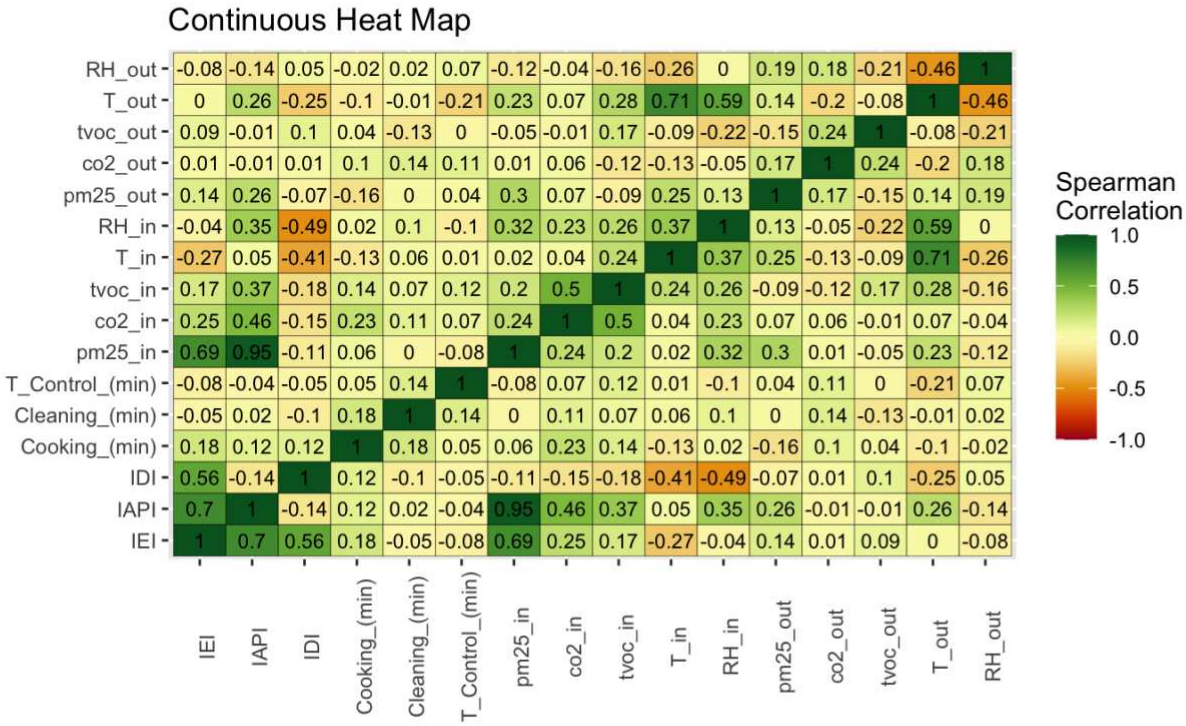

Figure 12: Spearman correlation coefficient heat map of continuous factors - The relationship between the daily dependent variables (indoor environmental index, IEI; indoor air pollution index, IAPI; and indoor discomfort index, IDI), and many potential independent continuous factors are presented. In addition, the five indoor parameters that were used to calculate the IEI (indoor $PM_{2.5}$, indoor CO_2, indoor TVOC, indoor T, and indoor RH) are included.

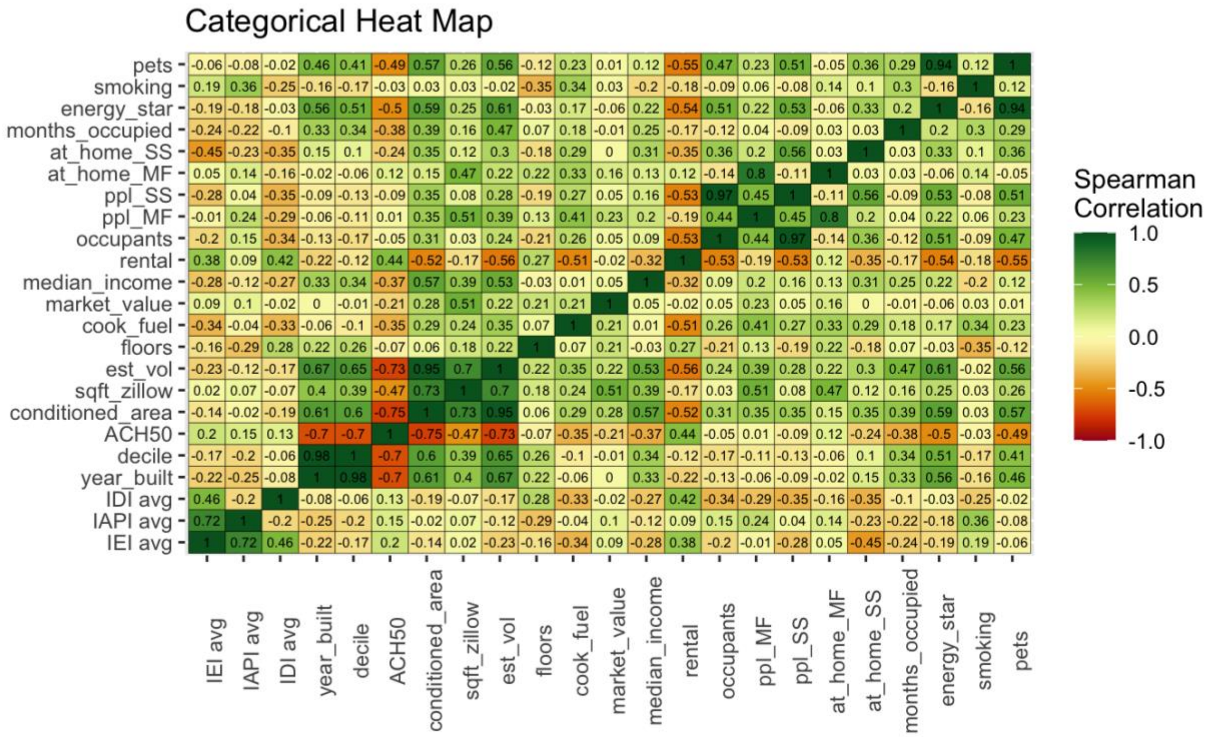

Figure 13: Spearman correlation coefficient heat map of categorical factors – The relationship between the averaged dependent variables (indoor environmental index, IEI; indoor air pollution index, IAPI; and indoor discomfort index, IDI), and many potential independent categorical factors are presented.

The independent variables that are correlated with all three indices (IEI, IAPI, and IDI) include: Cooking_(min), floors, median income, occupants, and smoking. Independent variables that are correlated with at least one index include: year built, cook fuel, rental, percent home M-F, percent home S-S, months occupied, and energy star. The following independent variables were not correlated with any indices: Cleaning_(min), T_Control_(min), co2_out, tvoc_out, market value, and pets. Independent variables that are correlated, but did not make it into the model because they were highly correlated with another variable that was selected include: decile, conditioned area, estimated volume, people home M-F, people home S-S.

4.4.2 Multivariate Linear Regression Model

Based on the heatmaps above and the thresholds for inclusion (as explained in the Methods Section), the following multivariate linear regression models were developed:

$$IEI = f(cooking_{\min}, PM_{2.5,out}, year\ built, ACH_{50}, floors, cooking\ fuel, median\ income, rental, occupants, \%\ home\ SS, months\ occupied, energy\ star, smoking)$$

$$IAPI = f(cooking_{\min}, PM_{2.5,out}, \mathrm{T_{out}}, \mathrm{RH_{out}}, year\ built, ACH_{50}, floors, median\ income, occupants, \%\ home\ M-F, \%\ home\ S-S, months\ occupied, energy\ star, smoking)$$

$$IDI = f(cooking_{\min}, \mathrm{T_{out}}, ACH_{50}, floors, cooking\ fuel, median\ income, rental, occupants, \%\ home\ M-F, \%\ home\ S-S, smoking)$$

Most predictors were not significant, and the only significant predictor for estimating IEI was smoking (Table 8). Post regression diagnostics demonstrated that the linear regression assumptions (linearity between predictors and outcome, normality of residuals, and homoscedasticity) were met by the IEI model.

*Table 8: multivariate associations between occupants and household factors in estimating IEI, IAPI, and IDI (N=23). Bold text indicates p-value ≤ 0.1. Furthermore, * indicates IEI p-value ≤ 0.1, # indicates IAPI p-value ≤ 0.1, ^ indicates IDI p-value ≤ 0.1*

Factors	**Dependent variable: IEI**		**Dependent variable: IAPI**		**Dependent variable: IDI**	
	coefficient	**p-value**	**coefficient**	**p-value**	**coefficient**	**p-value**
(Intercept)	1.25E+01	4.92E-01	-1.65E+01	5.40E-01	3.94E+00	2.96E-01
cooking (min) ^	3.66E-03	5.11E-01	-1.35E-03	8.89E-01	**1.47E-02**	**6.44E-02**
$PM_{2.5,\ out}$	2.82E-02	5.45E-01	-1.34E-02	9.08E-01	NA	NA
T_{out}	NA	NA	1.46E-02	8.72E-01	2.26E-02	6.15E-01
RH_{out}	NA	NA	-2.24E-02	7.48E-01	NA	NA
year built	-2.41E-03	7.84E-01	1.38E-02	3.11E-01	NA	NA
ACH50	-4.46E-02	6.06E-01	-3.98E-02	7.36E-01	6.26E-02	5.50E-01
floors	-1.51E-01	6.38E-01	-5.64E-01	3.35E-01	-8.22E-02	8.44E-01
cooking fuel	-6.82E-02	8.99E-01	NA	NA	1.45E-01	8.57E-01
median income	5.25E-07	9.57E-01	3.24E-06	8.21E-01	-3.17E-06	7.92E-01
rental	1.63E-01	7.45E-01	NA	NA	-9.70E-02	8.91E-01
occupants	-7.47E-02	7.28E-01	5.01E-01	1.82E-01	-2.70E-01	3.08E-01
at home M-F	NA	NA	7.65E-03	5.78E-01	4.45E-03	6.42E-01

at home S-S	-2.54E-02	1.87E-01	-3.27E-02	3.51E-01	-1.03E-02	6.61E-01
months occupied	-8.03E-03	1.04E-01	-6.00E-03	4.52E-01	NA	NA
energy star	1.28E-01	4.75E-01	-3.28E-01	3.80E-01	NA	NA
smoking *	**7.78E-01**	**8.89E-02**	1.22E+00	2.17E-01	-4.27E-01	4.97E-01
multiple R^2	0.5992		0.5826		0.5281	
adjusted R^2	0.02026		-0.1477		0.05623	

CHAPTER 5: DISCUSSION

5.1 Major Takeaways

Analyzing the results of the final index, indoor environmental index (IEI), leads to four major indoor environmental quality (IEQ) takeaways:

(1) *The indoor environmental quality (IEQ) within a home was influenced by home characteristics, occupant behavior, and outdoor continuous factors.* Although the model results showed limited explanatory power and few significant factors, the correlations from the heatmap may still be indicative of some potential trends. For example, the age of homes and their leakiness (evaluated according to the ACH_{50}) were correlated with the home IEQ: older homes, and less tight building envelopes were correlated with worse scores on the indoor environmental index. The relationship of year built and IEQ is consistent to findings from the Colorado Home Energy Efficiency and Respiratory Health (CHEER) (Shrestha, 2019), yet our study highlights ACH_{50} as a directional factor rather than home volume, which had a high correlation (0.7) with one another.

The linear regression model demonstrates that smoking was significant in predicting IEQ (p-value < 0.1). From the continuous heat map (Figure 12), other occupant behaviors such as time spent cooking, rental, and number of occupants show a correlation to IEQ (Spearman correlation coefficient > 0.1). The finding that household activities such as smoking and cooking relate to poor IEQ is consistent with the conclusion from a recent systematic review of 141 studies in 29 countries (Vardoulakis et al., 2020). The heatmap (Figure 12) allows for a more compressive understanding as to why cooking time may be correlated with the indoor environmental index (IEI); it is positively correlated with indoor CO_2 (Spearman correlation coefficient = 0.23), positively correlated with indoor TVOC (Spearman correlation coefficient = 0.14), and negatively correlated with indoor temperature (-0.13).

Outdoor fine particulate matter ($PM_{2.5}$) also shows a correlation with home IEQ (Figure 12). This is likely because outdoor $PM_{2.5}$ is positively correlated with indoor $PM_{2.5}$ (Spearman correlation coefficient = 0.3). This result aligns with previous studies (Ścibor et al., 2019; Liu & Zhang, 2018; Long & Sarnat, 2010) that also found outdoor concentration of $PM_{2.5}$ influential of the indoor concentration of $PM_{2.5}$ and overall indoor air quality.

Other factors correlated with IEQ included: cooking fuel, the number of months the participant had lived at the residence, and the number of energy star appliances. Previous studies have not incorporated the number of months the participant lived at the residence or the number of energy star appliances in relationship to IEQ. Although these factors were not significant explanatory factors in our final model, the trend observed from the heatmap (Figure 13) suggests that it would be worth investigating again in a model with a larger sample size to see if these factors have utility. The combination of categorical and continuous factors in estimating IEQ, and the lack of factor significance in the model, underscore the complexity of evaluating variability in IEQ and suggest that, in the future, a priority should be placed on higher sample sizes, as well as on potential inclusion of additional domains (e.g., building materials, products in home) that may provide additional explanatory insight on IEQ trends and drivers.

(2) *There are certain conditions when all homes in the study behaved more like one-another and at most other times they are stratified.* Figure 5 demonstrates that for much of the study time, there is not a within or between home temporal pattern of IEQ. The example homes in Figure 6 further demonstrate that each home's IEI fluctuated without an emerging pattern relative to itself or to other homes. However, there seem to be a few exceptions: extreme outdoor conditions (e.g., wildfire) and seasonality.

Figure 12 indicates that outdoor conditions influence indoor conditions: as outdoor temperature increased so did indoor temperature, indoor $PM_{2.5}$, and indoor relative humidity. This correlation implies a directional relationship between outdoor and indoor conditions, yet it alone is not sufficient in determining causation. In July 2021, there is a set of days where every home experienced extremely poor IEQ. During this time, the Morgan Creek Fire near Steamboat Springs (~160 mi west of Fort Collins), had recently begun and was uncontained. This is evidence that all homes' IEQ, even those with the tightest building envelope (low ACH_{50}), can be influenced by extreme outdoor conditions.

Figure 5 presents that all homes experience good indoor environmental quality (low IEI) from late May 2021 to July 2021 (before the fire), indicating that seasonal factors may influence IEI similarly across homes at that time of year. In this time frame, the example homes indicate that both IAPI and IDI improve (Figure 6) due to a lower indoor T, RH, and CO_2 score (Figures 8 & 10). Lower indoor T and RH may reflect the influence of outdoor conditions, which are often "ideal" indoor conditions during this time frame. Participants may open doors and windows during this time more frequently, allowing their homes to similarly interact with the outdoor environment, and because all participants in this study lived within the same general outdoor conditions (i.e., subject to the same regional and local weather patterns), their estimated IEI values were more closely aligned during this time. Lower CO_2 concentrations over this same time period also indicate that participants spent more time outside of their homes, or increased ventilation in their homes (likely through increased natural ventilation – i.e., intentional opening of windows and doors), both of which would improve the IEI score.

This finding – i.e., that outdoor conditions influence IEQ more at some times than at others – aligns with previous research that outdoor climate conditions, specifically wildfires, and season impact indoor environmental quality (Shrestha et al., 2019; Marć et al., 2018; Frontczak & Wargocki, 2011). In addition, this study reveals that specifically during a wildfire, homes that otherwise generally behave heterogeneously, tend to converge on similar IEQ values. A natural follow-up would be to look at these time periods when homes seem to behave more similarly, in a more quantitively rigorous manner.

(3) *Time spent cooking was the only significant electrical energy proxy for activity in estimating IEQ.* From the continuous heat map (Figure 12), daily time spent cooking was the only electrical energy proxy for activity that was correlated with IEQ. Time spent cooking has long been expected to relate to IEQ; the HOMEChem study found cooking as a source of $PM_{2.5}$, CO_2, and TVOC (Farmer et al., 2019). Cleaning time and temperature control time were not correlated with any of the indices (IEI, IAPI, or IDI). It was expected that cleaning would contribute to TVOC emission and cooling periods would relate to dehumidification (Farmer et al., 2019). The electrical energy monitor provided a useful proxy for cooking, while it may have underestimated cleaning and

temperature related activities. One of the reasons the electrical energy signature proxy may not have much utility, as it was applied in this study, is because electrical energy signatures are a relatively new data source and are optimized for energy conservation efforts; they are not designed for IEQ implementation (Sense, n.d.). As electrical detection devices improve on their ability to identify appliances, the following would be helpful to incorporate range hood, bathroom fan, electric blanket, rechargeable battery device, etc. Despite the limited application of using electrical energy signatures as a proxy for behavior in this study, in the future we anticipate that improvements to energy monitors coupled with increasing “smart” home devices provide additional insight into home activity data.

(4) *To improve a home’s overall indoor environmental quality (IEQ), there is more room for improvement of a home’s indoor air pollution index (IAPI), than the indoor discomfort index (IDI).* A home’s daily IEQ was estimated by averaging the home’s daily IAPI and IDI. For all indices, the higher the index value represents poorer conditions. The average IEI, IAPI, and IDI scores were 5.1, 6.7, and 3.6 out of 10, respectfully. The decomposition of IEI graph (Figure 6) demonstrates that almost always, the IAPI remains higher than the IDI. Of the example homes that represent the range of IEI scores, the middle (Home 2) and high (Home 13) IEI homes both have median IAPI values above 5 with median IDI values below 5. A majority of homes (96%) have a higher IAPI value than IDI value, resulting in more room for improvement of indoor air quality than indoor thermal comfort.

In this study, the IAPI was higher (worse) than the IDI in most homes. This may be explained, in part, by one of the IAPI composite agents, total volatile organic compounds (TVOC). TVOC concentrations were consistently elevated relative to the demarcation value, leading to high values within the IAPI index (Figure 8). Recall from the method's section that the demarcation value for TVOC was set to 200 ppb µg/m^3. Anytime the observed TVOC concentration exceeded the demarcation value, the subindex for TVOC was 10 (worst index score possible). From the descriptive statistics (Table 5), the median TVOC concentration was 334 ppb, indicating that many times the measured TVOC concentration exceeded the demarcation threshold. Recall from the literature review that there is not agreement on the extent to which VOCs serve as a useful metric of IAQ, and what threshold value should exist. Contradictory to our results, Moschandreas & Sofuoglu (2004) found that the average IAPI (6.4) was greater than the average IDI (2.6); notably not selecting a demarcation value for TVOC. Likely, TVOC can serve as a useful metric in some circumstances and less so in others. The TVOC concentrations measured in this study are a strong contributor to the resulting IAPI and subsequent interpretation that indoor air quality was poor, at times, in most homes. This finding is in agreement other studies (Meyer, 2021). A literature review of VOC guidelines in the UK by Dimitroulopoulou et al., (2019) concludes that TVOC measurements may be one indicator of IAQ, but the inability of the measure to reflect diversity in chemical composition of air pollutants motivates future studies to incorporate species-specific VOC measurements in combination with tracking emission from household products. In the field of indoor air quality, the most studied parameters have included particulate matter (PM_{10} and $PM_{2.5}$), carbon dioxide (CO_2), and radon (Wei, 2019). Findings presented in this thesis demonstrated that many homes have poor indoor air quality, at times, predominantly owing to high TVOC concentrations (as compared to the 200 ppb threshold). Although the TVOC measure has noted limitations, it is a readily accessible measurement that may provide insight on both in-home behaviors and trends and may warrant further investigation into its explanatory power in the context of in-home IAQ monitoring and evaluation.

5.2 Limitations

5.2.1 Index

The purpose of the indices was to holistically quantify indoor environmental quality (IEQ) from the perspective of indoor air pollution and indoor thermal comfort. The tree-structure aggregation, as proposed by Barbiroli et al. (1992), to estimate IEQ allows for the scientist to select the individual parameters and to group the parameters into sub-indices that are fitting for the study. The decisions in this study to include and exclude parameters was limited by the monitoring equipment (e.g., the OMNI device does not record radon or carbon monoxide). Furthermore, the arrangement of parameters into sub-indices followed the suggestion of Moschandreas & Sofuoglu (2004). Other arrangements would likely yield different results by changing the weighting of each parameter. In addition, other components of IEQ were not included into our final index (e.g., lighting, noise). Inclusion of these variables could provide a more diverse, and potentially informative, representation of the indoor environmental quality.

5.2.2 Electrical Energy Proxy for In-Home Activities

The Sense home energy monitor provides disaggregated electric appliance data, which was used to estimate time spent on in-home daily activities that relate to IEQ: cooking, cleaning, and temperature control. The result of categorizing electrical appliances to an associated daily activity likely underestimated the true activity time for two reasons. First, the Sense monitor was good at detecting and identifying appliances that used alternating currents (AC), such as refrigerators, dishwashers, and toasters. However, the Sense monitor most often does not identify DC appliances such as cell phones and laptops. Often, the Sense named a device as “mystery” or “other.” The inability of Sense to identify all devices led to unintentionally excluding devices that contribute to the activity time. Secondly, there are behaviors that fall into the activity category, but either do not use electricity at the time, or are non-electric. For example, our data is incapable of capturing cleaning activities that include vacuuming with a rechargeable battery or using a rag to dust a shelf. In noting these limitations, it is also worthwhile to point out that these proxies show promise in accurately representing activities. For example, temperature control was negatively correlated with outdoor temperature, indicating that as outdoor temperature decreases the time spent controlling indoor temperature increases. In the future, an improved electrical monitor and additional survey data on non-electric activity related behavior (e.g., frequency of sweeping floors, dusting, opening windows, etc...), could provide supplemental information to accurately estimate in-home activities.

5.2.3 Model

The linear regression model adjusted R^2 values are very low (IEI: 0.02, IAPI: -0.15, IDI: 0.06). Most likely, the model performance is limited by the sample size (n=28). Larger samples sizes are presently being pursued in this study – enrolling more participants and modeling with daily resolution that accounts for clustering at the house level – yet they were not ready at the time of preparing this thesis. Even with larger sample sizes, such models may still suffer from a lack of explanatory power because it is difficult to elucidate the full breadth of factors that should, and can, be incorporated. The included parameters accounted for many factors researchers anticipated relate to IEQ (e.g., year built, smoking, cooking, etc.), as well as a few additional factors (e.g., energy star rating, months occupied, percent at home, etc.). Even though, it is not surprising that the model has very low predictive power considering several previous IEQ modeling efforts have encountered a similar result. Naturally, this leads to a necessity to look beyond the "traditionally" considered factors that impact IEQ to other domains of activity (e.g., building materials, garage to home infiltration). The model accounted for only fixed effects, averaging each home's data to a single observation (N=23 homes). The data collected in the IEQ Study has repeated daily measurements allowing for future mixed effect models to account for within home, day, week, and month variability.

5.3 Future Work

With the IEQ Study in partnership with the City of Fort Collins' energy efficiency program, it is reasonable that future work would track the change of IEQ in homes before and after energy efficiency upgrades. This analysis would allow for a better understanding of which energy efficiency measures are most effective for improving IEQ, as well as if there are unintentional negative consequences of implementing energy efficiency measures. Also, future work could expand upon the correlation of owner vs renter occupied homes, as well as the number of months occupied in the distribution of IEQ. Understanding how various sociodemographic characteristics influence IEQ could allow cities to more equitably allocate resources to homes and residents. In addition, the model could expand to consider other factors that influence IEQ, as well as mixed effects to understand outcome variability. At the time of this thesis, the sample size of homes with completed upgrades was too few to conduct pre- and post-energy efficiency or renter/owner analysis, yet the framework of this thesis could serve as a template for future work.

CHAPTER 6: CONCLUSION

The continuous (N= 6107) and categorical (N=28) Spearman correlation coefficient heat maps suggested directional relationship between several factors and indoor environmental quality (IEQ). The multivariate linear regression model (N = 23) indicated that only smoking was significant in estimating the indoor environmental index (IEI). Even though the model lacked utility, analysis of the indices revealed trends; there may be certain outdoor conditions and seasons that influence homes similarly, and homes in this study tended to have higher air pollution than thermal discomfort. In addition, using an energy detection monitor to categorize electrical devices as a proxy for in-home behavior showed promise. Lastly, estimating IEQ without direct indoor measurements will require that future studies explore unfamiliar domains.

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APPENDIX

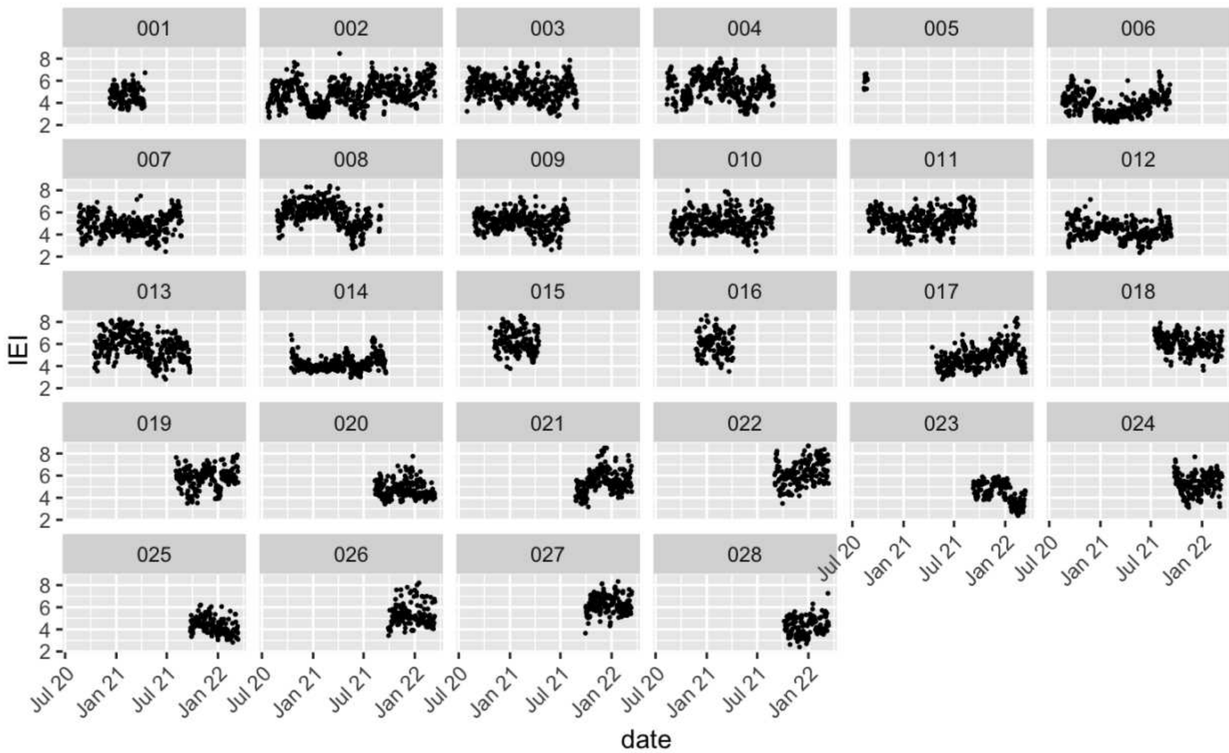
A. Data Dictionary

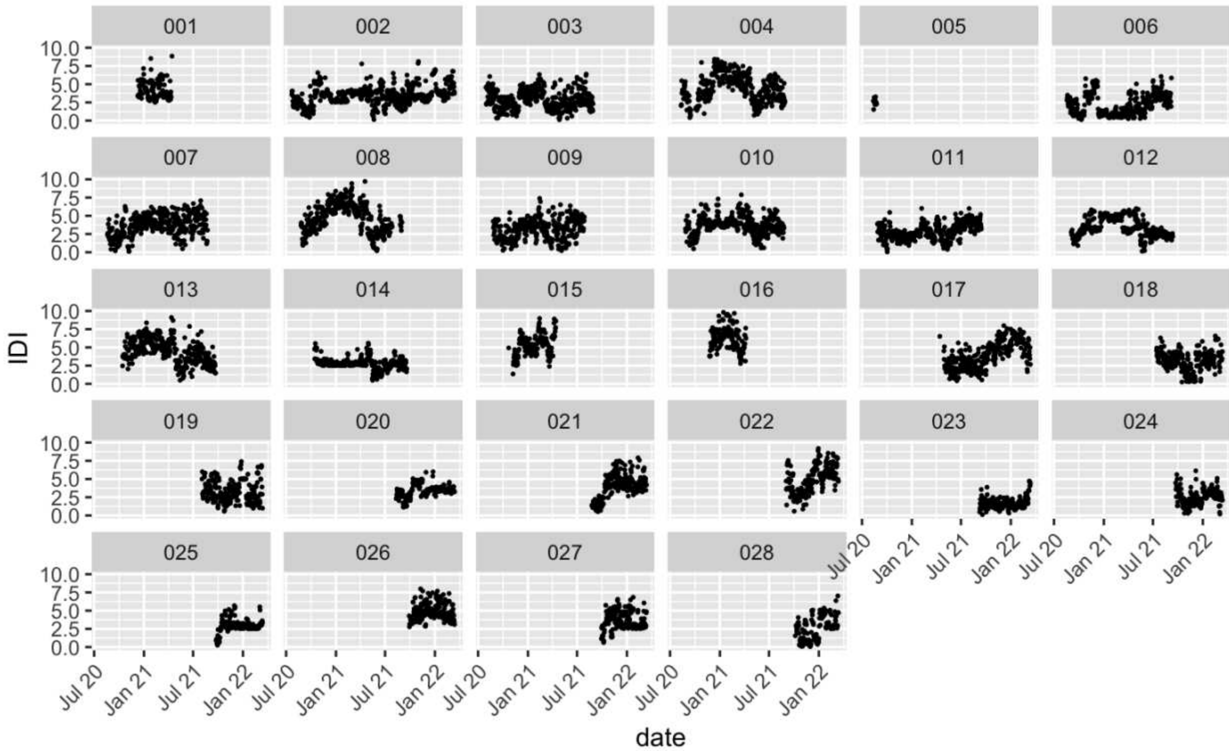
Abbreviated Variable Name	Full Variable Name	Description
Participant / Home Characteristics		
year_built	Year Built	[unitless]; year home was built
decile	Decile Built	[unitless]; decade home was built
median_income	Census Block Median Annual Household Income	[U.S. dollars]; from 2021 Census data
market_value	Market Value	[U.S.dollars]; Market Value of home as determined by Zillow in 2021
renter	Owner or Renter Occupied	[unitless]; binary (0 = owner occupied, 1 = renter occupied)
occupants	Total Number of Occupants	[people]; Number of people who live at residence
ppl_MF	People at Home During the Day Mon. - Fri.	[people]; Number of people typically at home during the day Mon. - Fri.
ppl_SS	People at Home During the Day Sat. - Sun.	[people]; Number of people typically at home during the day Mon. - Fri.
at_home_MF	Percent of Occupants at Home During the Day Mon. - Fri.	[%]; Normalized ppl_MF
at_home_SS	Percent of Occupants at Home During the Day Sat. - Sun.	[%]; Normalized ppl_SS
months_occupied	Months at Current Residence	[months]; Number of months participant has lived at the current residence
floors	Number of Floors	[unitless]; Number of floors in home excluding basement
conditioned_area	Estimated Conditioned Area	[ft^2]

est_vol	Estimated Volume	[ft^3]
ACH50	ACH50	[ACH]; air changes per hour at 50 pascals of pressure differential
energy_star	Number of Energy Star Rated Appliances	[unitless]; the number of major appliances (main refrigerator, dishwasher, clothes washer, clothes dryer), which are energy star rated; 0 (none energy star rated)-4 (all energy star rated)
smoking	Number of occupants who smoke	[people]; Number of occupants who smoke; indoors only; cigarettes, cigars, vape/e-cigarettes, marijuana, other
pets	Number of pets in the home	[unitless]; number of dogs and cats that live at residence
	Measured IEQ Data	
pm25	Fine Particulate Matter (PM2.5)	[µg/m3]
co2	Carbon Dioxide (CO2)	[ppm]
tvoc	Total Volatile Organic Compound (TVOC)	[ppb]
T	Temperature	[°C]
RH	Relative Humidity	[%]
…_in	indoor	average of living room and kitchen measurement
…_out	outdoor	outdoor measurement
	Measured Energy Data	
Cooking_(min)	Daily Cooking Time	[min]; Daily time spent using electrical appliances related to cooking activities; oven, stove top, microwave, toaster oven, toaster, coffee maker, electric tea kettle, blender

Cleaning_(min)	Daily Cleaning Time	[min]; Daily time spent using electrical appliances related to cleaning activities; garbage disposal, dishwasher, clothes washer, clothes dryer, vacuum
T_Control_(min)	Daily Temperature Control Time	[min]; Daily time spent using electrical appliances related to temperature control activities; furnace, space heater, fan, air conditioning
	Indices	
IEI	Indoor Environmental Index	[unitless]; an index that takes into account indoor air pollution and thermal comfort; scale 0 (best indoor environmental quality) to 10 (worst indoor environmental quality)
IAPI	Indoor Air Pollution Index	[unitless]; an index that takes into account fine particulate matter (PM2.5), carbon dioxide (CO2), and total volitile organic compounds (TVOC); scale 0 (best indoor air) to 10 (worst indoor air)
IDI	Indoor Discomfort Index	[unitless]; an index that takes into account temperature (T) and relative humidity (RH); scale 0 (least indoor thermal discomfort, most comfortable) to 10 (highest indoor thermal discomfort, least comfortable)

B. Time Series Indices of All Homes

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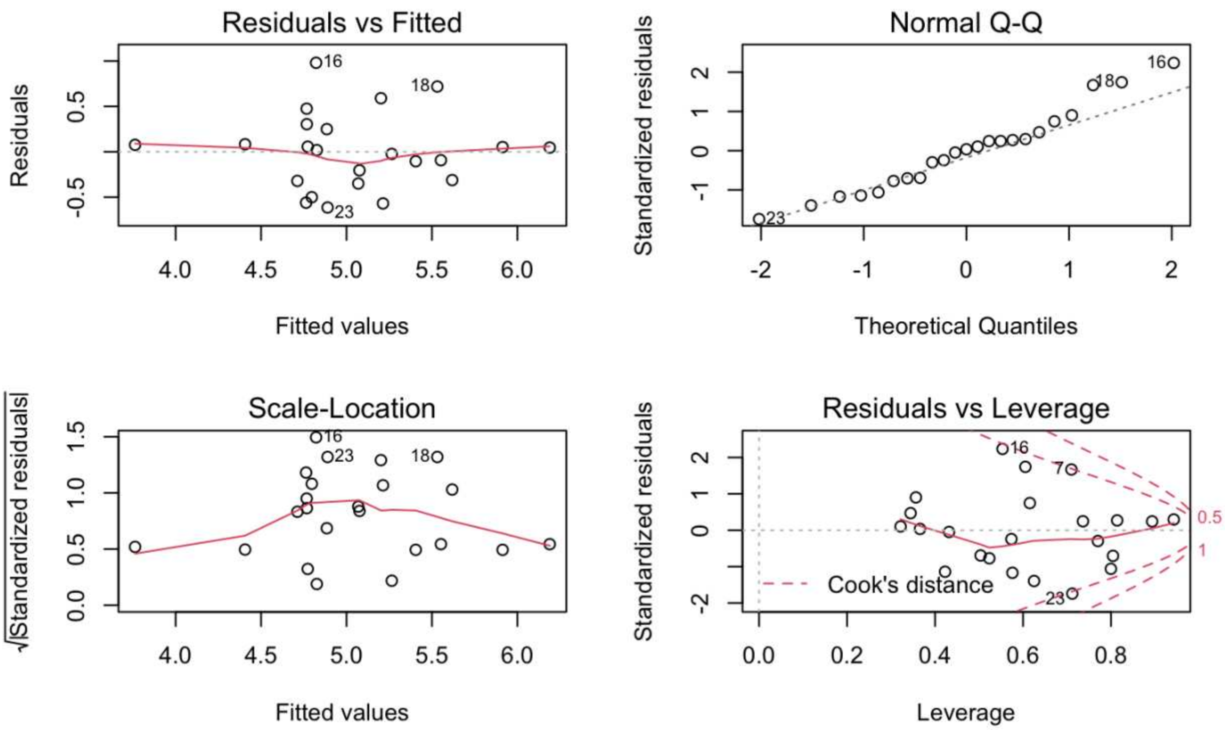
C. Post-Model Diagnostics

IEI



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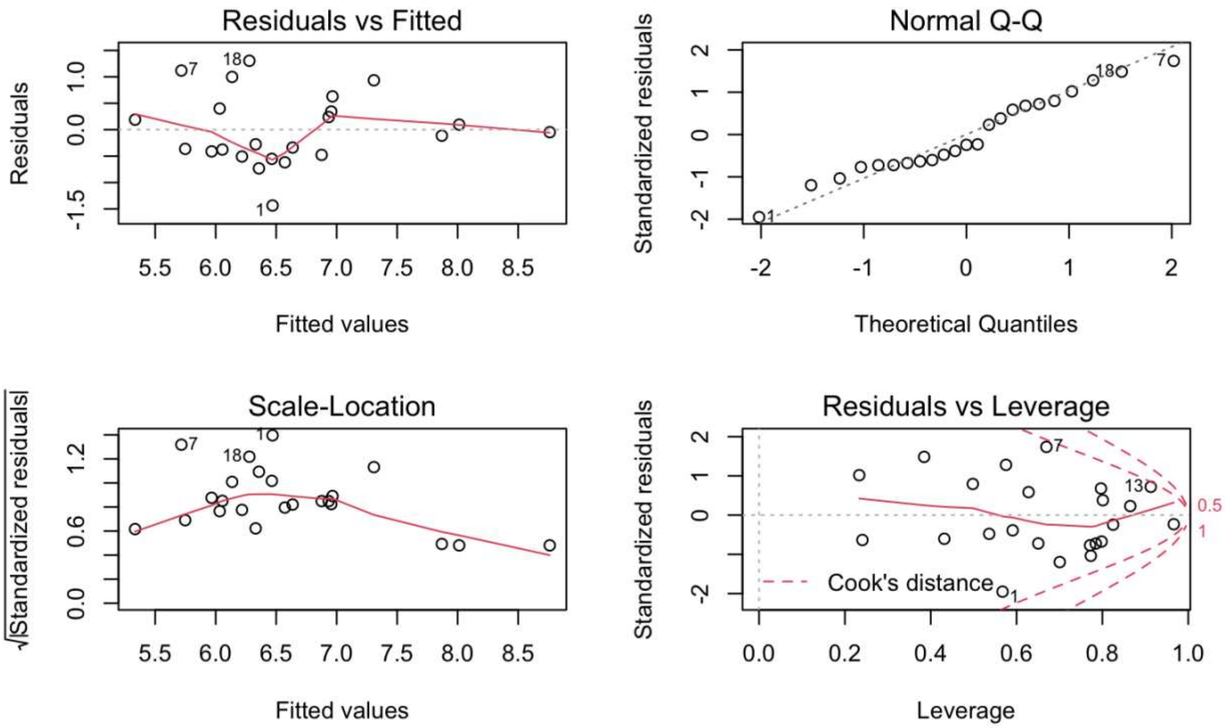
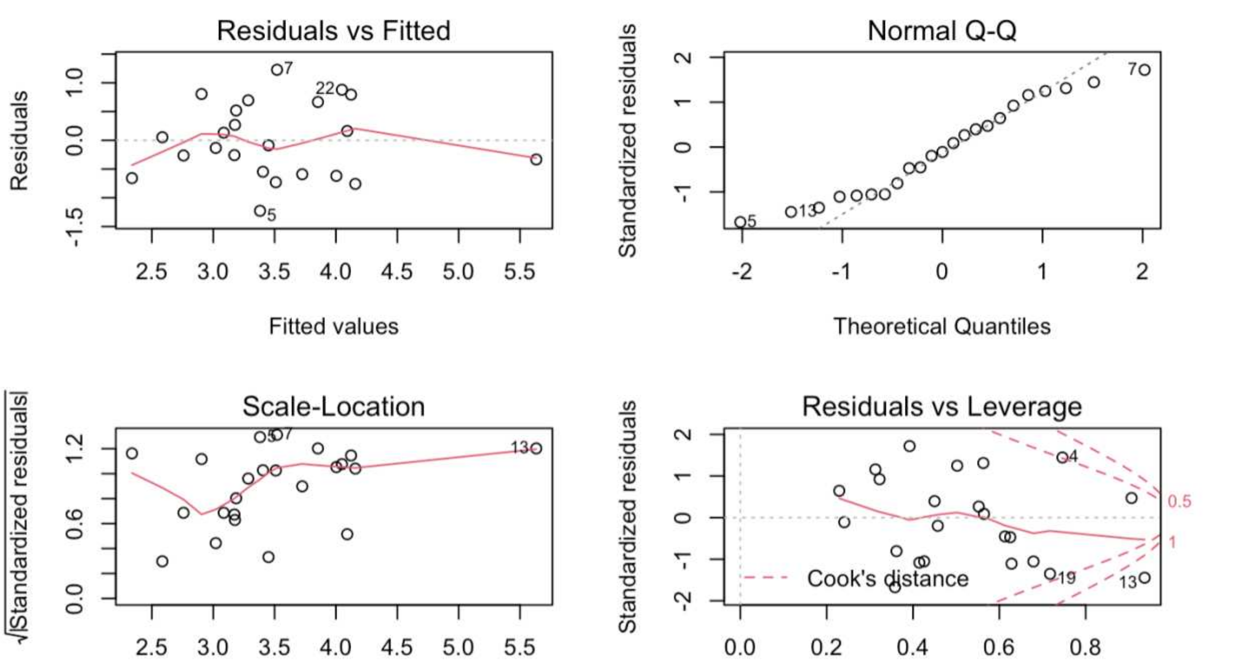

Residuals vs Fitted
Residuals
Fitted values
Normal Q-Q
Standardized residuals
Theoretical Quantiles
Scale-Location
√|Standardized residuals|
Fitted values
Residuals vs Leverage
Standardized residuals
Cook's distance
Leverage

IDI


Residuals vs Fitted
Residuals
Fitted values
Normal Q-Q
Standardized residuals
Theoretical Quantiles
Scale-Location
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Residuals vs Leverage
Standardized residuals
Cook's distance