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Review

The Role of Occupants in Buildings' Energy Performance Gap: Myth or Reality?

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Abstract: Buildings' expected (projected, simulated) energy use frequently does not match actual observations. This is commonly referred to as the energy performance gap. As such, many factors can contribute to the disagreement between expectations and observations. These include, for instance, uncertainty about buildings' geometry, construction, systems, and weather conditions. However, the role of occupants in the energy performance gap has recently attracted much attention. It has even been suggested that occupants are the main cause of the energy performance gap. This, in turn, has led to suggestions that better models of occupant behavior can reduce the energy performance gap. The present effort aims at the review and evaluation of the evidence for such claims. To this end, a systematic literature search was conducted and relevant publications were identified and reviewed in detail. The review entailed the categorization of the studies according to the scope and strength of the evidence for occupants' role in the energy performance gap. Moreover, deployed calculation and monitoring methods, normalization procedures, and reported causes and magnitudes of the energy

performance gap were documented and evaluated. The results suggest that the role of occupants as significant or exclusive contributors to the energy performance gap is not sufficiently substantiated by evidence.

Keywords: buildings; performance gap; energy; occupant behavior

1. Introduction

1.1. Objectives

There is not a unique and all-encompassing definition of the term "energy performance gap" (EPG). Indeed, it has different connotations in different domains and contexts. It is thus necessary to clarify, at the outset, our understanding of this term. First, the domain we focus on covers buildings. Second, the energy we refer to is what is required for the operation of buildings. This includes energy needed for space heating, cooling, lighting, ventilation, equipment, and appliances as well as domestic hot water (DHW). Third, the gap we talk about is the one between expected (i.e., estimated, calculated, computed, predicted) and actual building-related energy use [1]. Fourth, whereas the deviation of buildings' actual energy use from the predicted magnitude may have different causes, we specifically focus on the potential role of building occupants with regard to the emergence and extent of the EPG.

As such, the present paper entails a review of recent publications deemed to be relevant to the initial objectives of our inquiry. These could be formulated in terms of a number of basic questions:

(i)   What is the general frequency and scope of publications that address a building-related EPG?
(ii)   Do these publications entail a clear and widely shared understanding of the meaning of the EPG?
(iii) What fraction of these publications suggests that building occupants are responsible for a significant share of the EPG?
(iv)   What kind and level of evidence is provided for the purported role of occupants in the EPG?
(v)   Assuming there is evidence for the existence and relevance of an occupant-caused EPG, does the study of the literature entail suggestions as to how it could be reduced?

It is of critical importance to understand what the present contribution is not concerned with. We do not question the assertion that occupants' patterns of presence and behavior in buildings can, in principle, influence buildings' energy performance. Such a possibility is entirely plausible. Aside from their numbers and patterns of their presence in buildings, occupants can—in most buildings—manipulate the control parameters of environmental control systems for heating, cooling, ventilation, and lighting. Instances of such parameters include temperature set-points and schedules for heating and cooling systems. Similarly, occupants' operation of luminaires, windows, blinds, as well as electrical equipment and appliances can impact mass and energy transfer processes in buildings and hence their overall energy performance. Such scenarios of occupants' impact on buildings' energy performance can be demonstrated via rational analyses and simulation studies [1,2]. However, there is a fundamental distinction to be made between the plausibility of various effects and phenomena on the one hand and the existence, extent, and frequency of their actual occurrence on the other hand. Whereas the former may be accepted merely on logical grounds, the latter requires empirical evidence. Consequently, in this paper we are predominantly concerned with the existence and quality of the evidence for the claim that occupants' carry the bulk of responsibility for building-related EPGs.

Note that the present paper considers existing publications in this area and does not include any direct statistical treatment of empirical data. Nonetheless, its underlying

main objective may be formulated in terms of a qualitatively expressed null-hypothesis as follows:

There is no conclusive and sufficient evidence available for the claim that occupants' behavior is responsible for the bulk of building-related EPGs.

As such, the outcome of this review is expected to support the effort to find out if this null-hypothesis can be rejected.

1.2. Motivation

The scientific literature and case studies report the existence of a gap between the predicted and actual energy use of buildings. Instances of such a gap have been reported in relation to existing buildings, building retrofit projects, and new constructions. For retrofit projects, this so-called performance gap is split into a prebound and a rebound effect, while for new constructions no such distinction is made. The prebound effect describes the difference between the predicted and actual energy use before the renovation measures and the rebound effect denotes such difference after the completion of the project.

Building occupants and their preferences, needs, socioeconomic conditions, and interactions with the building are often held responsible for a large part of this EPG and the variation in energy use between nominally identical buildings. Whether accompanied by numbers or not, the alleged contribution of occupants to this gap is then used as an argument for the detailed study of occupant behavior (OB) and the introduction of ever more complex OB models for energy use prediction. Computing power and more advanced simulation tools are suggested to improve the accuracy of energy use predictions. If occupants are indeed a major contributor to the gap, then the incorporation of more accurate occupant models in the simulation models could alleviate the problem. However, before making the occupant a major culprit, the basis and evidence for the above claims need to be examined.

The motivation behind the present review is to ascertain if there is indeed sufficient evidence for the claim that OB is a major contributor to the EPG. This review is also expected to shed light on further questions. For instance, even if occupants could be shown to be responsible for a considerable fraction of the performance gap, to which extent could we enhance the reliability and predictive accuracy of OB models? More generally, would closing the EPG improve the process of designing more energy efficient buildings? The present contribution is also intended to contribute to the identification of shortcomings in research related to the EPG.

1.3. Overview of the Paper

Section 2 provides an overview of the study's approach, including the paper selection process, the key research directions explored, and how the data are synthesized to extract the relevant information. Section 3 presents the results of the review. The section starts with the descriptive statistics of the selected publications, followed by the characteristics of the buildings and occupants studied, the type of data used, and the normalization approaches applied to the data. The section then continues with a critical analysis of the reported magnitudes and causes of the EPG. Section 4 discusses the main findings, and puts those in the context of the objectives of the review, their implications, and their practical applications. Section 5 concludes with a high-level summary of the work and way forward.

2. Approach

2.1. Selection Process and Key Review Aspects

The literature search process aimed to collect papers that directly address and document the role of occupants as the cause of the EPG. The initial process included screening of the authors' individual repositories for relevant papers and unstructured literature searches using various databases. Next, a structured search process was followed using both the Scopus [3] and the Web of Science databases [4]. The strings used for the literature search are reported in Appendix A. This process included two steps:

1.   A first search that looked for the relevant terms (e.g., performance gap, rebound, prebound, gap) in either the title or the keywords;
2.   A second search within these findings that looked for entries with variations of the terms "buildings" and "occupants" or "uncertainty".

The literature search was then further refined (using available filtering options in the two databases) in order to only include records:

(a)   Published in English.
(b)   In relevant "subject areas" (Scopus) or "categories" (Web of Science), and
(c)   In relevant "source titles" (both databases).

The latter (c) was performed via refining by "source titles", whilst attention was paid so that relevant interdisciplinary studies were not mistakenly omitted.

This process, as illustrated in the Prisma diagram in Figure 1, identified 242 potentially relevant publications. A first screening step was performed considering titles and abstracts, reducing the list to 102 publications that were fully screened. This structured process identified 74 relevant publications that were not included in the initial compilation of known research (items included in authors' collections and identified via unstructured search). In the next step, all references cited by the identified articles were screened for relevance. The entire process identified 144 articles.
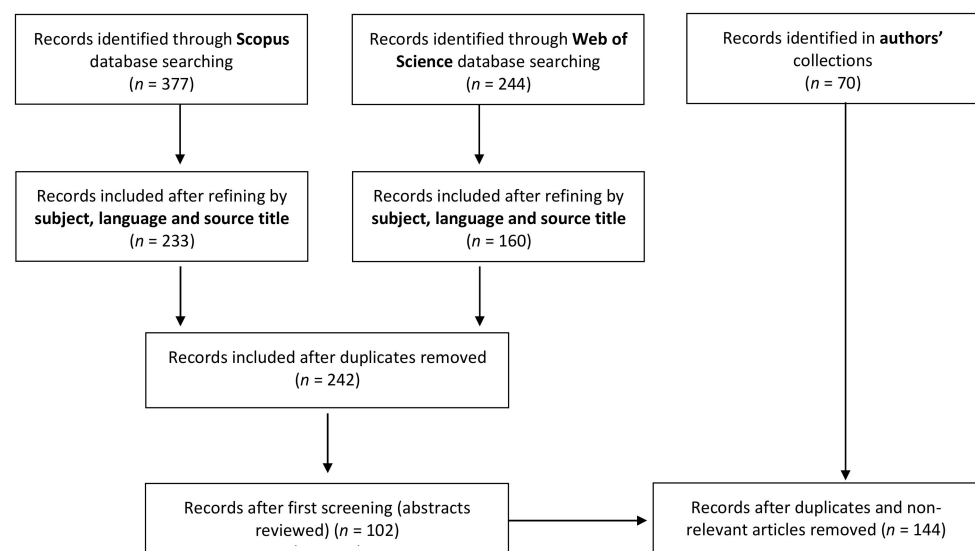
Figure 1. Process of identifying relevant publications.

Subsequently, the articles were split into two groups, i.e., those which directly addressed and documented the role of occupants as the cause of the performance gap ("main category") and those which addressed the performance gap without the strict requirement to provide evidence for the role of the occupants ("secondary category").

Lastly, a further high-level differentiation concerned the level of the entailed evidence for the EPG. Accordingly, the articles were divided into three groups: (i) the "gold" level denotes articles that contain empirical data of both energy use and occupant behavior, (ii) the "silver" level denotes articles that include empirical data only on energy use, and (iii) the "bronze" level denotes articles that may have included some occupant-related data but include no energy use data.

Table 1 provides key information for a subset of the articles with the above mentioned "gold label". References with the "silver" and "bronze" labels are listed in Appendix B, which includes a table with all reviewed publications. It includes, for each paper, summary information with regard to buildings, predicted energy, the source of occupant-related model assumptions, measured energy use, normalized energy data, and the magnitude of the EPG, together with primary conclusions.

Table 1. Summary information regarding papers classified as "gold label".

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[5]	Residential; Switzerland; 2009	Heating load (simulation)	(Standard) Swiss Society of Engineers and Architects (SIA)	730	Electricity, pellet, solar (energy metering, energy bills, in situ measurements)	Air temperature (NA)	NA	Occupancy, window opening behavior, use of shades (observations)	Energy consumption for heating and hot water (adjusted for degree days)	−1% (simulation), 81% (SIA calculation)
[6]	Residential; United Kingdom; 2007	Heating load (simulation, standard assessment procedure calculation)	Standard Assessment Procedure (SAP) assumptions	365	Electricity, biomass, district heating (energy metering)	NA	NA	Temperature set-points, window behavior, MVHR use, programmer control (survey)	NA	7% higher on average, for the surveyed sample it ranged from −48% to 67%
[7]	Residential; China; 2007	Electricity (NA)	NA	365	Electricity (energy metering)	Air temperature, relative humidity (Testo 175-H2 data loggers)	NA	Length and frequency of daily use of lighting and appliances (survey (paper questionnaire))	NA	NA
[8]	Non-residential; England; 2008	Energy demand (simulation)	International Performance Measurement and Verification Protocol (IPMVP)	730	Electricity, natural gas (energy) bills, energy metering)	NA	NA	Occupancy, temperature set-points, ventilation rates, schedules of operation for heating, ventilation systems (POE (interviews, on-site observations))	Gas consumption for heating, electricity consumption for external lights and lifts (adjusted for degree days, NA)	3.1%

Table 1. *Cont.*

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[9]	Residential; Netherlands; NA	NA	NA	1095	Gas, electricity (energy bills)	NA	Weather (national climatic data)	Occupancy, temperature set-point, ventilation behavior (survey)	Energy consumption for heating and hot water (NA)	NA
[10]	Residential; Belgium; 2008, 1960	Heating load (standard (Belgian EPBD))	Standard	2920	Gas (energy bills)	Air temperature, relative humidity, CO_2 (sensors)	Weather (national climatic data)	Occupancy, thermostat use; set-point and frequency, ventilation behavior; mechanical system and window opening (survey)	Gas consumption for heating and hot water (adjusted for degree days)	Case study 1: 25% to 125%, case study 2: 25% to 75%
[11]	Residential; Italy; NA	Heating load (energy certificate)	Standard	105	Ground water supply heat, electricity, solar energy, gas (energy metering)	Air temperature (data loggers)	NA	Occupancy, temperature setting, use of windows and shutter (sensors)	Energy consumption for heating and DHW (adjusted for degree days)	Heating: 77% to 222%, DHW: 96%

Table 1. *Cont.*

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[12]	Residential; Austria; 1968–1975	Heating load (energy certificate, simulation)	Standard	210	Electricity, gas, oil, district heating (energy bills)	Air temperature, relative humidity (sensors)	Weather data (local weather stations)	Window opening (interviews)	Weather data, indoor temperature, air change rate, energy consumption for heating and hot water (NA, take monthly mean indoor temperatures, consider air change rate higher than the energy certificate assumptions by a factor of 4–6)	400% to 600%
[13]	Residential; Iran; NA	Energy demand (simulation)	Surveys	1095	Gas, electricity (energy bills, field studies and interviews)	NA	NA	Occupation schedule, usage of appliances, lighting, heating and cooling appliances (survey)	NA	13.5% to 25%

<div style="text-align: center">**Table 1.** *Cont.*</div>

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[14]	Residential; UK; 2011–2012	Energy demand (Standard Assessment Procedure (SAP))	Standard Assessment Procedure (SAP)	365	Gas, PV, electricity (energy bills)	Temperature, relative humidity (RH) and CO_2 (sensors)	NA	Occupancy, (A) opening and closing of doors and windows (sensor), (B) washing and showering regimes and thermostat settings (self-completion activity logging of occupants)	NA	Up to 250%
[15]	Residential; Landshut, Germany; 2011	Heating load (Norm DIN V 4108-6)	Code calculation, simulations	1460	Heating (thermal energy), DHW, electricity (sensors)	Air temperature, CO_2, humidity (sensors)	Air temperature, windspeed, humidity, rain, radiation (weather station on the roof)	Thermostats, energy use behavior (monitoring, meta data)	Heating energy (adjusted for degree days), square meter normalized vs. person normalized-DHW (cross validation between units)	Heating: avg. 30%, domestic hot water: avg. −26%
[16]	Residential; Aarhus, Denmark; 2017	Energy demand (simulation)	Occupancy schedules (survey, databases)	180	Electricity, district heating (energy metering)	Air temperature, air humidity, ventilation speed CO_2 (sensors)	Air temperature (sensors)	Occupancy (CO_2 sensor), appliance usage (power meter per appliance)	NA	Heating: −2.43% electricity: 0.2%

Table 1. *Cont.*

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[17]	Residential; Madrid, Spain; 1972	Heating, cooling load (simulation)	Actual occupancy schedule by observation	365	Gas consumption (energy metering)	Air temperature (sensors)	Air temperature (sensors)	Appliances use Opening window behavior boiler set-points (sensors)	NA	Heating: −15.4% to −5.5% cooling: +5.1% to +12.7%
[18]	Residential; Denmark; before 1962 until after 1999	Energy demand (regression models)	Questionnaire survey	182	District heating (energy labels, energy metering provided from a national database)	NA	NA	Frequency of adjusting thermostats, window opening, clothing during winter, the perceived temperature level compared with friends (questionnaire survey)	NA	NA
[19]	Residential; France; up to 2009	Heating load (The French EPC, simplified calculation)	Survey	365	Gas, fuel oil, wood, electricity (energy bills from survey)	NA	NA	NA (survey)	Space heating consumption (adjusted for degree days, intensity factor integrates energy price, income and rebound effect into a theoretical budget share elasticity)	3% on predictions if EPC is modified for theoretical budget share, error 30% if EPC is modified for behavioral patterns. Simple EPC error > 65%

<div align="center">Table 1. *Cont.*</div>

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[20]	Residential; Jeddah, Saudi Arabia; 2011	Energy demand (simulation)	Interviews	365	Electricity consumption (electricity bills)	NA	NA	Use of air-conditioning (interviews)	NA	NA
[21]	Residential; Davis, California; NA	Energy demand (simulation)	Questionnaire	182	Electricity (electricity bills)	Air temperature (thermographs, survey)	Radiation, dry bulb temperature, air pressure, wind speed, and wind direction (U.S. department of energy solar meteorological research and training site - SEMRTS)	Frequency of use of household appliances, air conditioning use (surveys and interviews)	NA	50%
[22]	Non-residential; Pakistan; NA	Energy demand (simulation)	Survey, questionnaire	1095	NA (energy bills)	NA	NA (resources at the university of California, Davis)	Occupancy, use of equipment, window opening/use of blinds, use of artificial lighting, use of HVAC (questionnaire survey and interviews)	NA	25.4% in three years (an average 8.5% of energy can be saved annually)

Table 1. *Cont.*

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[23]	Non-residential; Botswana and South Africa; NA	Energy demand (NA)	Standard	365	Electricity consumption (energy auditing equipment (data logger))	NA	NA	Occupancy, use of air-conditioning (working-hours schedule, interviews, site inspection at night)	NA	23% to 36%
[24]	Non-residential; UK; NA	Energy demand (simulation)	Standard	2555	Electricity, gas (utility bills)	NA	NA	Occupancy, frequency of equipment use (survey)	Weather data (NA)	Electricity: 175% to 274%, gas: 147% to 214%
[25]	Residential; Scotland; NA	(A) Heating load, (B) energy demand (SAP calculation)	Standard	365	(A) Gas, (B) electricity (energy metering)	Air temperature, surface temperature, air pressure, volume flow rate of air (thermograms, sensors)	Air temperature Surface temperature air pressure (thermograms, sensors)	Occupancy, service control systems, use of appliances (survey)	NA	(A) control house: 42%, passive house: 37%, (B) control house: −43%, passive house: 6%
[26]	Residential; Belgium; building permits of 2012–2013	Heating load (energy certificate)	Standard	365	Electricity, gas (energy bills)	NA	Air temperature, solar irradiance (national climatic data)	Occupancy, heated rooms, heating hours, temperature set-points, number of baths/showers per week and duration (survey)	Energy use for space heating and DHW (adjusted for degree days)	Gas: −25%

Table 1. *Cont.*

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[27]	Residential; Germany; 1950s	Heating load (NA)	NA	365	NA (energy metering)	Air temperature, relative humidity, CO_2, VOC (sensors)	Air temperature, solar radiation, wind speed, wind direction (weather station)	Window use, thermostat settings (sensors)	NA	NA
[28]	Non-residential; Germany; 1920–2000	Heating load (energy certificate)	NA	730–1825	NA (on site, energy metering)	NA	NA	Occupancy, window opening, heating control/set-point (interviews)	Energy consumption for space heating (weather-adjusted (NA))	Pre-retrofit: −13.8% to 2.1%, post-retrofit: −43.5% to −8.3%
[29]	Residential; Netherlands; 1946–1995	NA	NA	NA	Gas (energy providers)	NA	NA	Use of heating and ventilation systems (survey, questionnaires)	Thermostat settings: temp set-point (used standard deviations from the mean), ventilation hours (consider the type of ventilation with most hours)	NA
[30]	Residential; UK; NA	Energy demand (SAP calculation)	Standard	NA	NA (energy metering)	NA	NA	Occupancy patterns (NA)	NA	60%
[31]	Residential; UK; 1930	Energy demand (simulation)	Survey	30	Gas, electricity (energy metering)	Air temperature (Hobo sensors)	Air temperature, irradiance (weather station 20 km away)	Temperature set-points (sensors)	NA	−14% to 74%

Table 1. *Cont.*

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[32]	Residential; UK; NA	NA (SAP calculations)	Codes	365	Electricity (energy metering)	NA (sensors)	Air temperature (sensors)	Window opening, temperature set-point (NA)	NA	NA
[33]	Residential; Netherlands; NA	Heating load (energy certificate)	Standard	365	Gas (energy bills)	NA	Weather (national agency)	Occupancy, heating and ventilation practices, showering (survey)	Gas consumption (adjusted for degree days)	−62% to 0%
[34]	Non-residential; Switzerland; NA	Lighting load (simulation)	Standard	2920	Electric lighting energy (energy metering)	Air temperature, Illuminance, luminance (sensors)	NA	Occupancy, blinds position, electric lighting behavior (sensors)	Electric lighting consumption (consider the impact of different occupancy rates)	Advanced controller: 72% (simulation), "Best practice" controller: 19% (actual)
[35]	Non-residential; UK; 2001–2005	Energy demand (CIBSE calculation)	Codes (CIBSE, BB87, SAP)	NA	Electricity, natural gas (energy metering)	NA	Air temperature (local weather office)	Lighting control ON/OFF status (observations and sensors)	NA	57% to 66%
[36]	Non-residential; Canada; NA	Energy demand (simulation)	Standard, database	365	Electricity (energy metering)	Air temperature, set-points, CO_2 Total Volatile Organic Compounds (TVOC) (sensors)	Weather (sensors)	Occupancy, window status, temperature set-points (sensors)	NA	60%

| Ref. | Building Type, Location, Construction Date | Predicted Energy Variable (Method of Prediction) | Source of Occupant-Related Model Assumptions | Observations/Measurements | | | | | Normalized Energy Data (Normalization Method) | EPG Magnitude (in %) |
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[37]	Residential; Munich, Germany; 2010	Heating load (code/norm)	Standard (DIN V 4108-6 (EnEV 2009))	365	Electricity, other (energy metering)	Air temperature (sensors)	Air temperature, global radiation (sensors)	Window opening frequency (sensors)	Heating energy (additional component from DHW (60% losses); weather adjusted)	Building: +15%; apartment: −59% to +318%
[38]	Non-residential; USA; NA	Energy demand (simulation)	Standard	3304	Electricity (energy metering)	NA	NA	Occupancy patterns (IR and video-based sensors)	NA	9%
[39]	Residential and Non-residential; Canada; NA	Energy demand (simulation)	Standard	2555	Electricity (utility bills)	Illuminance (NA)	NA	Occupancy (survey)	NA	0% to 69%
[40]	Residential; Belgium; 1960s	Heating load (quasi-steady state model calculation)	Standard	365	Gas (energy metering)	Heat flux, air tightness, CO_2, air temperature, relative humidity (sensors)	Air temperature (NA)	Occupancy (surveys)	Gas consumption (adjusted for degree days); Set-point temperatures (deducted from the average point of stabilization of the indoor temperature during occupancy)	Base model: −25% to −75%, (average −46%), calibration: 0% to −75%, (average: −43%)
[41]	Non-residential; USA; 2010	NA	NA	365	Energy demand (energy metering)	NA	NA	Occupancy, equipment usage (sensors)	NA	40% (HVAC)

Table 1. *Cont.*

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[42]	Non-residential; London, UK; NA	Energy demand (simulation)	Standard	(A) 365, (B) 120	(A) Gas; (B) electricity (energy metering)	NA	NA	Occupancy (swipe card and WIFI data)	NA	−6% to 5%
[43]	Non-residential; France; 1987–1997	NA	NA	1095	Electricity, gas (energy bills, built-in smart meters)	NA	Air temperature (NA)	Occupancy (courses schedules with absence factor (no real-time measured occupancy))	Weather (adjusted for degree days)	NA
[44]	Residential; Norway; 1987	Heating load (simulation)	NA	NA	NA (site inspection)	Lighting, equipment (NA)	NA	Occupancy, other (site inspection, survey)	NA	NA
[45]	Residential; Madrid, Spain; 1972	Energy demand (simulation)	Standard	365	Electricity (energy metering)	Air temperature, humidity (sensors)	Air temperature, external relative humidity, solar radiation, wind speed and direction (weather station)	Use of heating boiler (on/off), window opening (questionnaire)	NA	Winter = −57.6% Summer = −38.16%
[46]	Non-residential; USA; 2000–2006	Energy demand (simulation)	Standard	365	Electricity (energy bills)	Air temperature (NA)	NA	Occupancy (database)	Temperatures, schedules, occupancy (NA)	−30% to 25%

Table 1. *Cont.*

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[47]	Non-residential; Spain; 2016	Energy demand (energy certificate)	Standard (Spanish building regulations)	NA	Natural gas, electricity (energy bills)	NA	NA	Office equipment operation (on/off) when not in use (site visits and informal user interviews)	NA	30% (average)
[48]	Residential; Sweden; NA	Energy demand (simulation)	NA	80	NA	Air temperature (NA)	Air temperature (NA)	Occupancy (observations)	NA	13.30%
[49]	Residential; Germany; 1950s	Energy demand (calculation)	NA	1460	Electricity, gas, district heating (energy metering)	Air temperature relative humidity, CO_2, volatile organic compounds (VOC), light on the ceiling (Lux), in-frared/visible light ratio (to recognize the light source), (sensors)	NA	Occupancy, window opening (open/closed) (sensors)	Indoor air temperature (corrected by −2.5 K)	41% to 117%

Table 1. *Cont.*

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[50]	Non-residential; Odense, Denmark; 2015	Energy demand (simulation)	Standard	120	Electricity, other (energy metering)	Air temperature, humidity, CO_2, PIR, illuminance, radiator valve position, ventilation damper position, blinds position and multiple temperature and pressure along the energy supply scheme (sensors)	Air temperature, wind speed, solar irradiation (local weather station)	Occupancy (cameras)	NA	Calibrated model vs. measured Heating: −8.4 to 6.9, annual regulatory performance vs. design certificates: 27.2% to 122.3%, overall dynamic energy performance gap −3.47% to 5.48%
[51]	Non-residential; London, UK; NA	Energy demand (simulation)	Standard occupancy profiles	NA	Electricity (energy Metering)	NA	NA	Use of appliances and equipment, occupancy (sensor)	NA	18%
[52]	Residential; Norway; 1987	Heating load (simulation)	Standard	365	Electricity (energy metering)	Air temperature, mechanical ventilation rate (sensor)	Weather (weather station)	Heating set-point (visual inspection)	NA	50%
[53]	Residential; UK; 2012	Energy demand (SAP predictions, spreadsheet calculations)	Standard	365	Electricity (Ewgeco energy monitoring devices)	Air temperature, RH and CO_2 (wireless RT:Wi5 data-hub)	NA	Operation of thermostats (surveys and interview)	NA	180% to 250%

Table 1. *Cont.*

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[54]	Non-residential; UK; 2009, 2008	Energy demand (energy certificate)	Standard	365	Electricity, biomass, solar energy, gas (energy metering, Ewgeco energy monitoring devices)	Air temperature, RH and CO_2 (sensors)	NA	Occupancy (sensors), window opening, temperature controls, ventilation controls, lighting and BMS (questionnaires)	NA	180% (library)
[55]	Residential; Estonia; 1986	Energy demand (simulation)	Standard	365	Electricity, district heating (energy metering)	Air temperature, ventilation air flow (NA)	NA	Occupancy (NA)	NA	34%
[56]	Residential; Germany; NA	Heating load (calculation)	Standard	720	NA (energy metering)	Carbon dioxide, room humidity, air temp, volatile organic compounds (NA)	Air temperature, radiation (NA)	Window opening [in %] (sensors)	Heat Energy consumption for weather (NA)	10% to 50%
[57]	Non-residential; London, UK; 2014	Energy demand (energy certificate)	NA	1460	Electricity, gas (energy metering)	Air temperature, RH, CO_2, PM2.5, PM10, VOCs, reverberation time (RT), illuminance (sensors)	Air temperature, VOCs (sensors)	Occupancy patterns (NA)	NA	344% to 381% (electricity), 591% to 778% (fossil fuel)

Table 1. *Cont.*

Ref.	Building Type, Location, Construction Date	Predicted Energy Variable (Method of Prediction)	Source of Occupant-Related Model Assumptions	Observations/Measurements					Normalized Energy Data (Normalization Method)	EPG Magnitude (in %)
				Duration (Days)	Measured Energy Type (Source of Energy Data)	Indoor Conditions (Source of Data)	Outdoor Conditions (Source of Data)	Observed Occupant Behavior (Source of User Behavior Data)		
[58]	Residential, Non-residential; Switzerland; 2012–2013	Heating, cooling load (simulation)	NA	30	Electricity, other (NA)	Air temperature (NA)	NA	Temperature set-points, operation of the ventilation system (observations)	Energy consumption for weather (NA)	49% (electricity), 127% (heating energy), 11% (hot water)
[59]	Residential; Kuwait; NA	Energy demand (simulation)	Survey	NA	Electricity (survey)	NA	NA	Occupancy patterns, occupant activity, operation of lighting and appliances, hot water and AC (surveys)	NA	21%
[60]	Non-residential; UK; NA	Lighting load (calculation)	CIBSE TM22 energy assessment	180	Electricity (energy metering)	NA	NA	Occupancy, illuminance (sensors: photocells and absence detection)	NA	−14% to +27%
[61]	Residential; UK; NA	Energy demand (simulation)	Standard	365	Gas, Electricity (NA)	Air temperature (NA)	Weather (weather station)	Temperature set-point, occupancy (survey)	NA	−50% to +18%

After systematically reviewing studies on the EPG, we focused on those papers that had provided quantitative evidence when suggesting that the performance gap is caused by OB. To this end, studies that have empirical measures of both occupant and non-occupant related causes of the performance gap were considered particularly relevant to the aim of this review.

2.2. Synthesis

Subsequent to the selection process, the papers were reviewed to extract details of the relevant geographical area, the building-related data (e.g., typology, project details), and occupant-related information (e.g., number of people, household composition, age). Second, the methods applied to predict and measure the performance gap were investigated. In terms of measured energy performance, the characteristics of the empirical data used (temporal and spatial granularity) and the data sources (sensors, records) were taken into consideration. In terms of predicted energy performance, the applied methods (e.g., energy certificates, energy simulation) and the assumptions concerning OB were extracted, analyzed, and synthesized. Finally, the methods used to identify the causes of the performance gap were investigated. Potential solutions to bridge the performance gap were discussed to address methods for and inconsistencies in the prediction and measurement of building energy performances and analysis methods of performance gaps.

3. Review Results

3.1. Overview

The vast majority of the studies (90%) mentioned in this review were published after 2010. Only a few papers (10%) were published prior to 2010 (Figure 2). Specifically, the scientific production in the 2015 to 2020 period was twice as high as the preceding five-year period (2010–2015). Most of the papers were published in the journals "Energy and Buildings" (33%) and "Building and Environment" (10%). The most frequently used words in the papers' titles were as follows: energy (53), performance (43), building or buildings (33), gap (20), consumption (10), actual (9), analysis (8), occupant (8), evaluation (7), residential (7), impact (7). Figure 3 illustrates the most frequently used words in the papers' titles as well as the frequency of included key words.
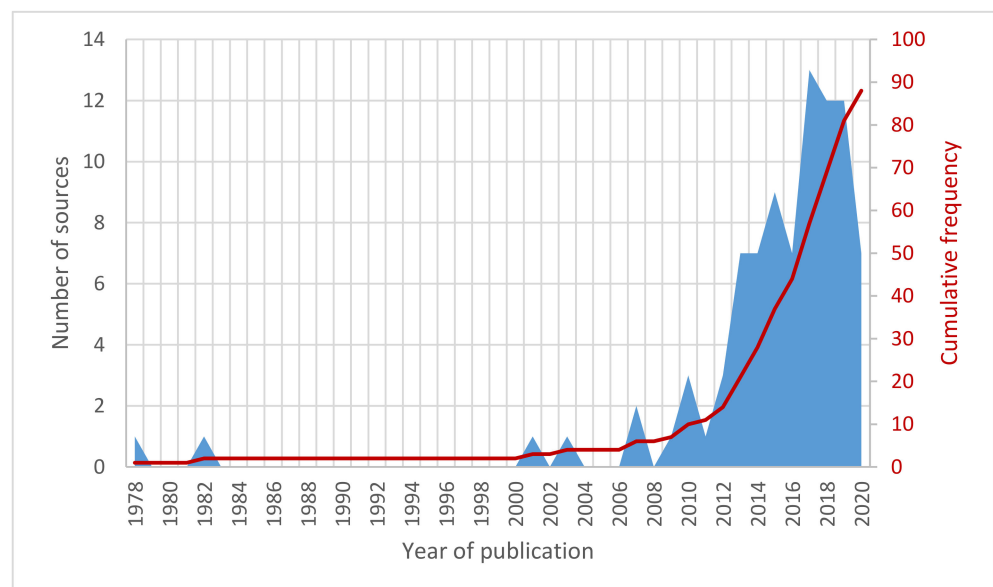

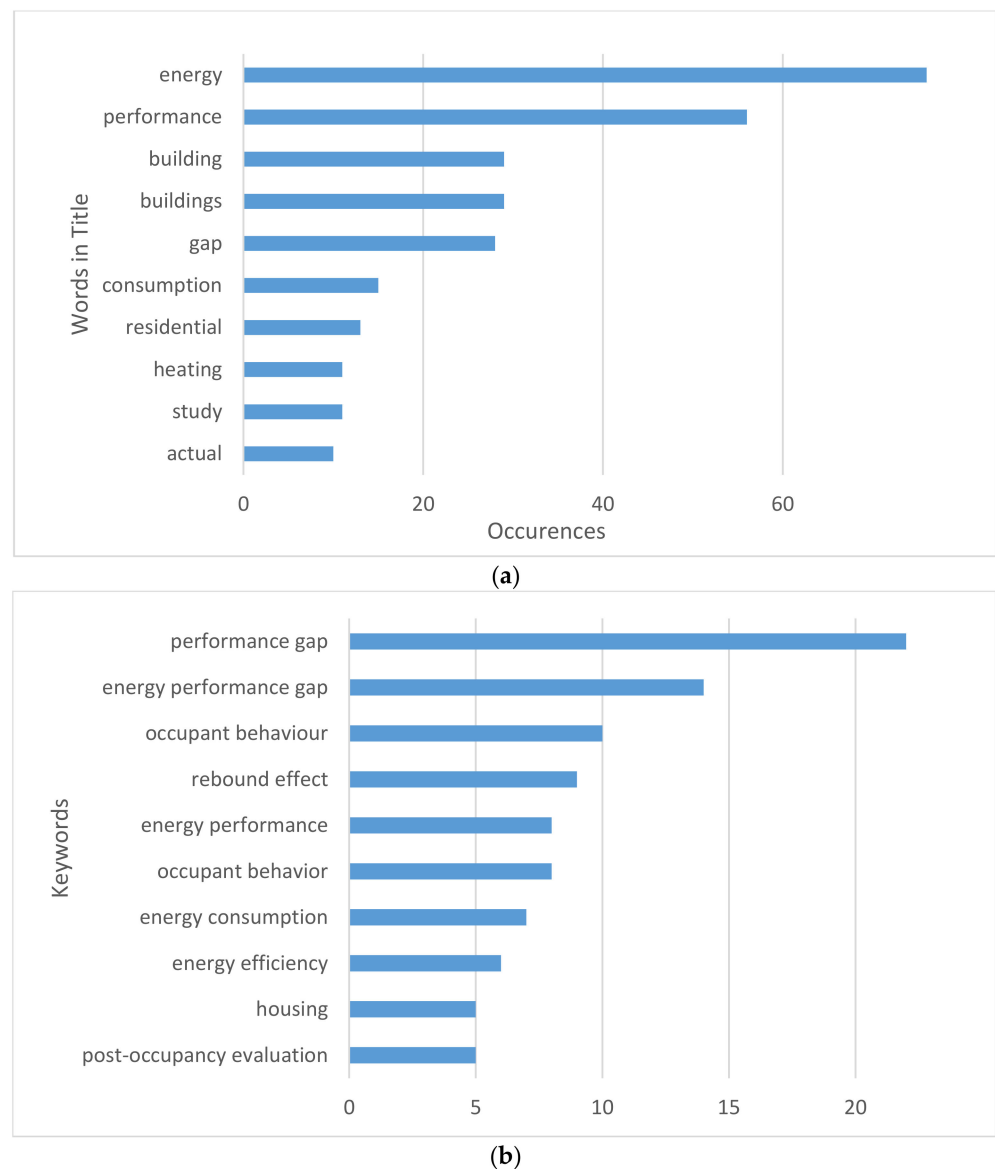**Figure 2.** Distribution of the reviewed articles with regard to publication year.

(**a**)

(**b**)

Figure 3. Frequency of relevant terms in papers' titles (**a**) as well as used keywords' frequency (**b**).

3.2. Basic Characteristics of the Studies' Objects

This review encompasses studies from 26 different countries (Figure 4). The vast majority (78%) of the studies include data gathered in Europe, with the largest number of studies from the United Kingdom (25). Other studies originated from the United States, Canada, Iran, Pakistan, Saudi Arabia, Kuwait, China, South Korea, Hong Kong, Australia, South Africa and Botswana. Most studies were conducted in temperate climates. A few studies were conducted in an arid climate with very dry and hot summers (Australia, Saudi Arabia, Kuwait, Pakistan, Iran and Botswana), a subtropical climate with hot and wet summers (Hong Kong, China, South Africa) and a Mediterranean climate with hot, dry summers and cool, wet winters (Italy, Greece, South Africa). Most studies were conducted in Western countries. As such, other building contexts, related lifestyles, and occupant densities appear to be under-researched.
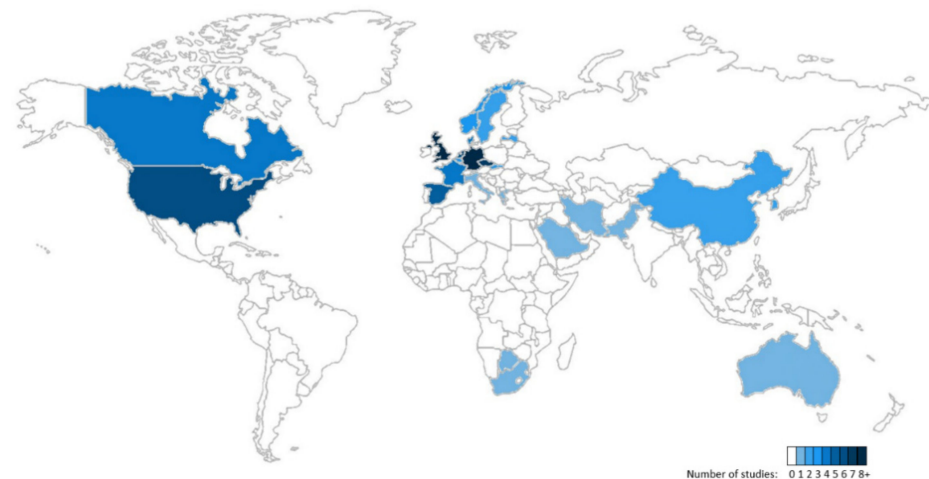
Figure 4. Illustration of the location/number of the studies.

Almost 60% of the studies investigated residential buildings. Other typologies investigated were offices [51,62–65], educational buildings [8,47,50,62,66–69], and other building types such as laboratories [41,70]. However, for non-residential buildings, very little additional information was available beyond the basic typology classification. For residential buildings, the typology classifications were reported at different levels of resolution and with varying terminology. Studies using statistical data sets at the scale of building stocks classified the buildings as "residential buildings" or "dwellings" without further differentiation [9,19,71]. The other studies mainly differentiated between sub-typologies "multi-residential" (most studied, including social housing), and "single-family houses" (attached and detached), combinations of both or specific typologies such as "student housing" [5]. For multi-residential buildings and social housing, studies varied in their spatial granularity with equal shares between apartments and the overall building, with one study investigating individual rooms [72]. The difference in spatial granularity is likely to limit the comparability of results, especially among residential buildings. Single-family buildings were investigated at building scale. Apart from the country scale data sets, the number of investigated entities for multi-residential buildings was largely below 10, with fewer studies in the range between 11 and 100 and a small number of studies above 100 [73,74]. For single-family houses, the number of investigated buildings was equally distributed in the range between 1 and 10 as well as 11 and 100, with few studies above 100 [75,76]. The only other building-related information was dwelling size, reported by few studies [17,77]. It can be concluded that the resolution of available information on the investigated buildings tends to be low. The terminology around the residential typologies can be ambiguous and the scale of investigation varies from whole buildings to single apartments and rooms. Moreover, the apartment size, which would have a significant impact on heating and cooling energy consumption, is largely not reported, with the exception of single studies from China [7], Iran [13], Kuwait [59], and Saudi Arabia [20].

The construction year of the buildings is relevant to the applicable building directive or building code. Approximately 48% of the reviewed studies recorded relevant information about the building construction year and other timelines relating to renovations and retrofitting. In Figure 5, the studies are organized based on the construction year and country. Approximately 76% of the studies were conducted on buildings constructed or retrofitted after 2006, followed by the studies conducted on buildings built between 1971–1980 and 1946–1970 (with approximately 8% each). However, it should be pointed out that this statistic is not indicative of the number of buildings considered by the individual studies. In cases where studies span several locations with relevant year of construction data such as in [78], they have been associated with their corresponding countries.
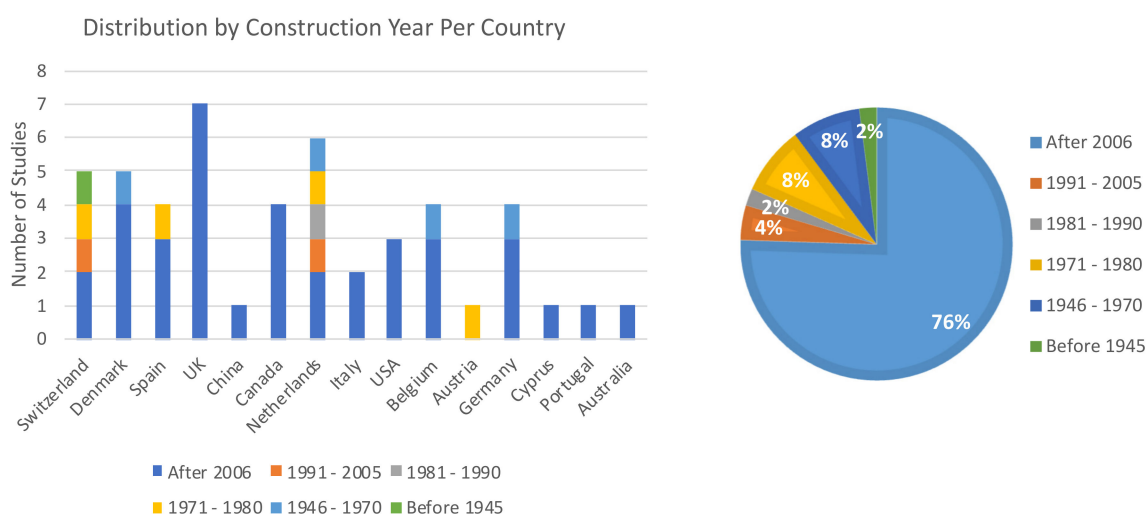
Figure 5. Classification of the studies with regard to construction year and country.

3.3. Basic Characteristics of Occupants in the Studies

With regards to occupants, the investigated papers were reviewed from two different perspectives, firstly occupant characteristics and secondly occupant behaviors. For the purpose of this paper, characteristics were defined as socio-demographic information or mindset, which are not consciously changed on a short time scale to adapt to comfort and energy performance. In contrast, behavior relates to active and conscious behaviors and observable actions that reveal patterns over a shorter time frame (i.e., hour, day, season).

Occupant characteristics are generally underreported in the investigated studies, with less than 20% of all studies reporting any information at all. The reported information is almost exclusively from residential contexts. The characteristics reported are generally inconsistent across the studies due to differences in research foci and data availability issues. The most reported characteristics are the number of people [9,10,15,26,33,49,59,60,79–81], age [9,10,15,17,21,26,33,59,77,80,81], household composition [6,7,12,14,17,30,59,77,80,82,83], and income [9,10,21,26,29,33,79,80]. Additional characteristics reported were ownership status [9,10,26,79,80,84] and education levels [17,21,26,59], with sporadic mentioning of physical condition [17], country of origin [73], sex [17,21,59], race [21], and occupation [21]. A spectrum could be observed across the use of generic statistical occupant data at country scale and more individual observations of characteristics derived from a specific building in its cultural and social context. For example, the largest number of different occupant characteristics is reported in studies using country scale statistical data sets for the overall residential building stock [9,80]. However, this is due to the nature of the dataset, and does not necessarily mean that these characteristics are the most important ones in the context of the performance gap. In contrast, studies from Kuwait and Saudi Arabia [20,59] reported more in-depth occupant characteristics derived from a sample much smaller than the large-scale statistical data. These reveal important cultural differences in household composition, unit size, and use patterns in comparison to the European studies. The studies which reported occupant characteristics were with few exceptions [7,20,21,59] exclusively from European countries, and thus may not be applicable to other contexts.

It appears that occupant characteristics were not the focus of the investigated papers and thus reported data are limited to available or accessible data. The reviewed papers display a focus on quantifiable characteristics, with little consideration of more qualitative characteristics such as health and cultural background. The currently available information does not allow for the identification of those occupant characteristics that may be important in the context of the performance gap.

Papers were further examined with regard to provided OB-related information, including occupancy patterns and control actions such as changing the heating or cooling

temperature set-points and operating the windows. A large number of the reviewed papers used behavioral assumptions derived from the standards or provided no details in this regard. In 25% of the studies, some data on occupant characteristics are included. Most of these studies provided data on the number of occupants, the age of the occupants, household composition, and occupants' employment type. Data on education level, gender, income, ownership and the physical condition of the occupants are also included.

In 44% of the studies, such data are collected via different means, including surveys (35%), interviews (11%) and observations (15%), sensor-based measurements (35%) or via Building Management System (BMS) (2%). One study [85] gathered OB data through virtual reality. Similar to the occupant characteristics information, the captured behavioral information is also largely focused on residential contexts, social and student housing, and a few instances of university buildings (e.g., [5,6,9,10,12–14,16,18,49,50,68,77]). The monitored behavioral information primarily relates to the number of occupants, occupancy schedule, and systems control habits concerning, for instance, operational set-points, the use of appliances and (natural or mechanical) ventilation. Other investigated behavior types include the use of solar shades, blinds, luminaires, and hot water. A few studies include collected data on the activity patterns and clothing behavior. A limited number of the studies conducted surveys and collected some information about the thermostat adjustment frequency, the usage of equipment and appliances, window operation, as well as occupancy patterns. Note that each of the studies captured some but not all of the parameters mentioned above. To consider a level of diversity in occupants' behavior, some studies associated occupants' control habits with behavioral styles in terms of austerity, normal, and wasteful [64,86]. In one study, monitored data were used to develop the probability profiles for occupants' presence and control actions in different rooms of the single-family houses under study [10]. This study demonstrated the importance of in-situ measurements and surveys in defining the occupants' interactions with buildings. The review of the OB reported in the investigated studies highlights the lack of a structured and detailed reporting of the monitored occupancy. Note that the availability of this information is essential if the studies are to provide insights into the role of building occupants in the EPG.

3.4. Sources of Data

3.4.1. Empirical Data

To be able to assess the performance gap, both empirical data and predicted data are required. The empirical data usually pertain to energy use, user behavior, indoor environment, and outdoor environment.

From 64 papers that reported data on energy-related measurements, parameters such as type of the demand (heating, cooling, ventilation, plug loads, lighting, etc.), measured energy type (electricity, gas, heating demand, etc.), the source of data (bills, metering, etc.), as well as spatial and temporal granularity information were included to some extent. Energy data are not consistently reported. Some cases document final energy (electricity, natural gas, heating oil, etc.), whereas others mention net energy (space heating and cooling loads, domestic hot water). Electricity was primarily used for lighting, plug loads, appliances, and auxiliary equipment of the HVAC system. The most common sources of energy data were bills (electricity, gas consumption) and data from principal meters and submeters. There were very few studies (7%) that had dedicated energy use metering [15,37,66,83,87].

Statistical data on building stock were also a source of data for large-scale projects [62,75,80,88]. Most of the publications (76%) used aggregated annual data on energy use, while 10% of studies used monthly data. The rest of the studies (14%) included high-resolution data, involving 5 min intervals [15,83], 15 min intervals [38,58,74], 30 min intervals [35], and daily measurements [22,48,89]. In terms of spatial granularity, studies on non-residential buildings focused on reporting energy use mostly per building and

rarely per floor [51]. In case of residential buildings, data concerned both building and apartment/dwelling levels, and occasionally room level [29,44,90].

Indoor conditions were monitored in 20% of the selected studies to evaluate discrepancies between assumed and actual indoor conditions. Air temperature was the most commonly monitored indoor parameter to investigate the performance gap, followed by the relative humidity [7,10,12,14–16,49,72] and the CO_2 concentration levels [10,14–16,27,35,53,54,83,91], which were often used as a proxy for occupancy. Indoor environmental conditions were usually monitored via sensors placed in dwellings, but rarely in non-residential buildings. Only two studies monitored operative temperature [83,91] and only one TVOCs [27]. In a third of the studies, the deviation of the actual measured indoor temperatures from the assumed set-points was used to explain the performance gap.

Outdoor conditions are monitored in a number of studies (31%) in order to normalize the measured energy use data and to examine if the assumptions in the energy simulations regarding the outdoor climate apply [9,10,12,15–17,21,25–27,31,33,35–37,40,43,45,52,56,57,89,92,93]. In the other 69% of the studies, outdoor conditions were not monitored or were not disclosed in the article. In 21% of the studies, the data on the outdoor conditions were obtained from a (national) climatic institution, hence not directly via on-site measurements [9,10,21,26,33,94]. When on site measurements were performed, air temperature data were monitored. Additionally, some studies measured the wind speed [15,27,45], wind direction [27,45], solar radiation [15,27,31,37,45,56], precipitation [15], relative humidity [15,45], as well as VOC's [57]. A few studies did not explicitly mention which variables were measured but maintained that there was a weather station on site [12,36,50,52,92].

3.4.2. Basis for Predicted Energy Use

Predicted energy use data are based on standard assessment procedures (SAPs), (dynamic) simulations, or taken from existing databases. SAPs are either based on general assessment tools (e.g., the Passive House Planning Package, PHPP) [77] or national standards, such as the French [19], British [14,23,30,35,93], Belgian [10], Dutch [33,71], Swiss [89,95], Danish [75], Spanish [47], South African [23], or German [15,37,49,56,87] standards. The vast majority of SAPs provide energy estimates in the form of energy use intensities (e.g., in $kWh \cdot m^{-2} \cdot a^{-1}$) per building type and characteristics, or, in the case of certification-based standards (e.g., [33]), per certification level. Distinctions are typically made between different energy types (e.g., electricity and natural gas) and end-uses (e.g., heating, hot water, and lighting).

The second source of energy predictions is based on simulations, mainly performed using software tools such as EnergyPlus (e.g., [15,45,96]), TRNSYS (e.g., [94,97]), or IES (e.g., [8,20]). These applications offer energy prediction capabilities with high temporal granularity (e.g., per minute) and spatial granularity (e.g., per zone or per room). However, in most reviewed articles, the software applications are used to extract aggregated data to allow benchmarking against monitored data with similar granularities. Common metrics include absolute energy consumption (e.g., in kWh) [16], energy use intensity (e.g., $kWh \cdot m^{-2} \cdot a^{-1}$) [17], or a similar CO_2-focused metric (e.g., kg $CO_2 \cdot m^{-2} \cdot a^{-1}$) [8]. Distinctions are often made between different fuel types and end-uses. Some authors focus their analysis on one of these metrics (e.g., heating consumption in [48]), while others target multiple metrics (e.g., space heating, domestic hot water, ventilation, and lighting in [77]). It is important to note that many studies do not provide information regarding occupant related model assumptions or how default values provided by the simulation software are used.

Databases used to derive predicted energy use data are for example the SHAERE database (Sociale Huursector Audit en Evaluatie van Resultaten Energiebesparing) [98], the Kwalitatieve Woning Registratie (KWR) of the Ministry of Housing of the Netherlands (VROM) [9] or the Rekenkamer dataset from Amsterdam [33]. These databases or datasets

are typically composed of data from energy certificates collected by national municipalities, housing authorities, or other relevant entities.

3.5. Approaches to Normalization

Normalization approaches are commonly used to isolate the contribution of occupant-related factors to the EPG. Hence, the influence of other factors (e.g., weather conditions, construction data) must be accounted for in the calculation method. The aim is to facilitate a valid comparison of the predicted energy demand and the subsequent observed energy consumption of the building. Normalization (or "correction") with regard to weather conditions enables a proper comparison of predicted and actual energy use. It can be combined with other normalization steps regarding, for instance, building geometry, construction and occupancy patterns when comparing before-after energy use or simply differences in the energy use of different buildings. Calculated energy performance indicators (PIs) in directives and standards are commonly expressed in area-related terms (e.g., $kWh \cdot m^{-2} \cdot a^{-1}$). In some papers, other expressions of PIs are used for comparison. PIs might be expressed, for instance, in reference to the number of occupants ($kWh \cdot person^{-1}$) [15], to the hours of system operation ($kWh \cdot h^{-1}$), or to climate-related terms ($kWh \cdot HDD^{-1}$, $kWh \cdot CDD^{-1}$) [99]. Another instance of normalization in the reviewed literature involved the temperature set-point (e.g., [40]).

Among the different instances of normalization, the one referring to weather is most common. This approach relies mostly on the use of the degree days method [100] and was applied in a considerable number of reviewed papers [5,10,15,19,33,40,43,62,71,79,80, 89,93,94,101,102]. Heating and cooling degree days (HDD/CDD) are a measure of how cold or warm a particular geographic location is during a given period of time. In order to normalize the measured energy consumption for heating or cooling at a site, the HDD/CDD values are calculated from the measured weather data (temperature) and are used to modify/adjust the measured energy consumption. These measures are purely temperature-based. As such, they do not consider other potentially relevant climatic influences on buildings' energy performance, such as solar radiation, humidity, and wind speed. In Berggren and Wall [94], the energy use for heating is normalized by using the energy index [103]. This index is defined as the ratio of the measured heating degree days to the standard heating degree days (both adjusted for solar radiation and wind). A number of other studies also considered normalizing the heating energy based on weather or climate, but did not include an explicit specification of the applied method [26,37,56,58,92]. Sonderegger [104] normalizes the "variations caused by the "obvious" physical features from the 205 houses" on the energy (gas) consumption. Thereby, the measured gas consumption is compared to the gas consumption as estimated by a regression model [104].

A frequent issue when normalizing energy use for heating is whether or not the DHW is included in the available data. If this is the case, the DHW has to be subtracted from the total heating energy use for a correct comparison. One way to do this is to estimate the DHW heating consumption by averaging the mean daily power of the heating system when the mean ambient temperature exceeds a fixed threshold (e.g., 23 °C). Subsequently, the calculated mean power is multiplied by the number of hours to obtain the annual heating demand for DHW. However, as pointed out in IEA SHC Task 44 [105], the downside of this method is that the selected threshold applies only to the summer months. Both summer vacation and the general rise in hot water consumption in winter can lead to a miscalculation of the DHW demand. Due to this circumstance, Mojic et al. [89] increase the DHW heating consumption determined from the power characteristic by a constant rate of 15%.

Some publications normalize energy-related OB in buildings. For example, [94] replace the measured value for DHW with assumed normal use in order to compensate for energy losses included in the measured value. Moreover, the heating energy consumption is reduced by 5% per each degree Celsius whenever the measured indoor temperature was higher than the assumed value. Following the Swedish recommendations for boundary

conditions, they assume that only 70% of lighting and plug loads contribute to internal heat gains. Delghust et al. [40] normalize for temperature set-point, whereas [29] considers temperature set-point and ventilation hours for normalization. In the context of energy consumption for lighting, Motamed et al. [34] consider the impact of different occupancy densities.

To reduce the gap further, another approach besides normalization is to consider net energy (obtained as per standard calculation methods) instead of the final energy. This eliminates influencing parameters including operational faults as well as system efficiency for (heat) generation, storage, and distribution (e.g., sub-metering of flats [15,37,49]).

Among the reviewed papers, a few mention only the variable relevant to normalization and not the normalization method [9,11,75,95,106]. Table 2 provides a summary of the most frequently applied methods for normalization and the related normalized variables, together with the respective references. Surprisingly, the large majority (60%) of the reviewed publications did not include any information on normalization and are thus not included in Table 2.

Table 2. Summary of the normalization variables and methods.

Normalization Method	Normalized Variable	References
Heating degree day (HDD)	Space heating or gas consumption	[5,10,15,19,33,40,43,71,79,80,89,93,101,102]
Cooling degree day (CDD)	Cooling	[62]
Based on climate/weather (method not further specified)	Space heating	[26,37,56,58,92]
Measured energy use for heating is: (i) adjusted by 5% for each degree Celsius deviation from the average indoor temperature; (ii) adjusted considering that the share of internal loads that may affect heating is fixed to 70%; (iii) normalized using the energy index (ratio of measured to assumed HDD).	Space heating	[94]
Elimination of variations by physical features: measured consumption is normalized by the amount of energy that "should" have been used (calculated from regression model for each house).	Gas consumption	[104]
Not specified	Space heating	[106]
Not specified	Heating and DHW	[9,75]
Not specified	Final/primary energy use (for heating and DHW)	[11,95]
Averaging the daily mean power of the heating system when the mean ambient temperature exceeds 23 °C. Mean power was multiplied by the number of hours to obtain DHW heating demand.	DHW	[89]
Replace measured value for hot water with assumed normal use, excluding energy losses due to hot water circulation (compensated as space heating).	DHW	[94]
Used standard deviations from the mean.	Temperature set-point	[29]
The temperature set-point was estimated based on the temperature profile during occupancy.	Temperature set-point	[40]
Consider the type of ventilation with most hours (grills, windows, mechanical systems).	Ventilation hours	[29]

3.6. Magnitudes of Performance Gap

This section discusses the magnitude of the performance gaps associated with OB observed in previous studies. Only studies that included monitored data on energy use and occupants, or at least energy use measurements, were included, such that the reported EPG could be classified as evidence-based (i.e., the subset of studies classified as "gold" and "silver" in Section 2.1). As mentioned before, the EPG magnitude is calculated as a deviation of the measured energy use from the expected energy demand at the design stage [87]. The expected or predicted energy demand is typically estimated through standard assessment procedures numeric simulation, or is taken from existing benchmarking databases.

Of all the studies, 68 reported a quantified performance gap and are shown in Figure 6. Studies including only one building are represented by circular markers. For studies that included multiple buildings, and thus multiple EPG magnitudes, the gaps are represented by a range. The EPG across all studies is, on average, 55% ($\pm$89.8%). Figure 7 shows mean and median EPG magnitudes separately for residential and non-residential buildings.
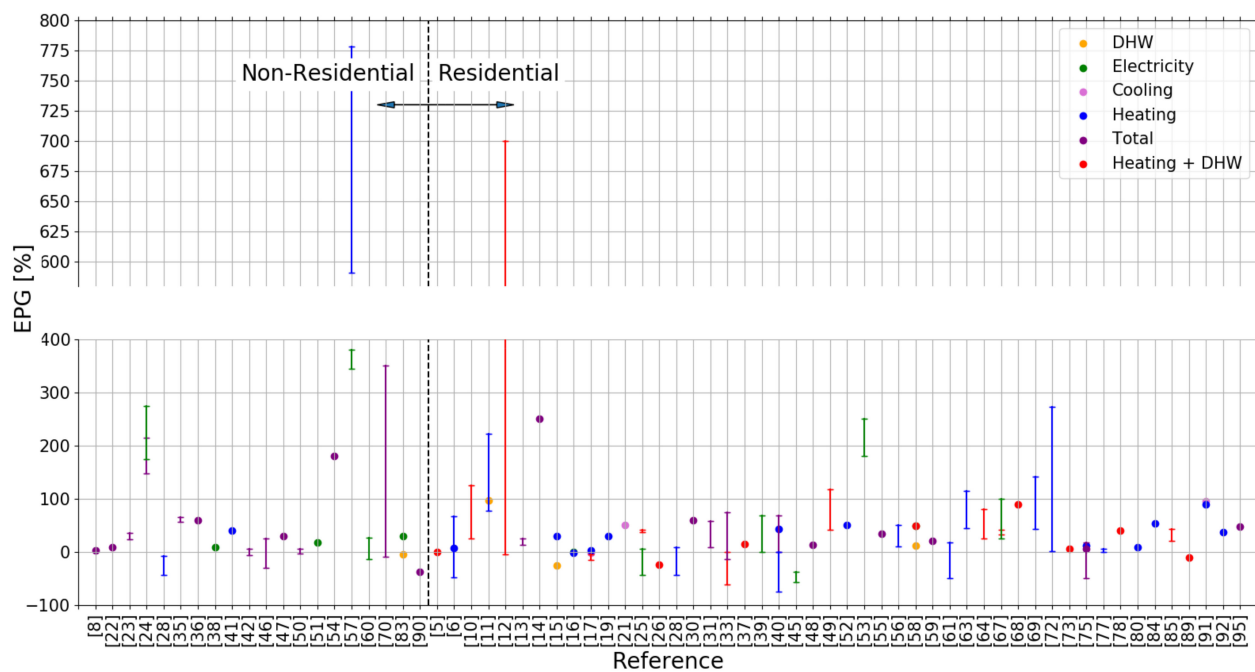

Figure 6. Distribution of the EPG between the residential (43) and non-residential buildings (17).

The reviewed studies did not report the EPG consistently. For example, some studies reported EPG as a percentage or in absolute terms in units related to total energy or area-normalized energy use, while a few reported their results in terms of CO_2 emissions (e.g., [8]). Some studies reported gaps with respect to total building energy consumption, while others reported detailed gaps for one energy source (e.g., natural gas or electricity). Another group of studies focused on the energy end use (e.g., domestic hot water, heating, cooling), but this approach was typically used when studies compared the performance of different functional units such as a whole building compared to an apartment or commercial unit (e.g., [15,37,49]).
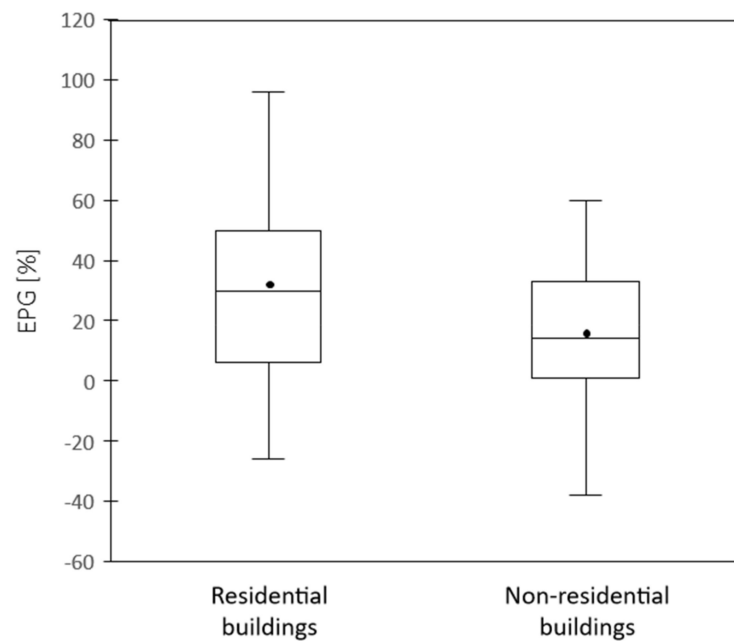
Figure 7. Distribution of EPG (in %) for residential and non-residential buildings.

Note that the heterogenous nature of the approaches of the reviewed studies (object specification, data collection, data resolution, estimation methods, normalization procedures) as well as certain levels of existing opacity and inconsistency in the reporting of the results make it difficult to formulate general findings regarding the magnitude of the EPG. To illustrate this challenge, consider a listing of exploratory inquiries that could be processed via a meta-analysis of a set of consistently structured and reported studies. Such a listing could include, for instance, the following conjectures:

(i) Given the assumption that occupants, in residential buildings, tend to have more control over systems and envelope operation, it is less likely for predictive models to capture the dynamics and variance of occupants' behavior, resulting in a potentially larger EPG.

(ii) Energy usage dependent on OB (e.g., lighting) is more difficult to predict and may thus result in larger EPG magnitudes as compared to energy usage that is less or not at all dependent on occupant intervention (e.g., continuously operated ventilation system).

(iii) The expression of the EPG in relative terms (i.e., in percentage) is likely to be larger in the case of highly energy-efficient buildings, as even relatively small differences between modelled and actual values can result in high relative EPG magnitudes.

(iv) The application of detailed numeric energy simulation methods would yield smaller EPG magnitudes as compared to energy estimates generated by default values based on standards. Likewise, calibrated energy models of existing buildings could be expected to result in smaller post-retrofit EPG.

The information provided in the reviewed studies could only contribute to the clarification of the first conjecture above. As shown in Figure 7, the median gap is larger in residential buildings (30% ± 51%) than in non-residential buildings (14% ± 27%). Likewise, standard deviation is larger in the former case. This may be explained in part by larger differences between assumed and measured temperatures in several residential studies. However, the smaller sample size of the non-residential buildings may have also been responsible for the reported larger EPG magnitude in the case of residential buildings.

Due to the aforementioned inconsistency between studies in the presentation of findings, it was not possible to judge the validity of the second conjecture in the above listing (dependency of the EPG magnitude on the level of occupants' control). As the reported gaps regarding electricity usage were not separated by energy-end use, the gap size between occupant-controlled and non-occupant-controlled loads could not be determined. Likewise, an examination of the third conjecture (higher sensitivity of energy-efficient buildings to occupant-driven loads) was not possible due to insufficient data availability. Construction dates were generally reported; however, whether a building was standard or high-performance was not reported consistently. Finally, the examination of the last conjecture (lower EPG magnitudes in cases involving the deployment of detailed simulation) was hampered due to insufficient evidence (e.g., [15,48]).

3.7. Identified/Assumed Causes of Performance Gap

As described before, the selected studies were reviewed to examine suggested causes of the performance gap. Thereby, we first classified the studies according to their objectives and context (Section 3.7.1) followed by a discussion of the causes of the EPG related to occupants (Section 3.7.2), the drivers of occupants' behavior (Section 3.7.3), and, lastly, other contributors to the EPG (Section 3.7.4).

3.7.1. Approaches to Quantification of Gap

The reviewed papers were first classified based on their objectives into three groups: (a) those that consider multiple performance gap causes (both occupant and non-occupant related); (b) those focusing on occupant-related causes; and (c) those with other objectives or foci. Out of these three, group (b), which focused only on the occupant-related causes, included the least number of papers. Next, the causes were grouped according to their relevance to the occupants. Occupant-related causes include occupants' presence and behavior. Other causes of the performance gap are those related to buildings' design, construction, and operation. Both categories are explained in detail in Section 3.7.2, Section 3.7.3, and Section 3.7.4.

The aforementioned gold, silver, bronze classifications from Section 2.1 identify which studies contained energy data, occupant data or both. However, a further classification was required regarding the context of the study in terms of the methodology employed and the type of evidence presented to support the identification of the gap cause. Hence, the studies were further categorized as follows (see Figure 8):

- Experimentally-based studies: Comparisons were made between data collected from the same building at different times or concurrently from very similar buildings or units. For instance, energy consumption in various buildings with identical attributes (type, geometry, construction and systems, climate) was compared to determine the reason for the observed differences in energy performance.
- Modeling-based studies: Comparisons were made between various cases exclusively via simulation. For example, a computational study that explores the impact of two different occupancy schedules on energy consumption falls into this category.
- Combined modeling and experimental studies: Comparisons were made between data collected from the building and those obtained from the computational (simulation) model of the building. For example, actual energy consumption in a code-compliant building was compared to the building's energy model.
- Other studies: These studies included discussions of performance gap causes elicited from other sources such as expert opinion, surveys, review of other studies, etc.
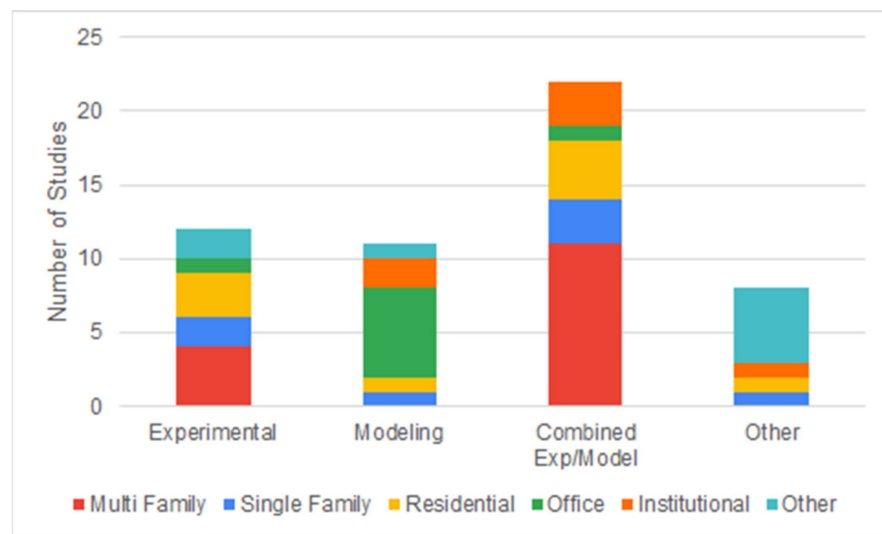
Figure 8. Distribution of studies' methods broken down by building type.

The most common approach to assessing the performance gap is to compare actual building data with modeled data ("Combined Exp/Model" in Figure 8). This appears plausible given that many performance gap investigations are undertaken to determine why a building is not performing as the design-stage prediction suggested. Additionally, this combined approach allows for easier normalization of factors beyond the researchers' control, such as weather or occupancy status. However, one drawback of this approach is the potentially unrealistic assumptions about building operation during the prediction phase, if these assumptions are not updated according to the actual building operation.

The review of the reported causes of the performance gap revealed that whereas in some cases such causes are directly based on evidence, in other cases they are simply presumed. We refer to these as "Actual" and "Assumed". "Actual" causes in an experimental context are relevant to instances where the researcher used collected data in the field to identify the performance gap cause. For example, it was suggested that a difference between monitored set-point temperature and the initially assumed set-point was correlated with a deviation of the metered energy use for space conditioning from the expected value. In a modeling context, "Actual" causes included instances where the researcher varied parameters in a model to demonstrate how different aspects of building function would impact performance. This involved, for example, modeling the differences in occupancy schedule and predicting the impact on lighting energy use. "Assumed" causes were instances where the researcher made assumptions about the performance gap cause based on anecdotal observations that were not supported by collected detailed data. For example, occupants' statements regarding daily behavioral practices were found to be consistent with the performance gap as manifested in energy bills. For a subset of 46 studies for which the cause determination was examined, 56% were considered to have identified actual causes and 44% had assumed causes.

3.7.2. Occupant-Related Contributors to EPG

The review revealed that the majority of the reviewed papers (more than 70%) report a form of occupant-related cause for the performance gap—either identified or presumed. These studies are summarized in Table 3 and discussed in the remainder of the section. The occupant-related contributors to the performance gap were grouped into four categories, according to the building model component they influence. These categories are envelope, mechanical systems, plug-loads and lighting, and internal heat gains.

Table 3. Overview of occupant-related EPG contributors in different categories.

Category	Building Model Ingredient	Occupant-Related Performance Gap Contributors	References
Envelope	Operation schedules of windows and shading devices (e.g., blinds)	Occupants opened windows more frequently or for longer periods (as compared to model assumptions)	[5,6,12,14,18,22,28,32,37,45,52, 54,55,58,67,72,77,79,82,89,95]
		Occupants turned off the installed MVHR (mechanical ventilation with heat recovery) and used windows instead for ventilation	[6,14,49]
		Discrepancies between assumed and actual operation of shading devices resulting in the deviation of actual solar gains from model assumptions	[5,21,22,89]
Mechanical systems	Set-point temperature, thermostat settings, system operating schedules and settings	Higher actual indoor temperatures than those assumed in the model	[6,9,11,14,15,18,29,37,53,55,58, 75,79,82,90,101,104,107,108]
		Lower indoor temperatures or shorter heating durations than assumed	[19,33,40,45,109]
		Schedules of the ventilation system and air flow rates do not match actual occupancy patterns	[10,75,95]
Plug-loads and lighting	Occupant density and/or schedule	Discrepancies between actual and assumed occupant density or schedule lead to higher or lower use of IT equipment, lighting and appliances	[7,16,21–23,30,35,36,38,39,41,42, 47,50,51,57,59,60,65,67,110,111]
		Use of secondary heating/cooling, such as electric heaters	[95]
Internal heat load	Occupant density and/or schedule	Standard occupancy schedules imply high heat gains, which can result in underestimation/ overestimation of energy use for heating/cooling	[16,17,75]

The envelope category mainly entails operation schedules of windows and shading devices (e.g., blinds). The frequency of window opening is one of the most recurrent occupant-related candidate causes of the EPG, appearing in 36% of the studies listed in Table 3. For instance, actual heating demand was found to be higher than expected, as occupants opened windows more frequently or kept them open longer than assumed. Other studies [6,14,49] report that occupants turned off the installed MVHR (mechanical ventilation with heat recovery) and used windows to ventilate instead, with significant energy implications. Similar discrepancies were found with the operation of shading devices [6,22,23,88,90] in approximately 10% of the above studies, leading to higher or lower solar gains than modelled.

Relevant to the "mechanical systems" category are set-point temperature, thermostat overrides, system operating schedules, and settings. One-third of the studies in Table 3 report higher actual indoor temperatures than assumed [6,9–11,14,15,18,29,37,53,55,58,75,82, 91,101,104,107,108]. This discrepancy was seen in some instances as the factor responsible for the performance gap [104]. Cuerda et al. [45] noted that the actual heating periods were shorter than those suggested by standard schedules, leading to a lower energy consumption level than modeled. Similarly, there are a few studies (approx. 10%) that report lower indoor temperatures or shorter heating durations than assumed. In some studies [10,75,95],

a discrepancy was found between the schedules of the ventilation system and air flow rates on the one hand and the building occupancy on the other hand.

The plug-loads and lighting category pertains mainly to assumptions regarding occupant density and/or schedule. Discrepancies between actual and assumed occupant density or schedule can explain higher or lower use of IT equipment, lighting, and appliances as compared to respective expectations, as seen in nearly 40% of the above studies. Four studies [41,47,51,67] report that office equipment and lighting that remained switched on outside operating hours resulted in increased electricity consumption. Other plug-load related contributors to the EPG may include the use of secondary devices for heating and cooling, such as electric heaters [95].

The internal heat load category entails occupant density and/or schedule. Occupant density and presence/appliance schedules not only influence plug-loads, but can also lead to discrepancies between assumed and actual internal heat loads. Carpino et al. [16,75] report a case where standard occupancy schedules led to an overestimation of internal heat gains. This, in turn, resulted in an underestimation of the energy use for heating. In another study [17], actual occupancy schedules were found to deviate from standard profiles. This resulted in higher internal heat gains than predicted and, consequently, in a lower heating load and a higher cooling load than simulated. As shown in Table 3, the most frequently identified occupant-related causes in the reviewed literature are plug-load schedules (40%), window operation (36%), and set-point temperature (33%).

Note that a number of studies among the reviewed articles conduct parametric and sensitivity analyses. Thereby, the occupant-related parameters in a building model are varied to computationally explore their impact on energy performance [2,69,75,97,112]. As such, these studies cannot identify or confirm occupants' role in the EPG, but rather estimate the magnitude of their influence under assumed scenarios of OB variation. These studies are therefore not considered as providing hard evidence for the occupants' role in the performance gap.

3.7.3. Drivers of Occupant Behavior Leading to EPG

We discussed above the assumptions regarding occupant presence and behavior in different categories and how they can influence the estimated or modeled energy consumption and thus contribute to the EPG. A further level of analysis involves the exploration of the background of the behavior itself, which may be related to occupants' socio-economic characteristics [113]. This background includes, for instance, income [19,76,80,114], lifestyle (e.g., employment status) [17,30], energy billing practice [12], environmental attitude [27,115], occupant expectations [18], building's energy efficiency level [29], and renovation versus new construction [80]. In certain cases, the improper operation of systems (contrary to their intended use as designed/simulated) may be the consequence of the inadequate design of control interfaces [6,14,53,116].

In the majority of the reviewed articles, the underlying cause of the reported OB, assumed to be responsible for the EPG, was not explored. When the rebound effect is directly addressed, it is attributed to psychological mechanisms, e.g., lifestyle changes, moral licensing [13], and lack of knowledge [49]. The prebound effect is seen mainly resulting from low income and fuel poverty [76,109].

3.7.4. Other Potential Contributors to EPG

Besides occupant-related factors, the reviewed studies also considered other drivers of the EPG. These can be classified as related to building design, construction, and operation. During the design phase, poor, overly simplified, or unrealistic modelling assumptions can lead to the overestimation or underestimation of the predicted energy use of buildings. Improper modeling assumptions can pertain to, for instance, buildings' space usage and operational conditions [13,95,117]. Similarly, making the right assumptions concerning future projections of contextual factors and boundary conditions such as weather [17] and solar gains [5] remains a major challenge and can be the source of large discrepancies

between predictions and reality [50,95]. Moreover, calculation methods such as those embedded in energy certification tools can also involve technical inaccuracies [76] or inappropriate simplifications [19,47].

The performance gap may also emerge from the building construction process and the resulting frequent discrepancies between the as-designed and the as-built versions of the building. Construction-related contributors to the energy gap can also include the constructed building's deviation from inaccurate model assumptions concerning the building envelope's thermal transmittance [17,53] and air-tightness [5,17,32]. Faults in the installation of energy systems represent a common cause of underperformance in buildings [49,117], which could also be due to a lack of proper commissioning [14].

Finally, operation-related issues may also act as drivers of the EPG. The most frequent instances of inefficiencies pertain to the facility management [14,49,66,95,110] or sensor errors and related negative consequences for systems controls [95].

4. Discussion

4.1. Overview

We discuss in this section the findings of the study in terms of a number of questions raised in the introduction. Specifically, we reflect on the general understanding of the EPG in the literature, we discuss the degree of the representativeness of the reviewed studies, the consistency and quality of required modeling, monitoring, and normalization steps, we look into the evidence for the existence and extent of the occupant-induced EPG, we explore the suggested causes of the occupant-related EPG, and we consider the implications of the findings for future efforts.

4.2. Views on EPG

As stated at the outset, the primary objective of the present paper is to gauge the existence and extent of evidence for the purported occupant-induced gap between expected (i.e., estimated, calculated, computed, predicted) and actual building-related energy use. As such, the definition of the EPG is not consistent across the board. Implicit definitions of the EPG and their variance in different papers are reflected in the classification of the deployed methods to measure the EPG (see Section 3.7.1). Nonetheless, one major category in this classification (combined use of measurement and modeling) does indeed involve the comparison of the predicted energy use (based on standard calculations or simulations) with the actually monitored energy use (Figure 8). However, there are studies that include modeling, but not measurements. Furthermore, there are studies that include monitored energy use, but involve no modeling. The former, purely modeling-based category may provide a sensitivity analysis with regard to the model's response to variations of occupant-related input assumptions. As mentioned previously, this—useful as it may be for certain considerations—does not yield any kind of hard evidence for the actual relevance of occupants' role in the EPG. The latter, purely measurement-based category approaches the EPG via comparison of the actual energy use of the same building at different times, or through comparison of the monitored energy use of very similar buildings. These types of studies enable the identification of the magnitude of occupant behavior on the energy use. However, without further analysis, they do not identify causes of the EPG. Note that the decisive factor in any EPG analysis, namely the actual energy use, is not reported consistently in the reviewed studies. This especially concerns the resolution of the monitored energy data in view of its spatial and temporal granularity. For instance, only 10% of studies report monthly energy use data. Some 14% report higher-resolution data. The rest are based on annual energy consumption values.

4.3. Building Locations and Types

The distribution of papers displays a number of limitations both in view of the covered locations and the studied buildings (see Section 3.2) (Figure 4). The majority of the studies (78%) were conducted in temperate climates (mostly in Europe). Moreover, a large fraction

of the studies investigated residential buildings (60%). Other typologies investigated included offices (15%), educational buildings (13%), laboratories (1.5%), and others (10.5%). As such, whatever conclusions are derived from the bulk of existing publications on the subject, they cannot be suggested to represent the circumstances globally.

It is hypothesized that it is difficult for researchers to obtain detailed building-related data. Likely sources for larger data sets are governments or housing associations. These could be more indicative of average building stock characteristics rather than the embedded variability. There is a need to identify which building-related parameters are important and must be considered in future studies as well as what should be the proper scale. Similarly, the process of the sharing of building-related data needs to be more efficiently organized.

4.4. The Role of Occupants

Generally speaking, some 70% of the reviewed papers report occupant-related causes of the EPG. However, the strength of the provided evidence varies significantly across the reviewed articles. Around 40% of the reviewed articles involved empirical data on both energy and occupants. Among these, only about one-third included sensor-based monitoring of the occupancy, and only 2% included data from BMS (Building Management System). Another 15% of the papers relied on snap-shot types of observations (e.g., of the state of thermostats). The remainder of the reviewed papers entailed less certain information on occupants, such as surveys (35%) and interviews (11%).

These observations imply that, among all reviewed studies, only 14% included quantitative data on both energy use and occupant behavior. For this group of studies, the magnitude of the reported EPG can vary significantly. The reliability of the latter inference is of course dependent on the quality of the deployed normalization procedures.

Moreover, the reviewed studies mainly originated from Europe. This means that the global diversity, especially related to different ways of occupying residential buildings in different climate zones or cultural contexts (e.g., family size), as well as different energy prediction in countries are unlikely to be reflected in the investigated papers. More interdisciplinary research using dedicated frameworks or approaches would be helpful to quantify these aspects in the context of the performance gap.

4.5. Modeling Approaches

Methods for the estimation of future energy use vary considerably across the studies. Some studies rely on rather simple standard-based calculations (34%), whereas others deploy simulation tools (43%). More critically, the majority of the reviewed studies do not provide information concerning the source of occupancy-related model input assumptions. Such circumstances make it difficult to compare and generalize the studies' conclusions regarding the existence and extent of the EPG and the suggested role of occupants therein.

4.6. Challenges of Normalization

As alluded to before, in most EPG investigations, the types of modelled and metered energy data are not directly comparable. For instance, whereas the measured energy data may be related to end energy use as inferred from energy bills, the simulation may have been focused on energy loads. Hence, to make meaningful comparisons of modelled and monitored energy data, normalization procedures must be followed. Only 7% of the reviewed articles could rely on the dedicated monitoring of energy. This implies that, in the overwhelming majority of the existing studies, a direct comparison of simulation-based and monitoring-based space-level energy loads is not possible. This underlines the critical importance of the robustness of the normalization approaches. For instance, a comparison of modelled and actual energy use at the space level would require the isolation of thermal energy delivered to the space. In the absence of a dedicated space-level energy monitoring, measured indoor air temperatures could support the estimation of the respective magnitudes. However, indoor temperatures were measured in only 20% of the reviewed studies. More importantly, 60% of the reviewed articles did not include

any information about normalization. As far as normalization with regard to weather conditions is concerned, the reviewed studies display a number of issues. The reliability of weather normalization in 76% of the studies is arguably uncertain, as they did not record outdoor conditions. In 10% of the studies, outdoor conditions were obtained from an existing weather station. Moreover, micro-climatically relevant variables (e.g., temperature, solar radiation) considered for normalization are not consistent across the different studies. Most studies mostly use the aggregate climatic indicator HDD for normalization purposes. This indicator considers only air temperature. Hence, other factors of climate are ignored in the normalization. This suggests that the same EPG investigation could yield different outcomes if researchers would use different criteria and methods for normalization.

Speaking in more general terms, the OB normalization (or more specifically, energy-related OB normalization) must be handled with caution; the normalization for the deviation from user behavior or the expected use of the building, such as window opening, shading or indoor temperature, inevitably has an impact on one of the "potential" sources of the performance gap. For example, the normalization of the energy consumption for indoor temperature set-points reduces the effect of the related OB action (thermostat setting). The theoretical optimum (eliminated gap) would be to normalize the complete user behavior with measurements to calibrate the measured consumption to the calculated demand.

4.7. The EPG Magnitude

The EPG magnitude, emerging from the studies, ranges from −38% to +96% in Figure 7. The mean and median of EPG magnitudes (in percentage) are +37 and +30 for residential buildings and +16 and +14 for non-residential buildings. This would indicate that it is more likely that buildings' energy use is underestimated rather than overestimated. However, this cannot be asserted with certainty, given the previously mentioned unbalanced distribution of the studies (in terms of location and building type).

4.8. Proposed Measures to Reduce Occupant-Related EPG

An obvious response to the problem of energy use prediction is the improvement of the prediction models in general and the enhancement of occupancy-related model input assumptions in particular. To this end, studies underline the importance of post-occupancy investigations of buildings' use patterns and client requirements. This rapid feedback loop is assumed to enable building planners and modeling experts to continuously improve the quality of their assumptions regarding building occupants. A key input assumption pertains to the assumed number of occupants and the duration of their presence in the buildings. Likewise, it is essential to ensure that the occupancy profiles adopted by compliance tools are appropriate for the building type. The fidelity and empirical grounding of the occupancy-related model assumptions have been argued to be more essential than the specific algorithmic features of the prediction tools [118,119]. As such, even relatively simple calculation methods could yield reasonable results, if they are based on reliable empirical data. Consequently, the use of historical data and the availability of more comprehensive repositories of actual high-granularity occupancy information (covering multiple climatic boundary conditions, building types, populations) could contribute to the improved marksmanship in the representation of occupants in building energy models.

A further, highly important issue pertains to the socially and demographically relevant background of the buildings' occupants. Factors such as family size, income levels, and fraction of energy-related expenditures are suggested to be relevant to occupants' behavior. Such information is rarely considered in the course of energy use prediction processes. Less than 20% of the reviewed papers included any detailed information concerning the background (household composition, family size, income, age, etc.) of the users of the buildings studied. As such, the judicious use of socio-economic variables in addition to the default technical analysis can contribute to a more realistic assessment of energy use behavior. Model calibration based on actual energy usage is suggested as a further

remedy. However, strictly speaking, this option applies only to building retrofit scenarios or building operation cases.

Certain recurrent recommendations in the reviewed studies with regard to occupant behavior are worth mentioning, assuming occupants' influence on buildings' energy performance, independent of its magnitude, should be a matter of concern. For instance, it is suggested that there is a need for better information for occupants as to how the buildings' systems and equipment should be properly used. However, recommendations occasionally entail certain contradictions. Whereas occupants' lack of understanding of control systems is mentioned, the authors also highlight the need for occupant-centric buildings and system designs, whose mode of operation could be understood without long explanations. Moreover, buildings' control systems and devices, their interfaces, and their operation regimes could proactively consider and address certain aspects of human behavior. These include, for example, presence detection technologies and smart scheduling procedures. The intelligent automated control of windows, blinds, and luminaires guided, for instance, by monitored levels of CO_2 concentration, indoor illuminance, or incident irradiance has the potential to anticipate and accommodate occupants' needs and reduce the probability of counterproductive user actions. Needless to say, efforts could be made to encourage more energy-conscious user behavior, for instance, via information campaigns or dynamic energy-centric feedback mechanisms.

5. Conclusions

A key motivation behind the present paper was critical concerns with a relatively recent common narrative in the community of building-related energy efficiency stakeholders. This narrative unfolds along the following lines: our projections of buildings' energy use frequently deviate from their actual energy performance—a circumstance referred to as the EPG. As buildings are increasingly endowed with thermally enhanced envelopes and systems, the relative role of occupants (specifically their energy-relevant behavior) is suggested to have increased, thus becoming the main contributor to this discrepancy. Based on this assertion, a number of inferences are made, two of which pontificate the need for a) more detailed (preferably stochastic) occupant models in energy simulation tools, and b) feedback systems and information campaigns to correct adverse occupant behavior. Notwithstanding the potential and usefulness of these recommendations, the question remains if their underlying premise, namely the assumed centrality of occupants' role in the EPG, is sufficiently documented. We pursued this question in terms of the null-hypothesis stated in the introduction of the paper as follows:

There is no conclusive and sufficient empirical evidence supporting the claim that occupants' behavior is responsible for the bulk of building-related EPGs.

In an effort to reject this null-hypothesis, we examined in this paper recent publications relevant to the subject. The focus was mainly on EPG studies concerning the discrepancy between computationally predicted and actual energy use. However, a number of studies were also included that addressed the EPG by the comparison of similar buildings with different occupancy patterns. Furthermore, the selected studies also included a number of cases involving only (typically parametric) simulation.

Notwithstanding the exact definitions, the studies do report a considerable range of the EPG (somewhere between −38% and +96%). However, the nexus to the occupants' role is not thereby convincingly established. As summarized in the discussion section, the investigation of the previous research in this area does not provide a basis strong enough to reject the above null-hypothesis. On the one hand, there is a considerable level of inconsistency among the studies in view of the scope of the cases, adopted approaches, the comprehensiveness and quality of collected data, the quality of the normalization procedures (in applicable studies), and the robustness of the conclusions. The inconsistency is reflected in the choice of prediction tools (anything from standard-based simplified calculations to dynamic simulation), spatial (zone, room, apartment, whole building) and temporal (minute, hour, day, month, year) granularity of collected data, real occupancy information

(none at all, snapshot observations, surveys and interviews, sensor-based monitoring), and factors involved in normalization (energy use versus energy load, construction and systems, indoor and outdoor climate). This makes the potential for meta-analyses—and ultimately generalization—of the reported findings infeasible. Only 40% of the reviewed publications included, at least formally, what could be considered to constitute the minimum criteria toward an evidence-based confirmation of the purported decisiveness of the occupants' role in the EPG: such criteria would include traceable documentation of the energy prediction models (including, especially, details of occupant-related modeling input assumptions), carefully conducted and transparent normalization procedures, and—most importantly—observation-based documentation of occupants' actual behavior. This percentage further decreases down to 14% if we look for detailed (sensor-based) monitoring data concerning occupants' actual behavior.

The above observations also constitute the basis for recommendations toward future EPG studies. As such, the community would benefit from consistent standards of research design, such that individual investigations could be synthesized at a higher, more inclusive and representative manner via, for instance, cross-section studies and meta-analyses. To this end, we could reiterate the key general recommendations for improving the quality of future occupant-related EPG studies. Such investigations should:

- Document in a detailed and explicit manner the research design, target buildings, energy use monitoring, and occupant behavior observations.
- Examine the integrity of the energy use prediction tool, its consistent and correct application, and the correspondence of the temporal and spatial resolution of the modeling results with the corresponding monitored energy use data.
- Clearly distinguish between predicted and observed attributes and magnitudes of the energy data (e.g., differentiation between energy loads versus end energy use, as well as differentiation between energy quantities used for separate purposes such as heating, cooling, lighting, and equipment).
- Openly present any kinds of assumptions made to match the granularity of observed and calculated data, for instance, when wholesale energy use data (e.g., annual or monthly energy bills) are computationally disaggregated into subcategories (e.g., cooling versus heating versus lighting).
- Apply systematic and transparent normalization procedures that isolate and eliminate EPG sources not related to occupants' presence and behavior (e.g., the deviation of as-is versus as-planned construction properties and building systems specifications, prevailing external boundary conditions and their deviation from those assumed in the modeling phase).

Needless to say, the failure to reject the above hypothesis does not mean occupants do not have a role in the EPG. Rather, what the results advise against are across-the-board and nonchalant claims about the central role of occupants in the EPG, which are sometimes stated at the outset of otherwise meaningful efforts and contributions toward improved energy efficiency of the built environment. Such meaningful efforts encourage, for instance, the provision of:

(i)　　Environmental control systems with high zonal granularity.
(ii)　　Individual control opportunities versus purely central control.
(iii)　Smart control features that modulate indoor climate services (heating, cooling, ventilation) depending on the occupant control behavior.
(iv)　The pervasive application of occupants' presence information toward energy-efficient system operation in non-occupancy periods.
(v)　　Adequately designed building control systems with intuitive, transparent, and responsive user interfaces for operation support.
(vi)　Effective information (both real-time and historical) to the individual occupants regarding the energy implications of their behavioral patterns.
(vii)　Clear and intelligible information regarding the proper operation of control systems and devices.

(viii) General initiatives and campaigns to raise occupants' level of consciousness, both regarding environmental issues in general and possibilities (such as adaptive behavior) to save energy without compromising comfort in particular.

Most of these efforts represent rationally arguable and common-sense options. As such, their pursuit is entirely justified, and their realization potential would be perhaps even larger if our discourse does not assign the occupants a priori as the main culprits responsible for the EPG, but as partners in a collective endeavor to enhance the energy performance of the built environment.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

In Scopus:

(TITLE ("performance gap" OR "rebound" OR "prebound" OR "gap" AND NOT "knowledge gap*") OR KEY ("performance gap" OR "rebound" OR "prebound") AND TITLE-ABS-KEY (building*) AND TITLE-ABS-KEY (occupan* OR resident* OR user* OR uncertaint*))

In Web of Science:

((TI=(("performance gap" OR "rebound" OR "prebound" OR "gap") NOT "knowledge gap*") OR (AK=("performance gap" OR "rebound" OR "prebound"))) AND (TI =(occupan* OR resident* OR user* OR uncertaint*) OR AB=(occupan* OR resident* OR user* OR uncertaint*) OR AK=(occupan* OR resident* OR user* OR uncertaint*)) AND (TI =(building*) OR AB=(building*) OR AK=(building*)))

Appendix B

Appendix B entails a dynamic open-access review table that is available online at https://osf.io/dq9tj. This table includes further detailed information regarding all references with the "gold", "silver", and "bronze" labels (as defined in the paper).

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