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Review

Utilisation of Machine Learning in Control Systems Based on the Preference of Office Users

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Abstract: Reducing energy consumption is vital to save natural resources and contribute to the sustainable development in any sector of society. In the building sector, there are many well-known energy efficiency strategies currently being applied. However, considering the advances in technology and in comfort studies, it is possible to see that the current building sector scenario demands new energy efficiency strategies. Such strategies need to be capable of identifying and assuring comfortable environments according to users' perceptions. Machine learning techniques can be a useful alternative to identify users' preferences and control lighting and heating, ventilation and air-conditioning systems in buildings. This paper shows a systematic literature review on the use of machine learning algorithms on preference identification and environmental adequacy according to users' demands. Its contribution is to explore beyond the performance and configurations of the algorithms, addressing users' preference aspects as well. The strategies found in the literature provided promising results. The most used approach was supervised learning because data can be treated as categories. In general, the control systems have shown good performance, and so have the algorithms. Users were mostly satisfied with environmental conditions. Situations of dissatisfaction were associated with the occupant's willingness to use the system more than with the control system's performance. Furthermore, it is also possible to ally user-centred control and energy savings but this relies on occupants' characteristics and the control strategies used. We underline the importance of identifying whether the users are willing to deal with an automatic control system before making any decision, even if the operation of the system is based on their preferred environmental conditions.

Keywords: sustainable development; energy efficiency; occupant-centred control; user preferences; comfort

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1. Introduction

Buildings should be built to meet the occupants' needs. Yet, in a scenario of climate change and search for sustainable development, it is important to find strategies to provide what the users need with less energy consumption. Neglecting some interactions between the user and the building can lead to a building that neither reaches the comfort levels required by regulations nor satisfies the occupant [1]. Therefore, the design and operation of occupant-centred buildings appear as a good option to increase the energy performance of buildings and the comfort of their users [2].

Some automated systems were developed to achieve energy efficiency. Their main goal is to avoid energy waste and prevent increases in energy consumption due to users' bad behaviour, especially in non-residential buildings. Nonetheless, users can feel that they do not have control over their environment, leading to dissatisfaction. Additionally, the control rules may not provide the environmental conditions they want, also making them uncomfortable [3–5].

Occupants tend to feel more comfortable when they can make manual adjustments in the environment or when it is controlled according to their preferences [6]. Such preferences can be identified by different procedures in the design or operation phase of the building. The most common are the questionnaires, feedback (required or volunteer) and the monitoring of actions and interactions between users and the systems' interface [7–9]. It is also possible to detect preferences by using immersive virtual environments [10–12]; however, some aspects of reality are not easy to simulate with realism [13]. Another alternative is to use machine learning, if the solution is not previously known [14], like in the prediction of users' preferences and behaviour.

The association of machine learning algorithms and the identification of occupants' preferences—monitoring their actions and interactions with building systems or applying questionnaires—is an approach that has presented promising results in terms of user satisfaction and energy consumption optimisation. The data collected can be used to feed real control systems such as heating, ventilation and air-conditioning (HVAC), lighting, windows opening, shading and other systems made for residential applications (activity detection: use of computers, television, washing machine, etc.) [4].

There is an increasing number of research papers aiming to provide comfortable environments to users by using machine learning techniques in different ways. The rising interest in this area can be motivated by Annex 79 of the International Energy Agency [2], which addresses occupant-centred design of buildings. One of its main interest areas is developing occupant-centred control systems [1]. Since this area is under exploration, there is no "good practice" manual to guide the decision-making process to achieve satisfying results. The utilisation of machine learning in the user-centred building context has been gaining attention among other solutions and, recently, it has been presented as the main approach.

Machine learning has been addressed in reviews about thermal comfort [15–18], control of HVAC [19–22] and lighting systems [19–22], and occupant-centred control overall [8,23]. Moreover, reviews that address machine learning specifically bring together the authors who have used this approach to predict occupation [24,25] and windows opening [25], improve different aspects of lighting (technologies, efficiency, security, comfort) in in- and outdoor environments [26], create personalised thermal comfort models [27] and analyse the impact of thermal comfort on users' cognition, work and health [28]. For example, Han et al. [29] reviewed the use of reinforcement learning to maintain occupants' comfort in buildings.

However, in the abovementioned reviews, visual and thermal comfort aspects are mostly evaluated in terms of the accuracy of personalised models, and according to regulations and classic models from the literature, disregarding the intrinsic subjectivity of the topic. Thus, this paper aims to present a systematic literature review on the user-centred control systems that address users' preference while using machine learning. The contribution of this paper is to explore beyond the performance and configurations of the algorithms, addressing user preference aspects as well. It explores configurations such as user detection and main variables, the methods most used to find the environmental conditions preferred by users (comprising their points of view), the most popular approaches and algorithms, and their assessment in terms of user satisfaction and potential energy savings. This systematic literature review can provide valuable information to guide new research and help the decision-making process in the design of occupant-centred control systems. Furthermore, we hope to contribute to more assertive decisions and, consequently, provide comfort to building occupants. In this way, one can comprehend how the user-centred approach can influence energy consumption, allowing researchers and professionals in the area to minimise—or avoid—negative impacts.

2. Method

The Scopus database was used to conduct this systematic literature-review paper because it provides a broader range of peer-reviewed publications. Original papers containing the following expressions (in the title, abstract or keywords) were selected:

- Machine learning OR artificial intelligence OR algorithm OR internet of things OR IoT—to find papers that have used machine learning algorithms and/or the ones capable of dynamic learning;
- ((Occupant OR user OR human) W/2 (design OR control)) W/3 (behav* OR preference OR comfort)—papers that include the human dimension in the problem formulation;
- (HVAC OR light) AND ((visual OR thermal) AND (comfort)) AND office—papers that address thermal or visual comfort of office users.

To identify the first publications about the topic, no temporal filters were used, returning 660 articles. The ones unrelated to the topic were excluded, at first, by reading the title and, if necessary, the abstract. There were exclusion criteria based on the following characteristics:

- Focusing only on energy consumption, regardless of users' comfort;
- Assessing comfort based on regulations or classic models from the literature, that provide pre-calculated setpoint values rather than a preference-databased control strategy;
- Researchers did not test at least one algorithm in the system control—in the field or by means of simulation;
- Only addressing windows and shading control, since office occupants tend to operate such systems based on long-term events rather than reacting to short-term discomfort [30].

Throughout such a process, papers cited in review papers were also revised, which, being in the scope of this research, could be included in the sample. From the 181 remaining papers, 26 papers were included in this study, all published between 2014 and December 2023 (Figure 1) in different journals and proceedings, and considered due to their relevance in the computer area.

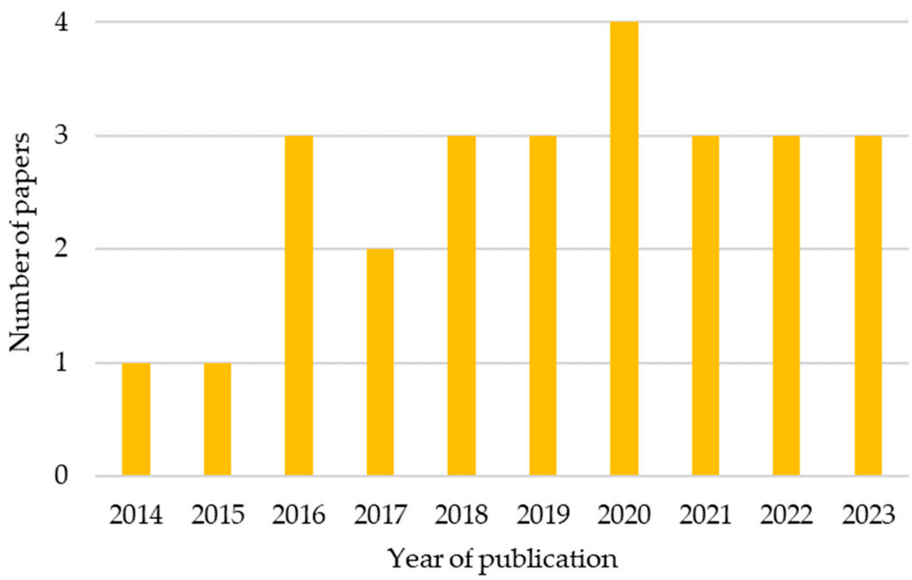

Figure 1. Quantity of publications between 2014 and December 2023.

Figure 2 shows the flow diagram for this systematic review paper.

The papers were fully revised aiming to answer the following questions:

- Is there an algorithm used for the user-centred control of lighting and HVAC systems that shows performance superior to that of others?
- Is the personalisation of control settings through a machine learning approach capable of creating a comfortable environment for users?
- Is it possible to combine comfort and energy savings in an occupant-centred context?

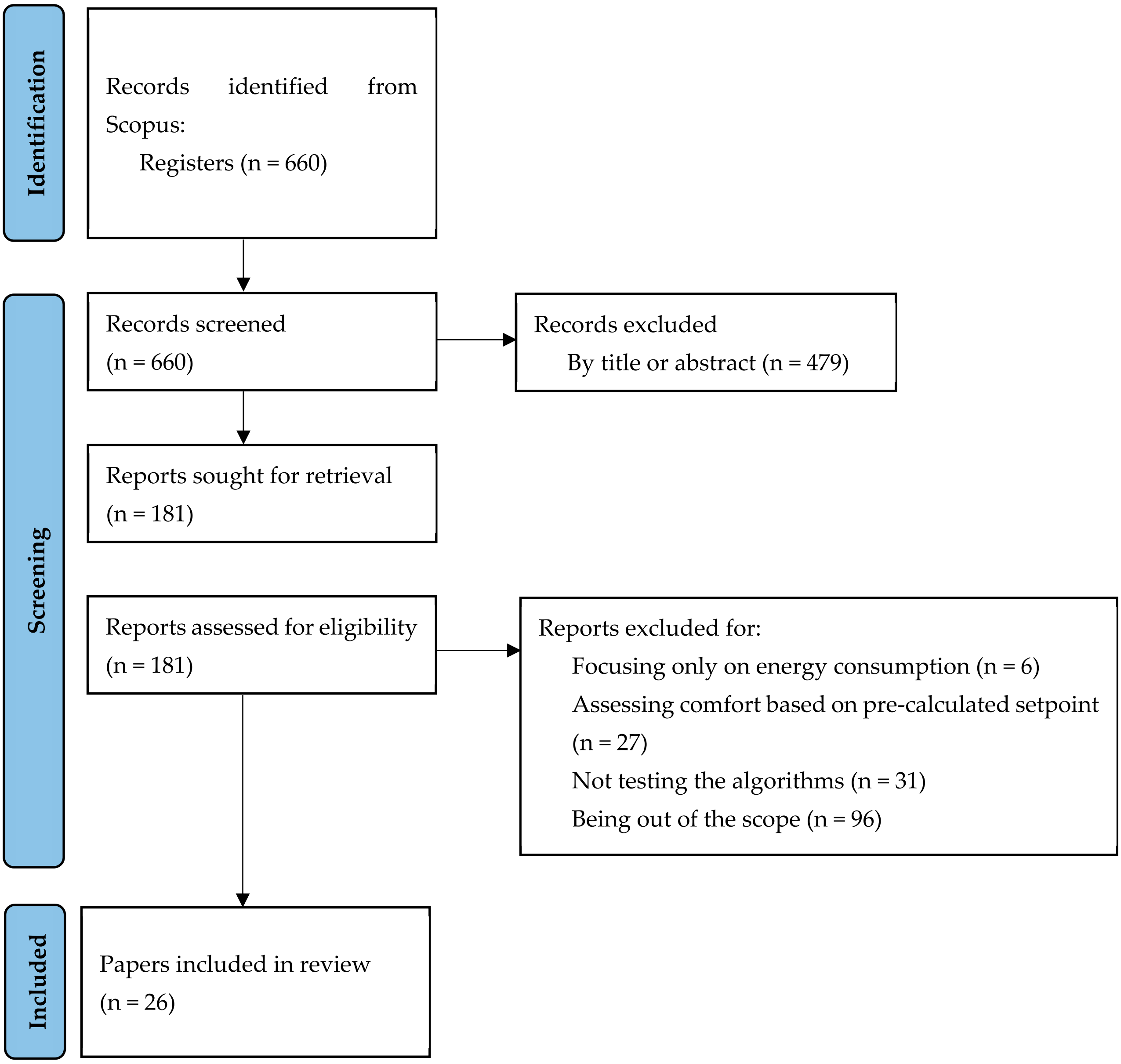

Figure 2. Flow diagram for this systematic review.

3. Results and Analysis

Table 1 shows the occurrence of papers in each journal. Most of them were found in *Energy and Buildings*, and *Building and Environment*. Among the publications, studies that analysed HVAC, lighting and shading systems simultaneously, as well as field and simulation studies, were found.

Table 1. Quantity of publications by journal between 2014 and 2023.

Journal	Number of Papers
Building and Environment	7
Energy and Buildings	7
Applied Energy	1
Building Research and Information	1
Building Simulation	1
Automation in Construction	1
Science and Technology for the Built Environment	1
Sustainable Cities and Society	1
Proceedings	6
Total	26

The literature review showed that machine learning is often used in HVAC systems rather than in artificial lighting systems, as shown in Figure 3. Since 2021, all the papers about machine learning have addressed HVAC systems. We highlight that this paper does not focus on shading control, so we considered only studies that performed such analysis combined with other systems.

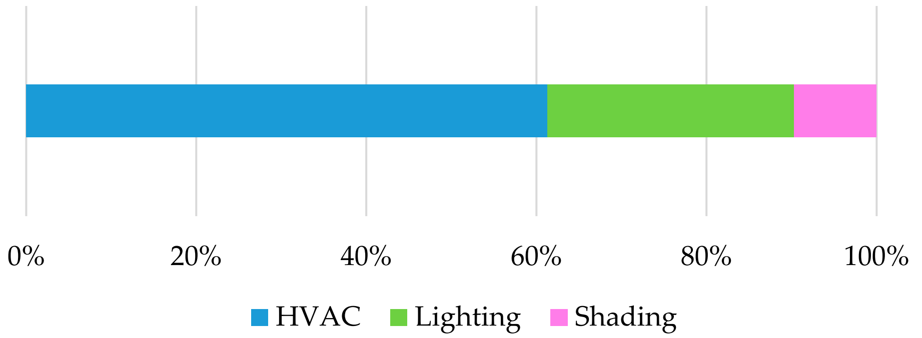

Figure 3. Proportion of papers that used machine learning in HVAC, lighting and shading systems (categories are not mutually exclusive).

The studies' durations had significant differences, as shown in Figure 4. Among the ones with a larger span, four used the simulation approach. One of them is a three-year study that assessed the use of HVAC, lighting and shading systems under many circumstances. Another one was the first paper published on this topic [31] and one more was published in proceedings [32], both within 12 months. The others implemented and assessed control in real systems [33–35]. Tekler et al. [36] collected data for ten days and used the information to simulate a whole year. Among the studies of shorter duration, three were carried out through simulation [37–39]. The biggest advantage of simulation is the possibility of assessing different scenarios, test strategies and approaches. Nevertheless, it is not possible to analyse a system's performance with real users, daily. It is not possible for the users to give an opinion about the system or indicate if they are satisfied or not, and the reasons for that either.

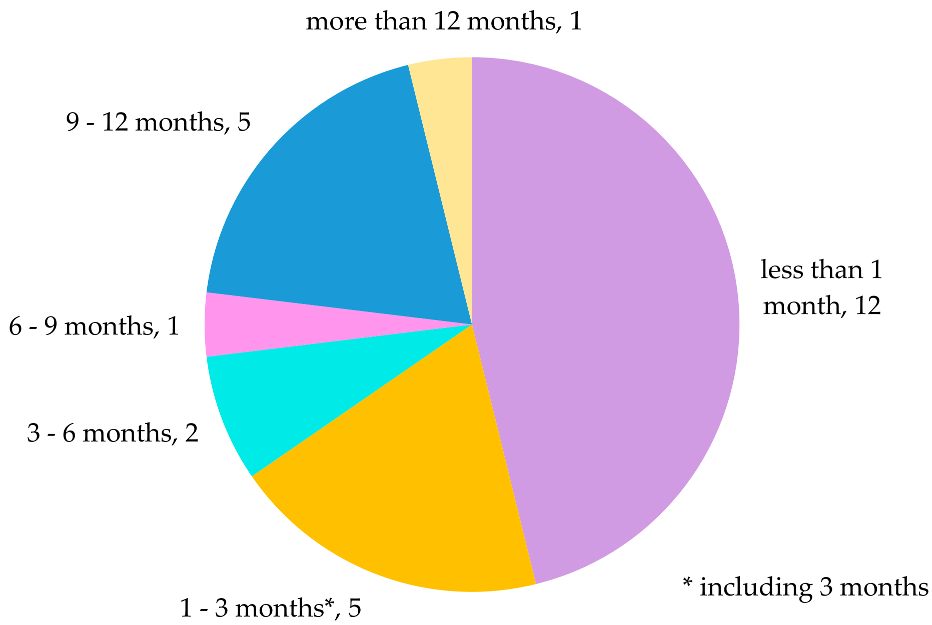

Figure 4. Duration of studies available in the literature.

It was also observed that the majority of papers that lasted less than a month were conducted in controlled environments [38,40–44] and, among the ones that asked for users' votes, only two lasted more than 30 days [33,45]. One can assume that this was related to possible inconvenience or nuisance caused by frequent interaction or the presence of researchers and equipment in the environment.

Another issue about the duration of the studies is that short-duration studies cannot address changes in preferences and behaviour due to seasonality, and how such changes affect the control system's performance. Despite that, the relationship between the amount of data (or period of data collection) and the final results is not simple or evident. The information presented in this section is summarised in the Supplementary Materials.

3.1. Machine Learning on Control Systems Based on Occupant Preference

Most authors used supervised, unsupervised and reinforcement learning algorithms. Some also used mathematical models to dynamically learn occupants' preferences. Table 2 shows the algorithms and their classification according to the learning approach.

Table 2. Algorithms classification according to learning approach.

Approach	Algorithm	Reference(s)
Supervised learning	C-Support vector classifier (C-SVC)	[46]
	Decision tree (DT)	[46,47]
	Gaussian naive Bayes (GNB)	[46]
	Gradient boosting (GB)	[47]
	Extreme gradient boosting (XBG)	[36]
	K nearest neighbour (knn)	[48]
	Multilayer perceptron (MLP)	[46,49]
	Random forest (RF)	[47,48,50]
	Artificial neural networks * (ANN)	[38,39,45,47,51]
	Linear regression (LR)	[40,41]
	Logistic regression (LogR)	[34,35,43,48,52]
	Support vector machine (SVM)	[47,48]
Unsupervised learning	Clustering *	[33]
	k-means	[37]
Reinforcement learning	Branching dueling Q-network	[44]
	Q-learning	[32,53,54]
	Reinforcement learning-based **	[42]
Mathematical model with dynamic learning	Dynamic statistical analysis	[52,55,56]
	Kalman filter	[31]

* Algorithm not specifically described. ** Adapted reinforcement learning algorithm.

In general, the most common approach was supervised learning. Reinforcement learning and unsupervised learning were ranked second and third, respectively. Mathematical models were found in only four studies, especially in the early papers about this topic. One paper combined a mathematical model and supervised learning [52]. More specifically, the most used algorithms were artificial neural networks and logistic regression with seven and five occurrences, respectively. Considering the different algorithms and types of systems, no standard solution was found, although some authors used the same approach in subsequent papers: dynamic statistical analysis [55,56], logistic regression [34,35], Q-learning [32,54] and linear regression [40,41].

The preference for supervised learning algorithms can be related to the fact that preferences (labelled by the users) can be treated as categories, such as "too hot", "hot", "warm", "neutral", "cool", "cold", "too cold", "dark" and "bright". In unsupervised learning, the algorithm "creates" the categories (clusters) by itself and classifies data, so there is no reference from the user's point of view to know which conditions are pleasant or not. In addition, reinforcement learning can demand a lot of interactions between users and interfaces to reach satisfactory performance. Still, it is necessary to find a way of weighing users' preferences in shared environments to achieve the best result in terms of user satisfaction.

3.2. Main Variables for Occupant-Centred Control of HVAC and Lighting Systems

There is still no agreement about the ideal way of identifying users' preferences (or comfort and satisfaction as well) to incorporate them into control systems. Despite that, the literature shows that this has been achieved by monitoring the interactions between users and interfaces or by voting (questionnaires and/or scale votes). In both cases, the information collected is gathered with environmental conditions (temperature, humidity, illuminance), and physiological or personal data (clothing, for example) in the moment of the answer. This is particularly helpful because, by reporting their perception, users are labelling that specific environmental condition. Something similar happens when users interact with system interfaces, by changing the switch position or the setpoint temperature. Table 3 shows the variables used as input data to train the algorithms in occupant-centred backgrounds.

Table 3. Main variables used in occupant-centred control systems (• input variable).

Reference	**Time**	**Attendance**	**Illuminance**	**Switch Status**	**Indoor Temperature**	**Indoor Relative Humidity**	**Outdoor Temperature**	**Outdoor Relative Humidity**	**Irradiance/Solar Radiation**	**Heart Rate**	**Skin Temperature**	**CO_2**	**Setpoint Temperature**	**Feedback/Survey**	**User-System Interaction**
[31]	•	•	•		•									•	
[32]		•			•									•	
[33]		•	•		•									•	
[34]		•	•	•					•						•
[35]		•			•	•	•								•
[36]	•	•			•		•	•						•	
[37]		•											•	•	
[38]					•	•							•		•
[39]					•	•				•	•			•	
[40]					•	•	•	•		•	•	•	•	•	
[41]					•	•	•	•		•	•	•	•	•	
[42]					•	•				•	•			•	
[43]					•	•	•		•					•	
[44]	•	•			•		•	•	•					•	
[45]			•		•	•						•		•	
[46]	•	•			•		•					•	•		•
[47]	•	•			•	•				•				•	
[48]		•	•		•	•	•	•		•	•	•	•	•	
[49]					•	•	•	•					•		•
[50]					•	•					•			•	
[51]	•	•	•												•
[52]		•	•		•										•
[53]			•											•	
[54]	•	•	•	•											•
[55]	•	•	•	•											•
[56]	•	•	•	•											•

In the context of this paper, considering users' attendance is important not only to inform the system that someone is in the room, but also to adapt the environment according to the preference of the users. Moreover, allying attendance and time can provide important information about users' routines, like arrival and departure time, and patterns of short and long absences. The combination of such variables also allows the system to prepare the environment before users' arrival, leading to an increase of their satisfaction [46].

The choice for the variables depends on the main goal. Studies addressing HVAC control tend to use a greater number of variables than the ones addressing lighting control. The most used variables in the latter case are the illuminance and the switch position, besides attendance and time. As already stated, these aspects can be associated with the perception of the users when linked to feedbacks, surveys or user-system interactions.

Controlling HVAC systems in an occupant-centred manner depends on many aspects. That may be because thermal comfort is affected by many variables, such as environmental, physiological and psychological. Environmental variables are well known (some of them are also used in traditional thermal comfort models): temperature, relative humidity, solar radiation, air speed, etc. To address physiological aspects, researchers have measured users' heart rate and the skin temperature (cheek, hand and pulse, for example). The heart rate is associated by some authors with a person's metabolism, and it has been measured by using wristbands [40,41,48].

Clothing insulation is an important factor for the classic thermal comfort models. It is a human aspect that can be considered as an adaptive action, since users can adjust it to restore their comfort sensation [57]. For that reason, clothing insulation has been used to describe the conditions in which the research takes place more than the control of HVAC systems. However, to establish a scenario of fair comparison, in controlled environments, people are usually asked to wear something specific, standardising the clothing insulation. Another possibility is to include questions about such a topic in the survey. That is common in non-controlled environments.

Some aspects are more challenging to measure or estimate, though. This is the case with psychological aspects, for example, that are subjective. To assess such aspects and find out users' perspective about comfort, researchers can rely on surveys or users' feedback. The information requested by the researchers is usually like the scales proposed by American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE); however, the kind of information may be different. Some authors request sensation votes [32,39,40,42,47], while others request preference [36,43,45] or acceptability [51]. Still others request multiple information: sensation and satisfaction [41]; sensation, preference, comfort and acceptability [44]; sensation and preference [48]. It is also possible to identify users' preferences by offering them the option to vote for increasing or decreasing temperature [37] or in qualitative ways, such as "bright" and "dark" [53], "preferable", "friendly", "uncomfortable" and "hostile" [33]. In general, vote collection is carried out via the web or smartphone app. Some authors request users' votes periodically [40,47], while others leave occupants free to vote whenever they want.

When computational cost, data storage and time are not limitations, collecting as many data as possible may not be a problem. In fact, one may argue that the more variables an algorithm uses, the more patterns can be found and the more accurate the results will be. That is not completely true, though. Sometimes, data may contain noise that leads the algorithm to find wrong patterns. In such cases, it is important to remove the noisy data or variable. This is also interesting when computational cost or storage data are important issues from a technical point of view. In the scope of this research, only a few authors assessed different scenarios in order to find which variables would lead the algorithm to a better performance [40,48,50]. In addition, Tekler et al. [36] assessed the possibility of reducing the amount of data used to train the algorithm. The authors found that it was possible to reduce the labelling necessity in 31% and still achieve acceptable results in terms of users' acceptability and energy savings.

3.3. Detection and Identification of Users by Control Systems

User detection varied considerably among the papers. One problem related to this topic is user privacy violation. Different possibilities were explored, some to distinguish users, some to count or detect them. The most used devices were motion sensors [34,35,46,55,56]. Despite that, the main issue with such technology is the absence of movements to trigger the sensors, because office activities may be monotonous. In addition, this kind of monitoring device cannot distinguish users, which can damage the system performance of personalised control in shared spaces. Studies conducted in controlled environments could take into account data from the users who are in the room [36,38,40–44]. Something similar was observed in Rajith et al. [45], who considered full occupation during the experiment. Such a decision can lead to the generalisation of preference models, which will consider data from users that may not be there when the system is working. Other authors consider user interactions (with the interfaces or by voting) as an attendance signal, counting the occupants but not distinguishing them [48,49]. In addition, Cheng et al. [53] asked the occupants to remain in the room during the observation period. They came up with an interface for users to indicate their preferences after login.

Some alternatives to detect and distinguish users are Bluetooth technology [39,54], the location tool on smartphones [33,47] and RFID (radio-frequency identification) cards [37]. Although they are useful to distinguish users, they depend directly on occupants' participation, which can be a problem if users are not well-oriented or unaware of the importance of being with their devices or RFID cards all the time. In addition, one paper indicated the use of a smart lock to detect and distinguish occupants [51], but it did not describe if that happened by fingerprints, RFID cards or other means.

Some of the papers that assessed the control systems by simulation used occupancy and preference models available in the literature [31,32,50,52]. The ways of detecting the occupants are useful to confirm if there are users in the room (and some are able to identify them). However, they are not capable of predicting occupancy in any time horizon. To achieve that goal, it would be necessary to collect data for some time and use an algorithm to make predictions [58].

Detecting the presence of one or more occupants is a fundamental step to the correct functioning of an occupant-centred control system. Such a step allows the system to identify if it is necessary to make changes to lighting, cooling or heating in the environment. This systematic review found different ways of doing that, each one with its advantages and disadvantages. Giving the users the task of confirming their attendance can give some sense of responsibility and control over the environment, but it can also be seen as an extra task that one may not be willing to do.

Identifying each user is equally important because it allows the system to be more precise concerning the environmental conditions that must be provided. Additionally, in the case of shared spaces, identifying who is present allows the personalisation of environmental conditions according to group tolerance. In other words, the attendance of a sensitive user can force the system to increase the number of actions, which would not be necessary if there were only tolerant users. This kind of adjustment is still an issue, which will be discussed in the following sections.

3.4. Control Systems' Performance Assessment

The control systems were evaluated by means of different parameters, not mutually exclusive. The algorithms' quality was assessed by means of performance parameters such as R^2, mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and accuracy. The performance of the whole control system was assessed by observing users' satisfaction. Even though energy saving was not the main goal of the papers reviewed, some authors used this aspect as one of the evaluation parameters.

3.4.1. Algorithms' Performance

In the studies about lighting control, two papers used performance parameters to assess the algorithms. Mandaric et al. [51] found an accuracy of 88.5% by using neural networks for the identification of the preferred lighting scenarios. Park et al. [54] evaluated five scenarios by using light utilisation ratio (LUR), unmet comfort ratio (UNC) and lights to comfort ratio (LCR), in addition to user satisfaction. The LUR ranged from 0.40 to 0.99 because some users turned the automatic system off. The maximum UNC was 0.27 and the LCR was between 0.98 and 1 for all scenarios.

A higher number of research addressing HVAC systems used performance parameters. Laftchiev et al. [38] changed the error parameter into degrees, reporting that their system was capable of identifying, through neural networks, the correct temperature to control the HVAC system. The MAE found was 0.5 °C and RMSE was 0.6 °C, errors that the authors considered adequate. Zhu et al. [49] assessed the performance of a neural network to identify the preferred temperature and to classify the users according to their changes in the setpoint. The authors used the MSE and found an error of 0.28, attesting to the quality of the results. Neural networks also had good results in predicting thermal sensation votes, with R^2 equal to 0.89 [39].

The RF was used to predict thermal sensation and showed accuracies of 84.0% [50] and 80.0% [48]. On the prediction of personalised thermal sensation, this algorithm had an average accuracy of 88.0%, but for multiple users, its performance was unsatisfactory, with an accuracy of 54.4% [47]. Identifying the preference of multiple users can be a hard task, though, regardless of the algorithm. In this context, some authors tested different algorithms and compared their performance to choose the best one. Jeoung et al. [47] compared RF, SVM, DT, GB and ANN in the prediction of thermal sensation votes, alone and collectively. GB showed the best performance, with an average accuracy of 88.2% for personalised prediction and 55.8% for multiple users. SVM had the worst performance, with an average accuracy of 51.2% and 28.3% for individual and multiple users. The comparison of accuracies led Peng et al. [46] to discard GNB and DT (accuracies of 90.0% and 96.0%, respectively) on the identification of users' preferred temperatures. They also tested C-SVC and MLP, which had the same accuracy (both with 97.0%), so the authors decided on MLP due to its stability.

One can assume the algorithms showed promising results, each one in its context. The possibility of assessing the algorithms' performance in advance through accuracy is one advantage of such an approach. Despite that, using parameters such as precision and recall would be valuable to identify the false positives and false negatives in case of an unbalanced dataset. In other words, if 90% of the data were from switching on the lights, the algorithm accuracy could reach 90% but it would not identify any circumstance in which they should be turned off. In that case, checking the results' precision and recall would help to identify if the algorithm's training was biased.

3.4.2. Satisfaction with Lighting Systems

The studies related to lighting systems tended to use occupants' interactions with the system interface as indicative of the system's good performance. In practice, users tend to override the actions realised by the system when they are not satisfied. So, it is possible to affirm that the decrease in the number of interactions means that the users are comfortable or, at least, tolerating the environment in which they are [52].

Gunay et al. [31] verified that the interactions with the interfaces of the lighting system (artificial light and shading) were reduced by 85% after the implementation of occupant-centred control. In Gunay et al. [34], users overrode 6% to 8% of the turn-off actions in the lighting system to restore the previous condition. In Nagy et al. [56], the percentage of overrides was 23.6% and 12.6% for turn-offs and turn-ons, respectively. It is important to consider that sensitive occupants tend to interact more often with interfaces and give more feedback than tolerant users [52], especially if the feedback is not required. In addition, Sarkar et al. [33] verified that, on average, 78% of feedback showed comfort when the lighting level was adjusted because of glare or darkness, indicating that users only remember giving feedback when their comfort sensation is restored.

Cheng et al. [53] proposed a system that made adjustments to lighting using "bright" and "dark" votes. The authors used a 7-point scale to assess the users' satisfaction with the system. According to the study, 92% of the satisfaction votes were over 4. However, the study of Mandaric et al. [51] evidenced the challenge in shared spaces. In a single-occupant scenario, 86.37% of lighting adjustments were graded 3 and 4 (on a 1–4 scale). For multiple occupants, there was a decrease in votes for 4 and some users reported they would leave the room if the lighting did not change.

In Park et al. [54], two of five users decided to turn off the automatic control system throughout the whole study, making manual adjustments. In another study, an occupant reported considering automatic control unimportant. According to this occupant, task lighting would be the best option to solve any issue in the office [56]. Such facts indicate that users' willingness to use the system is another decisive factor in their satisfaction.

3.4.3. Satisfaction with HVAC Systems

Studies related to HVAC systems often asked for user votes to identify user satisfaction. Overall, some authors consider that the absence of votes means that users are comfortable [45,48]. The same premise is adopted by the authors who monitor users' interaction with system interfaces. In other words, users' interaction with systems interfaces (changing the environment) is seen as a way to restore comfort sensation [38,46]. In Park and Nagy [32], the use of reinforcement learning led to a 40% reduction in "too hot" interactions. Therefore, it is inferred that when users interact with the systems, they are indirectly showing their preferences and satisfaction. By using logistic regression during the automated control period, Gunay et al. [35] observed that there was a total of between one interaction in three weeks and one interaction in 25 weeks. The use of artificial neural networks helped Peng et al. [46] to reduce changes in the set point from 4 to 9 times a month to 1 to 5 times over the same period.

The incorporation of users' votes in controlling the HVAC system increased thermal acceptability by 11% [44]. Comparing systems functioning with manual control, the discomfort levels decreased by 10.9% [42] and 53.7% [48]. In Jeoung et al. [47], the thermal sensation vote on a 7-point scale changed from 0.7 (maintaining a fixed temperature setpoint) to 0.4 using the thermal sensation prediction algorithm. The discomfort votes were reduced by 33%. The system proposed by Li et al. [40] used occupants' feedback to make adjustments to the temperature. On a satisfaction scale from 1 to 7, the system received 5.56 points. In a similar study [41], the average satisfaction vote was 4.61 for fixed setpoint temperature, 5.20 for feedback-based control and 5.30 for temperature prediction control.

Including multiple user preferences in control systems may be challenging, as evidenced by Deng and Chen [39]. For a single occupant, the authors reduced discomfort by 100%, however, for five occupants the reduction was only 85%. In such situations, the strategy of classifying users according to profiles such as radical (5 °C in setpoint temperature) and conservative (1 °C changes) can be helpful [49]. Tekler et al. [36] used extreme gradient boosting to find the set point temperature comfortable for most users. According to the authors, it would be possible to achieve from 98.3% to 99.5% acceptability.

Nevertheless, it is very important to be careful with generalisations, keeping in mind the subjectivity associated with each user's comfort and tolerance level. Wu et al. [50] experimented with a group of occupants using a control system based on comfort, sensation and acceptability votes from another group of people. The average thermal sensation vote remained between ±0.5, though there were "unbearable", "unacceptable" and "totally unacceptable" votes.

It is essential to reinforce that identifying users' preferences and including them in a control system may not create a comfortable environment and satisfy users. Such a situation might be even more complicated in shared environments. Even if data do not point to negative effects on comfort after the implementation of automatic systems, feedback analysis can show some significantly dissatisfied users.

The dissatisfaction may happen due to a lack of perceived control, difficulties in the comprehension of the system or thinking its implementation is not important. In that case, it is possible that users declare they are dissatisfied and even refuse to use the system [54,55]. Furthermore, in order to assess the systems correctly, it is necessary to consider the whole context in which the user is, looking for new parameters and ways of assessment, not only in terms of comfort but also to assess satisfaction with the control system itself.

3.4.4. Impact on Energy Consumption

Control systems that operate with fixed setpoints are common, but they can lead to a rise in energy consumption. This kind of system usually works based on conservative parameters (minimum of 500 lx, for example) to avoid uncomfortable situations for users. However, if the users prefer (or tolerate) darker environments, as one can see in the literature (140 lx in Nagy et al. [55]), there can be a waste of energy. Such a situation was observed by Gunay et al. [31]. The authors compared the energy consumption of lighting and shading systems during manual and fixed setpoint operation. They verified that energy consumption increased about 30.0% in the second case. After the implementation of an adaptive system using the Kalman filter, the authors observed a decrease in energy consumption of about 13.0% compared to manual control. Compared to the fixed setpoint, the difference reached 35.0%.

Also working on lighting systems, Cheng et al. [53] achieved an energy-saving potential of 10.0% when using reinforcement learning. Using clustering techniques, Sarkar et al. [33] achieved 27.0–39.0% in energy savings. Nagy et al. [55] proposed operation modes favouring comfort or energy savings. When compared to the baseline case (in which the only efficiency strategy is to turn off the lights after 7 p.m.), the comfort mode showed a decrease of 23.2% in energy consumption. The energy-saving mode reduced the energy consumption by 37.9%. Despite that, implementing occupant-centred control caused a rise in energy consumption in some rooms, such as the printing room. The authors verified that users entered and left the room and did not turn on the lights. Therefore, the utilisation of motion sensors associated with the lighting system—even according to user's preferences—increased the energy consumption.

When it comes to the HVAC systems, occupant-centred control also had promising results. Comparing adaptive control with a fixed set point, some significant differences were found, such as in Zhang et al. [43], reaching 35.0%. Other authors had positive results comparing adaptive systems with the automatic ones that operate based on a schedule or a fixed setpoint. Lei et al. [44] used reinforcement learning and achieved an energy-saving potential of 13.9%. Li et al. [40] used linear regression and achieved a daily saving potential of up to 13.8% by using thermal sensation feedback-based control. In Li et al. [41], the authors verified that thermal sensation prediction-based control could lead to energy savings of about 10% more than they obtained in their previous work. Jeoung et al. [47] also compared the performance of a personalised system to a manual one and found a difference in energy consumption of 27.0% using gradient boosting.

Rajith et al. [45] used artificial neural networks and found energy-saving potential of between 20.0% and 40.0%, avoiding waste without compromising user satisfaction. Carreira et al. [37] found similar energy-saving potential. Using k-means and user votes on the HVAC system to control it, the authors achieved a saving potential of about 26.0%, maintaining more than 70% of users in thermal comfort. Peng et al. [46] observed variations in the energy-saving potential of between 4.0% and 25.0% in four different offices due to differences in user profiles. The saving potential found by [36] was lower, ranging from 3.5% to 4.6%.

In this scenario, it is important to highlight that energy-saving potential is related to occupants' profiles. Users can decide to turn off automatic control because they prefer manual control. Likewise, their habits can directly influence energy consumption. All these facts reinforce the idea that it is necessary to observe the context in which the occupant-centred control would be implemented to achieve better results.

4. Discussion

This systematic literature review presented the main characteristics of user-centred control systems that use machine learning to identify occupants' preferences, the most used algorithms and their performance, forms of detecting users and their preferences and energy-saving potential. Table 4 summarises the main aspects that were assessed in this paper and the potential gaps to be filled.

Table 4. Main issues that can be addressed in future research.

Main Aspects		Advantages	Disadvantages	Main Issues
Duration	Short	Reduction of possible inconveniences to users due to the presence of equipment or researchers.	Cannot address changes in the users' preferences and potential impacts of seasonality.	To find the period that allows the system to identify preferences and update them while they change. Can be different for each case.
	Long	Possibility of assessing changes in preferences and their reasons.	This might annoy some users due to the presence of researchers and equipment.	
Test	Simulation	Allows the assessment of different scenarios, strategies, approaches and periods.	Cannot address users' satisfaction with the system's performance.	Users need to understand how the system works and be willing to participate in the tests. Otherwise, they may become uncomfortable for reasons that are not related to their preferred environmental conditions.
	Field	Possibility of collecting users' feedback and their opinions about the whole system's performance. Users can continuously label the environmental conditions of their preference.	More intrusive procedure. It may cause discomfort, especially for sensitive users.	
Variables		The collection of many variables may increase the chance of finding unknown and less obvious patterns.	Some variables may add noise to the dataset and lead the algorithm to identify wrong patterns.	The identification of the variables that are more relevant to achieve better predictions, especially when computational cost is limited.
Users' detection	Controlled environment	Precise information.	May be intrusive and affect users' behaviour.	Requires user allowance and/or participation, which may affect the way they act. The inability of a system to detect and identify the users may lead to mistakes in providing their preferred environmental conditions. Such a problem becomes more evident in an environment with multiple users. To weigh users' preferences and set a comfort condition in shared spaces has been a challenging task.
	Motion sensors	Well-known technology.	The sensor itself cannot distinguish users. Monotonous activities tend to not trigger the sensors.	
	RFID, Bluetooth	Identification of users.	Depends on user attention and willingness to participate.	
	Schedule	Includes all users in the analysis.	May not represent reality.	
Assessment	Algorithm	Allows the comparison between algorithms in order to choose the one that best represents users' preferences.	By itself, it cannot address and solve users' potential dissatisfaction. Requires verification of the dataset or the use of more than one assessment parameter to detect bias.	To identify the algorithm that leads to the best accuracy for each case (which depends on the dataset, variables, period of data collection). However, such an assessment is not enough to ensure that users are satisfied with the systems' performance. For that reason, the algorithm performance needs to be assessed together with the users' satisfaction.
	User satisfaction	Addresses the way users perceive the system. Allows the identification of potential improvements.	Requires user participation. Potentially complex because of the subjectivity related to comfort perception.	
	Energy saving	Indicative of users' profile (sensitive or tolerant).	May be related to habits and not to preferences.	

Bearing these issues in mind, the following subsections aim to answer the research questions that guided this paper.

4.1. Is There an Algorithm Used for the User-Centred Control of Lighting and HVAC Systems That Shows Superior Performance?

Some algorithms, such as artificial neural networks, were frequently used. However, after the systematic literature review, it was not possible to affirm that one algorithm was the best. Still, the most popular approach was supervised learning. Such a fact can be related to the variables, which can be considered categories. The supervision is carried out by the user, who labels the environmental conditions when answering the surveys or interacting with the system. After this step, the algorithm can understand what is comfortable or not from the user's point of view. Another advantage of the approach is the possibility of easily assessing algorithms' performance because there are evaluation parameters and data are labelled by the user. The algorithms' accuracy tends to be high when they are trained with large and correctly labelled datasets. However, it is important to pay attention to the training dataset. First, it is necessary to check the existence of noisy data. Second, in the case of a biased dataset, accuracy may be masked and the algorithm can lose generalisation ability. In other words, algorithms using small or biased datasets can have good test accuracy, but at the same time be incapable of predicting what users need under circumstances that are different from the ones in the dataset. Therefore, it is important to check parameters besides accuracy, such as precision and recall, to verify the existence of these problems and ensure the correct performance for the control system.

Reinforcement learning is versatile and can solve different kinds of problems. However, it depends on the occupant interacting with the system to improve its experience and provide suitable environmental conditions. Additionally, the complexity of such a solution can make its implementation and evaluation difficult, since there is no parameter like accuracy for reinforcement learning. Similarly, it is difficult to assess unsupervised learning algorithms. As an advantage, it is not necessary to label data and the algorithms can find patterns previously unknown. All things considered, in a context in which one needs to know users' favourite conditions, the utilisation of this approach may not be worthwhile.

It is important to remember that each approach has advantages and disadvantages. Consequently, it is up to the researcher or professional in the area to check the context in which the system will be installed and what are the main goals before taking any decision. Unfortunately, there is no method, so far, that allows the comparison of algorithms (especially from different approaches) before their implementation in the field. In addition, assessing just the algorithms is no guarantee that the performance of the system will meet users' expectations due to the subjectivity related to the concept of comfort.

4.2. Is the Personalisation of Control Settings through a Machine Learning Approach Capable of Creating a Comfortable Environment for Users?

Despite the discussions around the concepts of comfort and tolerance, and the complexity related to obtaining such information [59], the systematic literature review suggests it is possible to presume that machine learning can, mostly, ensure pleasant environments for users.

Even if there is no discussion about the decision of collecting preference data by vote or monitoring the interactions, both showed efficacy. The use of direct voting can provide information more objectively, but the frequent request for information can be annoying. There is no such problem in monitoring the way users interact with the system, though. Furthermore, if the votes are not requested, the occupants can remember to provide them only when they are uncomfortable or immediately after restoring their comfort, which can lead to a biased dataset. This can also occur in the case of collecting information only when the user interacts with the system's interface. Therefore, it is valid to consider that users are comfortable when they do not interact with the system or do not voluntarily answer the survey questions, but it is also necessary to find a way to balance the dataset. As an alternative, it is possible to identify the comfort zones by exclusion (taking into account that what the user did not report as uncomfortable is tolerable) or to balance the dataset by computer techniques.

In single environments, it is not necessary to ponder preferences according to the user's tolerance level, being easier to find the preference pattern and, consequently, to operate the system. In shared environments, though, the algorithm must consider the preferences of all users, especially the less tolerant ones. In addition, to consider all users' preferences, the system needs to distinguish each user in the room. Among all the possibilities found in the literature to distinguish occupants, none presented a clear advantage over the others. Such a fact shows the importance of verifying users' willingness to actively interact with the system.

Theoretically, providing environmental conditions that are suitable for all users is a complex task (note that some people have the perception that a room with 140 lx is dark [55], while others have the same perception at 200 lx and still others at more than 400 lx [53]), leading to the possibility of testing different algorithms before system implementation. However, considering the papers reviewed, the levels of user satisfaction remained high, each one according to the way they were assessed. Still, it is important to highlight the necessity of being careful to check for signs of unsatisfied users, especially the less tolerant ones. Therefore, it should be possible to avoid boycotts [54,55], high levels of discomfort [50], and users leaving the room due to unpleasant conditions [51]. Regarding this, it is interesting to consider the idea of applying qualitative assessment (surveys, for example) to understand users' expectations and take assertive decisions.

4.3. Is It Possible to Combine Comfort and Energy Savings?

The possibility of associating energy savings with users' comfort is intimately connected to each one's profile, their perception of comfort and needs. Ouf et al. [52] showed that the increase or decrease in energy consumption is intimately related to the control system settings, which depend directly on the user's profile. According to the authors, personalised systems can lead to energy savings if the users are tolerant. Otherwise, sensitive users can induce the system to spend more energy. Nevertheless, in most of the projects that assessed the impact of basing the control system on users' comfort and energy savings, it was verified there was a possibility of achieving both. Still, there may be the necessity of sacrificing one to improve the other [55].

Such a situation highlights the necessity of identifying the conditions in which users feel satisfied and/or what discomforts they are willing to withstand until deciding to act on their environment. Occupants may not be willing to give up comfort to save energy [56], though some of them tolerate small discomforts to avoid the inconvenience of walking to switch on/off the lights [60].

In single-user environments, the energy-saving potential depends, essentially, on the user profile. Therefore, users who are more tolerant and willing to save energy tend to achieve better results. In shared environments, however, the energy-saving potential depends not only on the preferences of each user, but also on the presence of more sensitive users among the others, and on the impact of the differences in their comfort perceptions.

4.4. Research Opportunities

The systematic literature review showed the necessity of making deeper comfort analyses. Most studies that accomplished such assessment, before or after implementing the control system, tried to quantify comfort more objectively, by means of scales. Such analysis is valid, but it does not allow us to clearly identify the systems' strengths and weaknesses. Additionally, one cannot understand the reasons behind the eventual user's discomfort and dissatisfaction, hindering possible improvements. Formulating and applying more qualitative questionnaires, in which occupants can answer openly (such as in Nagy et al. [56]), seems to be a possible solution to the problem. Using questionnaires ahead of the control system's implementation can be helpful in the identification of users' preferences and the choice of technology. The maintenance of comfort in shared spaces also needs attention, especially if there are users with different profiles and preferences. Then, one can check the existence of an algorithm with a higher potential to solve such problems. Furthermore, it may be necessary to find a way to compare algorithms from different approaches.

In terms of the control system itself, one proposal is related to the importance of each variable on the algorithm's performance. Investigating the variables most relevant to both visual and thermal comfort may lead to better results, and allow the reduction of computational costs and data storage. Comparisons such as those made by [36,40,48,50] could be helpful to identify the most influent parameters; also, fewer sensors may be necessary, decreasing the cost of the system. Assessing the ideal period of time to achieve the best performance from the system can also be useful to avoid unnecessary (and maybe noisy) data. At last, but not least, algorithms are not enough. There is an engineering problem that may require changes in the indoor environment to adapt and place technical equipment. Collecting data or implementing possible solutions may create uncomfortable situations. Research on non-intrusive systems is encouraged.

4.5. Future Works

The authors are working on a method to identify the best configuration (in terms of algorithm and number of days) for a control system to identify and update users' preferences in a realistic scenario.

5. Conclusions

This paper reviewed the literature focused on the control systems centred on users' preferences that used machine learning algorithms. The systematic literature review showed that no strategy can be considered efficient by itself. It can also be necessary to balance the initial goal, available technologies and users' expectations in taking project decisions. Regarding the research questions, the main conclusions are:

- It is not possible to affirm that one algorithm performs better than others in all scenarios. However, the most popular algorithms were the supervised classification ones. Despite that, there is no indicative of an analysis step before choosing among the several algorithms using this approach. When such analysis happens, it is based on accuracy comparison. In addition, the criteria for choosing the settings of the control system—based on the variables used herein, users' detection or their preferences identification—were not mentioned. Additionally, an ideal configuration for the control systems was not found among the papers. The assessment of the control systems was focused on users' point of view, energy savings or algorithm evaluation. In terms of accuracy verification, it is important to remember that such an assessment parameter is not the only one. Parameters like precision and recall are equally important to avoid incorrect assessment in case of unbalanced and/or biased datasets.
- The final results indicate that the utilisation of machine learning has accomplished its goal—providing comfortable environments for users according to their own perspectives. However, it is not possible to affirm that one particular specific environmental condition is pleasant to all users. We emphasise the necessity of making deeper comfort analyses, verifying users' comfort sensation, acceptability and satisfaction with the environment, willingness to save energy in detriment to comfort, as well as the perception of control and satisfaction with the operation of the control system.
- All these things can also influence the potential for energy savings associated with the implementation of such systems. Thus, such aspects could be addressed after identifying—or achieving—the comfort condition of the users, aiming to contribute to the sustainability in the building sector.

Furthermore, this article reinforces the importance of observing users' profiles before taking any project decision.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su16104258/s1, Table S1. Synthesis of the main characteristics of occupant-centred systems based on users' preference.

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