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A Review of Thermal Comfort in Primary Schools and Future Challenges in Machine Learning Based Prediction for Children

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Abstract: Children differ from adults in their physiology and cognitive ability. Thus, they are extremely vulnerable to classroom thermal comfort. However, very few reviews on the thermal comfort of primary school students are available. Further, children-focused surveys have not reviewed the state-of-the-art in thermal comfort prediction using machine learning (AI/ML). Consequently, there is a need for discussion on children-specific challenges in AI/ML-based prediction. This article bridges these research gaps. It presents a comprehensive review of thermal comfort studies in primary school classrooms since 1962. It considers both conventional (non-ML) studies and the recent AI/ML studies performed for children, classrooms, and primary students. It also underscores the importance of AI/ML prediction by analyzing adaptive opportunities for children/students in classrooms. Thereafter, a review of AI/ML-based prediction studies is presented. Through an AI/ML case-study, it demonstrates that model performance for children and adults differs markedly. Performance of classification models trained on ASHRAE-II database and a recent primary students' dataset shows a 29% difference in thermal sensation and 86% difference in thermal preference, between adults and children. It then highlights three major children-specific AI/ML challenges, viz., "illogical votes", "multiple comfort metrics", and "extreme class imbalance". Finally, it offers several technical solutions and discusses open problems.

Keywords: thermal comfort; classroom thermal environment; primary school students; machine learning; children thermal comfort; illogical votes; class imbalance

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Citation: Lala, B.; Hagishima, A. A Review of Thermal Comfort in Primary Schools and Future Challenges in Machine Learning Based Prediction for Children. *Buildings* **2022**, *12*, 2007. https://doi.org/10.3390/buildings12112007

Academic Editors: Mengjie Han, Pei Huang and Xingxing Zhang

Received: 30 October 2022
Accepted: 14 November 2022
Published: 17 November 2022

1. Introduction

Students typically spend 15,600 h in classrooms by the time they graduate from high school. The amount of time spent in classes is second only to the amount of time spent at home [1,2]. A significant relationship exists between indoor environment quality (IEQ) of classrooms and student's learning abilities, psycho-social development, problem-solving abilities and health [3]. Poor environments of indoor air temperature, indoor relative humidity, and unacceptable radiant temperature have a negative effect on the academic achievement of students [4]. Thus, it is extremely important to ensure a comfortable thermal environment in schools and classrooms.

Figure 1 illustrates some of the various factors of indoor thermal comfort and their importance for health, well-being, and productivity of occupants. Children aged 6–11 years comprise the most vulnerable student-groups to the classroom IEQ and thermal stress due to several reasons. Their limited cognitive capacities make it difficult for them to gauge how comfortable they are in the classroom and the immediate surroundings. Further, young children tend to have a higher metabolic rate, higher respiratory rates, and thinner skin than secondary school children and adults [5]. They are also often unable to modify the classroom environment or adapt to it, e.g., opening/closing a window [6–8]. As compared to students of higher grades and ages, in the presence of teachers/instructors, primary students are unable to express their thermal discomfort or adapt to changes in the thermal environment [9].

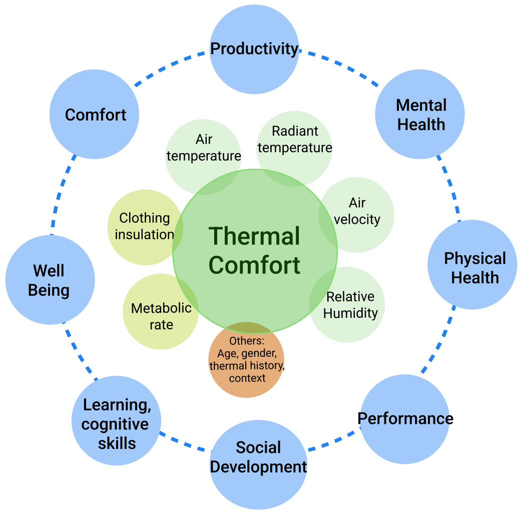

Figure 1. Thermal comfort factors and their effects.

Thus, despite being the principal end-users of the learning space, they often have to passively accept the classroom environments, which are shaped by the teacher's preference. To add to the challenges of school-going children, the international thermal comfort standards for thermal requirements for human occupants in indoor spaces have been prescribed only for adults [10,11]. Thermal Comfort (TC) estimation models, such as the Predicted Mean Vote-Percentage of Dissatisfied (PMV-PPD) model [12] and the adaptive thermal comfort model (ATC) [13,14], are not applicable to children.

1.1. Motivation

Machine Learning (ML) algorithms to predict thermal comfort offer efficient solutions to these research problems. The progress in the field of ML [15,16], and the increase in the affordability of computational resources, has paved the way for ML-based solutions for complex TC problems. ML models perform significantly better than the PMV-PPD model and the ATC models in predicting the subjective TC perception of occupants [17,18]. In addition, ML models can be built and trained for individuals, called Personal Comfort Models (PCM) or groups of people, called Group Comfort Models (GCMs). Encouraged by the prediction capabilities of ML, there has been a significant rise in the amount of TC prediction studies that employ ML algorithms [19–23].

Surprisingly, many ML-based thermal comfort (MLTC) studies have been conducted for adults [17,18,24], yet school-going prediction studies are performed for children or primary school students [25–27]. Given the lower cognitive capabilities, limited opportunities and ability to adapt and express themselves, and the early physiological developmental stage of primary students, their subjective response votes are likely to suffer from data bias and data imbalance. Therefore, predicting thermal comfort of primary school students is shown to be more challenging as compared to adults [25,26].

Due to a limited number of MLTC studies for children, the problems specific to primary students have not been explored. As a consequence of this gap in the literature, the recent comprehensive review articles on MLTC studies have focused only on adults [17,18,24,28,29]. Some survey articles have reviewed a few studies performed in schools but their focus is on aspects of AI/ML application [30,31]. Consequently, the new challenges expected in predictive modeling for children are yet to be addressed. Similarly, the review articles that have surveyed the thermal comfort literature for primary students or children have been unable to consider the application of ML-based prediction [32–39]. Thus, the challenges in ML-based prediction specific to children remain unexplored.

This work bridges the past work on TC estimation of children with the ML-inspired future vision. It combines a comprehensive review of TC studies on primary school students with the challenges expected in ML-based prediction that are specific to children.

To overcome the absence of MLTC studies for children/primary students, it employs an empirical approach. It uses a case-study to highlight the differences between thermal comfort ML models for adults and children.

Therefore, this review paper seeks to analyze the state-of-the art and propose solutions for future challenges to create a comfortable classroom environment for primary school students.

1.2. Contributions and Novelty

Given the motivations and problems discussed above, this paper offers a comprehensive review of key studies on thermal comfort in primary school classrooms conducted over the past 60 years. The major contributions of this work are discussed below, followed by novelty with respect to existing surveys.

1.2.1. Contributions

1. Analysis of 54 important studies spanning 60 years (1962–2022): themes, such as adaptive opportunities of children, comfort temperature, clothing, gender, etc., are analyzed.
2. Adaptive opportunities: primary students' adaptive behaviors are analyzed in relation to their physiological, metabolic, and psycho-social influences.
3. Overview of machine learning for TC prediction: state-of-the-art in ML-based TC prediction is presented by covering themes, such as classification of ML algorithms, distribution and scope of studies, model inputs (features) and objectives, followed by a a brief discussion on TC prediction for children (due to a lack of studies).
4. Three unique children-specific challenges for ML-based prediction: challenges specific to primary school students are highlighted. A comparative case study is performed on ASHRAE-II (adult data) and a recent primary student dataset [25] through Support Vector Machine (SVM) based multi-class classification models. Three challenges are highlighted using model performance metrics (F1-score, accuracy, etc.), confusion matrix, and probability mass functions. They are:
   (a) The challenge of illogical votes;
   (b) The challenge of multiple TC outputs;
   (c) The challenge of extreme class imbalance.

   We also present possible actionable solutions to the three challenges.
5. Open problems: finally, open problems are discussed with a view towards ML-based predictive modeling and analysis.

1.2.2. Novelty vis-a-vis Other Surveys

Table 1 summarizes the comparative analysis of this review article with recent literature surveys of thermal comfort and MLTC studies. The first major contribution of this work is a specialized focus on the thermal comfort of primary school students and young children in general. The review articles in the past [32–35], and the ones published more recently [37,38] have offered meaningful insights on classroom thermal comfort. However, they cover thermal comfort studies completed for occupants of all ages and buildings of all types, and not children and primary students in specific. Only a few review articles such as [37] are dedicated to students/classrooms.

More importantly, the studies on children/primary students reviewed in these articles employ conventionally used non-ML models and techniques.

This becomes highly relevant, given that the direction of thermal comfort research for adult occupants in the last 3 years is towards AI/ML-based prediction and analysis. Several recent surveys have covered the fast-growing body of research on thermal comfort prediction of adults using ML algorithms [17,18,24,28–31]. Further, the usefulness of a case-study based approach in a survey primarily for adults is demonstrated in [40].

Table 1. Comparative analysis of this review article with recent literature surveys.

Author (Year)	Target Group	Number of Studies	Type of Studies	Span (Years)	Children vs. Adults	Case Study Validation	Future AI/ML Challenges	Children Specific AI/ML Solution
Dear et al., 1998 [38]	Mainly Adults	50–80	Non-ML Only	1998–2020	No	No	No	No
Zomorodian et al., 2016 [33]	Children + Adults	45	Non-ML Only	1965–2015	Yes	No	No	No
Lamberti et al., 2021 [37]	Children	143	Non-ML Only	1965–2020	Yes	No	No	No
Yao et al., 2022 [40]	Mainly Adults	≈100	Non-ML Only *	1973-2022	No	Yes *	No	No
Martins et al., 2022 [17]	Adults	37	ML Only	2011–2022	No	No	Yes	No
Fard et al., 2022 [18]	Adults	60	ML Only	2016–2021	No	No	Yes	No
Xie et al., 2022 [24]	Adults	105	ML Only	2010–2020	No	No	Yes	No
Ngarambe et al., 2020 [28]	Adults	37	ML Only	2005–2019	No	No	Yes	No
Ma et al., 2021 [30]	Mainly Adults	45	ML Only	2005–2019	No	No	Yes	No
Han et al., 2019 [31]	Mainly Adults	33	ML Only	1997–2018	No	No	Yes	No
This Article (Lala et. al.)	Children (ML + Non-ML) Adults (ML Only)	54 38	ML + Non-ML	1960–2022	Yes	Yes	Yes	Yes

* Includes statistical techniques, such as linear regression and correlation.

Thus, a survey focusing entirely on children and primary students, which combines state-of-the-art AI/ML solutions with future challenges anticipated in thermal comfort prediction for children, is still needed in research literature.

To the best of our knowledge, this review article is the first step in that direction for children and primary school students.

It covers non-ML TC estimation studies for children over the past 60 years and the recent ML-based TC prediction studies for adults and children. Thereafter, the challenges in TC prediction which are specific to children are highlighted through a comparative case study using SVM for predictive modeling. Finally, practically implementable solutions are proposed for the children-specific thermal comfort prediction challenges.

1.3. Paper Organization

The rest of the paper is structured as follows. The methodology for paper selection is discussed in Section 2 followed by an overview of the approaches to evaluate indoor thermal comfort in Section 3. The analysis of limited adaptive opportunities of students inside classrooms is presented in Section 4. Section 5 explores the state-of-the-art in application of ML algorithms for predictive modeling. Section 6 presents the three major challenges to ML-based prediction for primary students and children, and offers actionable solutions. Finally, the open problems are discussed in Section 7.

2. Methodology

Figure 2 illustrates the process adopted to screen and select the papers reviewed in this work. There have been 54 significant studies on primary school students' thermal comfort in classrooms, performed in various countries are identified from indexed scientific journals and proceedings of major international conferences.

Table 2 presents the selected studies. The geographical location, climatic zone, season, ventilation types, sample sizes, age group, and the range of comfort temperatures determined are listed. The climate zone of each study is categorized according to the Koppen–Geiger classification, i.e., A (tropical), B (dry), C (temperate), and D (continental). Figure 3a shows the percentage of studies completed in each climate classification. In total, 36 among 54 studies were carried out in Koppen Climate Group C, while 13 studies were conducted in regions of Group B. Finally, 4 studies are performed in Group D while there is only one study in Group A. With regard to the geographical distribution of the thermal comfort studies being considered, the majority of the investigations have been carried out in Europe (47%), followed by a few in Asia (33%), Australia (11%), and South America (6%), as seen in Figure 3b. Only one study has been conducted in North America and Africa. It is evident that the distribution of the climate zones where research has been performed is strongly concentrated in the mid-latitude conditions. The distribution of comfort temperature across all Koppen climate, collated from all the reviewed papers is demonstrated in Figure 3c.

The age of students in these studies varies from 6 to 17 years, as illustrated in Figure 4a and the classrooms can be categorized into mechanically ventilated (MV) classrooms, naturally ventilated (NV), and classrooms with mixed-mode ventilation, that combines mechanical cooling systems in addition to a combination of natural ventilation from open windows Figure 4b. Figure 4c shows various approaches, such as PMV-PPD, adaptive thermal comfort methodology, or mixed approach performed by the authors.

Table 2. Statistics on notable thermal comfort studies on primary school students in the past 60 years.

Paper No.	Author	Country	Koopen Climate	Month of Survey/Season	Type of Ventilation	Outdoor Temperature	Age (Years)	Sample Size	Clo Value	Range of Comfort Temperature
1	R D Pepler, 1972 [41]	USA	CSB	April to May, September to October	Mixed	19.8	8-12	372	NA	Spr= 22.4–24.8 °C Aut = 21.7–23.6 °C
2	Auliciems A., 1975 [42]	Australia	CFA	May to August	NV	18	8–11	3481	NA	24–25 °C
3	Humphreys, 1977 [43]	UK	CFB	June and July	NV	19.3	7–9	641	NA	17–23 °C
4	Theodosiou et al., 2008 [44]	Greece	CFA	September to May	MV	NA	NA	NA	NA	NA
5	Zeiler and Boxem, 2009 [45]	Netherlands	CFB	January to March	MV	5	9–10	322	0.97	24 °C
6	Hwang et al., 2009 [46]	Taiwan	CWA	September to January	NV	20	10–11	1614	Sum = 0.3; Win = 0.6	17.6–30 °C
7	Mors et al., 2011 [47]	Netherlands	CFB	Win, Spr, Sum	NV	24	9–11	NA	Sum = 0.3; Win = 0.9	15–25 °C
8	Giuli et al., 2012 [7]	Italy	CSA	April to May	NV	15	9–11	NA	NA	20.5–25.9 °C
9	Shamila Haddad et al., 2012 [6]	Iran	BSK		NV		11–12		0.85	
10	Liang et al., 2012 [48]	Taiwan	CFA	September to February	NV	16 to 30	10–11	1614	NA	Win = 22.4 °C, Sum = 29.2 °C
11	Teli D et al., 2012 [49]	UK	CFB	March to August	NV	10.6 to 16.7	7–11	1300	0.5–0.7	20.6–22.8 °C
12	Teli D et al., 2013 [50]	UK	CFB	April to July	MV	10.6 to 16.7	7–11	1314	0.5	20–24 °C
13	Valeria De Giuli et al., 2012 [7]	Italy	CFA		NV	13 to 17	9–11	614	NA	21–26.4 °C
14	Al-Rashidi et al., 2012 [51]	Kuwait	BWH	March to May	MV	NA	6–10	NA	NA	NA
15	Barrett et al., 2013 [52]	UK	CFB	1 Year	MV	NA	7–11	NA	NA	NA
16	Ahmed Abdeen et al., 2012 [53]	Egypt	BWH	October	NV	28 to 37	NA	NA	NA	25.5–29.5 °C
17	Richard de Dear et al., 2014 [54]	Australia	CFA	Summer	Mixed	NA	10–18	NA	0.36–0.93	22.5 °C
18	Gao et al., 2014 [55]	Denmark	DFB	May to June; November to December	MV	Sum = 2.5 to 30.5; Win = −7.3 to 10.9	10–11	163	NA	NA
19	Teli et al., 2014 [56]	UK	CFB	June to July	MV	10.6 to 16	7–11	NA	0.5–0.7	20.6–22.8 °C
20	Yun et al., 2014 [57]	Korea	DWA	April to June	MV	23.1 to 25.9	4– 6	119	NA	23–26
21	Maureen Trebilcock et al., 2014 [58]	Chile	CSB	August and December	NV	8 to 32	9–10	1389 + 774	NA	Win = 16.7 °C, Sum = 21.1 °C
22	Paraskevi Vivian et al., 2015 [59]	Greece	CSA	April to May	NV	19 to 23	11	665	0.8	18
23	Huang et al., 2015 [60]	Taiwan	CFA	May, June, September and October	NV	24	NA	NA	0.8	26–28 °C
24	De Dear et al., 2015 [54]	Australia	CFA	Sum 2013	NV	22.2	10–11	NA	NA	
25	Barrett et al., 2015 [61]	UK	CFB	2 Years	MV	NA	3–11	NA	NA	
26	Guili et al., 2015 [8]	Italy	CSA	February to June	MV	15	9–11	NA	NA	
27	Nam et al., 2015 [62]	Korea	DWA	June to May	MV	Spr = 15.9 °C; Sum = 27.4 °C; Aut = 12.3; Win = 1.2	4–6	994	0.29–0.81	
28	Huang and Hwang 2016 [60]	Taiwan	CFA	April to June; September to November	MV	15-to 30	9–11	NA		
29	Antonio et al., 2016 [63]	Spain	BSK	October to December	Mixed	12.3 to 19.1	6–7	104	0.32–0.34	
30	Sılay Emir, 2016 [64]	Turkey	CSA	May	MV	27.9 to 31.5	13–15	74	0.48–0.53	
31	Haddad et al., 2017 [65]	Iran	BSK	Aut, Win	MV	27.3	10–11	1605	0.7	22–25 °C
32	Liu et al., 2016 [66]	China	BWH	Nov and Dec	MV		10–11	763		
33	Thi Ho Vi Le et al., 2017 [67]	Vietnam	AW	September–April	NV	26 to 37	8–11	2145	0.55	29.9 °C
34	Dengjia Wang et al.,2016 [68]	China	BWH	November to December	NV	−4 to 10	9–16	1126	1.5–1.7	13.4–14.3 °C
35	Jungsoo Kim et al. 2017 [36]	Australia	CFA	March	Mixed		10–15	4866	0.42–0.51	
36	Martinez-Molina et al., 2017 [63]	Spain	BSK	October to December	MV	16	6–7	NA	0.32 to 0.34	
37	Trebilcock et al., 2017 [69]	Chile	CSB	July to August; November to December	MV	Win = 3.9–14.9 °C; Spr = 13 29.5 °C	9–10	NA	NA	Win = 14.7–15.6 °C; Spr 22.5–23.1 °C
38	Stazi et al., 2017 [70]	Italy	CSA	January 2013, March to April 2015	MV		10–11	NA	NA	
39	Teli et al., 2017 [71]	UK	CFB	2011 to 2015	NV	15.4	NA	NA	NA	22.6 °C
40	Montazami et al., 2017 [72]	UK	CFB	June and July of 2014–15	NV	27	8–11	NA	NA	20–24 °C
41	Sepideh S Korsavi et al., 2018 [73]	UK	CFB	July, September to December	NV	2 to 25	9–11	600	NA	22.56
42	Philomena M. et al., 2018 [74]	Netherlands	CFB	Spr	Mixed	13 to 30	9–12	1311	NA	NA
43	Kim and de Dear, 2018 [36]	Australia	CFA	1 Year (March-March)	NV	21.3	10–15	NA	0.48	NA
44	Aradhana Jindal, 2018 [75]	India	CSA	August–October, January–February	NV	13 to 29	10–16	640	0.47 to 1.72	Win = 19.4 °C; Sum = 29.5 °C
45	Bin Yang et al., 2018 [76]	Sweden	DFB	September–May	Mixed	−9	8–10	150	NA	21 °C
46	Bluyssen et al., 2018 [74]	Netherlands	CFB	April to May	MV	NA	8–12	1145	NA	NA
47	Jing et al., 2018 [77]	China	BWH	November to December		10–20	10–12	30	1.5	15
48	Kim et al., 2018 [36]	Australia	CFA	Sum	Mixed	24.5	10–15	3356	0.42	24.4
49	Haddad et al., 2019 [78]	Iran	BSK	Aut, Win and Spr	Mixed	26.8	10–12	1605	0.7	22–25 °C
50	Korsavi et al., 2020 [9]	UK	CFB	Win and Sum	NV	0.7–25.10	9–11	1390	0.55 to 0.74	20.2–20.9 °C
51	Jing et al., 2020 [79]	China	BSK, BWK	Win	Mixed	−18.9 to 4	9–16	1126	NA	13.0–18.0 °C
52	Fusheng Ma et al., 2020 [80]	China	BWH	December	NV	−5	8–11	141	1.2	17.3–20.1 °C
53	Aparicio-Ruiz et al., 2021 [81]	Spain	BSK	June	NV	35 to 45	10–11	2010	0.29 to 0.32	24–27 °C
54	Rodríguez et al., 2021 [39]	Colombia	CSB	May to June; October to November	NV	15.3	7–16	5338	0.82 to 0.9	NA

Note: Sum = Summer, Win = Winter, Aut = Autumn, Spr = Spring, NV = Naturally Ventilated.

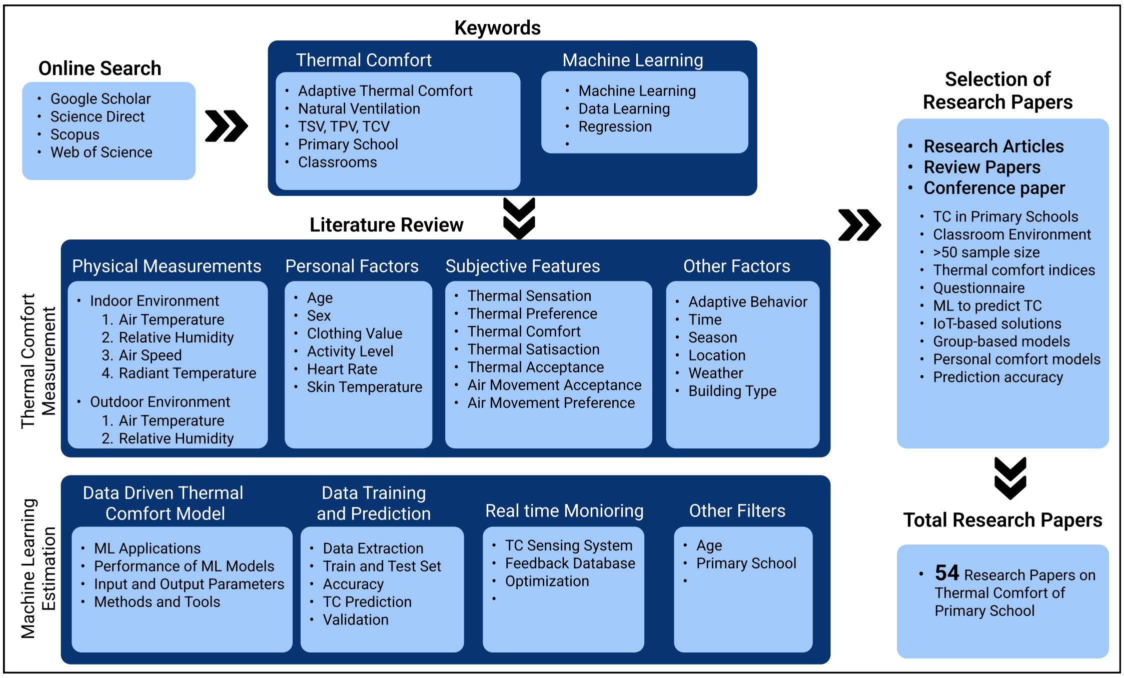

Figure 2. Research paper selection process.

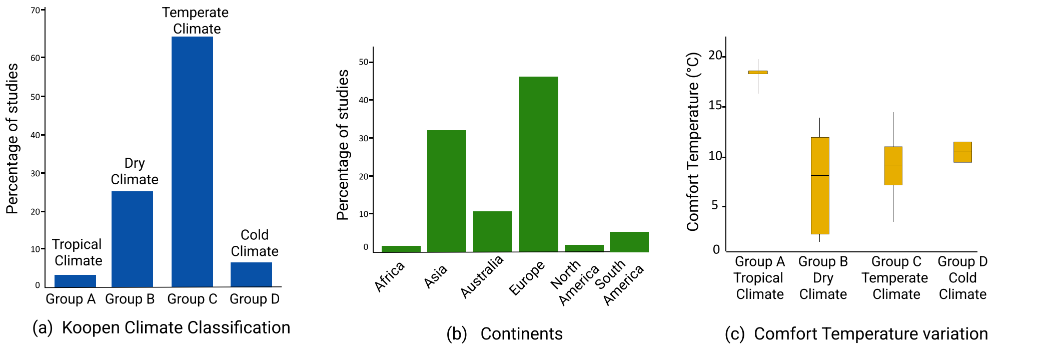

Figure 3. Distribution of studies across (**a**) Climatic regions, (**b**) Continents, and (**c**) Comfort Temperatures.

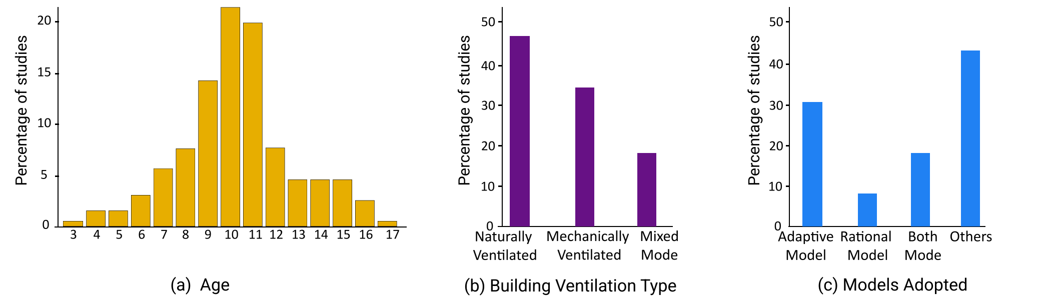

Figure 4. Distribution of studies across (**a**) Age, (**b**) Type of ventilation in buildings, and (**c**) Type of TC models.

3. Evolution of Indoor Thermal Comfort—Estimation and Prediction

3.1. Predicted Mean Vote (PMV)

Fanger [12] developed the Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfaction (PPD), an index to measure thermal comfort, based on human thermo-physiological model. PMV can be quantitatively expressed by a seven-point scale: hot (+3) to neutral (0) to cold (−3). The PPD Index offers a quantitative prediction of the occupants level of dissatisfaction with a certain environment. As a thermal comfort index, PMV-PPD has been incorporated into international standards including ISO 7730, ASHRAE 55, and CEN 15251.

However, research by ASHRAE (RP-884) collected from 21,000 observations worldwide from 160 buildings, concluded that the statistical analysis of thermal sensation, acceptability, and preference, highlighted by the conventional approach of PMV predictions varied from the observed mean thermal sensation. Furthermore, numerous investigations have demonstrated that there is a discrepancy between the thermal prediction by PMV and the actual thermal comfort vote of the occupants [82,83]. Additional factors, such as climatic context, past thermal experiences and present thermal expectations, and preferences of the occupants were also not considered [13], leading to the Adaptive Thermal Comfort Model (ATC) [84].

Studies involving school classrooms have reported the limitations of PPD/PMV as an index to measure thermal comfort. A study in classrooms of Kuwait suggests that PMV under-predicted the students' (age 11–17) actual TSV on the warmer side and over-predicted TSV on the cooler side [85]. In the Netherlands, Hensen et al. [47] compared the actual mean vote of TSV with the calculated PMV and found a mismatch between the PMV and the TSV perceived by students (age 9–11). In their work, Mors et al. [49] observes that, in contrast to adults, children (ages 7 to 11) have a warmer TSV and prefer an indoor thermal environment with lower temperatures. Similarly, in Korea, Yun et al. [57] suggests that students (age 4–6) prefer lower temperatures (3 °C) and have warmer TSV than adults. As a result of this distinction between adults and children, standards derived from subject experiments that focused on adults rather than children may not be deemed appropriate for determining children's thermal comfort.

3.2. Adaptive Thermal Comfort Model

Adaptive Thermal Comfort Model (ATC) is an index that assumes occupants proactively try to improve their thermal sensation depending on their behavioral state, psychological disposition, and personal thermal preferences by controlling the immediate surroundings. Considering that such personal behavioral (changing clothing insulation, metabolic rate) and environmental adaptive behavior (control of fan, windows, shades) is different from adults and children, thermal comfort indices and the applicability of standards ISO7730, ASHRAE 55, and CEN 15251, which are based on adult measurements, have shown the limitation to predict and estimate a child's thermal comfort.

The conventional solutions for thermal comfort estimation of indoor occupants viz., the PMV-PPD model [12] and the Adaptive model [13,14], have a major limitation. They fail to offer high accuracy and reliability in predictive modeling of thermal comfort [17,18]. Consequently, researchers and building administrators have looked towards more advanced mathematical modeling techniques.

3.3. Machine Learning—From Estimation to Prediction

Rapid developments in the paradigm of ML/AI [16], have made it possible to build reliable thermal comfort prediction models utilizing cutting-edge ML models. Many thermal comfort studies have transitioned to using ML techniques in the past five years rather than the conventional approaches, and the findings have been significantly better [17,18,24,28–31].

A high-level schema of AI/ML inspired thermal comfort prediction is presented in Figure 5. Further, ML/AI algorithms can be classified into several categories depending on whether the data are labeled (viz., supervised, un-supervised, etc.), the objective of the ML model (viz., regression, classification, etc.), and the evolution of AI/ML algorithms (viz., traditional, deep, reinforcement, etc.). These algorithms are capable of non-linear mappings of large dimensions, between subjective TC responses of occupants, indoor ambient environment variables, several environmental parameters and predict subjective thermal comfort perception of occupants more accurately than the PMV-PPD and adaptive models. Additionally, ML models can be developed and trained to predict both individual and group thermal comfort, corresponding to Personal Comfort Models (PCM) and Group Comfort Models (GCMs) respectively.

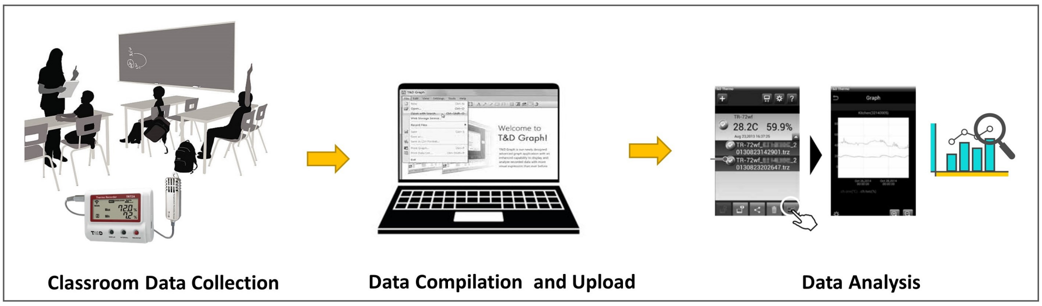

Figure 5. High-level process for machine learning-based prediction.

4. Adaptive Opportunities for Students in Classrooms

The study conducted by Humphreys [43] was the first to suggest that the classrooms can offer a favorable ambient environment to children if they are permitted to adapt to it, and are able to adjust to the indoor temperature. Similarly, several studies [6–8] highlight the limited opportunities of students in their classrooms to adapt to their surroundings. Study by Kim et al. [36], highlights the limited adaptive capabilities of school students, who prefer air-conditioned (AC) classroom environments. Students are also shown to have a greater preference for AC over other adaptive choices for thermo-regulation, such as altering their clothing, opening or closing the windows, changing the fan settings, etc. The study also examined two important aspects, (a) the impact of age or "maturity" and (b) the impact of having experienced an AC classroom. The results show that "older" students have a greater preference for AC classrooms and a greater tendency toward adaptive action such as opening a window and adjusting clothing. Secondly, in AC classrooms, students are less likely to resort to adaptive behaviors. Both these findings are interesting. Although a discussion on aspects of "age" viz., metabolism, cognition, and agreeableness, was not presented, the study demonstrated a clear impact of age on adaptive preference.

Psychological perception of thermal comfort and its effect on the adaptive behavior of primary school students has also been a focus of recent research. For example, in [79], authors show that the psychological acceptance of ambient classroom temperature varied depending on whether students entered the classroom from a cooler or warmer outdoor environment. As a result, when students transitioned from a cooler outdoor space to a classroom, the expected neutral classroom temperature increased by 2.2 °C and 0.6 °C, in heated and non-heated classrooms, respectively. In addition, the study also highlights that the main mode of behavioral adaptation by primary students is clothing modification. However, a recent study carried out in Spain points out that given an opportunity, students prefer to modify the classroom environment (e.g., open/close windows) rather than modify clothing [81].

Further, students' adaptive behavior in heating and non-heating sessions in naturally ventilated classrooms were compared in [9]. Authors found that students tend to have a lower comfort temperature than adults in both heating and non-heating environments, by 1.9 °C and 2.8 °C, respectively. Further, in heating environments, 40% fewer children resort to behavioral adaptation when compared to non-heating environments. Consequently, 80% of the time, environment modification behavior such as opening/closing the windows was carried out by the teacher/instructor.

Another study by Yang et al. [76], conducted in the subarctic climatic region of Sweden explored a more fine-grained 13-point TSV scale, for a more reliable representation of thermal sensation. The major findings include: (a) TSV as an indication of thermal adaptation by children was always higher than PMV; (b) overheating in the classrooms led to behavioral action, such as removal of a clothing; and (c) the 13-point TSV scale yielded slight deviations in thermal neutrality when compared to the 7-point TSV scale. However, a greater number of options in the TSV scale might pose a greater cognitive load on the primary school students, which is likely to confuse them, and intensify the problem of "illogical votes", discussed ahead.

Together, these studies provide important insights into thermal comfort perceptions primary school students. The most frequent finding in both NV and AC classrooms is that applying existing adult-specific thermal comfort benchmarks and clothing values, is not suitable for primary school students [9,36,76,79,81]. Children seem to find the classroom temperature relatively hot and prefer lower temperatures than adults, even in winters [9,76,79–81]. Furthermore, it has been demonstrated that thermo-neutrality, or neutral temperature sensations, is a poor indicator of children's thermal comfort [76,79,81]. Most importantly, the PMV approach to thermal comfort estimation does not seem suitable for primary students, as it is often not aligned with their perceived thermal sensation [36,76,81]. The significance of ML in thermal comfort studies has also been summarized by various researchers [9,76,79,81], highlighting that ML performs substantially more accurately in determining non-linear relationships between independent and dependent variables than conventional regression techniques. Therefore, recent attention has been focused on the applications of ML in TC studies and on establishing the relationship between occupants' comfort and the variables affecting it.

5. Machine Learning for Thermal Comfort Prediction—An Overview

Machine learning techniques are being frequently applied to predict occupant/group thermal comfort or optimize HVAC efficiency, with the aim to achieve maximal accuracy [17,18,24,28–31]. There exists a considerable body of literature on ML and AI for TC that focuses on adults in various settings of environments along with data-driven building performance predictions. However, ML-based predictive models for children or school students are only recently being proposed in research works [25–27].

This section begins with a concise analysis machine learning in thermal comfort (MLTC) works regardless of age of participants or the type of building/indoor space. The recent studies are reviewed on themes such as, classification of ML algorithms, distribution and scope of studies, and ML model parameters and objectives. Thereafter, an analysis of the few MLTC works aimed at children in general, and primary school students in particular, is presented.

5.1. System Architecture

A typical system architecture for ML-based thermal comfort prediction is shown in Figure 6. The first step entails data gathering for relevant features, such as indoor air temperature, indoor relative humidity, clothing insulation levels, and students' thermal comfort perception, among others. These data can also be collected dynamically through an app that can be accessed on the web or on a mobile device. Generally, the data are gathered using paper questionnaire surveys [25,86]. Similarly, weather data can be gathered from the local meteorological office.

Thereafter, in the pre-processing stage, missing information is handled and the data are organized in a format appropriate for further analysis. The third step involves the design, development, and training of ML model to accurately predict occupants' TSV, TPV, TCV, and other metrics. Additionally, this module can also identify the best model parameters or the most important features. Finally, the trained model is stored for future use. New data gathered at any time can be used to assess the thermal comfort of an occupant by feeding the inputs to the trained model.

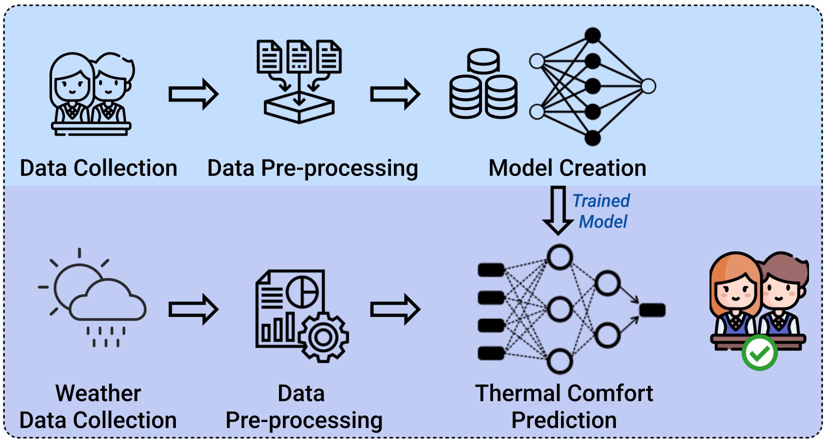

Figure 6. System architecture for machine learning-based TC prediction.

5.2. Classification of ML Algorithms

Machine learning algorithms can be typically be classified into two broad categories described below.

5.2.1. Traditional ML Algorithms

Several conventional ML algorithms have been used to model personal or group thermal comfort problems. The most commonly used traditional algorithms include: (a) the family of linear and non-linear regression algorithms [87–93], (b) Decision Trees (DT) and Random Forests (RF) [87,89,94–96], (c) Support Vector Machine (SVM) [23,87,95,97–101], and (d) K-Nearest Neighbors (KNN) [87,91,102–106]. The less commonly used ML techniques include Bayesian Models (BM) [87,107], Ensemble Learning (ENL) [87,88,97], Gaussian Models (GM) [108], Markov Models (MM) [88], Fuzzy classification [109,110], and Genetic Programming [111].

However, the traditional ML algorithms, whether supervised or unsupervised require domain expertise for feature identification and pattern recognition. Further, algorithms such as SVM first solve parts of the problem and then combine the results at a later stage, e.g., object detection through SVM. Moreover, to solve TC problems, such as ensuring optimal HVAC efficiency in a building, the ML algorithm should have a feedback mechanism built in to the model [112,113]. As a result, traditional ML algorithms are not suitable for complex problems, such as multi-task learning [25], where an end-to-end solution is required for simultaneous learning of multiple outputs.

5.2.2. Advanced ML Algorithms

The challenges highlighted above paved the way for the development of more advanced ML algorithms, such as the family of neural network (NN) algorithms, deep learning (DL), and reinforcement learning (RL). Neural Networks can be deep or shallow depending on the number of layers in the ML model. Shallow NN algorithms, such as Artificial Neural Networks [87,93,97,105,106,114–116] and Bayesian Neural Networks [117], are increasingly being applied to TC modeling and prediction. Deep learning represents a problem through a nested hierarchy or hidden layers of interconnected neural networks through which abstract categories can be computed from less abstract ones [15]. Thus, DL algorithms offer a powerful and flexible end-to-end solution that is learned incrementally by its hidden layer architecture. Recent studies have applied DL algorithms to improve the accuracy of TC-related problems [92,118].

Reinforcement learning (RL) is a feedback-based technique that is applied to systems where a reward signal or desired action needs to be maximized [16]. Studies which seek to optimize HVAC control to ensure occupant thermal comfort often use RL or a model-free RL known as Q-learning [22,99,112,113,119]. DL further enhances the capabilities of these techniques in training highly intelligent agents through approaches, such as deep reinforcement learning (DRL) [113,120] and deep Q learning (DQL) [119].

DL is typically better suited for accurate multi-task learning [121]. First, DL algorithms have the capability to learn non-linear features better than traditional ML models [122]. Second, joint task learning results in better generalization performance only if the tasks are related. Often, assumptions made in task associations may lead to performance degradation, due to the phenomenon known as *negative transfer* [123]. DL overcomes this problem as layer-sharing of multi-task networks enables it to learn shared representations from interrelated tasks more effectively. [124].

5.3. Distribution and Scope of MLTC Studies

5.3.1. Climatic Regions and Building Types

Most recent MLTC studies (>50%) are performed in hot and humid climates [17]. The other most studied regions are Europe and North America (≈25% of studies) [18]. Very few studies, if any, have been conducted in the most populous regions, such as Africa and the South Asian subcontinent. It is noteworthy that ASHRAE II database does not feature any study conducted in NV classrooms in India [125].

A severe imbalance can also be seen in a climate-specific distribution of ML-based studies, with twice as many studies performed for the summer season than in winters [17,18]. Further, only a small fraction of MLTC studies (around 1/6th) are performed in NV spaces [17]. Natural ventilation adds greater complexity to TC prediction as the immediate ambient environment of occupants is likely to differ depending upon the factors, such as proximity to doors and windows, penetration of sunlight, layout, etc.

5.3.2. Personal vs. Group Thermal Comfort Models

Machine learning algorithms can be designed to predict thermal comfort of individuals or group of occupant groups. Models focused on individuals are called Personal Comfort Models (PCM) while group-centric ML models are referred to as Group Comfort Models (GCM). In general, PCMs [22,23,126] gather personalized data through sensors and Internet of Things (IoT) devices. These models are relatively easier to train and offer high accuracy as they have to contend with the subjective preference of only one occupant. In contrast, GCMs have to learn the subjective preferences of all occupants to make predictions, and lack the high accuracy and reliability of PCMs [19–21]. However, GCMs are more feasible and scalable for implementation in shared/public indoors spaces, such as classrooms, offices, *etc.* Given the desirability of GCMS and the challenges involved in achieving high accuracy, the focus of recent MLTC studies is on group-based predictive modeling [18]. Studies often utilize the ASHRAE Databses I and II [125,127] to validate GCMs designed using state-of-the-art ML models [99,128].

Consequently, recent comprehensive surveys [17,18] on the state-of-art of ML applications in thermal comfort studies suggest that future TC studies ought to focus on:

1. Unexplored geographical and climatic regions.
2. Seasons other than summer.
3. Built environments with natural ventilation.
4. Achieving high accuracy for group-based models.

5.4. Input Parameters, Objectives, and Outputs

Most MLTC works take into account features or parameters that are a combination of measurements of the indoor and outdoor environments, as well as individual features. These aspects are discussed ahead in detail.

5.4.1. Choosing Features for Prediction Models

To select suitable model “features” (input parameters), most MLTC works tend to focus on indoor environmental parameters (e.g., indoor temperature, relative humidity) as compared to outdoor parameters (e.g., daily rainfall). This approach is suited for thermally controlled built structures [18]. However, for NV environments, outdoor environmental parameters can also affect thermal perception as past research on adaptive thermal comfort has revealed [18,19]. The input parameters used in MLTC studies include outdoor and indoor temperature, personal parameters (clothing and metabolism), behavioral parameters with regard to controlling HVAC systems, CO_2 concentration, etc. [18]. Figure 7a illustrates the percentage of input parameters used in MLTC studies. Architectural and building parameters were elucidated in only 2 studies [118,129].

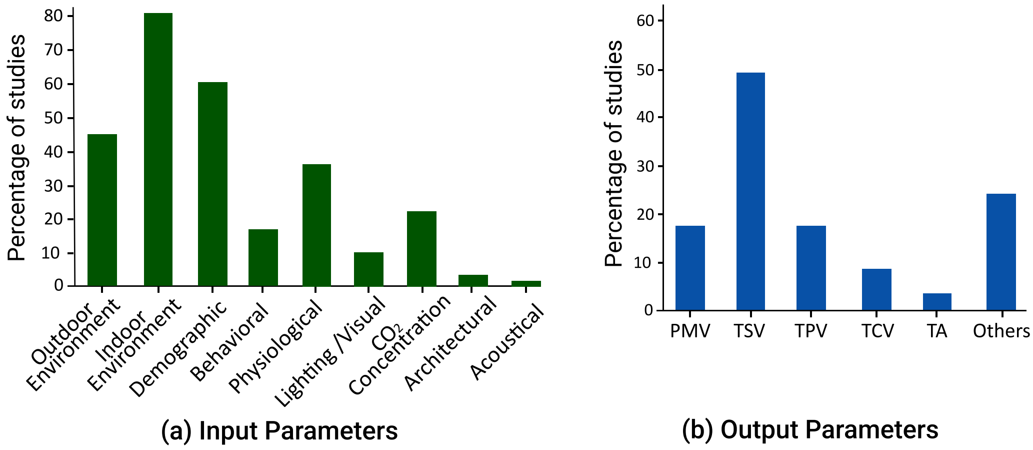

Figure 7. Distribution of (**a**) Input Parameters (Features) and (**b**) Output Parameters (Labels) of MLTC studies.

5.4.2. Model Outputs for TC Prediction

The choice of appropriate model outputs is crucial to quantify the subjective perception of the occupants. Thus, multiple TC output metrics have been used for different contexts, viz., thermal sensation, comfort level, desire for change in the environment, etc. The popularly used TC outputs, e.g., PMV, TSV, TPV, TCV, TA, etc., are presented in Figure 7b.

Analysis of ASHRAE I and II databases reveals that in conventional (Non-ML) TC estimation and prediction solutions, the three most popular subjective metrics used to quantify thermal comfort are TSV, TPV, and TCV [125,127]. Our analysis of 54 research papers revealed that TSV is employed as the sole or primary output in nearly 50% of MLTC studies and that TPV is used in 12% of the research. In other MLTC studies (Figure 7b), TSV is considered to be the main model output on which prediction accuracy is measured [19–21,128]. TPV and PMV are the next most popular output/label, and TCV is also considered in a few studies [87,98,107,130]. Other output parameters include energy consumption [131], occupant behavior [93,132], etc.

5.5. TC Prediction for Children

Studies and literature reviews that address the importance of MLTC assessment and prediction, focus entirely on adults. To the best of our knowledge, only a handful of articles have leveraged AI-ML algorithms to develop TC prediction models for children or primary school students. A few recent studies that hold relevance are discussed below.

The authors Chemingui et al. [133] propose a deep reinforcement learning agent to regulate indoor environmental conditions in a school building while enhancing thermal comfort, and minimizing energy consumption. Likewise, using artificial neural network (ANN) based on an integrated model, authors Cho et al. [134] and, Duran et al. [135] could predict PMV, concentrations of carbon dioxide (CO_2) and estimate heating energy demand and indoor overheating degree, respectively.

In another work, authors Jiang et al. [77] investigated the impact of students' thermal comfort on their learning outcomes, using supervised learning methods, such as regression. However, R-squared is a measure of feature relationship strength and is insufficient for the predictive modeling of the metrics taken into consideration in the study, namely TSV, TCV, and TA, which call for multi-class classification solutions.

More recently, a few studies have leveraged state-of-the-art AI/ML algorithms to investigate several aspects that affect TC perception of students in a classroom. A recent work employs *Multi-task Learning* for TC prediction in naturally ventilated buildings [25]. It analyzes the dataset gathered through a TC questionnaire-and-measurement conducted in the composite climate of India, in 14 NV classrooms of 5 schools, involving 512 primary school students. The work proposes a DNN-based multi-task Learning model called "DeepComfort". which predicts multiple TC output metrics viz., TSV, TPV, and TCV, simultaneously through a single model. In another study the effect of temporal variability on primary school children's comfort is shown through a "time of day" analysis in [27]. The study demonstrates temporal variability through variances of up to 80% in deep learning model prediction accuracy. Likewise, in [26], the impact of building environment on student comfort in NV buildings is demonstrated through a 71% variation in prediction accuracy and feature importance. The study also evaluates the generalization capability of TC models in naturally ventilated classrooms to test the feasibility of "train once deploy anywhere" models.

However, the number of AI/ML studies for children is still limited. Based on the analysis presented in this work, we infer several reasons as to why MLTC studies are not focused on children. These are discussed in the next section.

6. Challenges in Thermal Comfort Prediction for Children

A benchmark for MLTC works is the predictive performance of the models in terms of metrics, such as ML model accuracy, F1-scores, precision, recall, and area under the curve (AUC) in receiver operating characteristics plots. Due to the subjective phenomenon of thermal comfort perception, ML models are not always accurate and highly context-specific. For example, a model that demonstrates high accuracy in a naturally ventilated building may not be suitable for a HVAC-equipped building. As a consequence, the accuracy of resulting models can vary from as low as 15% to as high as 94% [18]. Model accuracies in the range of 60–80% are most commonly observed in MLTC works [17,18].

For children however, the subjective aspects of TC play a more central role. Primary school students possess limited cognitive ability to perceive the physical environment, assess the opportunities available to adapt to the environment, and seek help by expressing discomfort [136]. Students often have limited adaptive capacity and lack the authority to modify the classroom environment by taking actions. Thus, they can rarely operate windows, doors, and ventilators; alter the speed of fan; modify personal clothing; or adjust classroom temperature [6–8]. This applies even more to primary school students, who have little or no say in controlling the classroom environment, and silently accept the thermal environment, regardless of whether they perceive it as comfortable [6–8].

These factors translate into additional challenges which further lower the accuracy of TC prediction models. Since, no existing study has explored these problems, their impact is demonstrated through a case-study described ahead in detail.

6.1. Case Study on ASHRAE-II and Primary Student Data

This section highlights three major challenges that will be encountered when developing prediction models for primary school students, viz., (a) greater volume of illogical votes, (b) variability across multiple thermal comfort metrics, and (c) extreme class imbalance. To demonstrate the impact of these challenges a case-study is performed on three thermal comfort datasets using a popular ML algorithm. The details are described ahead.

6.1.1. Datasets Considered

The case-study considers the ASHRAE-II database [125] and the primary student dataset gathered from 14 NV classrooms [25]. For similarity of context, ASHRAE-II data for adults ($\text{ASHRAE}_{\text{Adult}}$) is considered for NV buildings. ASHRAE-II data for children

($ASHRAE_{Under14}$) in the primary student age-group, i.e., under the age of 14 is very limited (<250 samples). Apart from a small sample size, it suffers from two more problems. First, it lacks distribution across all classes, e.g., it has $\geq$5 samples each for only 4 values on the TSV scale and 3 values on the TPV scale. Second, it does not have any data for the thermal comfort perception of primary students, i.e., no TCV values. Thus, the primary student dataset ($Primary_{Data}$) consisting of 2038 samples gathered from 512 primary students is considered for the case-study analysis [25]. In terms of features, thermal comfort metrics (labels), and sample size, the primary student dataset taken into consideration in the case study is currently the largest for children aged 6 to 13.

6.1.2. Methodology

The case-study is conducted through TC prediction models created using the Support Vector Machine [137] algorithm. The SVM algorithm is used because it is effective for smaller datasets with many features and helps manage overfitting concerns. Due to its ability to handle small, complex datasets, it also provides results that are more accurate when compared to other algorithms. For both datasets, thermal comfort of the occupants is predicted by considering TSV, TPV, TCV, and TA as the model outputs. SVM model performance for adult data is compared to that of primary school student data on four model parameters viz., accuracy, macro F1-score, precision, and recall. Further, wherever necessary confusion matrix is presented to demonstrate the ability of the classifier to learn minority class labels.

Problem Formulation: Let the occupant's TC dataset be represented by $\mathcal{D} : \{(x_i, y_i)\}_{i=1}^{N}$, where N denotes the number of samples and the number of classes in the dataset is given by $\mathcal{L}$. Further, $x_i \in \mathbb{Z}^d$ denotes the feature vector which comprises of a variety of input parameters from the datasets. These include continuous features, such as temperature, relative humidity, etc., and discrete or categorical features, such as gender, school-type, etc. Likewise, $y_i \in \{0,1\}^{\mathcal{L}}$ denotes the label vector for the ith sample, which comprise of TSV, TPV, or TCV.

For each dataset, the model tries to solve a binary classification optimization problem formulated as:

$$\arg\min_{w,b} \frac{1}{2} w^\top w + C \sum_{i=1}^{N} \zeta_i \text{s.t.} y_i (w^\top \phi(x_i) + b) \& \geq 1 - \zeta_i, \forall i \zeta_i \& \geq 0, \forall i \quad (1)$$

where y_i assumes the value "+1" if the label is assigned to ith instance, else it y_i "-1". Further, the weight vector is denoted by $w \in \mathbb{R}^d$ and the bias is denoted by b. C is a hyperparameter which is set through cross-validation. L2 regularization is used to ensure improved generalization ability and reduced overfitting in the model. It is controlled by the hyperparameter C.

Since TC prediction may require the model to learn non-linear mappings, class boundaries are learned through both linear and non-linear kernels viz., polynomial kernels (degree = 2, 3) and radial bias function (RBF). They are controlled by the kernel function ϕ. Since, Finally, TC prediction is multi-class classification problem. Therefore, once Equation (1), solves the binary-classification, one-vs-rest strategy is employed to transform it into a multi-class problem. Further, for proportional representation of minority-class samples in the train and test datasets, stratified sampling is considered. The results are averaged over 5 train-test splits in the ratio of 80:20.

6.2. The Challenge of Illogical Votes

The first challenge is the presence of high number of illogical votes in the primary student data. Since, the ASHRAE-II database [125] has insufficient samples, a distribution of $Primary_{Data}$ [25] is presented in Figure 8.

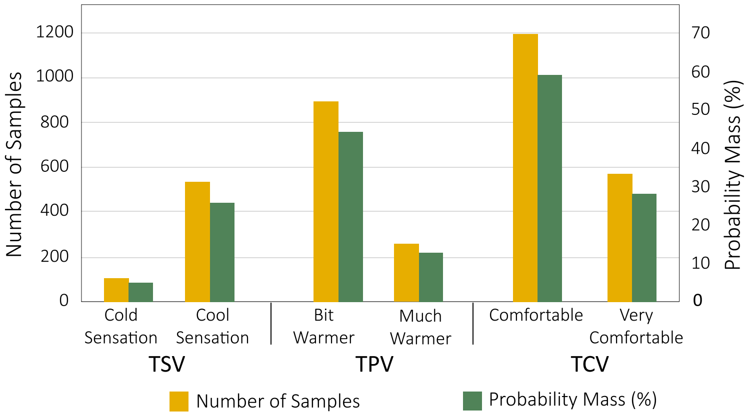

Figure 8. Illogical votes in student data.

Close to 31.7% students responded to feeling "Cool" or "Cold", while 56.96% students expressed the preference for a "Warmer" or "Much Warmer" classroom. Any classifier model will find it difficult to account for this incongruence in the distribution of the two comfort labels for the same set of input features. What is more surprising is that over over 88% students responded to feeling comfortable. This mismatch in student thermal response votes is known as the problem of "illogical votes" [130] and is known to make the task of TC prediction for primary students extremely challenging. Since it is actual participant data, it can not be considered to be noise or outlier and removed in the data sanitization. Doing so may lead to high-accuracy prediction models, but they will be useless in real-world implementations.

The impact of illogical votes can be seen in the prediction performance of SVM for $\text{ASHRAE}_{\text{Adult}}$), $\text{ASHRAE}_{\text{Under14}}$, and $\text{Primary}_{\text{Data}}$ presented in Figure 9.

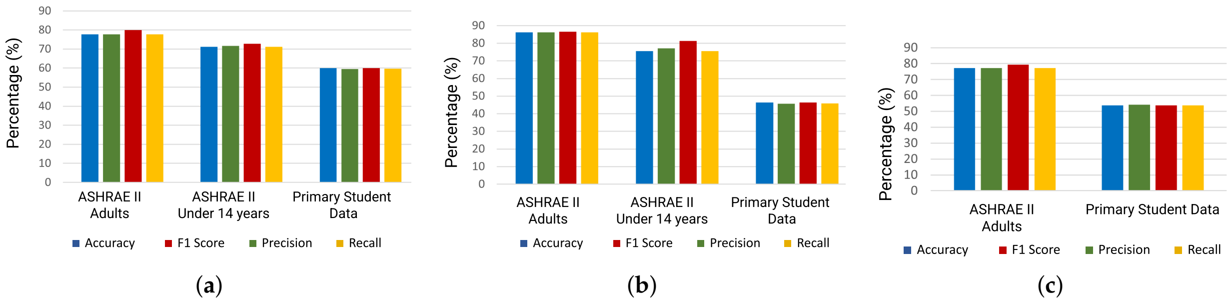

Figure 9. Prediction performance for adults and primary school students; (**a**) Thermal Sensation Vote; (**b**) Thermal Preference Vote; and (**c**) Thermal Comfort Vote.

The models for TSV, TPV, and TCV for adult data offer best performance in terms of all four parameters, with prediction accuracy as high as 86.17% for TPV. In contrast, SVM prediction models for $\text{ASHRAE}_{\text{Under14}}$, perform worse, for both TSV and TPV. However, for $\text{Primary}_{\text{Data}}$, the performance of all three prediction models is very poor, with accuracy as low as 46.32% for TPV.

These results demonstrate the presence of illogical votes causes data bias, that in turn leads to poor prediction performance.

6.3. The Challenge of Multiple TC Outputs

MLTC studies analyze the TC perception of occupants through one or more TC metrics (inputs) and propose predictive solutions formulated as binary or multi-class classification problems. For instance, TSV and TCV are applied in [19,95]; TSV, Effective temperature (ET), and Standard Effective temperature (SET) are used in [138], and TSV, TPV, TCV, and TA are used in [130]. However, even when studies consider "multiple" TC outputs, the proposed ML models are not "multi-output." The predictive solutions employ Single-task Learning (STL), resulting in *one ML model per output*. Therefore, every TC output metric, e.g., TSV, TPV, or TCV, has an independent ML model specifically designed for it.

The STL approach suffers from several problems when employed in the TC prediction [25]. For example, keeping track of the features and optimal model specifications (e.g., hyperparameters) of each TC output metric is impractical [17,25]. However from the perspective of primary school students, the challenges become more severe. Because of their limited ability to assess, evaluate, and express themselves, there is a lot of variation in the prediction performance of STL models for different TC output metrics.

In Figure 9, it is evident that there is a lot of variability in the model accuracies for TSV, TPV, and TCV, for $\text{Primary}_{\text{Data}}$. Further, it appears to be easy for children to assess their TSV, i.e., they are able to evaluate how they feel. However, they seem to have a limited ability to express their TPV and TCV. This can be discerned from Figure 9, that prediction accuracy for TSV are greater than TPV and TCV, for $\text{Primary}_{\text{Data}}$. TPV, in particular, seems to be a difficult parameter for children to understand, evaluate, and rate. This is evident from the low prediction accuracy of just 46.32%.

In contrast, adults seem to be fairly capable of assessing their environment and comfort levels. In fact, the SVM prediction model performs the best for TPV, implying that adults can express their thermal preference, i.e., warmer, same, or cooler environment, with high confidence. Moreover, use of multiple TC metrics is suitable to capture different aspects of thermal comfort for adult occupants.

However, using multiple TC metrics does not seem suitable for primary school students. Instead of enriching the qualitative understanding of children's thermal comfort perception by offering a multi-dimensional view, use of multiple TC metrics appears to be confusing children. Of the three metrics, TSV seems the most reliable, indicating that children are able to assess how they feel with greater confidence, than TPV and TCV.

6.4. The Challenge of Extreme Class Imbalance

An extreme class imbalance can also be observed in primary student data, as shown in Figure 10. Most real-world datasets have majority and minority classes, leading to a problem of imbalanced classification. Typical solutions include undersampling the majority class and weighted classification, with some success. Since SVM algorithms are typically not designed to handle extremely imbalanced classification, it is ideal to highlight this problem for thermal comfort datasets of primary school students.

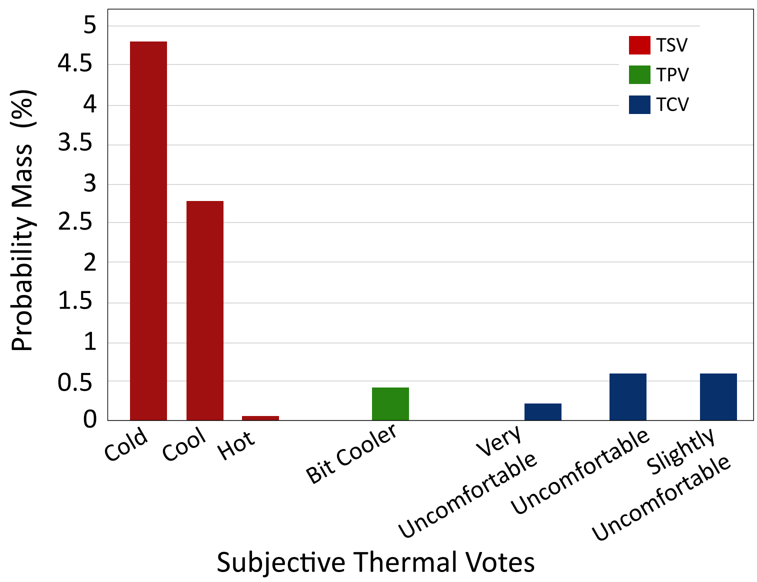

Figure 10. Class imbalance in primary student data.

The confusion matrix for $\text{ASHRAE}_{\text{Adult}}$ and $\text{Primary}_{\text{Data}}$, for models predicting TSV, is presented in Figures 11 and 12, respectively. TSV labels "−3" (Very Cold), "2" (Hot), "1" (Warm), and "3" (Very Hot), belong to minority classes for the adult dataset. Despite the imbalance, labels have been classified with decent accuracy. This is true even for extreme imbalance in minority classes "1" (Warm), and "3" (Very Hot). Contrast this with Figure 12, where classifier performance for extremely imbalanced classes "−2" (Cold) and "1" (Warm) is very poor, with high misclassification rates.

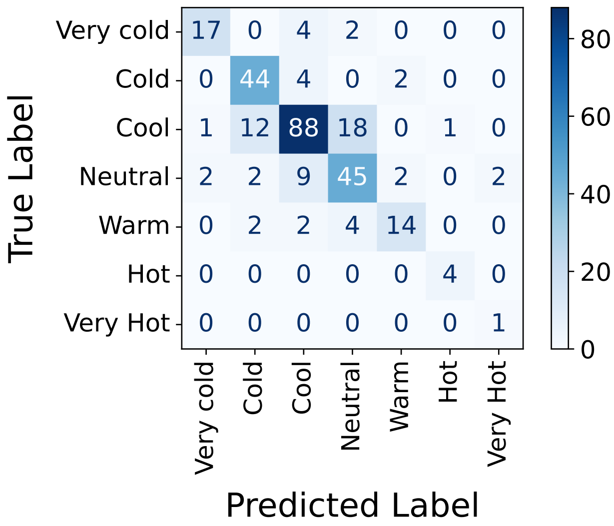

Figure 11. Confusion matrix for adult data.

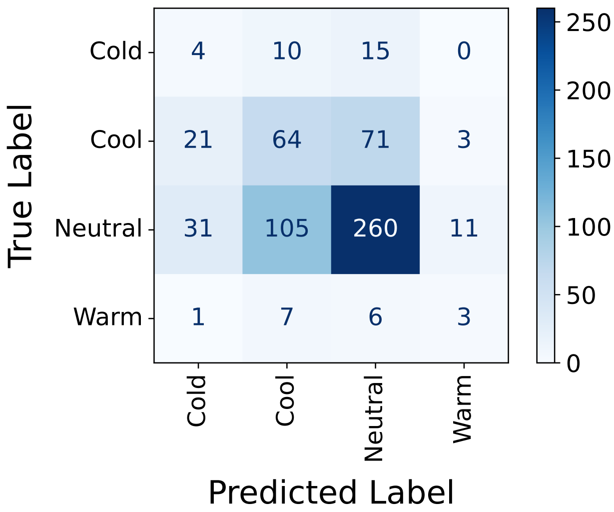

Figure 12. Confusion matrix for student data.

Thus, as compared to adult data, primary student data seems highly vulnerable to extreme class imbalance. This can be attributed to the presence of illogical votes, that confuse the classifier, leading to high number of incorrect classifications.

Multi-class imbalance can lead to misleading results, e.g., overall high-accuracy and macro F1-score, but extremely poor minority class performance. It can also impact the generalization ability, especially in multi-minority scenario viz., one majority class and multiple minority classes and multi-majority scenario viz., one minority and multiple majority classes [139].

Please note that, imbalance classification in itself is a problem that is largely unaddressed in MLTC works. This was experienced during literature review for this survey, and has been reported by other recent surveys on MLTC works too [17,18]. Most MLTC works focus on model performance in terms of accuracy, F1-score, precision, recall, confusion matrix, and AUC for ROC curves, which could actually be majority class performance. A study that discusses minority class performance in detail, has not come to the author's attention.

6.5. Probable Solutions to the AI/ML Challenges for Children

The challenges outline above can be addressed up to a great extent through one or more solutions prescribed below.

1. A familiar "frame of reference" in survey questions: since primary school students have limited cognitive ability to asses their environments, surveys can suggest a frame of reference. For example, with respect to the question regarding comfort levels or TCV in [25], a hint as to how comfortable the students feel in the classrooms as compared to their homes, would have ensured fewer illogical votes.
2. Fewer TC Metrics: children appear to be having a difficulty in expressing thermal preference, i.e., warmer or cooler classroom, and evaluating their comfort levels. However, they are able to assess and express the sensations that they feel. Thus, using fewer metrics, for example, only thermal sensation, might help reduce confusion.
3. Simpler TC Metrics: since multi-value TC metrics such as TCV may prove difficult for primary school students, binary (Yes/No) metrics, such as thermal acceptability may be beneficial.
4. Reclassification Strategies for TC Metrics: TC metric scales can be reclassified to address the challenge of extreme class imbalance. It can also make the task of comfort assessment less cognitively challenging for students. A distribution of different scales for popular TC metrics used in studies for adults is presented in Figure 13.

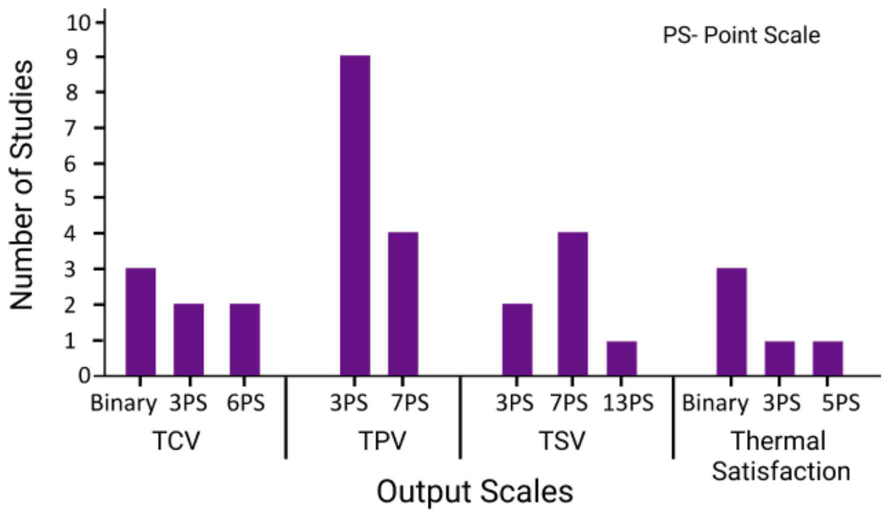

Figure 13. Reclassification strategies in MLTC works for adults.

Two strategies can be adopted for reclassification for children: (a) a simpler TC metric scale with fewer metric (comfort, sensation, etc.) categories, or (b) fine-grained TC metric scale with a greater number of precise metric categories. For example, a 13-point TSV scale is proposed for school students in [76]. From the perspective of multi-class classification, both strategies will be useful for specific contexts. For large scale studies, with the goal to solicit thousands of thousands of subjective responses, greater number of fine-grained metric categories (classes) are desirable. This will ensure enough data for each class to learn the classifier on.

However, for medium and small scale field surveys, where the expected number of data samples is low, a simplified scale will yield more robust prediction models. Binarization of TC metrics can also be considered through a suitable threshold so long as it is not reductionist. A possible reclassification scheme of the TCV scale for children is shown in Figure 14.

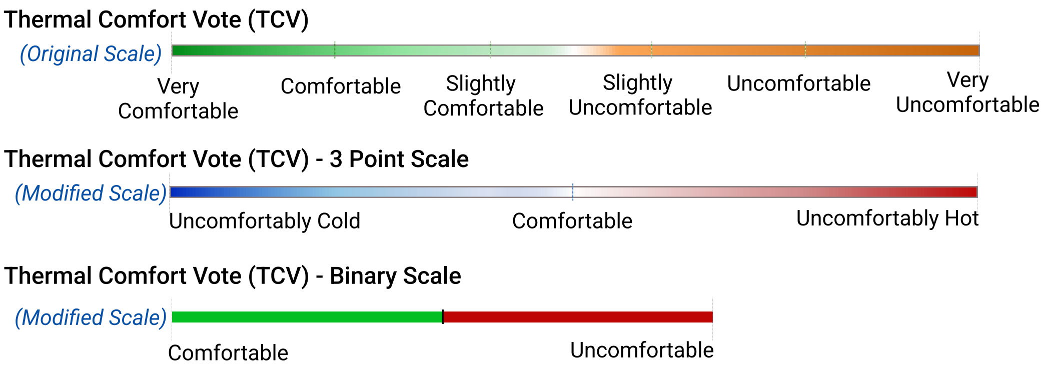

Figure 14. Example of reclassification of TCV metric.

5. Identification of Most Relevant TC Metrics: before embarking on a large-scale TC study for children, a pilot can be conducted to gather responses through which the most important TC metrics can be identified through correlation and feature relationship analysis. If possible, a single TC metric or a subset of TC metrics, that can be used to predict all other metrics in the study, should be identified. Wang et al. have demonstrated the utility of this approach on ASHARE II database [130]. However, as shown in the case-study, given the greater number of illogical votes, it needs to be explored if the solution works well with datasets for children as well.
6. Multi-task Learning (MTL): a more technically robust solution to overcome the challenges of multiple TC metrics, is to adopt a "common-input–multiple-output" approach. This paradigm is known as multi-task learning (MTL), as shown in Figure 15, and it typically employs deep learning [25] and/or reinforcement learning [112]. In particular, deep neural network enabled MTL systems have proven to be reliable for children with high generalization capabilities [25].

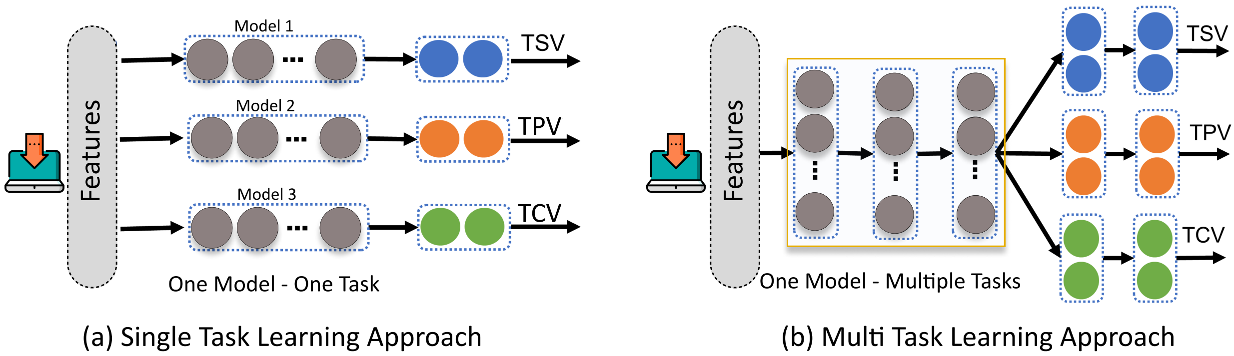

Figure 15. Single task vs. Multi-task learning.

7. ML Techniques for Class Imbalance: given the inherent class imbalance in the current primary students' dataset, ML techniques for multi-class imbalance must be considered. Methods such as multi-class decomposition, oversampling the minority class(es), undersampling the majority class(es), data augmentation of the minority class(es), weighted classification, multi-label and multi-instance classification, etc., can be considered [139,140].

7. Thermal Comfort in Classrooms: Open Problems

Having discussed and analyzed the current state of research in classroom thermal comfort, let us now look at the open problems that need to be addressed. Assessment of thermal comfort in a classroom is a complex problem that requires multivariate analyses involving multiple factors that may affect the educational and health outcomes of students. Despite its complexity, there has been a limited research and as a result, several major challenges and problems remain open that will shape the future direction of research in the domain. The prominent open problems in achieving thermal comfort in primary school classrooms are listed as follows:

- **Lack of studies in tropical regions**: most studies are conducted in Europe and the UK, particularly in countries falling in the temperate regions (mid-latitude regions), while there is very limited literature on thermal comfort in the primary school environment in tropical climate regions. This conspicuous lack of focus on tropical zones needs to be addressed as these regions are the most populous and with the youngest demographics. For example, in India, one-third of the population (400 million) is under 14 years of age, yet, the number of studies on thermal comfort in Indian schools is very limited [25,86].
- **Understanding risk of heat stress**: considering that subtropical and tropical countries experience high climatic temperatures, excessive exposure to heat remains a significant issue for health-related impact and comfort criteria. With rising global temperatures, the risk of heat stress that occurs among children in high-temperature environments is a concern that needs to be addressed.
- **Studying the impact of time-of-day on thermal comfort prediction**: international standards assume indoor TC to be constant throughout the day [141]. Recently, the importance of temporal aspects, such as circadian rhythm, "time of day", and variation in outdoor temperature, has been demonstrated [27,141]. In addition to occupant well-being, temporal variability is also important from the perspective of energy budget and sustainable living. However, in the current AI/ML-based TC research, the temporal variables are not considered.
- **Reliable thermal comfort prediction in naturally ventilated classrooms**: ML-based thermal comfort prediction solutions are proposed for HVAC-enabled buildings. However, the majority of schools and classrooms in the developing world are naturally ventilated (>97% in India). Although NV schools are ideal for energy conservation and long-term sustainability, due to the lack of thermal regulation through HVACs, they tend to be vulnerable to outdoor weather conditions and building designs, making TC prediction extremely challenging. Only a handful of AI/ML studies have focused on NV buildings, and the prediction performance is generally inadequate [26]. Thus, improved prediction models specifically for NV classrooms are required.
- **Standardization of children-specific thermal comfort metrics**: a recent TC prediction study for adults had sought to identify "ideal" TC metrics that can be used to determine other comfort perceptions [130]. This is desirable as it will do away with the problem of multiple-models and contradictory predictions for different TC metrics [25]. Similar studies are needed for students and children, as data distributions and AI/ML prediction performance for children are quite different from those of adults.
- **Comprehensive long-term evaluation of thermal comfort in classrooms**: longitudinal studies are needed to determine the effect of the classroom environment on students academic performance. The current body of work relies on the survey-and-questionnaire approach. It is limited to studying the short-term impact of the classroom environment. This is not a statistically sound approach, as a variety of factors influence the performance of students, which can only be identified and isolated when the scale of studies is enhanced in terms of student sample size, duration of analysis, benchmarks of evaluation, viz., class tests, exams, and extracurricular activities.
  Further, there exists a lack of studies that determine whether a statistically significant association holds between the ambient classroom environment and the learning skills

of primary school students. Further, it remains to be seen if causality between them holds true.

- **Optimizing thermal comfort while minimizing energy consumption in classrooms**: given the carbon emission reduction targets to prevent global warming and combat climate change, this is a major open problem. Energy sustainability must be achieved in schools and classrooms. Thus, the 'need' to mechanically condition school buildings to provide the best learning environment must be investigated through evidence.

8. Conclusions

This article presented a comprehensive review of thermal comfort studies for children in general and primary school students in specific. It reviewed both non-ML and ML thermal comfort studies for primary school students, going as far back as 1962. Through a discussion of comfort temperature, clothing values, and adaptive opportunities for children in earlier studies, it underscores the need for the application of AI/ML in thermal comfort prediction for children. It then presented a brief overview and analysis of ML-based prediction studies. The work adopted a case study approach to contrast the performance of AI/ML models for children and adults. ASHRAE-II database and a recent primary student dataset were analyzed and SVM prediction models were designed. The work demonstrated that AI/ML prediction accuracy for children and adults differs by as much as 29% and 86% for thermal sensation and thermal preference, respectively. Further, three three major AI/ML challenges specific only to children were discussed, viz., illogical votes, multiple comfort metrics, and extreme class imbalance. Several feasible solutions to these children-specific challenges were also discussed. Finally, the open problems for future work are presented.

- Given that tropical areas are the most populous and have the youngest populations, there needs to be more consideration given to thermal comfort research for children in these regions.
- With the increase in global temperatures, it is imperative to address the risks of heat stress in children who are exposed to high temperatures.
- Further investigations are required to determine the impact of temporal factors like circadian rhythm, "time of day", etc., in thermal comfort predictions.
- Limited studies on AI/ML have concentrated on naturally ventilated buildings, and the prediction performance is often insufficient. This calls for improved prediction models specifically for NV classrooms.
- Whether there is a statistically significant correlation between the learning abilities of primary school children and the classroom environment can be explored further.

Author Contributions: Conceptualization, B.L. and A.H.; Methodology, B.L. and A.H.; Validation, B.L.; Formal analysis, B.L.; Investigation, B.L.; Writing, B.L. and A.H.; Original draft preparation, B.L.; Writing—review and editing, B.L. and A.H.; Visualization, B.L.; Supervision, A.H.; Project administration, B.L. and A.H. All authors have read and agreed to the published version of the manuscript.

Funding: This work has received no external funding.

Acknowledgments: The authors would like to thank Srikant Manas Kala (Osaka University, Japan) for his technical support and assistance throughout the aspects of our study.

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

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