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Review

Electric Water Boiler Energy Prediction: State-of-the-Art Review of Influencing Factors, Techniques, and Future Directions

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Abstract: Accurate and efficient prediction of electric water boiler (EWB) energy consumption is significant for energy management, effective demand response, cost minimisation, and robust control strategies. Adequate tracking and prediction of user behaviour can enhance renewable energy mini-grid (REMD) management. Fulfilling these demands for predicting the energy consumption of electric water boilers (EWB) would facilitate the establishment of a new framework that can enhance precise predictions of energy consumption trends for energy efficiency and demand management, which necessitates this state-of-the-art review. This article first reviews the factors influencing the prediction of energy consumption of electric water boilers (EWB); subsequently, it conducts a critical review of the current approaches and methods for predicting electric water boiler (EWB) energy consumption for residential building applications; after that, the performance evaluation methods are discussed. Finally, research gaps are ascertained, and recommendations for future work are summarised.

Keywords: daily energy consumption; electrical water boilers (EWB); prediction model; residential buildings

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1. Introduction

The high energy consumption of high-rise residential buildings is due to the load demand from several individual loads, among them the electric water boilers. Electric water boilers experience demand throughout the year due to a wide range of daily and hourly activities involving hot water consumption. These activities include showering, running washing machines, using bathrooms, and operating kitchens [1–3]. Hence, accurate prediction of occupant's hourly and daily energy consumption is crucial for effective energy management in the mini-grid demand response system and for minimising the overall carbon footprint [4–8]. Hourly and daily predictions for electric water boilers offer the potential to enhance the integration of intraday markets by striking a balance between predicting energy consumption demand and grid supply [4,9–17]. Energy aggregators serve as essential connectors between electric water boilers energy consumers and the energy market, particularly in deregulated markets, thus optimizing economic benefits while addressing intra-hour demand fluctuations [18]. Aggregators can significantly improve demand response strategies by monitoring and predicting user behaviour [19,20]. For intraday trading, predictive analysis is essential for aggregators to fine-tune trading strategies and grid stability, leveraging past user behaviour data [9,20,21]. However, managing large-scale user unpredictability poses privacy concerns for aggregators [20,22,23]. As technology advances and more data become accessible, user behaviour-based energy consumption prediction and trading strategies will gain relevance, warranting immediate research attention [9,19].

Research has shown that the most accurate predictions are made using real-time data collected over time on hourly or daily consumption rather than monthly and annually because user behaviour in relation to energy (kWh) consumption changes as a result of influencing factors [1,4,24–28]. Kadir et al. review reveals that 84% of the studies focus on short-term energy consumption prediction due to its direct relevance to daily building operations. Conversely, only 12% of the studies concentrate on long-term (yearly) energy consumption prediction. Additionally, the research indicates that annual energy consumption prediction models, developed using hourly measurements spanning 1-day, 1-week, and 3-month periods, exhibit prediction errors of 100%, 30%, and 6%, respectively. De Simone et al. investigated the factors influencing the use of electric water boilers, classifying these aspects as contextual and personal factor variables based on daily usage [29]. Sborz et al. conducted a similar study; their findings suggested that user behaviour had a significant role, particularly in terms of a lack of information to users about available operations during peak hours of daily consumption in the morning and evening, which a robust prediction model could address [30]. Similarly, Fuentes et al. conducted a review of influential parameters affecting hot water consumption [2]. These studies classified the factors such as socio-economic factors, building type, seasonality, and climate conditions. Additionally, their work examined the modelling tools and techniques employed for predicting electric water boiler usage. Their research evaluated various models, including those based on technical standards, statistical methods, behavioural patterns, data-driven approaches, time-series forecasting techniques, and stochastic models, all of which are employed as tools and techniques for predicting electric water boiler usage. In recent years, prediction models have been examined using different tools and techniques to predict hot water usage, but they are subject to influencing input variables. Hadengue et al. developed an innovative framework that integrates a stochastic demand model with a process-based library of models to perform material and energy flow analyses (MEFA) for intricate electric hot water systems. Intriguingly, when non-stochastic water demand scenarios were considered, they resulted in less precise heat loss predictions, with an overestimation of heat losses by 12.6% from the system, in contrast to the more accurate 19.6% prediction associated with stochastic water demand scenarios. This framework also provided a useful platform for collaboration between water experts for adequate planning, energy management, design, and control strategies [31]. Similarly, Perez-Fargallo et al. proposed prediction models beyond stochastic and technical-based models to various time series models; their results showed that exponential smoothing and state–space methods achieved satisfactory confidence levels of 95% and percentage error minimisation of 80% [32]. Amasyali and El-Gohary proposed prediction methods and machine learning algorithms used in prediction [33]. Their study subsequently delved into assessing the performance of evaluation metrics, aiming to estimate the accuracy and suitability of the prediction models. Subsequently, Leiria et al. introduced a data-driven methodology to estimate hot water boiler prediction based on hourly measurements, where hybrid support vector regression (SVR) and Kalman filters yielded a better result but still required further investigation of other estimation methods of prediction [34].

This research critically reviews the three fundamental challenges associated with the prediction of electric water boilers' energy consumption, representing a significant research gap requiring urgent attention. Firstly, it addresses the identification of input variables and factors that exert a substantial influence on electric water boilers' energy consumption. Secondly, it explores prediction models and approaches used to predict energy consumption. Thirdly, it delves into the estimation and evaluation techniques that are essential in assessing the prediction model's robustness and fitness within the context of both data and the electric water boiler system. Figure 1 illustrates the framework for this review paper, which is structured as follows: Section 2 provides a review of the factors influencing the energy consumption of electric water boilers in residential buildings. Section 3 reviews the state-of-the-art prediction models and approaches used for energy prediction of electric water boilers. Section 4 examines the evaluation tools and validation techniques of the prediction models. Finally, future research trends and gaps, recommendations, and conclusions are presented in Section 5.

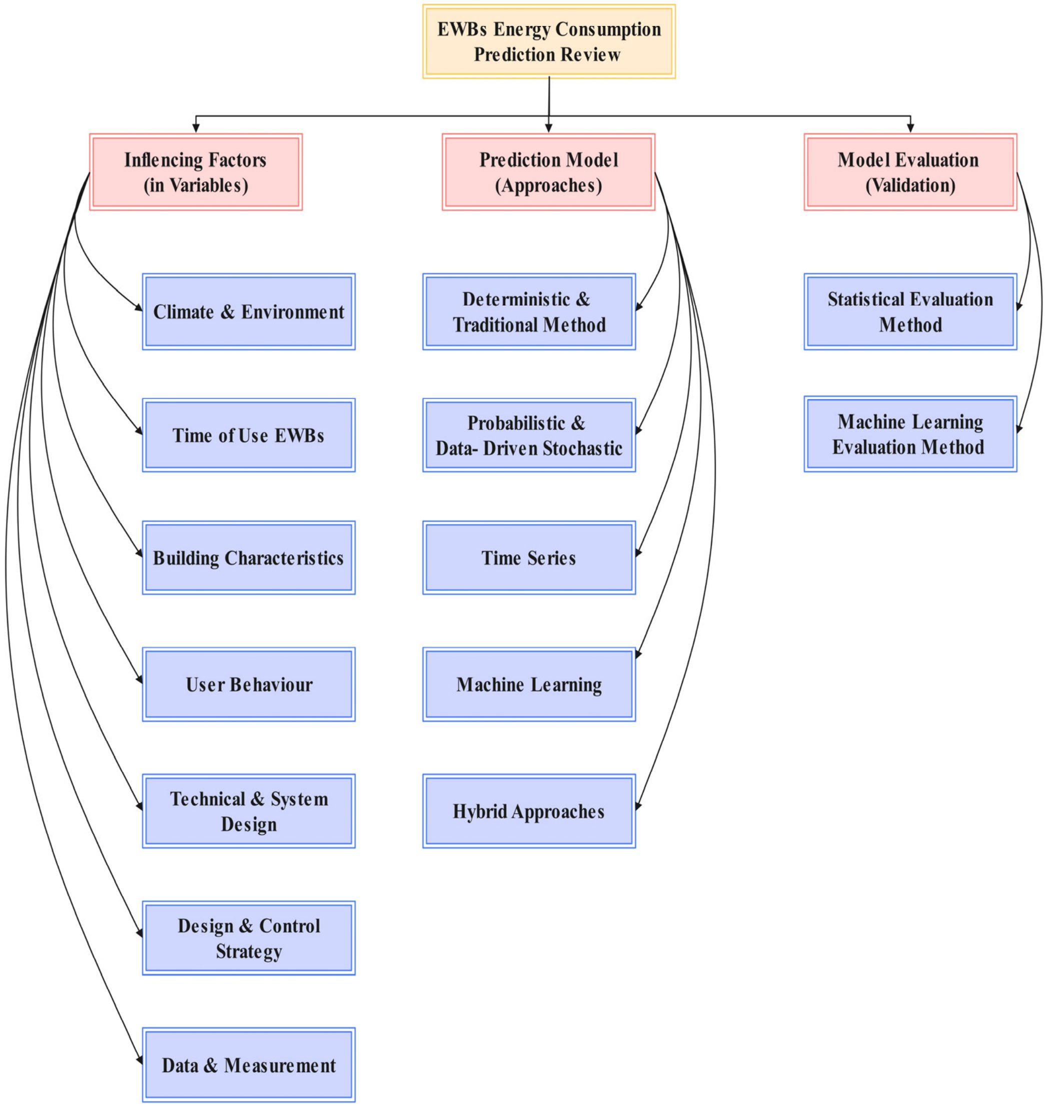

Figure 1. Framework of this research review.

2. Factors Influencing the Prediction of Electric Water Boilers Energy Consumption

The influencing factors can be categorised as follows: climate and environmental factors; time-of-use (ToU) of electric water boilers; building characteristics; user behaviour; technical factors and system design; design and control strategy; sources of data; and measurement techniques. These influencing variables, resulting in high energy consumption in residential buildings, are determined by occupant behaviour as hot water consumers. Moreover, personal factors such as economic status, family income, education level, occupation, and lifestyle significantly influence user behaviour concerning electric water boiler (EWB) usage, as shown in Figure 2 and Table 1. This is due to the building's daily hot water needs and operations, which are primarily for domestic reasons, personnel hygiene, and hot water consumption [2,6,35–37]. According to Ahmed et al., geographical location has a substantial impact on electric water boiler energy consumption, which can be assessed as being largely affected by climatic conditions, making occupants demand more hot water due to temperature drops and differing among countries and regions [1]. Similar research was conducted in Belgian residential buildings; seasonal fluctuations in hot water use showed that in summer, consumption was approximately 13% lower than average, whereas, in winter, an increase of approximately 12% was estimated [2]. Furthermore, input influencing variables include social and economic conditions [38–40], occupant behaviour towards electric water boiler usage considering age and gender [41,42], number of occupants and occupant lifestyle, weather conditions [43], energy pricing, work schedule, duration of time spent at home, and education [29,44]. These findings are consistent with the idea that time-of-use pricing strategies can significantly influence EWBs' energy consumption of EWBs, often resulting in reductions. Several studies have also investigated this phenomenon. Pérez-Lombard et al. found that time-of-use tariffs can lead to reductions of 10% to 15% in residential energy consumption, with a substantial portion attributed to hot water usage, especially when users shift their demand to off-peak hours [45]. Similarly, in a study conducted by Zhao et al., they observed a 12% reduction in energy consumption of EWBs when time-of-use pricing was implemented effectively, encouraging users to heat water during off-peak periods [46].

Table 1. Summary of research work on factors influencing the prediction of electric water boilers consumption.

Author/Research Work	Climate and Environment	Building Characteristics	Time of Use	User Behaviour	Design and Control Strategy	Personal Factors
Vine et al. [3]						✓ [a]
Papakostas et al. [47]	✓		✓	✓		
Masiello and Parker [48]	✓		✓			
Aguilar et al. [35]	✓			✓	✓	✓
S. H. Kim et al. [38]		✓		✓		✓
Beal et al. [41]				✓	✓	✓
Makki et al. [39]			✓		✓	✓
Bennett et al. [49]		✓		✓	✓	✓
Gerin et al. [50]	✓					
Krippelova and Perackova [51]	✓		✓			
Rathnayaka et al. [40]	✓					
Shan et al. [42]			✓			✓
K. Ahmed et al. [1]	✓		✓			
George et al. [36]	✓		✓	✓		
Edwards et al. [52]	✓	✓	✓	✓		✓
K. Ahmed et al. [4]	✓		✓			
Chmielewska et al. [53]		✓		✓		
de Santiago et al. [26]						✓
Ferrantelli et al. [43]	✓			✓		✓
Fuentes et al. [2]	✓			✓	✓	✓
Marszal et al. [6]		✓		✓		✓
Rouleau et al. [37]	✓			✓		✓
Ivanko et al. [5]	✓	✓	✓			
De Simone et al. [29]	✓	✓	✓	✓	✓	✓
Xie and Noor [54]		✓		✓	✓	✓
Tolofari et al. [55]		✓	✓		✓	
Mostafaeipour et al. [56]	✓	✓			✓	✓
Meireles et al. [57]	✓					
C. Chen et al. [58]		✓	✓	✓	✓	
Alipour et al. [59]	✓			✓		✓
Sarabia-Escriva et al. [28]	✓		✓		✓	

[a] Influencing factor considered by authors.

The continuous need to estimate and accurately predict energy consumption has paved the way for this review, considering the numerous factors that limit and influence the prediction of the energy consumption of electric water boilers. A summary of the research in this domain is presented in Table 1. The influencing input variables are also discussed in this section. Having sufficient knowledge of these traits is important for designing energy-efficient systems, developing policies, and creating accurate predictive models for energy management and demand response.

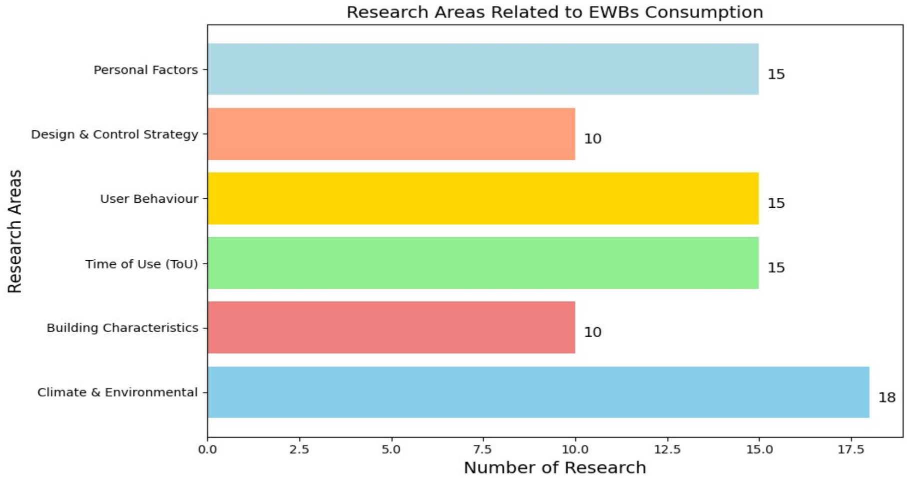

Figure 2. Research on influencing factors of prediction of electric water boilers consumption.

2.1. Climate and Environmental Factor's Influence on Electric Water Boilers' Consumption

Real-time and realistic prediction of electric water boilers' energy usage considers local meteorological conditions and seasonal fluctuations, climate, habits, environmental concerns, and socioeconomic level, all of which influence electric water boilers' use geographically. Table 1 presents a similar research summary for the season, response time, and daily usage. Figure 2 illustrates the interest in climate and user behaviour (18 papers related to climate and 15 papers related to user behaviour), highlighting the considerable research focused on this relationship over the years. This relationship is mostly driven by the varying energy requirements for heating water, which are determined by ambient temperature. In colder climates, the incoming cold water has a lower baseline temperature. Consequently, heating water to an acceptable temperature for residential use, such as showering or washing dishes, requires more energy. Electric water boilers use more energy during colder months and in colder climates [2,60,61]. Warmer seasons, on the other hand, may result in lower energy usage because the baseline temperature of the incoming water is higher, requiring less energy to heat to the setpoints and less hot water from occupants [62]. Table 2 and Figure 3 synthesize the literature on daily and seasonal prediction that deals with the percentage of energy consumption attributed to electric water boilers in various regions and countries. Historical data reveal a consistent trend of energy savings in electric water boilers over recent decades, with factors such as outdoor temperature and distinctions between weekends and working days being identified as influential contributors [52]. In the study conducted by Zuzana and Jana for one-year data collected from March 2013 to April 2014, hot water consumption in a building with 167 residents was recorded every hour. The highest daily consumption (around 50 L per occupant per day) occurred during the winter and spring seasons. In autumn, the average consumption dropped to about 45 L per day per occupant. The lowest consumption of the year was during the summer, with approximately 40 L per day per occupant in July and 34 L per day per occupant in August [51]. These effects are geographic, with electric water boiler consumption increasing in some regions (New York) and declining by 9% in others (Florida). Differences in daily energy consumption predictions are also noticeable between Finland and Germany at approximately 10% and 20%, respectively. In Finland, consumption is higher in the evening (from 18.00 to 21.00) by 15% and lower in the morning (from 6.00 to 8.00) by 5%, while in Germany, the pattern is reversed. Furthermore, when many parameters, such as age and employment, are included in the model's variables, it enhances the model's accuracy, adaptability, and robustness.

Table 2. Summary of research on seasonal and daily prediction of electric water boiler consumption considering the time of use.

Authors	Seasonal/Monthly	Day	Sampling Time (s)
Buchberger and Wells [63]	✓[a]	✓	60
Jorda and Vajen [64]	✓	✓	60
Yao and Steemers [65]	✓	-	60
Bakker et al. [66]	✓	✓	60
Popescu and Serban [67]	-	✓	–
Widén et al. [68]	-	✓	60
Blokker and Vreeburg [69]	-	✓	1
Heunis and Dekenah [70]	✓	✓	3600
Fan et al., 2014 [71]	✓	✓	–
Gerin et al. [50]	✓	✓	300
K. Ahmed et al. [1]	✓	✓	3600
Edwards et al. [52]	✓	✓	60
Richard et al. [72]		✓	60
McKenn and Thomson [73]	✓	✓	60
Magoules and Zhao [74]	✓	✓	3600
Roux et al. [75]	-	✓	60
Marszal et al. [6]	✓	✓	3600
Hadengue et al. [31]	-	✓	2
Ritchie et al. [8]	✓	✓	60
Xu et al. [76]	✓	-	60
Heidari et al. [77]	-	✓	3600
D. Kim et al. [78]	✓	✓	3600
Heidari et al. [79]	✓	✓	
Meireles et al. [57]	✓	✓	3600
M.J. Richie et al. [27]	✓	✓	3600
Kavya et al. [80]	✓	✓	3600

[a] Influencing factor considered by authors.

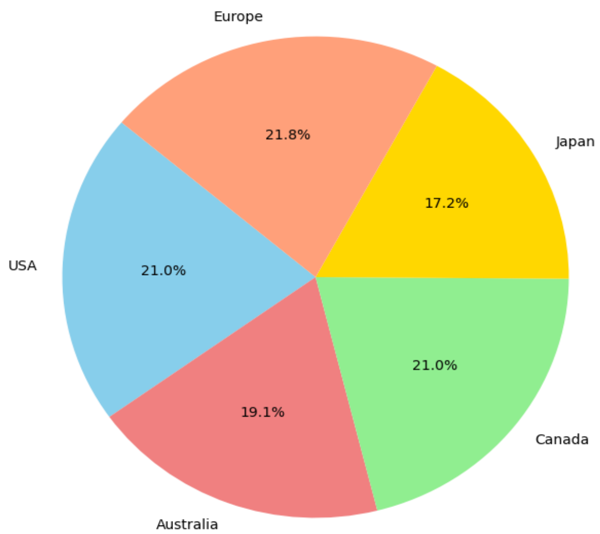

Figure 3. Average daily energy consumption percentage by region/country [2].

Ahmed et al. dived into the daily use patterns of electric water boilers across 182 Finnish apartments over two years, showing both individual consumption and seasonal fluctuations [1]. The study revealed fluctuations in electric water boiler consumption, highlighting the highest consumption in November and the lowest in July, along with variations between weekdays and weekends. Significantly, when these intricate predictions were integrated into solar thermal system simulations, energy delivery increased by 4.7% compared to models that did not account for these monthly fluctuations. This seasonality influences the energy consumption of electric water boilers. Research has also shown that the annual energy consumption of electric water boilers is more important because, throughout the year, hot water consumption is compared to other heavy energy-consuming systems like heating and HVAC systems that are seasonal. Figure 2 summarizes the research on seasonal and daily consumption of electric water boilers. Out of the 26 articles reviewed, 24 focused on daily consumption, 19 considered both daily and seasonal consumption, and only 17 explored seasonal consumption exclusively. These show an interest in the effect of daily prediction on annual consumption and highlight research trends in this domain, which is a research concern.

Due to the continuous nature of hot water consumption, with patterns on both daily and seasonal scales, researchers have turned to stochastic models to predict electric water boilers consumption over the years, with the aim of addressing the inherent challenge [2,37,81]. Burch and Christensen have developed a stochastic water temperature model that correlates the inlet water temperature to its impact on the indoor supply line, indicating that the hot water temperature is influenced by the duration of end-user extractions [82]. These changes can lead to reductions in consumption ranging from 20% to 50%. Furthermore, variables such as the number of residents may also contribute to seasonal consumption, depending on the building type [2,8,83,84].

Dongwoo Kim et al. conducted research on the link between COVID-19 and residential hot water needs [78]. A non-dimensional and principal component analysis was used to determine the relevant factors utilising demand data from the research conducted before and after COVID-19. The COVID-19 outbreak affected the daily peak time and the amount of household hot water usage, according to the analysis, and the active case number of COVID-19 was a good signal for linking the changes in hot water demand and patterns. Based on this, a machine learning model based on an artificial neural network was created to forecast hot water consumption based on the severity of COVID-19 as well as the relevant association. According to the model analysis, the increase in the number of active cases in the region affected the hot water demand, which increased at a certain rate and decreased at its peak in the morning during weekdays and weekends [78]. Furthermore, COVID-19, like other pandemics and viruses, is a major social and environmental issue that is seasonal in nature, affecting hot water usage when the pandemic occurs. Models that withstand pandemics should be the focus of future work.

2.2. Influence of Building Characteristics on Energy Consumption of Electric Water Boilers

The key issues related to building characteristics that influence hot water usage are the building size, insulation, and hot water distribution schedules. Larger buildings with more tenants are likely to have increased hot water demand, resulting in higher total energy use per person. Furthermore, there exists a clear correlation between the number of occupants in a building and the energy consumption of its electric water boiler system during evening hours, which corresponds to the peak usage period when individuals come home [2,45,60]. Although increased occupancy is expected to increase water use over time, as indicated in certain studies in Table 1, this is not always the case. However, electric water boiler consumption, on the other hand, is shown to decrease with increasing household size, which is thought to be due to an economy-of-scale effect [85] or user behaviour adaptations under high occupancy conditions where facilities are shared among users [86,87].

Well-insulated buildings retain heat for longer periods, meaning that residents might require hot water less frequently, especially during colder months. In buildings with efficient ventilation and well-sealed windows, the hot water demand for domestic purposes might be more consistent across different times. Most times, it is apparent that modern building insulations directly benefit thermal management efficiency and overall energy savings and result in less hot water consumption [88]. Similar research findings by Fabrizio Ascione et al. confirm that effective insulation enhances thermal gains and reduces hot water demand from electric water boiler systems [89]. The significance of pipe insulation in reducing heat loss cannot be overstated; it also minimizes heat loss to the surrounding environment and reduces the energy needed to heat water by 20–40%. Additionally, buildings with properly insulated hot water pipes consume less energy [2]. Energy usage is also influenced by the architecture of the hot water distribution system. Centralised systems that rely on a single hot water heater might result in significant heat loss (41.3 L per day) as the water travels great distances to reach different usage sites, while decentralised systems that use smaller water heaters situated closer to the point of consumption have the potential to reduce energy losses [90,91]. Energy consumption is affected by factors such as hot water usage schedule and location, as well as daily hot water consumption volume [92,93].

The energy consumption patterns in various settings, such as bathrooms, showers, and kitchen sinks, can be influenced by the temperature of hot water. Typically, these settings maintain temperatures between 40 and 45 °C, achieved by the blending of hot and cold water to ensure user comfort. In contrast, washing machines and dishwashers commonly utilise hot water, with temperatures typically ranging between 55 and 60 °C. These specific temperature thresholds are often employed as standardised criteria for assessing the energy consumption of water boilers [36,82]. Buildings that receive ample sunlight, especially during winter months, can naturally maintain warmer internal apartment temperatures. This is due to a 1–2% increase in ambient temperature resulting from the external sunlight effect. As a result, occupants may require less hot water usage during sunny hours, potentially reducing the frequency of electric water boiler usage. Recent research has focused on grouping apartments with similar consumption patterns into centralised or mini-centralised electric water boiler systems in order to limit network complexity and losses, reduce energy waste, and optimise the energy management of electric water boiler systems, particularly in complex and residential buildings. Finally, the design and operation of the hot water distribution system, combined with consumption patterns and temperature needs, have a significant impact on energy use and can aid in the design of more energy-efficient hot water system strategies for long-term home hot water supply. Larger buildings or those with more occupants tend to have higher hot water demands. While electric water boilers might appear as standalone systems, their energy consumption is intricately linked to the building's insulation characteristics and occupants' behaviour. Future research can use the link to improve energy management and efficiency measures, particularly when considering usage timing.

2.3. Effect of Time of Use on Electric Water Boilers' Energy Usage

The amount of time spent using hot water is determined by the occupant's behaviour. Hot water can be used for showers in the morning or evening chores. Recent studies (Table 2) have also explored the impact of time of use (ToU) tariffs on the prediction of electric water boiler consumption in residential settings. Time-of-use pricing, implemented by utilities, adjusts electricity rates according to demand. Peak hours experience higher rates, while off-peak hours, occurring at night or during mid-day in certain regions, feature reduced prices. This pricing strategy, similar to electric water boilers, promotes off-peak energy utilization. However, households with knowledge of time-of-use pricing may adjust their hot water consumption patterns accordingly [3,4,52,64,94]. Vidal Lamolla et al. presented an agent-based combination of traditional prediction models with behavioural analysis to predict electric water boiler consumption [81]. The results from this modelling indicate that the implementation of a time-of-use system would reduce hot water usage by 17.2%. Moreover, the reduction was not homogenous for the socioeconomic groups of households, while 20% of low-income households had the lowest water bill savings (9.3%). Nevertheless, high-income households present 11% water bill savings with 10% hot water use. Moreover, the use of smart metering in residential structures has demonstrated a substantial correlation between the input variable of hot water's time of use. The energy consumption of electric water boiler systems can utilise time delays to optimise demand response energy management [43,95]. Table 1 presents research carried out at the time of use. Ritchie et al. created a model based on the relationship between usages at different times of the day [27]. This model reduced hourly prediction errors by 19.6% for electricity usage and 25.0% for hot water usage when the first 12 h of the day were known. Future work could consider the time of year (yearly seasonality) from daily hour prediction, the total number of tenants, including the number of children, weather information, and user input (set of holiday dates). Furthermore, these estimates could be tested in the context of demand-side management (DSM) and demand response (DR) in the future.

The correlation matrix is presented in Table 3, and Figure 4 illustrates the assessment of similarity between the days of the week [5]. In Figure 4, the blue and red colours denote the minimum and maximum hot water consumption rates. Furthermore, electric water boiler data from nursing homes, spanning 52 weeks, were systematically compared within each week using Student's *t*-test and Fisher's exact test. To determine when profiles on different days could be considered statistically similar, factors such as the accuracy of Student's *t*-test and Fisher's exact test, as well as the percentage of atypical days, were considered. Accepting an error of 5% for both tests and estimating an acceptable error of 14% for atypical electric water boilers' heat-use days, days with statistically similar profiles in over 86% of the considered weeks were grouped into two categories: a from Monday to Friday group; and a Saturday and Sunday group. Researchers have stressed the importance of data granularity, especially from smart metres, for precise electric water boiler prediction in the context of time-of-use tariffs. This study suggests that incorporating real-time or hourly data from smart meters enhances the model's adaptability to sudden consumption changes influenced by time of use. Consequently, the integration of building energy simulation tools with predictive models for electric water boilers that consider the time of use variables is anticipated to improve the accuracy of residential energy consumption prediction models. Future work can examine the effect of the time-of-use tariff on user behaviour based on occupant composition, economic factors, and personal factors on hourly and daily consumption.

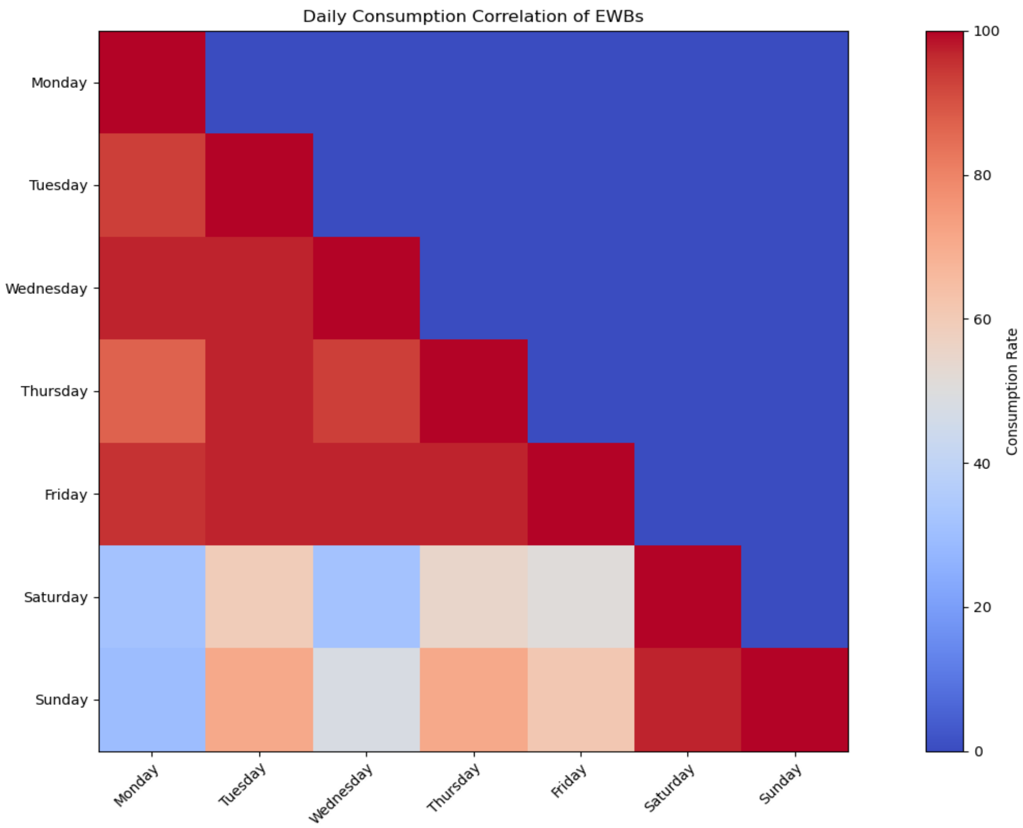

Figure 4. Daily consumption correlation of electric water boilers from Table 3 [5].

Table 3. Daily electric water boiler consumption correlation coefficient for nursing homes [5].

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Monday	100	-	-	-	-	-	-
Tuesday	93	100	-	-	-	-	-
Wednesday	97	97	100	-	-	-	-
Thursday	87	97	93	100	-	-	-
Friday	95	97	97	97	100	-	-
Saturday	32	59	32	55	51	100	-
Sunday	30	71	48	71	61	97	100

2.4. User Behaviour Influence on Energy Consumption of Electric Water Boilers

The energy efficiency of electric water boilers is primarily dependent on user behaviour rather than technical factors. Moreover, using the electric water boiler sporadically rather than in a regimented manner can affect its efficiency, especially when the boiler constantly maintains higher temperatures. Furthermore, users who leverage time-of-use tariffs and operate boilers during off-peak hours might influence not only individual costs but also overall grid efficiency. Energy consumption is heavily influenced by factors such as the frequency, duration, volume, and preferences of hot water users. Previous knowledge of user behaviour in plumbing fixtures, such as showers and bathtubs, is predominant since they contribute significantly to overall home hot water usage. Showers alone contribute to over half of a household's hot water consumption. Additionally, the study conducted by Papakostas et al. explores the influence of "family size" on hot water usage, finding that the majority of families consume between 25 and 35 L per person per day, with an average annual energy consumption of 0.83 kWh per person per day [47]. Beyond considering frequency and volume, certain users may desire higher temperatures when using hot water piped equipment like dishwashers or washing machines. Although this choice may elevate energy consumption by extending heating time, designers of prediction models need to assess its impact on user comfort and safety. Different persons have varying usage habits based on various demographics, such as age or gender. According to studies, women and children shower more frequently than men, while pensioners use more hot water [41,42,49]. Gender and age have been found to be two of the most relevant elements in influencing shower time in both Greece and Poland, according to studies [47,96]. Males typically take 9.1% less time than females, whereas children take 15.1% fewer showers per week, and among houses occupied by people of all ages, those occupied by seniors typically consumed 22 to 27.5% more hot water than those occupied by younger people possibly because retired senior occupants are at home more often according to the research conducted by Yixing et al. [42].

Table 1 shows a summary of similar work on user behaviour in the literature. Some experts believe that greater water appliance usage by seniors spending more time at home increases water usage; money and wealth also play a factor in deciding how much water a household uses [29,39,42]. This research gap could be attributed to the emergence of an economy-of-scale effect for shared facilities, in which individuals frequently modify their usage patterns [48]. However, by designing systems with user behaviour and temperature preferences in mind, efficient hot water utilisation is possible, hence increasing sustainability.

2.5. Technical Factors and System Design Efficiency Influence on Energy Consumption of Electric Water Boilers

Technical factors and effective system design have a considerable impact on the energy consumption of electric water boilers. Improving the precision of these parameters and their influences allows for more precise prediction of energy use, paving the way for improved prediction approaches and energy management. Most of the time, technical issues are related to the hurdles, such as the boiler's efficiency rating, which is a measure of its energy conversion effectiveness. Furthermore, operating conditions, such as the set-point temperature and frequency of boiler usage, influence energy consumption. Increased energy consumption is caused by high set-point temperatures or frequent use [82]. Furthermore, the overall system design of the hot water distribution network influences the energy losses and overall energy consumption [69,97], and an efficient system design can minimise these losses [2,98,99]. Fuentes et al. evaluated the impact of technical standards, such as heating element efficiency and system design, on electric water boilers' energy usage [2]. Additionally, Jordan and Vajen investigated hot water distribution systems, specifically pipe insulation and home-run plumbing designs [64]. The review discovered that addressing these parameters significantly reduced energy losses and boosted consumption efficiency. Other studies, such as B. Hendron et al., investigated demand-controlled recirculation loops, as well as the time and frequency of hot water draw events, which significantly showed that these variables were found to have an effect on electric water boilers' energy usage [93].

2.6. Design and Control Strategy Influence on Energy Consumption of Electric Water Boilers

The design and control strategy should incorporate the implementation of rescheduling control, considering the occupant's consumption patterns or behaviour. This approach aims to minimise wastage and maximise the functionality of each electrical water boiler, thereby reducing the energy required for hot water heating in residential buildings. Strategic operations must go beyond simple on/off switching to include controlled rate warming speeds without sacrificing the hot water comfort of occupants via intelligently managed thermostats integrated with timer sequences that reduce frequent temperature fluctuations as well as optimising utilisation, increasing usage efficiency, and reducing unwanted energy consumption by electrical water boilers [2,33,100]. The traditional means of scheduling and controlling electrical water boilers involve the use of a thermostat and timer control. However, the implementation of timers or scheduling control systems can enhance the efficiency of hot water control by operating the system during peak demand periods and minimising energy consumption during periods of low demand [101,102]. A higher thermostat set point necessitates more energy to heat the water to the desired temperature, resulting in increased energy consumption. However, lowering the thermostat temperature reduces energy consumption [103]. These measures can be aligned with utility demand–response programmes, which reduce energy costs during off-peak hours. Additionally, advanced machine learning algorithms can forecast hot water use patterns and adjust the operation schedule of electrical water boilers accordingly, resulting in additional energy savings [104–106]. Control tactics and design have a considerable impact on the forecast of energy consumption by electrical water boilers in residential buildings. Table 1 shows a review of similar studies on the design and control of electric water boilers. Their operating schedule can significantly alter their energy consumption by aligning the operation to coincide with periods of hot water demand, and energy savings can be achieved [107]. Electrical water boilers equipped with hourly smart prediction model controls can optimize their operation by leveraging real-time data on hourly daily energy pricing and user demand patterns, thereby enhancing efficiency [108,109]. Additionally, the incorporation of hot water recovery technologies in electric water boilers can further contribute to reducing energy consumption [107,110–112].

Kapsalis et al. investigated a comfort and cost-oriented optimisation method for operation scheduling of electric water heaters under dynamic pricing [44]. Utility-centred strategies used by electricity providers to reduce the peak load of aggregate electrical water boilers load in order to provide balancing and regulation services, such as ON/OFF control [84,113], water temperature adjustment [113–115], voltage control [116,117], were highlighted. Further study could look at developing predictive models that take these parameters into account for better prediction and optimisation of energy use in electrical water boilers [17,118], particularly in high-rise residential structures. Furthermore, most research places less emphasis on individual electrical water boilers' energy usage, which is impacted by the occupants' behaviours and preferences [2,119].

2.7. Data and Measurement Techniques for the Prediction of Electric Water Boilers Consumption

Data from numerous sources each contributes unique insights into various aspects of energy consumption behaviour, which are generally obtained from the electrical water boiler system specification, which normally contains its efficiency rating, capacity, and heating element specifications, among other things [120]. Regardless, data collection and measurement techniques must be methodical, rational, and standardised [2,34]. Table 4 shows the source of data and measures as found in the literature; these are sometimes obtained from the manufacturer's specification or from actual measurements collected during systems operation. The prediction accuracy is heavily dependent on the accessibility of accurate and comprehensive data gathered from various sources [83,121]. Direct measurements of user behaviour can be obtained using flow metres and temperature sensors [99,100]. Also, indirect data collection methods, such as user surveys or diaries tracking usage habits, can also provide valuable prediction outcomes [122]. Dishman et al. presented the sources of data and measures as documented in the literature [98]. In addition, the accuracy of predictions is greatly influenced by the availability of reliable and complete data obtained from many sources [83,121]. Flow metres and temperature sensors have been utilised to directly measure user behaviour [99,122]. Valuable insights can be gained through indirect data collection methods, such as user surveys or diaries that collect hot water consumption [123,124].

Non-invasive load monitoring (NILM) technologies have been employed to collect more detailed data on the utilisation of certain appliances [125,126]. Data collection capabilities of the Internet of Things (IoT) technology have been significantly improved in recent research. However, smart metres and sensors have the capability to provide real-time, high-resolution data, hence significantly enhancing the precision of predictive models [126–130]. Nevertheless, with the diverse array of data sources, there are persistent challenges in the areas of data collection, quality assurance, and processing. These challenges are crucial obstacles that require immediate attention in order to achieve accurate predictions of energy consumption. There is a need to ensure data quality, address missing or inaccurate data, and effectively manage data with high levels of complexity [74,131]. Accurate modelling of hot water usage can be enhanced by incorporating specific information regarding the timing and process in which hot water is used. This data can be gathered via several means, including the direct use of instruments such as flow metres and temperature sensors or indirectly via surveys or user diaries [132,133]. In addition, the collection of meteorological data are needed, particularly ambient temperature, which influences the heating requirements, affecting how often and for how long electric water boilers need to operate to maintain the desired water temperature. In colder weather, the ambient temperature is lower, and electric water boilers may need to work harder and longer to meet the heating demand. This impacts the thermal dissipation of the electric water boiler and the overall building performance [102,134,135]. The acquisition of real-time weather data for the purpose of precisely assessing energy consumption is typically facilitated through the use of local weather stations or online meteorological databases [57,136]. Future research can prioritise the improvement in data collection methods, measurement methodologies, and data quality and processing. These factors are significant in determining the energy consumption of electric water boilers, both in terms of energy consumption and future predictions. By refining these approaches and addressing issues related to data collection and data structure, the accuracy and reliability of electrical water boilers' energy consumption prediction can be enhanced.

Zhang et al. underlined the need for data pre-processing and cleaning in experimental situations where faulty or missing data could skew results and cause forecasts to be incorrect [137]. Similarly, Zhou et al. used multi-parametric feature collection to increase the forecast accuracy of electric water boilers' energy prediction [20]. Artificial intelligence (AI) and machine learning (ML) algorithms thrive on data, and the quality and size of the dataset significantly impact the performance and applicability of these models in real-world scenarios. Researchers emphasize the importance of large, high-quality datasets to train algorithms that can make accurate predictions and decisions across different situations [100,138,139]. It is evident that data privacy is essential in the realm of electrical water boilers' energy consumption prediction, surpassing the relevance of data quality, availability, and privacy. In order to achieve a resilient system and optimise energy use, it is imperative that the data employed are both accurate and comprehensive. The use of personal data for the purpose of estimating energy usage, particularly where user activity plays a significant role, gives rise to problems regarding data privacy. Greveler et al. investigated the issue of protecting user privacy during the data collection process for predictive models [140]. Furthermore, it is critical to recognise that the energy consumption forecast of an electric water boiler is dependent on the quality and privacy of data in order to improve data collecting, processing, and prediction model processes. Future research can focus on strengthening data collection and processing techniques, safeguarding data privacy, and optimising prediction models through the use of data.

3. Prediction Models and Approaches for Electric Water Boilers Energy Consumption

Researchers have explored several techniques for electrical water boilers' energy consumption prediction over the years. This paper reviewed these categories of some techniques as found in the literature: deterministic and traditional methods; probabilistic and stochastic methods; data-driven and machine learning methods, and hybrid approaches. Table 4 represents some of the techniques explored in this research.

Table 4. Summary of reviewed papers on methods, dataset, and research gaps for the prediction of electric water boilers consumption.

Authors	Methods/Algorithms	Nature and Sources of Data	Research Gaps
Ladd and Harrison [139]	Deterministic + Monte Carlo	EWBs consumption of US dwelling.	High computational time and limited to a scenario.
Belmonte et al. [7]	Deterministic + Stochastic	Data for 104 apartments in Madrid, Spain, dwellings.	Limited data, no robustness to increase in price.
Dolan et al. [141]	Monte Carlo + stochastic	Athens EWBs load distribution.	Does not represent all scenarios.
Aki et al. [24]	Statistical + Stochastic	EWBs consumption in Japan (Osaka) dwellings and 10mins timestamp	Does not consider user behaviours.
Buchberger et al. [63]	Statistical + Stochastic	EWB consumption for 4 single families in the USA.	Limited to 4 single families.
Widén et al. [68]	Statistical + Stochastic	TUD of 179 occupants Swedish and 5mins time-step.	Limited to data measurement.
Ritchie et al. [8]	Probabilistic + Stochastic	Seventy-seven residential households, at 1-h intervals.	Limited data limit efficiency and visualization models.
Jordan and Vajen [142]	Probabilistic +Statistical	EWBs consumption for Switzerland and German residents.	User behaviour was not considered, and significant fractional influences were found.
George et al. [36]	Statistical + probabilistic	A total of 119 households, 1 timestep Canada (Halifax).	Only Halifax region, limited data of 119 households, no occupancy behaviour considered.
Hendron et al. [93]	Probabilistic + Clustering	EWBs consumption from USA dwellings, 6-min intervals.	Parameters not valid for all climate conditions.
Diao et al. [115]	Parametric Stochastic	A total of 147 households EWBs.	Examine real-time realistic scenarios and other analytical methods.
Yao and Steemers [65]	Stochastic	EWBs consumption from UK dwellings.	Does not consider user behaviour scenarios.
McKenna and Thomson [73]	Stochastic	TUD of UK dwelling.	It is desirable to implement model on other dwellings not limited to the UK.

Table 4. *Cont.*

Authors	Methods/Algorithms	Nature and Sources of Data	Research Gaps
Richard [131]	Stochastic	REUWS database.	Model complexity, limited to single family users and sensitivity to parameters.
Fischer et al. [99]	Stochastic	Individual residential German households.	Occupant types and comfort need to be considered.
Ferrantelli et al. [43]	Stochastic	EWBs consumption in Finnish apartment dwellings and 1 h timestamp	Does not consider region, social, recurring user patterns and correlation.
Gelažanskas and Gamage [143]	Times series + seasonal decomposition	EWBs consumption for 95 dwellings and 24 h timestamps.	Seasonality and number of occupants are not considered.
Leiria et al. [34]	K-filter + SVR	Twenty-eight Danish apartments.	Limited data set, regional, investigating other estimation methodologies, separate heating, and EWBs system.
D. Kim et al. [78]	ANN	From 2017 to 2022, 1 h interval data of apartment complex in Seongnam-si, Korea.	Season, culture, and user behaviour also affect hot water demand, which was not considered.
Gelažanskas and Gamage [144]	ANN	EWBs consumption for 112 dwellings and 24 h timestamps.	Limited to 112 data to capture robust EWBs usage patterns.
Sonnekalb and Lucia [120]	NN	User behaviour + IoT data of Britain individual occupant.	Does not consider real measurements, other ML (LSTMs, etc.), and smart grid implementation.
Maltais and Gosselin [145]	MPC + NN	Forty EWBs consumption profiles.	High computational complexity leads to forecasting model inaccuracies.
Amasyali et al. [146]	RL	TUD price and hot water usage profiles for 30 days.	Needs to be deployed on real system, examining the representation of hot water patterns on set of proxy variables.
J. Cao et al. [147]	Deep RL + LSTM	--	Does not consider the uncertainty of future prices and variability of EWB types.
Roux et al. [75]	Meta-heuristic algorithm	Individual data of 34 EWB controllers in 34 weeks.	Does not capture unpredictable user behaviour, hot water variations, or energy fluctuations.

3.1. Deterministic and Traditional Methods

These approaches for modelling electrical water boilers' energy consumption are based on physical laws like balanced energy models (heat transfer) and fluid dynamics, which have traditionally been used for energy prediction modelling [64,148]. Also known as deterministic models, these models consider system thermal properties, user behaviour, and environmental conditions [64,124,149]. They have a solid theoretical base, but data availability and quality limit their accuracy, most specifically electric water boilers' testing standards, which define energy prediction and design flow rates for electric water boilers' tapping patterns [150–152]. Over the years, Monte Carlo simulations were used to generate hot water load predictions for residential users using statistical technical-based standards (STS) and equations to model the daily consumption of electric water boilers, which are correlation-based models [141,142]. Table 4 presents a summary of some technical and research gaps in these models.

Marini et al. compared five technical standard-based software calculation tools applied the CC BY-NC-ND 4.0 license and utilized versions 8.0.0, 2014.6.5.0, 8.5, 9.92, and 5.2.d respectively, for predicting residential buildings' monthly and daily electric water boilers' consumption [150]. This work further compared UK dwelling measurements with models based on several technical standards, including total hot water volume, energy losses, system efficiency, and hot water temperature. The results showed approximately 40% variation in measured data, but the accuracy of technical-based standards (STS) techniques mostly depends on input design values for evaluation, and methods based on the country's specific standards yield better estimates.

Jordan and Vajen examined how consumption patterns affect energy savings using electric water boilers' load prediction on a solar hybrid system [64]. Unlike in other studies, the authors used statistical methods to predict electric water boilers' load on a 1-min time scale using a TRNSYS (version 14.2) simulated hot water profile, considering use rate, flow rate, and time of use. Storage systems where duration and flow rate affected storage tank temperature stratification saved over 2% of energy [64]. Limiting its applicability to other systems or energy sources, electric water boilers' consumption distribution assumptions did not consider all end-user behaviour, including weather, system maintenance, and user behaviour, which greatly affected energy consumption. Future research can address these limitations by considering multiple users in residential buildings.

3.2. Probabilistic and Data-Driven Stochastic Methods

The techniques for estimating electric water boiler consumption widely used are stochastic and probabilistic models derived from monitored data and survey information. Stochastic methods based on time-used data (TUD) compute the probability density functions of resident activities and the resulting energy use prediction [68,153]. The probabilities of state transitions are modelled using methods such as the Markov chain process and Monte Carlo, where the resulting probability distributions are calibrated using consumption measurements and time-used data (TUD) [141]. In the context of hot water energy consumption, these simulations, with their probability distribution, could consider factors such as variability in hot water usage, changes in weather, and differences in appliance efficiency. The advantage of these methods lies in their ability to accommodate uncertainty and variability in prediction, which is particularly relevant given the numerous factors that can influence energy consumption, including user behaviour, appliance efficiency, and weather conditions. Although data-driven methods, including machine learning, are dependent on the quality and quantity of data available for training the models, they are also mostly perceived as black-box models due to their complexity and the difficulty of interpreting the model dynamics [100].

Data-driven stochastic methods and machine learning techniques, such as SVR and ANN, have been used to model and forecast energy use in residential buildings [119,154]. These methods can handle large amounts of high-dimensional data and can uncover complex non-linear relationships between input variables and energy consumption. Both methods provide valuable tools for predicting energy consumption in electric water boilers, each with its own advantages and limitations, as summarised in Table 4. Future research could focus on combining these approaches to leverage their respective strengths and mitigate their weaknesses. Additionally, scheduled electric water boiler control can reduce electricity use, but the achievable savings have not been purposefully and methodically analysed and quantified to find an optimal control strategy (including schedule and temperature) that considers actual hot water usage patterns without considering user comfort. These cannot be achieved without adequately predicting the electric water boilers' consumption for a robust scheduling and control strategy [155].

Ritchie et al. presented a probabilistic hot water usage model and simulator for residential energy management, addressing the research gap in the existing residential hot water consumption models that do not account for user preferences and seasonal and daily changes [8]. A probabilistic data-driven model of personalised hot water profiles and a hot water usage simulator account for these variables. For each of the four seasons, 77 homes provided data for model training and evaluation. Simulation match observed hot water use profiles. The aggregated energy load on the grid was also modelled to match measured data, halving the modelling error compared to hot water usage. The hot water usage simulator improves water heaters and demand-side management. More measured water flow data beyond 77 apartments may increase forecasting accuracy, efficiency, and probability density functions for clustered water usage. Furthermore, the model data visualisation may inspire future research.

3.3. Times Series Forecasting Models

Time series models predict future water consumption based on past trends, helping energy management and infrastructure planning, which includes optimising energy-intensive task scheduling, demand–response strategies, and water and energy system capacity planning [2,154–156]. Time series models use hourly, daily, weekly, or monthly consumption data to identify patterns and trends, which can be caused by daily routines (hotter water usage in the morning and evening), seasonal effects (more hot water usage in colder months), and specific events or anomalies. However, time series models like autoregressive differencing and moving average (ARIMA) models predict future values. Autoregression and differencing make the time series stationary [154], while seasonal ARIMA (SARIMA) models account for data seasonality [139]. State–space models and Kalman filter models are useful when the system's underlying states (hot water consumption patterns) are not directly observable but can be estimated from observed data [146]. Machine learning (ML) methods, like recursive neural networks (RNNs) and long short-term memory (LSTM), can detect complex time series patterns, improving prediction accuracy [103,150]. Likewise, Prophet, an additive model that fits non-linear trends with yearly, weekly, and daily seasonality and holiday effects to forecast time series data, identifies hot water use drivers and improves energy-saving interventions [20,25]. Although the models assume that past patterns will continue, which may not always be true because water pricing, water-saving technologies, and behavioural changes can disrupt past patterns and make models inaccurate, there are limitations associated with the models [157,158], which are presented in training time series models and require a lot of historical data, which is limited by the lack of or difficulty of collecting such data [68,119,136]. Nevertheless, time series models are difficult to develop and require statistical modelling and data analysis expertise. Most models neglect non-temporal factors like behavioural, socioeconomic, and demographic variables, which future work could consider minimising relative error of $\pm$10%. To improve model accuracy above 85%, these factors should be included. Moreover, advanced time series models, like those using machine learning or artificial intelligence, can improve prediction by capturing complex and non-linear data relationships.

Gelažanskas and Gamage paved the way for demand-side management strategy based on residential hot water consumption forecasting data analysis and validated the following prediction methods: exponential smoothing; seasonal autoregressive integrated moving average; seasonal decomposition; and their combination [144]. The benchmark models (mean, naive, and seasonal naive) perform worse than these models, indicating that the seasonal decomposition of the time series has the most effective forecast accuracy. Future work can include considering the time of year (yearly seasonality), the total number of occupants, the number of children, weather information, and user information (set of holiday dates). Furthermore, these forecasts could be tested in the context of demand-side management (DSM) and demand response (DR) in future research. Similarly, Gelazanskas et al. developed a management demand strategy based on residential dwelling data on the prediction of electrical water boilers' consumption for various time series models and a combination of them [145]. Seasonal decomposition, autoregressive integrated moving averages, and exponential smoothing are promising techniques for different prediction techniques that were used to forecast data over a 24-h period. However, their ability to account for factors such as seasonality, variations in the number of occupants, holiday dates based on user feedback, and family compositions. These models hold significant potential for Demand Side Management (DSM) control without compromising the comfort of the user.

Bacher et al. presented a method for separating spikes from noisy time-varying data series measuring a single-family house's total heat load [156]. It uses the fact that domestic hot water heating generates short-lived spikes in the time series, while space heating changes slowly throughout the day depending on climate and user behaviour. A non-parametric kernel smoother estimates space heating, and any value significantly above this estimate is a domestic hot water heating spike. First, simple kernel smoothing fails. Thus, the problem is generalised to a local least squares problem, enabling spike-resistant kernel smoother design. A generalised model estimates higher-order local polynomials. Finally, the results show that the method can accurately split the heat load into two components with an accuracy of approximately 85%, and this study also only applied to single-family homes, but the application to diverse and other types of buildings may be an interesting future research direction. Thus, future research should compare the proposed method to other time-series methods to prove its efficacy.

3.4. Machine Learning Methods

Table 5 shows a synthesis of the literature on machine learning models used for the prediction of electric water boiler consumption. The classification of machine learning methods is mostly determined by the type of learning employed by the algorithm, such as fitting a linear equation to observed data. The Multiple Linear Regression (MLR) approach models the relationship between two or more features and a response. It is also simple and does not necessitate extensive computational resources [159–161]. However, its main flaw is that it assumes that dependent and independent variables have a linear relationship, which may not always be true in real-world applications. Because of its ability to model complex non-linear relationships between input and output variables, artificial neural networks (ANN) have gained interest in energy prediction [49,149,162,163]. However, training the ANN model can be computationally demanding; it also acts as a black box, which means it lacks interpretability and can make knowing how it makes predictions challenging. Support Vector Machines (SVM) are useful for prediction problems because they can handle both linear and non-linear data [160]. SVMs are also less prone to overfitting and produce solid results even with small sample sizes [24,26,139,161,164]. Notwithstanding, the performance is largely dependent on a suitable kernel and parameter adjustment, which can be a difficult undertaking. Random Forest (RF) is an ensemble learning method that can effectively deal with non-linear and high-dimensional data. It also estimates the relevance of features and is less likely to overfit than other techniques [76,165,166]. However, it is computationally demanding and may not perform well with sparse data or categorical variables with several levels. Gradient Boosting Machines (GBM) are another ensemble approach that creates new predictors with the goal of correcting the residual errors of the prior predictor. Despite the fact that they are robust to outliers and can handle diverse types of predictor variables [164]. Nonetheless, GBMs can overfit if the data is noisy, and they require careful parameter tweaking.

Table 5. Summary of similar works on machine learning models.

Authors	Machine Learning Algorithm	Aim and Goals
Bakker et al. [66]	ANN	Cost and energy minimisation.
Barteczko-Hibbert et al. [165]	ANN	Cost and energy minimisation and user comfort.
T. Sonnekalb et al. [120]	ANN	Cost and energy minimisation and user comfort.
Maltais and Gosselin [145]	NN	Energy minimisation.
Guo and Mahdavi [167]	RNN	Cost and energy minimisation and user comfort.
Zhengwei Qu et al. [168]	FNN	Cost and energy minimisation and peak LDS.
Al-Jabery et al. [169]	Fuzzy Q-learning	Energy minimization.
De Somer et al. [170]	Actor–critic Q-learning	Cost minimisation.
Ruelens, et al. [171]	Auto-encoder network and fitted Q-iteration	Cost and energy minimisation.

Table 5. *Cont.*

Authors	Machine Learning Algorithm	Aim and Goals
Ruelens, et al. [172]	Q-iteration	Cost and energy minimisation and user comfort.
Aki et al. [24]	SVR	Cost and energy minimisation.
S. Cao et al. [164]	SVM	Cost and energy minimisation and user comfort.
Guo and Mahdavi [166]	SVM	Cost and energy minimisation.
Kara et al. [173]	K-means	Energy conservation.
Gong et al. [174]	K-means	Cost and energy minimisation.
Kazmi et al. [175]	BRL	Cost and energy minimisation, and user comfort.
J. Cao et al. [147]	DRL	Cost and energy minimisation and user comfort.
Amasyali et al. [146]	RL	Cost and energy minimisation over time of use (TOU).
Xu et al. [76]	RL	Energy minimisation.
Heidari et al. [79]	RL	Energy minimisation and user comfort.
Amasyali et al. [176]	RL	Cost and energy minimisation.

When household income, the number of adults, children, teenagers, and appliance stock efficiency are considered, artificial neural network (ANN) models can predict residential hot water end-user consumption per household per day with moderate accuracy of 10 to 20% of the total energy consumed [45]. Bakker et al. used an ANN model to predict daily electric water boilers' thermal energy 24 h ahead using household heat demand profiles from the previous day and week and weather data [66]. This model estimates daily electric water boilers' predictions well, but it needs more user behaviour variables. Furthermore, hotels, hospitals, sports centres, social facilities, and multifamily residential buildings are increasingly using central electric water boiler systems. Forecasting and aggregating diverse electric water boiler predictions to create a consumer-representative pattern are needed to optimise such systems [2]. Additionally, clustering techniques are needed to integrate electrical water boilers' consumption predictions from diverse users and buildings [165]. A clustering aggregation tool can predict patterns used by a centralised control system from electric water boilers' daily predictions from different buildings, and the tool can use parallel validation to test the output patterns used to make decisions against the input prediction. Nevertheless, future work should consider the following research gaps associated with machine learning (ML) methods:

1. The quality and availability of the prediction heavily depend on the quality and quantity of available data. Incomplete, inaccurate, or sparse data can lead to inaccurate predictions [66,149];
2. Model interpretability systems such as ANN operate as black boxes, making it challenging to understand how predictions are made. This lack of interpretability can be a disadvantage in contexts where understanding model decisions is important [66,120,148,165];
3. Computational resources: some models can be computationally intensive, particularly with large datasets. This can be a limitation in contexts with limited computational resources [49,149,160,161].

Maltais and Gosselin evaluated machine learning (ML) forecasting within model predictive control (MPC) systems for electric water boilers, testing four controllers: a rule-based controller; an optimal controller; an MPC with a prophet demand forecast; and an MPC with an ML forecast model [148]. In simulations involving 40 electric water boilers' predictions based on measurements in single-family residential units, ML integrated with MPCs outperformed other models. However, it faced research limitations related to inaccurate predictions, making MPC less viable for single-family or small systems. This underscores the need for better demand forecasting models. A comparison of controllers suggests that hybrid or advanced controllers could enhance electric water boilers' efficiency, and machine learning (ML) models play a significant role in improving electrical water boilers' demand forecasts. The MPC's poor forecasts and delayed action have resulted in more temperature constraint violations. To reduce constraint violations, forecasting models must be timely and accurate. Model predictive control (MPC) with ML should also be tested outside single-family homes. Future work direction can consider this.

Gough et al. presented a smart residential water heating device using machine learning (ML) that optimises water boilers' operation by predicting hot water demand using machine learning [106]. This forecasting mechanism predicts hot water volume and consumers' unpredictable behaviour using only non-intrusive data, which is a major challenge. Data collection and artificial intelligence methods reduced these, but the device's "heat now" function addresses consumer behaviour uncertainties by letting consumers override the predictive control mechanism. Moreover, in a six-month pilot on Sao Miguel island, Portugal, it accurately predicted hot water demand and optimised electrical water boilers' operation. This prediction model saved 1.33 kWh/day on water heating; the devices could reduce energy consumption by 2832 kWh daily, or 0.21% of total electricity generated; thermal generation could be reduced by 0.37% and CO_2 emissions by 693.31 metric tonnes per year if deployed more widely. A survey showed that this model's effectiveness and robustness did not compromise consumer comfort, and that is the significance of the forecasting algorithm based on non-intrusive vibration data. Nevertheless, the research relied on machine learning to accurately predict hot water demand from vibration data. The non-traditional data source shows the flexibility and potential of machine learning (ML) and artificial intelligence (AI) in energy management and optimisation. Finally, it points to promising research and development in this domain.

3.5. Hybrid Approaches

Hybrid models combine two or more methodologies to create a more accurate or efficient prediction model. These models have been increasingly used in energy consumption prediction because they can harness the strengths of multiple individual models and overcome certain limitations that single models may have. Table 4 presents some of the hybrid approaches reviewed. Also, combining data-driven and physics-based models can predict energy consumption by integrating heat transfer, energy usage, and conservation laws. Raissi et al. presented a physics-informed neural network (NN) model that guides learning using differential equations [160]. It uses neural networks to model complex data patterns while maintaining physical consistency with system propositions and dynamics. However, the Grey System approach is employed in modelling and prediction systems for its effectiveness in utilising limited information, particularly in situations with insufficient or uncertain data. In the prediction of electric water boiler energy consumption, Grey System Theory (GST) can be employed to handle incomplete or imprecise data, providing a method for modelling and forecasting energy consumption patterns. GST's capacity to handle uncertain information aligns with advanced machine learning models, which train multiple algorithms and combine their predictions. Furthermore, these models have demonstrated superior performance in terms of generalization and accuracy [176,177]. Though these models are often promising, they have relative limitations in complexity to implement and interpret compared to single models. The overfitting challenge is where the model fits the training data too closely and performs poorly on unknown data. Future work should mitigate the trade-off between model performance and complexity, the trade-off between predictive power and model simplicity, computational efficiency, and interpretability to prevent overfitting in hybrid models.

Khashei et al. proposed a hybrid ARIMA–ANN model for energy load forecasting that mitigates the ARIMA model's linear relationships while the ANN model's non-linear ones [154]. Additionally, the hybrid model outperformed the ARIMA and ANN models alone. Zhang et al. similarly proposed a hybrid model that combines ARIMA and SVM for the prediction of residential hot water consumption. The model uses ARIMA to model and predict the linear part of the time series data and SVM to model and predict the nonlinear part most significantly [137]. Their results showed that the hybrid model significantly outperformed the individual models. Keynia et al. proposed a model that uses the wavelet transform and neural networks to predict the electric water boilers' energy consumption [178]. The wavelet transform is used to decompose the load series into different frequency load demand components, and neural networks are used to predict each decomposed series. The final prediction is obtained by aggregating the predictions of each series. Although their work was on energy load prediction, the methodology could potentially be applied to electric water boilers' prediction of consumption. Recently, with the evolution theory GA-NN, a genetic algorithm has been used to optimise the weights of the NN, reducing the chances of the model getting trapped in local minima and potentially improving the prediction performance [171].

4. Prediction Evaluation and Validation Methods

There are numerous methodologies for assessing and validating the accuracy and dependability of prediction models for electrical water boilers' energy consumption. These evaluation techniques are broadly classified into two types: those that use statistical measures to compare predicted and actual energy consumption and those that employ more sophisticated machine learning and artificial intelligence techniques. The major challenge associated with the accuracy of these two categories is overfitting, which occurs when the chosen evaluation model deviates too far from the true values of the known observations or parameters [172]. Additionally, the evolution of model evaluation aims to address this problem by selecting flexible methods capable of accurately determining many different possible known true values. Overfitting leads to the model closely following the errors or noise [6]. This phenomenon forms the basis of the discussion in this section on the prediction of prediction evaluation techniques.

4.1. Statistical Evaluation Approach

Statistical methods are widely used due to their relative simplicity and interpretability, particularly in the evaluation of energy consumption prediction models. Typically, such methods use regression analysis, which uses historical energy consumption data to forecast future energy consumption [13,33]. Furthermore, statistical evaluation methods are basically used to assess the performance, accuracy, and reliability of models or predictions based on statistical measures and tests. Examples of the method are Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), *p*-values, confidence intervals, hypothesis testing, etc. These methods aim to provide insights into the statistical significance of the results, helping researchers and engineers understand the reliability of the prediction models. Various measures of fitness estimation are as follows:

i. Root Mean Squared Error (RMSE): the mathematical computation involves taking the square root of the average of squared differences between predicted P_i and actual values A_i,

$$RMSE = \sqrt{\frac{\sum_{i=0}^{n} |A_i - P_i|^2}{n}} \tag{1}$$

where n is the number of observations of the ith predictions.

The squaring operation in RMSE gives more emphasis to larger errors $|A_i - P_i|^2$, making RMSE valuable when large errors should be penalised more. Nevertheless, if there are extreme values in the dataset, it can disproportionately influence the RMSE result [84]. Also, the squaring operation eliminates the sign of the error, which limits RMSE in providing information about the direction of errors (overestimation or underestimation). It treats all deviations equally without distinguishing between over-predictions and under-predictions [34]. In cases where the distribution of errors is not normal, alternative evaluation metrics might be more appropriate;

ii. Mean Absolute Percentage Error (MAPE) is expressed as a percentage (making it scale-independent):

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_i - \tilde{Y}_i}{Y_i}\right| \times 100 \quad (2)$$

where N is the number of observations. The result is directly interpretable as the average percentage difference between predicted $\tilde{Y}_i$ and observed Y_i values. This allows for the comparison of prediction accuracy across different datasets. Furthermore, most deterministic and traditional probabilistic and data-driven stochastic methods use MAPE and RMSE to evaluate their models [6,178,179]. Lower MAPE values indicate better prediction accuracy, facilitating easy model comparisons. Nevertheless, MAPE can become undefined or extremely large when Y_i is close to zero, which may lead to numerical instability when N is relatively small. In addition, it might not be suitable for datasets with intermittent or sporadic demand;

iii. Mean Absolute Error (MAE) represents the average absolute difference between predicted Y_i and $\tilde{Y}_i$ observed values [6]:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_i - \tilde{Y}_i\right|^2 \quad (3)$$

Unlike the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), which are sensitive to outliers (meaning that if there are extreme values in the dataset, they can disproportionately influence the RMSE), MAE is not sensitive to outliers. It gives equal weight to all errors, making it robust in the presence of extreme values. Nonetheless, MAE treats all errors equally, irrespective of the magnitude. In circumstances where larger errors are more dominate, MAE might not appropriately penalise them. Since MAE considers only the absolute differences, it does not provide information about the direction of errors (overestimation or underestimation). In some scenarios, understanding the direction of errors is significant for model interpretation [6,84];

iv. Coefficient of Determination (R^2) is mathematically expressed as the proportion of the variance in the dependent variable Y_i that is predictable from the independent variable(s) X_i:

$$R^2 = \left\{\frac{1}{N}\,\frac{\sum\left(X_i - \dot{X}\right)\left(Y_i - \tilde{Y}\right)}{\left(\sigma_x - \sigma_y\right)^2}\right\}^2 \quad (4)$$

where N is a number of observations; X and Y are observations of i for X_i and Y_i; $\dot{X}$ and $\tilde{Y}$ mean of X and Y, respectively; σ_x and σ_y are standard deviations, respectively. It provides a standardized measure for comparing different models. Models with higher R^2 values are generally considered better predictors [6].

A value of 1 indicates that the model perfectly predicts the dependent variable, while a value of 0 indicates that the model does not provide any predictive value. The higher the R^2, the better the model fits the data [6,33]. Nevertheless, a high R does not guarantee accurate predictions; it can be influenced by the specific sample used for model estimation, which may result in the model performing poorly on new and unseen data [33,84]. There are other methods like Mean Squared Error (MSE),

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \tilde{Y}_i\right)^2 \quad (5)$$

Normalised Mean Squared Error (NMSE),

$$NMSE = \frac{\left\|\left(Y_i - \tilde{Y}_i\right)\right\|_2^2}{\left\|\tilde{Y}\right\|_2^2} \quad (6)$$

and Cross-Variation (CV)

$$CV = \frac{S_i}{Y_i} \quad (7)$$

where N is the number of observations; X and Y are observations of i for X_i and Y_i; $\dot{X}$ and $\tilde{Y}$ mean of X and Y, respectively; S_i is a variance in intertemporal [84,180–186].

Marszal-Pomianowska et al. initially validated their method using data from both single-family houses and apartments. Subsequently, they applied this method to a dataset comprising hourly total heat consumption readings from 38 single-family houses. The model's evaluation involved the use of the standard deviation as a preliminary classification criterion to determine whether the method could be applied or not. They established two limits: $\sigma > 240$ for apartments and $\sigma < 800$ for single-family houses [6]. Similarly, Zlatanovic et al. conducted simulations for the hot water line with a tuned flow over a 5-s time step, resulting in only slightly improved statistical parameters. Specifically, the correlation coefficient (R) improved from 0.978 to 0.982, while the Root Mean Squared Error (RMSE) and Nash–Sutcliffe efficiency (N-S) remained in the same order at 0.955 and 1.382 (1.384), respectively. Notably, excluding hours without demand from the statistical analysis (from 00:00 to 6:00 and from 19:00 to 00:00) led to enhanced R and Nash–Sutcliffe efficiency (N-S) values, reaching 0.984 and 0.999, respectively. However, RMSE increased to 1.748, although it remained at less than half of the standard deviation of the measured time series (6.478) [84]. Leiria et al. utilised the normalized mean bias error (NMBE) and the coefficient of variation in the root mean square error (CVRMSE) to assess the combined Kalman filtering and SVR–Univariable/multivariable estimator they developed. The error distribution is quite diverse, with five apartments showing an EWBs demand overestimation of more than +25%. Among these, one household had an extreme EWBs prediction with an overestimation of +85%, while four apartments had a slight underestimation of over −10% [34].

Statistical evaluation methods play a crucial role in assessing the performance, accuracy, and reliability of electric water boiler prediction models. These methods provide valuable insights into the statistical significance of the results, aiding researchers and engineers in understanding the reliability of their models. However, it is important to choose appropriate evaluation metrics based on the specific characteristics and objectives of the prediction model. While metrics like Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and R-squared (R^2) offer valuable information, careful consideration is necessary, as each metric has its advantages and weaknesses.

4.2. Machine Learning Model Evaluation Approaches

Machine learning model evaluations have been introduced into the field in recent years, and they showed promising results in forecasting the energy consumption of electrical water boilers [33,157,187]. These models are frequently more complex and require more computational resources than statistical models, but they are usually more accurate and can deal with non-linear relationships between variables more efficiently. However, the application necessitates significant computational resources as well as data expertise. These models are typically evaluated by dividing the data into a training set and a test set. To evaluate its predictive accuracy, the model is trained on the data set and then tested on another data set. In addition, to ensure robustness and avoid overfitting, different techniques are used.

i. Cross-validation ($k-$ fold Cross-validation),

$$CV_{(k)} = \frac{1}{N}\sum_{i=1}^{k} MSE_i \quad (8)$$

is computed by estimating the average MSE equation values represented in Equation (8), with $k-$ folds random values dividing the set of k groups, where the first fold is mostly treated, and the validation set fits across the $k-1$ folds, which is repeated k times, also known as the estimation error test [180,181].

K-fold cross-validation finds significance by training and testing on different subsets, reducing the bias introduced by overfitting to a specific training set [182]. Moreover, it may require substantial memory, especially for large datasets, as multiple models are trained and stored during the cross-validation process. For time-series data, random shuffling may not be appropriate, and the sequential order of data points needs to be preserved, which *k*-fold cross-validation may not address [33,181];

ii. Confusion Matrix (CM) provides a clear and detailed breakdown of different aspects of classification model performance by differentiating between false positives and false negatives. Confusion Matrix (CM) offers insights into the types of errors the model is making [183,184]. This information can guide model refinement, which is designed for binary classification problems [182]. Moreover, it becomes more complex and less intuitive when dealing with multi-class classification. CM treats all misclassifications equally, regardless of how confident the model was in its predictions. It does not consider the certainty or uncertainty associated with each prediction.

Table 6 presents the confusion matrix (MC) classification used to evaluate the performance of a predictive model, which consists of four main metrics: True Positives (TP); True Negatives (TN); False Positives (FP); and False Negatives (FN) [178]. Subsequently, some commonly used metrics derived from the confusion matrix (MC) are as follows:

1. $Accuracy(ACC) = \frac{TP+TN}{TP+TN+FP+FN}$;
2. $Precision = \frac{TP}{TP+FP}$;
3. $Recall = \frac{TP}{TP+FN}$;
4. $F1\ score = 2\left(\frac{Precision\ Recall}{Precision+Recall}\right)$.

Table 6. Confusion Matrix representation.

	Actual Positive	Actual Negative
Predicted Positive	True Positive (TP)	False Positive (FP)
Predicted Negative	False Negative (FN)	True Negative (TN)

These metrics offer a thorough assessment of the model's performance, encompassing several characteristics like overall accuracy, the capacity to correctly identify positive cases, and the trade-off between precision and recall [178,181];

iii. Area Under the Receiver Operating Characteristic curve (AUC-ROC)

$$\mathrm{AUC-ROC} = \int_0^1 True\ positive\ Rated(False\ Positive\ Rate) \tag{9}$$

is an essential metric in evaluating the performance of prediction models. It provides a comprehensive measure of a model's ability to distinguish between positive and negative instances across various decision thresholds, as represented in Equation (9) [187]. It is robust and less sensitive to class inequity, making it suitable for inequity datasets [178,180].

Research studies and applications often cite the AUC-ROC when evaluating the effectiveness of classification algorithms. Fawcett provides an in-depth exploration of ROC analysis and its applications, emphasizing the significance of the AUC-ROC as a performance metric for classification models [187]. However, in highly imbalanced datasets, where the number of negative instances significantly outweighs the positive instances (or vice versa), AUC-ROC might not fully represent the model's performance, especially if the model is optimized for the majority class. AUC-ROC does not inform about the model's calibration, i.e., whether predicted probabilities align well with actual probabilities. Well-calibrated models are important in certain applications. Amasayali et al. conducted a comprehensive review of studies that developed data-driven building energy consumption prediction models with a specific focus on evaluating the performance measures employed. The findings revealed that among the reviewed studies, 41% utilized Cross-Validation (CV), 29% used Mean Absolute Percentage Error (MAPE), and 16% relied on Root Mean Squared Error (RMSE) as their evaluation metrics [33]. Interestingly, Cross-Validation emerged as the most commonly employed evaluation measure, possibly due to two key factors. Firstly, it aligns with the performance evaluation measures recommended by ASHRAE for assessing energy consumption prediction models. Secondly, Cross-Validation normalizes prediction errors relative to average energy consumption, yielding a unitless measure that facilitates convenient comparisons.

Evaluating and validating the accuracy and reliability of electrical water boilers' prediction models pose a number of challenges and limitations. Firstly, the quality and quantity of data can also be a concern, as erroneous readings, missing data, and outliers can negatively affect the model's accuracy [182]. Furthermore, a lack of comprehensive data can lead to incomplete modelling and inaccurate validation results [183]. Secondly, the complexity of models, in theory, is often difficult to evaluate and validate due to their black-box nature. The dynamic models and identifying errors can be quite challenging. They are also prone to overfitting, especially when the dataset is small or noisy [165,182,184]. Thirdly, parametric uncertainty is associated with the predictive models, mainly due to unpredictable changes in user behaviour, weather conditions, equipment performance, and other variables. Lastly, selecting an appropriate validation methodology can also be a challenge. Common methods include hold-out validation, confusion matrix or error matrix, cross-validation, and bootstrap validation, each with its own strengths and limitations [33,185,186]. Future work can consider strategies to address these challenges, such as extensive data collection, advanced data pre-processing and cleaning techniques, and robust validation methods that need to be employed. Also, techniques to prevent overfitting, such as cross-validation and regularisation, and probabilistic models to account for uncertainty while adopting machine learning techniques that can handle complex data and uncertainties, among others. These can improve the accuracy of the prediction models.

5. Future Research Trends, Recommendations, and Conclusions

The ubiquitous use of electric water boilers in buildings, where hot water usage varies across all four seasons, accounts for 35% of the energy consumption in residential buildings, according to Matthew et al., making it imperative to predict electric water boiler energy consumption [108]. The results also showed an average reduction of 1.33 kWh/day per consumer, which equates to an average decrease of 35.5% in water heating costs. A significant research gap exists; previous studies have predominantly concentrated on aggregate energy consumption, with limited emphasis on predicting individual electric water boiler energy usage, especially in high-rise residential buildings, as indicated by some of the reviewed research in Table 1. The prediction could aid in the development of more energy-efficient management and reduction in overall energy use. Nevertheless, some research has been conducted on the impact of hot water use patterns like showering, hand washing, clothes washing, and dishwashing on electric water boilers' energy consumption [2]. The influence of these factors at an individual level, particularly in high-rise residential buildings, is less well understood and requires further investigation. More research is needed to determine how emerging technologies, like machine learning (ML) and artificial intelligence (AI), may be used to develop prediction models that consider variables such as user behaviour, building design, and weather patterns [34,121].

This paper reviews factors affecting electrical water boilers' consumption, prediction techniques for energy consumption patterns, and performance metrics for prediction methods. It identifies research gaps and offers recommendations for residential building applications. Summarised findings include the following:

1. Seasonal changes impact consumption patterns, necessitating data classification. Models ignoring inhabitant count may overestimate consumption rates;

2. Hot water consumption analysis should extend beyond residential buildings to different building types with distinct energy patterns and user behaviour;
3. Assessing the impact of building renovations on occupant well-being and behaviour requires more attention;
4. Further studies should analyse hot water usage across geographical zones and climates, especially for non-residential buildings, considering daily and seasonal variations;
5. Research should explore the influence of time-of-use on hot water behaviour, accounting for occupant composition, economics, and personal traits on hourly and daily usage;
6. Predicting individual electrical water boilers' energy consumption, particularly in high-rise residential buildings, merits focus. Machine learning, IoT, and AI methods can enhance predictive models;
7. The effect of specific hot water usage patterns (showering, bathing, dishwashing) on electric water boilers' energy consumption in high-rise residential buildings warrants investigation;
8. Future research should enhance data collection methods, quality, and processing to improve measurement precision for predicting electric water boilers' energy consumption;
9. Larger datasets would enhance prediction methods' reliability and applicability to different regions with similar metering practices and building features;
10. Addressing data privacy concerns when considering user behaviour in data collection for prediction models is essential;
11. Balancing model performance, complexity, predictive power, and interpretability, particularly in hybrid models, can prevent overfitting;
12. Future research may explore the involvement of market frameworks in aggregators' role for residential consumers in optimising flexible components in various markets;
13. Qualitative and empirical analysis of household electrical water boilers' energy consumption patterns, including energy usage and dynamics, can inform policymaking and market design.

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