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SHAP-Based Insights into Environmental and Economic Performance of a Shower Heat Exchanger Under Unbalanced Flow Conditions: A Feasibility Study

Sabina Kordana-Obuch * and Mariusz Starzec

Department of Infrastructure and Water Management, Rzeszow University of Technology, al. Powstańców Warszawy 6, 35-029 Rzeszow, Poland; mstarzec1990@prz.edu.pl
* Correspondence: sk@prz.edu.pl

Abstract

Heat recovery from greywater is one solution for improving the energy efficiency of buildings and reducing greenhouse gas emissions. Particular attention is paid to systems utilizing heat from shower water, which, due to its high temperature and regularity, represents a promising energy source. However, the interplay of parameters determining the financial and environmental effectiveness of such a solution has not yet been fully explored. Therefore, the aim of this paper was to identify key variables influencing the feasibility of using a shower heat exchanger operating under unbalanced flow conditions and to assess the consistency between financial and environmental effects. The analyzed net present values ranged from −€1381 to €52,168. Greenhouse gas emission reduction values ranged between 61 $kgCO_2e$ and 37,207 $kgCO_2e$. The analysis was conducted using predictive modeling and the SHAP (SHapley Additive exPlanations) method, which allows for the interpretation of the impact of individual variables on the forecasted net present value and potential greenhouse gas emission reduction. A global analysis was carried out to determine the relative importance of variables, as well as a local analysis for selected cases. The results showed that operational variables related to shower use, particularly shower length and mixed water flow rate, significantly influenced the prediction results of both models. In the case of emission reduction, greenhouse gas emission intensity and its change over time also had a significant impact, whilst the financial effects were determined by the energy price from the perspective of the subsequent years of the system's operation.

Keywords: European Union; greenhouse gas emission reduction; heat recovery; net present value; residential building; SHAP; vertical heat exchanger; XGBoost

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1. Introduction

Buildings, including residential buildings, are responsible for a significant portion of final energy consumption and greenhouse gas emissions. It is worth noting that one of the most energy-intensive processes in the construction sector is the preparation of domestic hot water (DHW) [1], the heating of which generates additional high costs. Unlike space heating, where energy demand systematically decreases with improving energy standards in buildings [2], the share of energy allocated to DHW is becoming an increasingly dominant component of buildings' energy balances. In highly energy-efficient buildings, it can even significantly exceed the demand for other purposes. For example, research by Hall et al. [3] has shown that water-related energy use can in some cases

reach as much as 7 kWh/person/day, accounting for up to 50% of energy consumption in households. As a result, technologies based on renewable energy sources [4] and enabling energy consumption reduction and recovery at the end-user level [5–7] are becoming increasingly desirable. Furthermore, growing energy consumption in cities increases the need to implement systems that balance energy efficiency with thermal comfort [8]. This, in turn, implies an increased demand for detailed analyses enabling a reliable assessment of the energy, environmental, and economic effects of the proposed solutions.

One solution for reducing energy consumption for DHW is a shower heat exchanger (SHE) [9]. During normal operation of the installation, the thermal energy contained in greywater is permanently lost, and its energy potential remains unused. By using SHEs, the thermal energy contained in shower water is transferred to the water, which is then used during the same shower [10]. This is one of the few examples of measures that do not require changing user habits and do not affect the comfort of using the shower system. Previous studies on assessing the effectiveness of SHEs, determining their financial efficiency, or reducing CO_2 emission [11–13] have focused mainly on the use of aggregated, simplified indicators and lacked a deeper analysis of the impact of individual operating and system parameters on the analysis results. At the same time, most studies only covered balanced flow conditions [14]. This means that even with advanced computational tools [15], the scope of analytical conclusions and their practical applicability is clearly limited. In installation practice, systems operating under unbalanced flow conditions are present [16]. In such a situation, the water flow rate through the SHE is significantly lower than the drain water flow rate, which is a consequence of supplying preheated water to only one of the devices (the shower mixing valve (SMV) or the DHW heater), while the other is supplied with cold water. Despite the limited possibilities of thermal energy recovery compared to the balanced flow variant, such solutions are used to reduce the complexity of the hydraulic system or to adapt the installation to existing DHW preparation systems in which parallel supply of both devices is impossible or technically unjustified.

Despite the growing number of publications on SHEs, their operation under unbalanced flow conditions remains relatively poorly understood, and their impact on key environmental and financial indicators is often marginalized, simplified, and sometimes even overlooked. Relying on balanced flow conditions, which are often impossible to apply in installation practice, leads to systematic overestimation of the achieved energy and economic effects. Furthermore, commonly used analysis methods rarely enable clear identification of the parameters determining the environmental and financial benefits achieved, limiting their usefulness both in the design phase of shower heat recovery systems and in implementing measures supporting the realization of this type of technology.

In response to these limitations, this paper adopts an approach aimed at systematic and quantitative decomposition of the impact of input variables on environmental and financial effects in conditions close to real-world conditions, with the main goal being to analyze the impact of variables determining SHE operation under unbalanced flow conditions on the projected greenhouse gas emission reduction (R_{GHG}) and the financial efficiency of the investment expressed as net present value (NPV). The novelty of the study lies in the parallel, coherent approach to both dimensions based on a partially common set of input variables and in the identification of potential discrepancies between financial and environmental optimality, which is poorly recognized in the existing literature. The analysis was conducted for a system configuration that assumed supplying preheated water exclusively to the shower mixing valve. This choice was dictated by its widespread use in installation practice and limited interference with the existing DHW heating system. The vertical heat exchanger was chosen as the research object due to its dominant position among solutions used in installation practice and its more favorable heat transfer

parameters compared to horizontal SHEs [17]. Furthermore, analyses of this shower heat recovery system configuration available in the literature focus primarily on horizontal heat exchangers [18], while vertical units, despite their widespread use in practice, remain relatively underexplored.

Interpretable machine-learning methods, along with SHAP analysis, were used in the analysis, which enabled transparent identification and quantification of the impact of individual input variables on the analysis results. The use of separate models for both dependent variables (R_{GHG}, NPV) allowed for the identification of key parameters determining their variability, which made it possible to assess the consistency between environmental and financial effects and to identify potential differences in the mechanisms shaping these effects. This approach represents a significant extension of the current state of knowledge, providing tools to support both design optimization and the development of policies supporting the implementation of heat recovery technologies in real-world conditions.

The research described here is a continuation of analyses conducted to assess the energy efficiency of vertical shower heat exchangers under various flow conditions, the results of which were described in [19]. The scope of this paper includes:

- Evaluation of the financial efficiency of using a vertical shower heat exchanger in a configuration where preheated water is supplied exclusively to the SMV.
- Estimation of the potential greenhouse gas emission reduction under similar operating conditions of the SHE.
- Development of eXtreme Gradient Boosting (XGBoost) models to predict NPV and R_{GHG}.
- Evaluation of the impact of individual input variables on the expected NPV and projected greenhouse gas emission reduction.

2. Materials and Methods

2.1. Environmental and Financial Analysis

2.1.1. Evaluation of the Performance of a Shower Heat Exchanger Under Unbalanced Flow Conditions

The analysis included an evaluation of the performance of a vertical "pipe-in-pipe" SHE, 1.68 m long and 50 mm internal diameter. A detailed description of the unit, along with a description of the measuring devices, can be found in [19]. Vertical shower heat exchangers are commercially available units used in residential buildings. Due to the need to meet specific installation requirements, primarily the need to install them in a vertical section of the sewage system, their application is easier in newly designed buildings, where adequate installation space can be provided for this type of unit. Failure to incorporate a vertical SHE into the building design may require a more complex retrofit of the existing facility, particularly in systems supplying preheated water to a DHW heater. In some cases, installing a vertical heat exchanger may even prove impossible.

Based on the input dataset, marked in green in Figure 1, a series of experimental studies were conducted to determine the preheated water temperature (T_{pw}) (Figure 2). The studies were conducted for a system configuration that supplied preheated water exclusively to the shower mixing valve (Figure 3). In practice, this type of configuration is often used in facilities where interfering with the existing domestic hot water system is difficult or would require significant capital expenditure. It should be noted that the heat recovery system configuration under consideration involves minimal interference with the existing internal water and sewage system and is less complex hydraulically than systems supplying a DHW heater. This makes the solution easier to implement in retrofit projects for existing buildings. In existing DHW systems, the possibility of interfering with the hydraulic system is usually limited, as a result of which preheated water can

only be supplied to selected points of the internal system. Due to the location of the SHE below the shower, this is most often an SMV. This arrangement of preheated water pipes results in unbalanced flow conditions in the heat exchanger. It should also be noted that a configuration ensuring balanced flow requires more complex modifications to the water and sewage system, which involves the purchase of additional pipes, fittings, and often interventions in the building structure. This, in turn, significantly increases investment outlays. Therefore, solutions characterized by unbalanced flow conditions represent a practical compromise between energy efficiency and the feasibility of a drain water heat recovery system. This justifies their analysis as a scenario representative of a wide range of real-world applications. Under such conditions, the heated water flow rate is significantly lower than the drain water flow rate, which results from the fact that only a portion of the water used for showering flows through the heat exchanger. As a result, the achieved temperature effectiveness of the unit is higher than when the SHE operates under balanced flow conditions. However, the heat transfer rate is reduced in such conditions [19], which, in turn, affects the achieved financial and environmental effects.

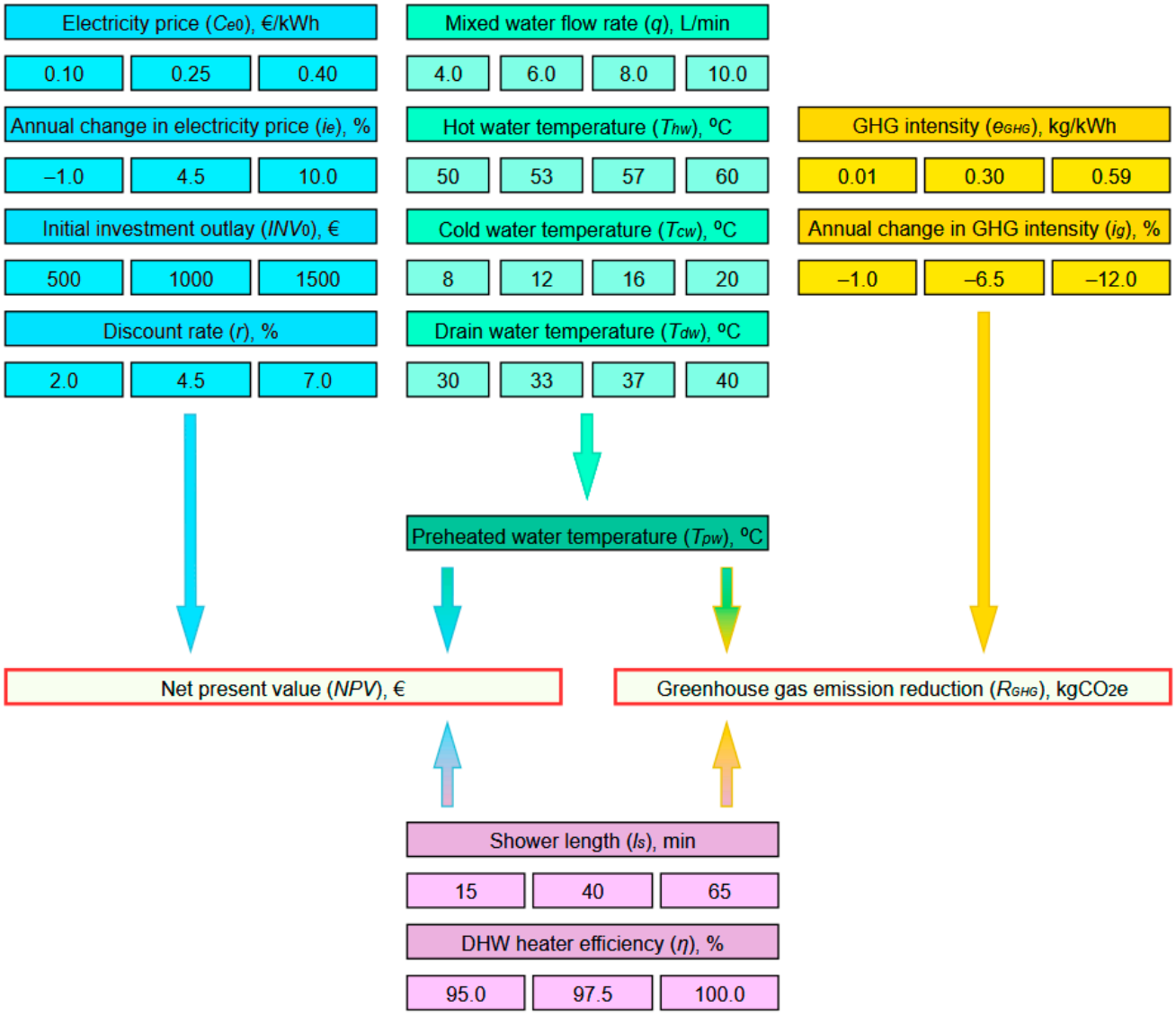


Figure 1. Input parameters with their assumed values and their corresponding output parameters (GHG—greenhouse gas; DHW—domestic hot water).

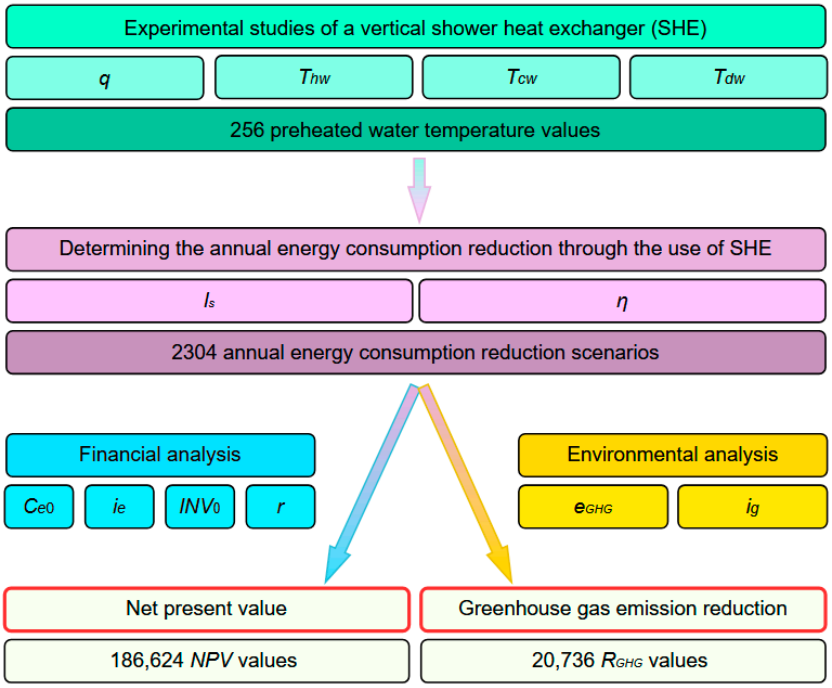
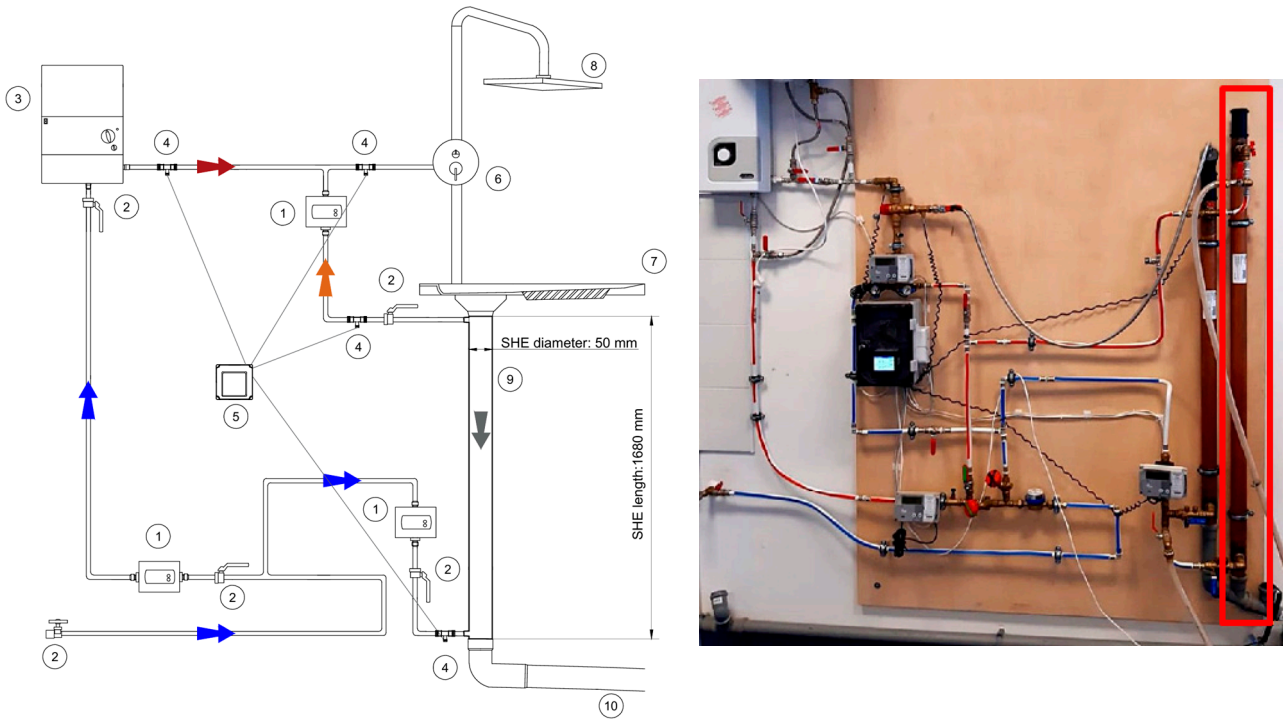


Figure 2. Research stages. Colors and designations are consistent with Figure 1.



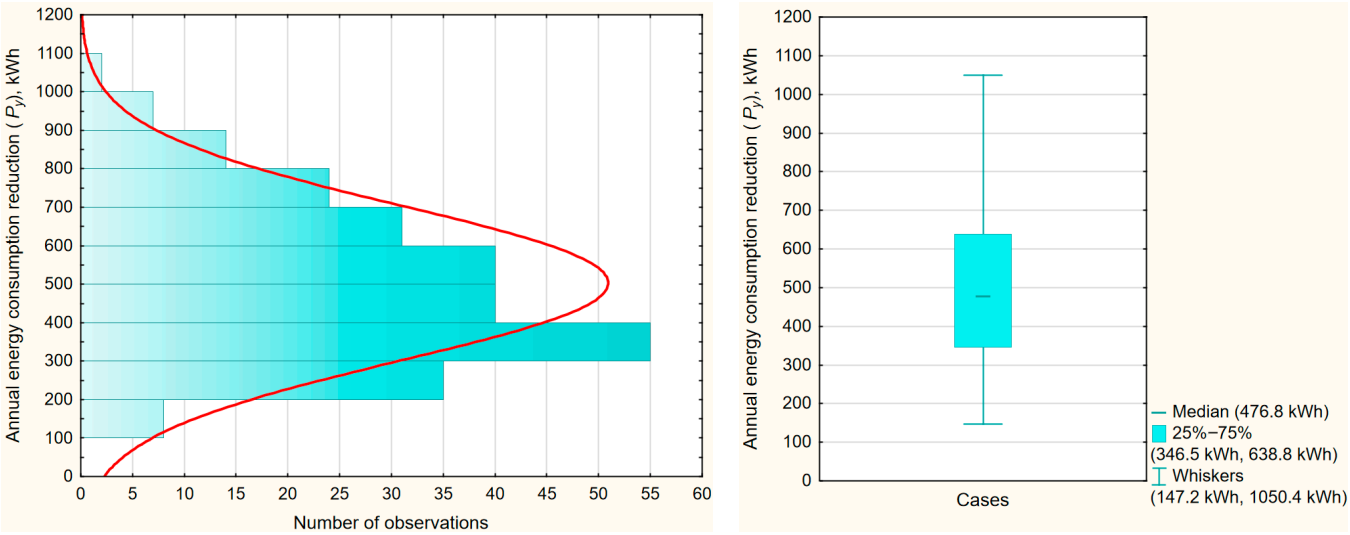
(**a**) (**b**)

Figure 3. Shower drain water heat recovery system: (**a**) System configuration diagram; (**b**) Research stand with a heat exchanger installed; the red box indicates the investigated unit (1—flowmeter; 2—cut-off valve; 3—domestic water heater; 4—temperature sensors; 5—data recorder; 6—shower mixing valve; 7—shower tray; 8—shower head; 9—shower heat exchanger; 10—drain pipe; SHE—shower heat exchanger).

For the assumed range of input variables, the water flow rate through the vertical SHE constituted several tens of percent of the drain water flow rate. Its value resulted from the assumed media temperatures in the individual sections of the system and the

mixed water flow rate (q). The tests were conducted over a 12-month period to reflect the annual variability of cold water temperature. The remaining parameters were adjusted accordingly to represent different combinations of input variables. Therefore, while the mixed water flow rate from the shower head was treated as an independent variable, the ratio of water flow rate to drain water flow rate in the SHE was not analyzed as a separate independent parameter. The unbalanced flow conditions resulted from the adopted thermal and hydraulic assumptions.

A total of 256 preheated water temperature values (T_{pw}) were obtained from experiments conducted across different combinations of input parameters. This, along with the cold water (T_{cw}) and hot water (T_{hw}) temperatures, as well as the mixed water flow rate (q), formed the basis for further calculations, which were performed over a fifteen-year time horizon. Annual energy savings (P_y), resulting from heat recovery from shower water, were calculated as the difference between the energy consumption in a building without a heat exchanger and one with the SHE installed. For the purposes of the analysis, it was assumed that water was heated using an electric DHW heater, as this is the most advantageous option, as noted by Ali et al. [20]. The domestic hot water flow rate to the shower mixing valve was determined based on the heat balance equation. For both the DHW heater efficiency (η) and the total daily shower length (l_s), three representative values of these parameters were assumed (marked in pink in Figure 1), which allowed for the consideration of various building operating scenarios. This approach enabled the mapping of diverse household shower usage conditions and the resulting annual energy consumption for DHW heating. As a result, the analysis included 2304 scenarios for reducing energy consumption for shower water heating. For example, Figure 4 shows the distribution of 256 annual energy consumption reduction values obtained assuming the most unfavorable scenario in terms of shower length, i.e., for l_s = 15 min. The results correspond to a DHW heater efficiency of 95%.



(**a**) (**b**)

Figure 4. Distribution of annual energy savings resulting from the installation of the SHE (l_s = 15 min, η = 95%): (**a**) histogram; (**b**) box-plot.

2.1.2. Net Present Value

The financial efficiency of the project involving the installation of the SHE in an existing residential building was determined based on net present value (NPV). This indicator can

be determined as the difference between the discounted cash flows generated by the project and the investment outlay incurred, as described by Equation (1).

$$NPV = \sum_{t=1}^{n} \frac{P_y \cdot C_{e0} \cdot (1 + i_e)^t}{(1 + r)^t} - INV_0, \quad (1)$$

where NPV is the net present value, €; P_y is the annual energy saving resulting from the installation of the SHE, kWh; C_{e0} is the initial electricity price, € per kWh; i_e is the annual change in electricity price; r is the discount rate; t is the year of operation of the SHE; n is the service life of the SHE; INV_0 is the initial investment outlay, €.

In the case under consideration, positive cash flows represented savings resulting from reduced energy consumption for DHW heating. This indicator is a commonly used metric in investment profitability assessments, as it accounts for the time value of money and enables a clear determination of whether an investment will be financially beneficial. Therefore, NPV is widely used in analyses of the implementation of pro-ecological technologies in residential buildings [21], including those aimed at improving energy efficiency [22].

In addition to the system's technical parameters, such as flow rate and media temperatures, system operating time, and DHW heater efficiency, the analysis also considered additional variables that significantly impact the financial benefits achieved. The assumed values for these variables are highlighted in blue in Figure 1. In each case, three values of the initial electricity price (C_{e0}), the annual change in electricity price (i_e), the initial investment outlay (INV_0), and the discount rate (r) were considered. As a result, the financial analysis was based on 186,624 cases characterized by varying energy demand for DHW heating and diverse economic assumptions.

The initial electricity price (C_{e0}) was assumed based on Eurostat data for European Union (EU) countries [23]. These data covered households with annual energy consumption between 2500 and 5000 kWh. According to these data [23], the highest electricity price in the first half of 2025 was recorded in Germany (C_e = €0.3835 per kWh), and the lowest in Hungary (C_e = €0.1040 per kWh). Based on data from recent years [24], the dynamics of annual changes in electricity prices in individual countries were additionally analyzed, and annual percentage changes in electricity prices (i_e) were assumed. Changes in the shorter term were not analyzed to avoid seasonal effects. Short-term, sharp price fluctuations occurring in some countries in individual years were also omitted. Such jumps are incidental and, therefore, do not provide a reliable basis for multi-year forecasting. Initial investment outlays (INV_0), including the purchase of the SHE and its installation, were estimated considering a wide range of required installation work. Notably, the heat recovery system configuration under consideration is characterized by lower hydraulic complexity than configurations involving preheated water supply to a DHW heater, thereby potentially leading to lower investment outlays than more complex systems. The adopted range of INV_0 values allowed for cost variability resulting from differences in installation conditions, location, and market prices of equipment and labor. The adopted discount rate (r) values reflect the variation in this parameter across EU countries [25]. The analysis adopted an approach based on discount rates interpreted as real rates. Values close to the lowest r levels observed in some EU countries, reflecting the overall downward trend, were considered, as well as higher discount rates corresponding to more conservative investor assumptions. This approach allowed for the incorporation of economic uncertainty into the analysis and increased the universality of the obtained results, regardless of the adopted scenario of changes in energy prices.

2.1.3. Greenhouse Gas Emission Reduction

The reduction in greenhouse gas emission was estimated based on the projected reduction in energy consumption resulting from the use of SHE (P_y) and GHG emission intensity of electricity generation (e_{GHG}), according to Equation (2).

$$R_{GHG} = \sum_{t=1}^{n} P_y \cdot e_{GHG} \cdot (1 + i_g)^t, \quad (2)$$

where R_{GHG} is the greenhouse gas emission reduction, $kgCO_2e$; e_{GHG} is the GHG emission intensity of electricity generation, $kgCO_2e/kWh$, and i_g is the annual change in the value of e_{GHG} (the study included only negative values).

For both e_{GHG} and i_g, three values of the input variables were considered, resulting in the analysis of greenhouse gas emission reduction based on 20,736 model cases. As with the initial electricity prices (C_{e0}), the initial e_{GHG} value was assumed based on current data for individual EU countries [26]. According to the European Environment Agency [26], in 2024, the lowest e_{GHG} value was in Sweden (e_{GHG} = 0.007 $kgCO_2e/kWh$), while the highest was in Estonia (e_{GHG} = 0.585 $kgCO_2e/kWh$). Additionally, the dynamics of changes in this parameter in recent years were analyzed [26], and based on this, annual changes in greenhouse gas emission intensity of electricity generation (i_g) were assumed. Although increases in e_{GHG} values have been observed in some EU countries in recent years, a long-term downward trend was assumed for this variable. For this reason, all assumed i_g values were negative (Figure 1). This is due to the ongoing decarbonization of the energy sector, the increasing share of renewable sources in electricity production, and tightening climate policy. Short-term increases in emissions are usually temporary and result from extraordinary circumstances. Assuming a long-term decreasing trend enabled a more realistic assessment of the future environmental impact of vertical SHEs.

2.2. Prediction Models and Their Interpretation

2.2.1. eXtreme Gradient Boosting

A variety of machine-learning models are used in contemporary research [27,28]. This also applies to environmental and economic analyses. Popular models include eXtreme Gradient Boosting (XGBoost), which is successfully used both to predict CO_2 emissions [29] and in financial risk analyses [30]. It is also used to predict the thermal-hydraulic characteristics of heat exchangers [31], including SHEs [32]. Previous studies by the authors [19] involving the use of various predictive models to assess SHE performance also showed that the use of XGBoost models allows for obtaining more favorable model fitting metric values than other machine-learning models. This analysis was conducted using XGBoost version 2.1.2.

XGBoost is an ensemble learning algorithm based on gradient boosting of decision trees, in which successive trees are constructed sequentially to minimize a predefined loss function. Each subsequent tree is trained to reduce the residual errors of the previous model, allowing the algorithm to capture complex, nonlinear relationships between variables. In addition to the loss function, XGBoost incorporates a regularization term that penalizes model complexity, improving generalization and reducing the risk of overfitting. As a result, the final prediction is obtained as a sum of contributions from all individual trees. The XGBoost method allows for modeling complex, nonlinear relationships and interactions between variables, making it an appropriate tool for analyzing economic and environmental processes. Its additional advantage is high predictive accuracy and robustness to varying input data scales, which is crucial when considering both hydraulic and technical parameters, as well as economic and environmental ones [33]. Two predictive models were developed as part of the study, enabling the parallel assessment of financial

and environmental effects. The first, based on ten input variables, predicted the net present value of a project involving the installation of an SHE operating under unbalanced flow conditions. This enabled the identification of key factors influencing its financial viability. The second model was used to forecast the cumulative reduction in greenhouse gas emissions over a 15-year time horizon, allowing for the assessment of long-term environmental effects resulting from the SHE installation. In this case, the model was based on eight input variables.

The SHAP (SHapley Additive exPlanations) method was used to interpret the models and determine the impact of individual independent variables on their predictions [34]. This method enabled a quantitative assessment of the significance of individual variables and the identification of the direction and strength of their impact on model results. This led to a better understanding of the mechanisms shaping both the project's financial efficiency and its environmental impact.

2.2.2. SHAP Analysis

The SHAP (SHapley Additive exPlanations) method is based on Shapley values derived from cooperative game theory. For a given observation, the model prediction can be expressed as:

$$f(x) = \varphi_0 + \sum_i \varphi_i, \quad (3)$$

where φ_0 is the base value, and φ_i represents the contribution of the i-th feature.

This formulation enables an additive decomposition of the prediction into the effects of individual input variables and ensures a comparable interpretation of variable effects regardless of their scale [35]. SHAP analysis assigns each variable a contribution to the prediction result for individual observations and globally for the entire model [35]. In the local analysis, the distribution of SHAP values for individual predictions is examined to identify the direction and strength of the influence of individual features. This paper presents the results of such an analysis for three observations representative of each model. In each case, a positive SHAP value indicates an increase in the model's prediction value, while a negative value results in a decrease. The global analysis, on the other hand, is based on the mean absolute SHAP values for each variable, which allows for determining its overall importance. The results of these analyses for both models are presented in the paper as plots.

3. Results

3.1. Financial Analysis

3.1.1. Results of the Net Present Value Calculation

Analysis of 186,624 combinations of input variables showed that for the studied range, their *NPVs* remained between –€1381 and €52,168 (Figure 5). Negative values were obtained for approximately 24,000 cases, which constituted less than 13% of all combinations considered. The mean *NPV* reached €4317, and the median value was €2445, which indicates a right-sided asymmetry of the results distribution. The skewness value in this case is 2.30. Most of the results are relatively low compared to the maximum value (almost 75% of the results fall within the €0–€10,000 range). However, there is a group of combinations of input variables for which the *NPV* reached very high values, on the order of tens of thousands of euros. When analyzing the distribution of *NPVs*, it can also be seen that 25% of the obtained results exceed €5995. The same proportion of results is below €672, implying an interquartile range of nearly €5500. This indicates significant variability in results and high economic uncertainty of the project, resulting from the high sensitivity of *NPV* to the adopted model assumptions. The relatively low value of the lower quartile suggests that in a significant portion of the scenarios, the project generates only a small

surplus of positive cash flows. A high upper quartile, on the other hand, indicates the possibility of achieving very favorable results under favorable conditions. This confirms that the project's profitability is asymmetric, with high-risk scenarios dominating, while fewer but very favorable observations are present.

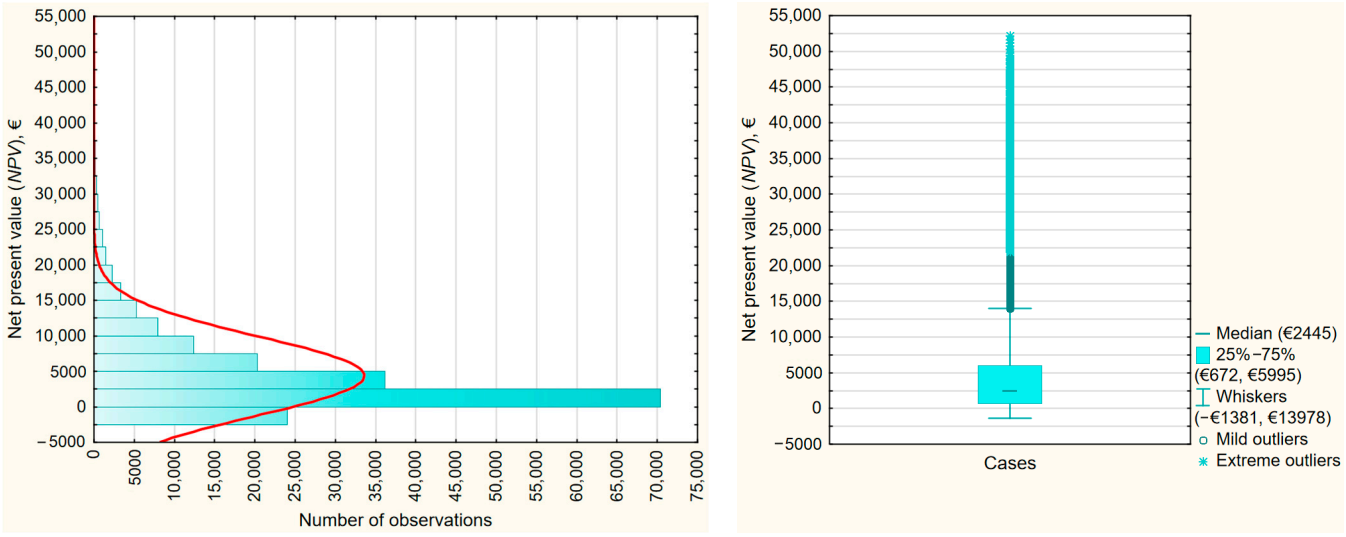


Figure 5. Net present value distribution: (**a**) histogram; (**b**) box-plot.

The above observations are also confirmed by the obtained kurtosis value of 7.4. Its high value indicates a clearly leptokurtic nature of the distribution, i.e., a strong concentration of observations around central values combined with a large number of outliers. High kurtosis combined with right-sided skewness indicates a low-probability, high-payoff profile, where most scenarios generate moderate results, but there is a certain probability of very large, positive deviations from the median, which should be considered in decision analysis.

As mentioned earlier, the observed high variability, right-sided asymmetry, and leptokurtic nature of the *NPV* distribution indicate that the project's profitability is largely determined by the presence of specific combinations of input variables. This distribution structure suggests nonlinear and potentially heterogeneous model sensitivity to changes in input variables, which complicates the identification of key risk factors. Nonlinearity and extreme values justify explainability methods like SHAP. For this purpose, the XGBoost model was developed. This model formed the basis for the SHAP analysis performed in the next stage of the research, enabling the identification of variables that most significantly determine the *NPV* and are responsible for the observed extreme scenarios.

3.1.2. Results of the SHAP Analysis

The XGBoost model was developed to simulate the relationship between input variables and *NPV*. The input data was divided into three datasets (training, validation, and test) in a 70/15/15 ratio, with each sample appearing in only one set, which excluded the risk of data leakage. The model was assessed using standard model fitting metrics, i.e., coefficient of determination (R^2), root mean square error (*RMSE*), and mean absolute error (*MAE*) [36]. The values of the metrics for the selected model are summarized in Table 1.

Table 1. Model fitting metrics for *NPV* prediction. *RMSE* and *MAE* are reported in euros.

	R^2	*RMSE*	*MAE*
Training dataset	0.999	19.99	13.24
Validation dataset	0.999	37.53	23.00
Test dataset	0.999	38.12	23.24

The results indicate a very good model fit to the data for the *NPV* prediction task, which in the analyzed case ranged from −€1381 to €52,168 (Figure 6). The coefficient of determination (R^2) reached almost identical, very high values (0.999) for all datasets, indicating good model generalization. Such high values of the coefficient of determination may suggest the risk of model overfitting or data leakage. In the present study, however, this is primarily a consequence of the nature of the input data. Net present values were determined based on deterministic relationships resulting from the adopted equations. The XGBoost model, therefore, reproduces existing mathematical relationships, leading to very high prediction accuracy. Achieving R^2 results close to 1 may also be due to the wide range of output variable values compared to the relatively small prediction errors.

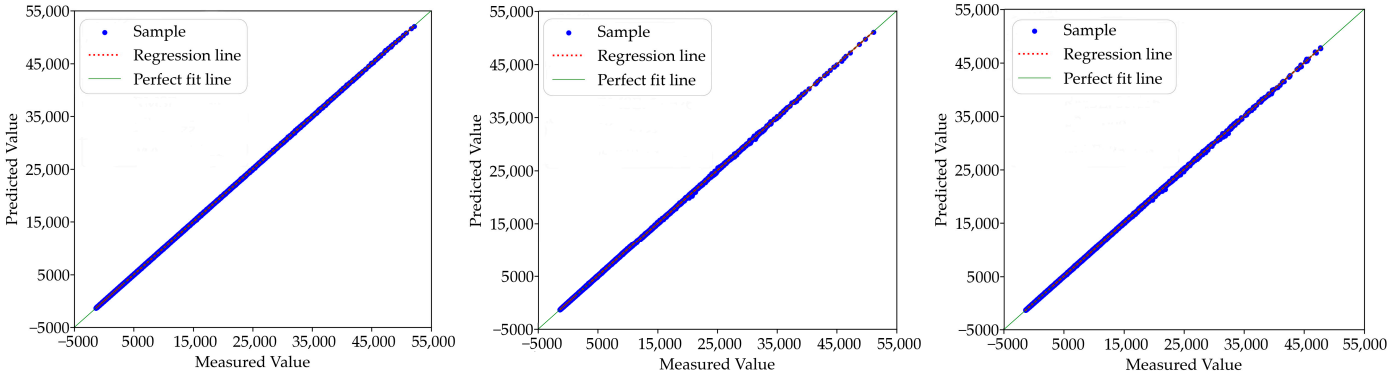


Figure 6. Comparison of predicted and observed *NPVs*: (**a**) training dataset; (**b**) validation dataset; (**c**) test dataset.

The high quality of the model, while maintaining realistic error estimation, was also confirmed by the values of the mean absolute and root mean square errors, which remained relatively low compared to the range of the predicted net present value. This demonstrates that the model is characterized by high predictive accuracy across the entire range of *NPVs* considered, as slight increases in *RMSE* and *MAE* on the validation and test datasets relative to the training dataset are expected. These results indicate that the model generalizes effectively, and the high R^2 is not the result of data leakage or overfitting.

To identify the key variables determining the financial profitability of the investment expressed as *NPV*, an analysis of the model's explainability was conducted using SHAP analysis. The prediction value can be interpreted as the sum of the baseline value and the contributions of all independent variables, expressed by their SHAP values. The model's base value, as shown in Figure 7, was €4322, meaning that individual input variables shifted the *NPV* forecast relative to this reference level. The direction of this shift was determined by the values of individual parameters.

The global analysis showed that the shower length (l_s) had the greatest impact on the *NPV*, with the mean absolute SHAP value exceeding €2200. This result confirms that the duration of installation use directly impacts the amount of energy saved and, consequently, the amount of positive cash flows generated by the project. The second most significant variable was the initial energy price (C_{e0}). However, it should be noted that the mean

|SHAP value| for this variable is only €87 lower than for l_s, suggesting that both variables are crucial to the analysis results. Considering that the percentage change in electricity prices (i_e) is ranked next in importance, it can be assumed that long-term market conditions, reflected in the forecasted dynamics of energy prices, may significantly determine the economic impact of the investment. The mixed water flow rate (q) has only a slightly lower impact on the net present value, with its mean absolute SHAP value, as with i_e, being approximately €1500. The hierarchy of features indicates that the financial efficiency of the project is determined mainly by operational variables related to shower use intensity and by economic conditions.

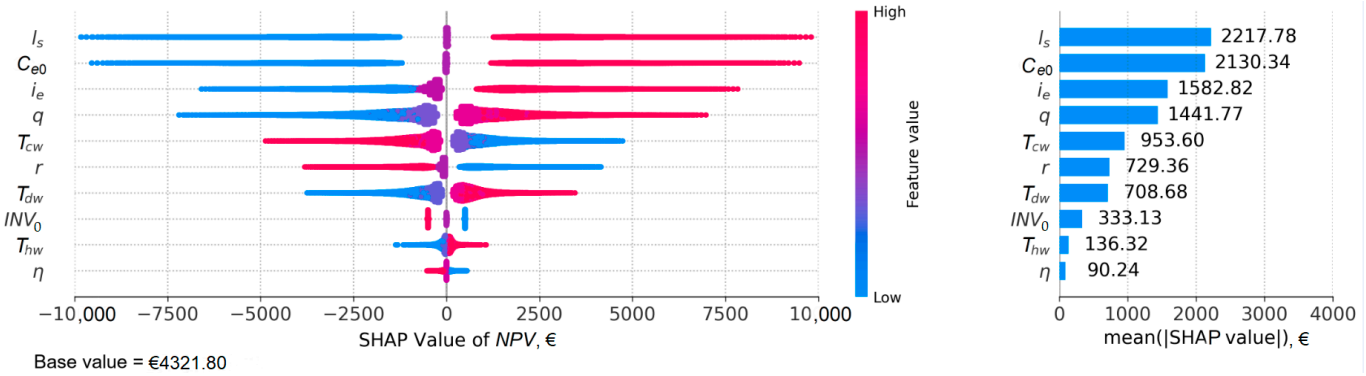


Figure 7. SHAP analysis of projected net present value (designations as in Figure 1).

Further bar plot analysis showed that the significance of the remaining input variables is significantly lower, and the mean |SHAP value| does not exceed €1000 in any case. For cold water temperature (T_{cw}), discount rate (r), and drain water temperature (T_{dw}), the mean absolute SHAP value was above €700. On the other hand, for the remaining variables, i.e., initial investment outlays (INV_0), domestic hot water temperature (T_{hw}), and DHW heater efficiency (η), it did not exceed €350. The hierarchy of significance, therefore, proves that in the case of a vertical SHE operating under unbalanced flow conditions, operational and market factors dominate over technical parameters, such as the efficiency of the primary heat source in the installation.

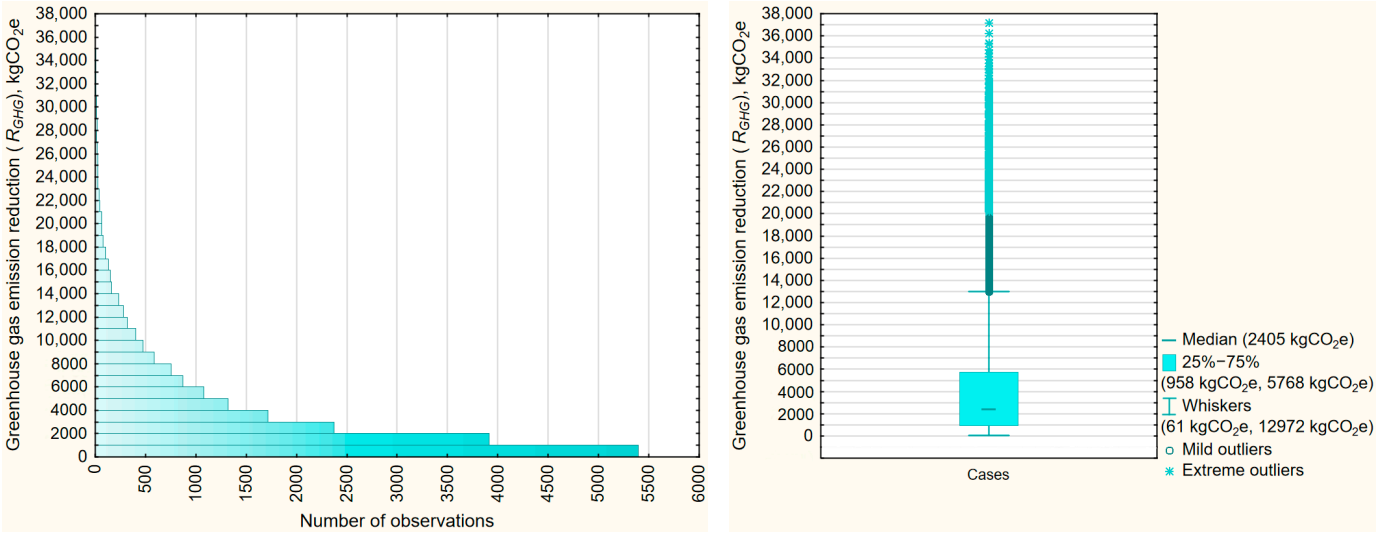
Beeswarm plot analysis allowed us to interpret the direction of the influence of individual variables relative to the base value (€4322). For shower length, initial electricity price, and its rate of increase, the *NPV* increased with increasing values of these variables, as evidenced by the location of the red points in Figure 7 to the right of the baseline value. A similar influence was observed for mixed water flow rate, drain water temperature, and DHW temperature. Increasing their values resulted in an increase in the projected investment profitability, resulting from greater energy recovery potential and higher financial savings.

For cold water temperature, discount rate, and DHW heater efficiency, lower values (blue points) are associated with higher *NPV*, indicating that increasing these variables negatively affects the outcome. Higher cold water temperature reduces the energy demand for heating, resulting in reduced potential savings. A higher r value reduces future cash flows, which worsens the *NPV*. In turn, the higher efficiency of the DHW heater reduces the difference in energy consumption between the reference variant and the variant with the vertical SHE, limiting the benefits of using a heat exchanger (Q-Blue B.V., Emmen, The Netherlands).

3.2. Environmental Analysis

3.2.1. Results of the Greenhouse Gas Emission Reduction Calculation

An analysis of 20,736 scenarios for the operation of a shower system in a building showed that installing a vertical shower heat exchanger operating under unbalanced flow conditions could reduce 15-year greenhouse gas emissions by up to 37,207 kgCO2e (Figure 8). However, it should be noted that the emission reduction potential varies depending on the national energy mix and the adopted decarbonization scenario for the coming years. The average R_{GHG} value obtained for European Union countries was 4185 $kgCO_2e$, while the median result was 2405 $kgCO_2e$. On the other hand, the minimum R_{GHG} value, obtained assuming the lowest input GHG emission intensity (e_{GHG}) and the highest assumed reduction in this variable in subsequent years (i_g), was only 61 $kgCO_2e$. The mean-to-median ratio itself suggests a strongly asymmetric distribution of results, as confirmed by a positive skewness of 2.1 and an increased kurtosis of 5.9. This suggests that in most of the scenarios considered, projected emission reduction is moderate, while in a limited number of cases, primarily related to high-emission countries, very high outliers appear, significantly inflating the mean. Therefore, also in this case, nonlinearity and extreme values justify the use of model interpretability methods. Importantly, however, despite the clear asymmetry of the R_{GHG} distribution, the *NPV* distribution is characterized by even greater skewness and kurtosis, which is most likely a consequence of the significant increase in energy prices over time.



(**a**) (**b**)

Figure 8. Distribution of projected greenhouse gas emission reduction: (**a**) histogram; (**b**) box-plot.

Further statistical analysis confirms significant uncertainty regarding the actual scale of the environmental effect. The interquartile range exceeds 4800 $kgCO_2e$. One-quarter of the results are lower than 958 $kgCO_2e$, and 75% of the obtained R_{GHG} values do not reach 5768 $kgCO_2e$, a value representing less than 18% of the potential maximum greenhouse gas emission reduction. The results, therefore, have a significant impact on the assessment of the environmental efficiency of the shower heat recovery technology. Relying solely on average R_{GHG} values may lead to an overestimation of the expected environmental benefits in countries with low-emission energy systems.

3.2.2. Results of the SHAP Analysis

To extend the analysis of greenhouse gas emission reduction by using a vertical SHE operating under unbalanced flow conditions, a predictive model based on the XGBoost

algorithm was developed and then used to conduct an explainability analysis using SHAP. The main goal of the model, similar to the financial analysis, was to identify the relative importance of individual input variables and the direction of their influence on the R_{GHG} value. This approach allowed the identification of which parameters are most decisive for the environmental performance of SHEs in different countries and energy transition scenarios. As a result, the model provides a tool supporting both the interpretation of the obtained greenhouse gas emission reduction results and the formulation of recommendations for climate and energy policy.

As with the net present value, the input data was split 70/15/15 to prevent data leakage. The model fitting metrics, summarized in Table 2, indicate the model's high ability to reproduce the analyzed relationships. This is also confirmed by Figure 9. The coefficient of determination of 0.999 indicates the model's high explanatory power of data variability and the absence of significant overfitting, as high predictive accuracy characterizes all datasets, including those not used in the training process. It should be noted, however, that also in the case of R_{GHG} predictions, the XGBoost model reproduced the existing mathematical relationships. The model's high quality is also confirmed by the *RMSE* and *MAE* values, which are relatively low compared to the range of analyzed R_{GHG} values, which reach tens of thousands of $kgCO_2e$. Therefore, it can be concluded that using the model as a reliable basis for performing SHAP analysis is fully justified.

Table 2. Model fitting metrics for R_{GHG} prediction. *RMSE* and *MAE* are reported in kilograms of CO_2 equivalent ($kgCO_2e$).

	R^2	*RMSE*	*MAE*
Training dataset	0.999	17.69	11.65
Validation dataset	0.999	33.89	20.74
Test dataset	0.999	33.26	21.26

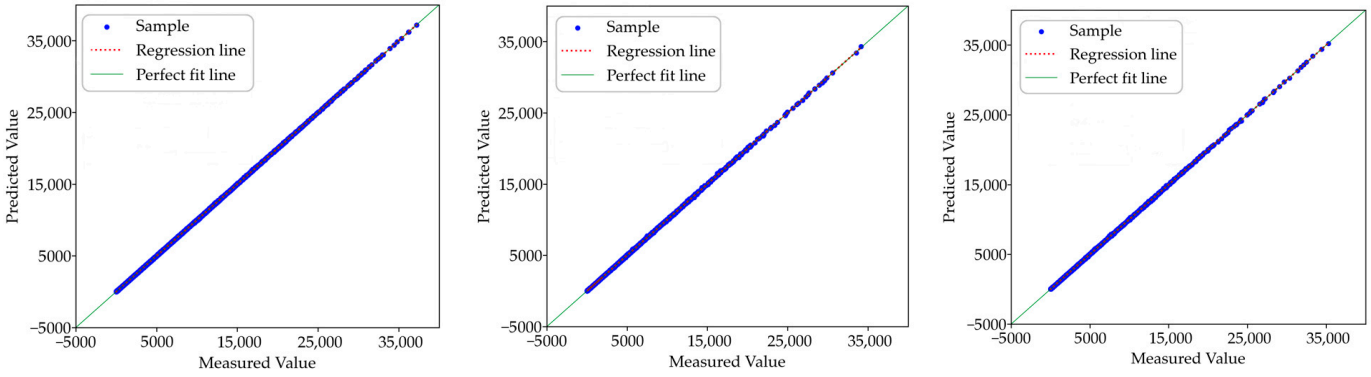


Figure 9. Comparison of predicted and observed R_{GHG} values: (**a**) training dataset; (**b**) validation dataset; (**c**) test dataset.

The global SHAP analysis (Figure 10) clearly demonstrated that the key factor determining greenhouse gas emission reduction through the use of the vertical SHE is e_{GHG}, with an average absolute SHAP value of nearly 2500 $kgCO_2e$. This variable, therefore, contributes the most to explaining the variability of the developed XGBoost model, confirming previous conclusions about the significant importance of the national energy mix for the environmental performance of SHEs. Reducing the energy source's carbon intensity is equivalent to limiting the potential for avoided emissions per unit of recovered thermal energy, resulting in significant variation in effects between countries with different energy

generation structures. This is evidenced by the beeswarm plot analysis, which allows for a detailed interpretation of the direction and scale of the impact of individual input variables on deviations from the base value (3804 $kgCO_2e$). In the case of greenhouse gas emission intensity, this range is the widest. Absolute SHAP values for individual observations reach almost 10,000 $kgCO_2e$, for both negative and positive values of this parameter. This wide range confirms that the variable can significantly increase or decrease the projected emission reduction (R_{GHG}) relative to the base value, depending on local conditions. The presence of high SHAP points (marked in red to the right of the base value) indicates that the high emission intensity of the energy system significantly increases the reduction effect of a vertical SHE operating under unbalanced flow conditions.

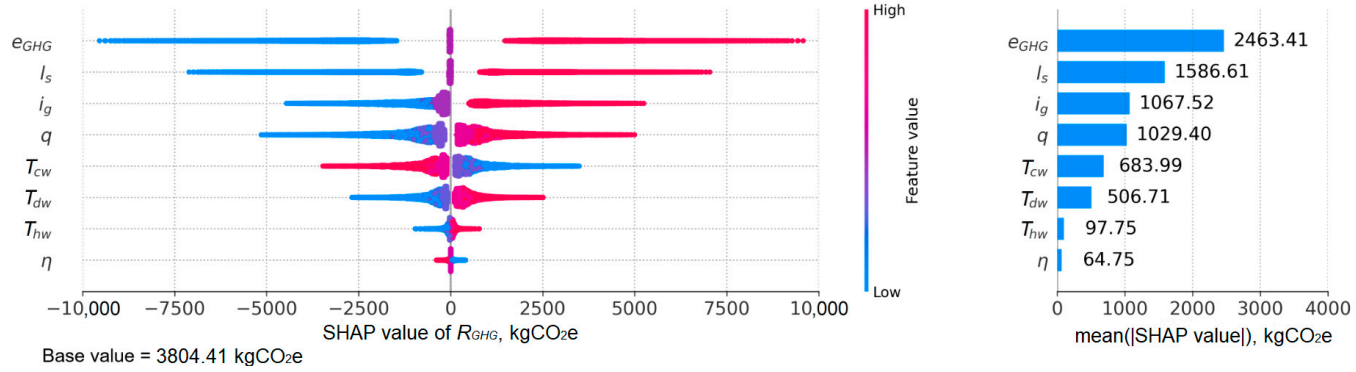


Figure 10. SHAP analysis of projected greenhouse gas emission reduction (designations as in Figure 1).

The second most significant factor was shower length (l_s), which directly impacts the amount of water used and, consequently, the amount of recoverable energy. In this case, however, the mean |SHAP value| is approximately 35% lower. This result indicates that user habits may be nearly as important as technological factors, highlighting the importance of consumption patterns in environmental efficiency analyses of projects that reduce energy consumption for water heating. Next in line were the annual change in GHG emission intensity (i_g), essentially a reduction in this indicator, and the mixed water flow rate (q). In both cases, the mean |SHAP value| exceeded 1000 $kgCO_2e$. This indicates that both energy transition dynamics and the hydraulic parameters of the building installation significantly influence long-term emission reduction potential. It should also be noted that all three factors demonstrate a similar direction of influence on the R_{GHG} prediction result as greenhouse gas emission intensity, although the range of SHAP values for individual observations is significantly smaller. An increase in water consumption per shower, resulting from extending the shower length or increasing the mixed water flow rate from the shower head, translates into an increase in the amount of recoverable thermal energy and, consequently, a higher emission reduction. The same applies to the variable i_g. The slow rate of decarbonization of the energy sector (lower emission reduction in subsequent years) may significantly enhance the environmental performance of a vertical SHE-equipped installation, especially since some observations indicate SHAP values exceeding 5000 $kgCO_2e$.

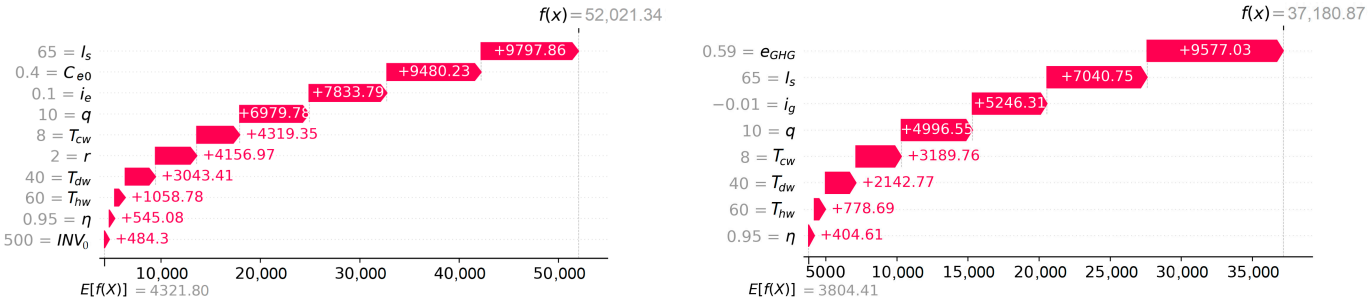
Significantly lower results were obtained for media temperatures in individual sections of the system. For cold water and drain water, they were in the range of several hundred kilograms, while the impact of DHW temperature was negligible, as the mean |SHAP value| did not reach 100 $kgCO_2e$. The significantly lower significance of temperature variables suggests that, within the considered range of their variability, they do not constitute a major limitation to the efficiency of the heat recovery system. The variable with the least impact on the projected greenhouse gas emission reduction was the efficiency of

the DHW heater, which is likely due to the high efficiency of electric DHW heaters and the narrow range of analyzed values of this parameter.

3.3. Evaluation of Extreme Cases and Medians

To broaden the interpretation of the results, an analysis of local SHAP values was conducted for three characteristic observations, corresponding to the maximum, minimum, and median values of the distribution. This analysis was performed for both models. This approach enabled an assessment of the impact of combinations of input variables on the *NPV* and R_{GHG} calculation results.

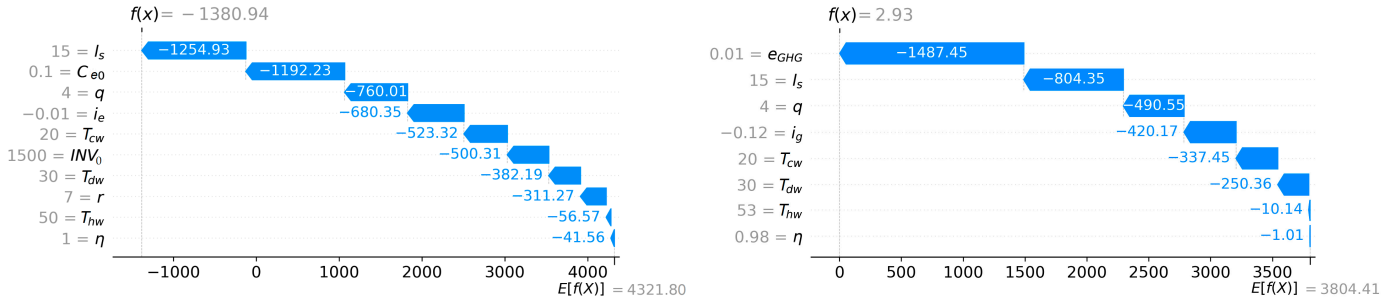
For observations corresponding to the maximum *NPV* and R_{GHG} forecasts (Figure 11), all input variables contributed to increasing the forecast compared to the baseline value. This suggests that the greatest benefits from installing a vertical SHE on the shower's greywater outlet are achieved under conditions of cumulative favorable factors, including operational factors (a large amount of water consumption), economic factors (high energy prices and their rapid growth), and environmental factors (high GHG emission intensity throughout the heat exchanger's lifetime). For the maximum *NPV* forecast, only a slight change in the hierarchy of importance of individual input variables was observed. The importance of investment outlays decreased relative to the average, resulting in this variable being moved to the last position. This means that under conditions of high positive financial flows resulting from significant energy savings for heating DHW, the INV_0 value loses its relative importance compared to the scale of generated financial savings. This phenomenon is further compounded by the fact that when preheated water is supplied exclusively to the SMV, the scope of installation work is small, significantly reducing the initial investment costs. In the case of R_{GHG}, on the other hand, the importance structure of input variables remained consistent with the global analysis.



(**a**) (**b**)

Figure 11. SHAP analysis results for maximum cases: (**a**) *NPV*; (**b**) R_{GHG} (designations as in Figure 1).

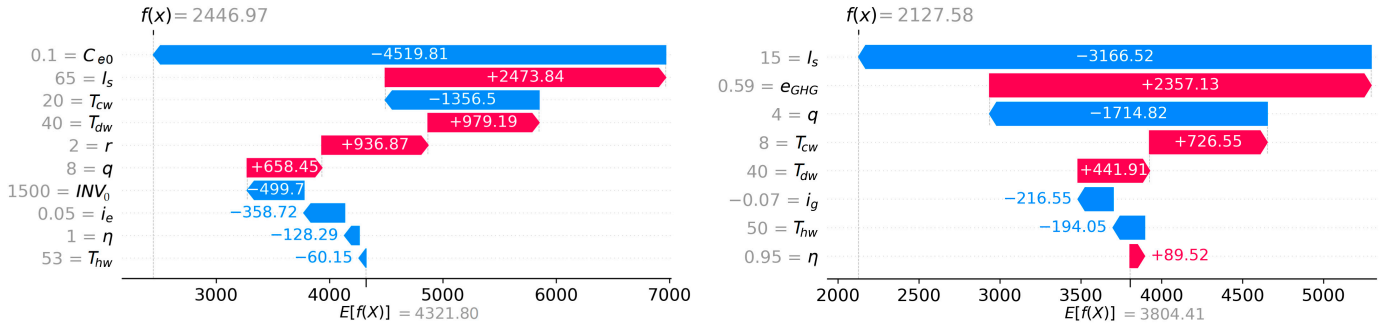
For observations corresponding to the minimum *NPV* and R_{GHG} values (Figure 12), all variables contributed to lower forecasted results. Therefore, unlike the maximum forecasts, the lowest results are a consequence of the coexistence of unfavorable conditions related to low shower system use intensity, low energy prices throughout the unit's life cycle, and parameters limiting heat recovery potential. With respect to the minimum *NPV* forecast, a slight change in the structure of variable significance was noted, consisting of an increased influence of mixed water flow rate (q) relative to the annual increase in electricity prices (i_e). A similar change occurred in the second model, where water flow rate proved more significant than changes in greenhouse gas emission intensity (i_g). This suggests that under conditions of extremely low financial savings, current operating parameters may be more important than long-term factors such as price dynamics or decarbonization.



(**a**) (**b**)

Figure 12. SHAP analysis results for minimal cases: (**a**) *NPV*; (**b**) R_{GHG} (designations as in Figure 1).

The most complex relationships were observed for observations corresponding to the median forecasts (Figure 13). In the case of the median *NPV*, the initial electricity price had the greatest impact, with a low value resulting in a lower forecast compared to the baseline. A similar trend was observed for high cold water temperature. High initial investment outlays, a moderate increase in electricity prices, high DHW heater efficiency, and low DHW temperature also contributed to the lower *NPV* forecast. On the other hand, a significant shower length increased *NPV* compared to the baseline by almost €2500. High drain water temperature, a low discount rate, and a relatively high mixed water flow rate also contributed to the increase in *NPV* forecast. This pattern indicates that, under average conditions, the effects of individual variables partially offset each other. Some of them enhance the project's financial efficiency, while others reduce it.



(**a**) (**b**)

Figure 13. SHAP analysis results for median cases: (**a**) *NPV*; (**b**) R_{GHG} (designations as in Figure 1).

An equally complex hierarchy of significance was observed for the median R_{GHG}. In the considered scenario, however, the minimum shower length and low water flow rate resulted in a reduction in the environmental impact compared to the baseline value by almost 3167 $kgCO_2e$ and 1715 $kgCO_2e$, respectively. The projected level of greenhouse gas emission reduction was significantly increased by a high GHG emission intensity of electricity generation. Low cold water temperature and high drain water temperature also contributed to the improvement in the environmental impact, while the efficiency of the DHW heater had only a minimal positive effect. On the other hand, the significant annual reduction in e_{GHG} and low domestic hot water temperature reduced the projected R_{GHG} value by approximately 200 $kgCO_2e$. The different directions of influence in the above observations confirm that the individual scenarios are the result of overlapping variables with opposing impacts. Unlike the extreme cases, where a unidirectional cumulative effect dominates, other cases reflect the true complexity of interactions between individual input variables. These results highlight the importance of local analysis in interpreting predictive models. Only such an approach allows us to understand how observations with

similar environmental or economic outcomes can result from different configurations of input variables.

3.4. Assessment of Consistency Between Financial and Environmental Effects

The assessment of consistency between financial and environmental effects was based on a comparison of the SHAP analysis results for two independent predictive models: the *NPV* model and the R_{GHG} model. Due to the different number of input variables included in both models, the comparison did not apply to full observations, but only to the part of the feature space common to both analyses. This included six input variables related to the operating and technical conditions of the shower installation (l_s, q, T_{cw}, T_{dw}, T_{hw}, η). For each combination of values of these six common input variables in the *NPV* model, there were 81 scenarios resulting from the combination of four additional economic variables, each of which assumed three values. Similarly, in the R_{GHG} model, for the same combination of common variables, there were nine scenarios resulting from the combination of two additional environmental variables, also analyzed for three different values. Therefore, representative cases were determined not for a single identical observation in both models, but within sets of observations with the same values of the common variables. For each of the analyzed common variables, SHAP values corresponding to three representative points of the prediction distribution were compared: the minimum value, the median value, and the maximum value. Detailed results for shower length (l_s), which turned out to be the most significant common variable in both models, are presented in Figure 14. Results for the remaining common variables are provided in Appendix A.

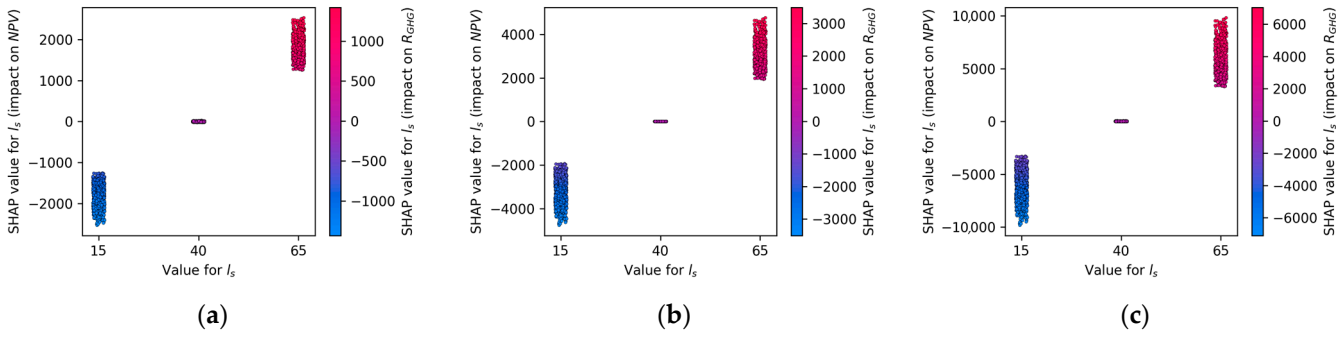


Figure 14. SHAP-based comparison of the impact of shower length (l_s) on *NPV* and R_{GHG}: (**a**) minimum; (**b**) median; (**c**) maximum.

The results indicated high consistency between the financial and environmental effects. In the minimum, median, and maximum cases considered, common input variables exhibited the same direction of influence on the prediction values of both models. This means that factors increasing the predicted *NPV* simultaneously increased the predicted greenhouse gas emission reduction, while factors reducing the financial effect had a similar effect on the environmental effect.

Furthermore, the relative importance of common variables was found to be consistent. In the global analysis, shower length (l_s) had the highest significance in both models, with subsequent common variables maintaining a similar position in terms of influence. This confirms that both financial and environmental benefits are largely determined by the same operational mechanisms, primarily related to the intensity of shower system use.

It should be emphasized, however, that in real-world conditions, the profitability of the project will also be determined by other input variables. In this context, the results obtained for the median scenarios (Figure 13) are particularly important, as they can be considered the most representative of actual operating conditions. The SHAP analysis showed that the relationships between input variables and *NPV* and R_{GHG} are more complex and less clear-

cut than in extreme cases. For key common variables, the general trend is maintained. For example, a longer shower increases the result, while a lower l_s value results in a reduction in the expected results. However, these variables do not fully determine the final values, as parameters specific to both models also play a significant role. Consequently, the observed variability in results under median conditions results from the overlapping influence of common variables and model-specific variables, whose impacts are not mutually offset. This leads to a situation in which the general trends remain unchanged, but their final effect is modified depending on the configuration of external parameters.

This indicates the necessity of apparent trade-offs between financial and environmental efficiency. However, it should be noted that not all input variables are controllable from the perspective of the user or system designer. Variables such as electricity prices and their variability over time, or greenhouse gas emission intensity, are external factors independent of the installation's operation. In the case of operational variables such as l_s or q, which the user can actually influence, a high degree of consistency is observed in the impact on *NPV* and R_{GHG}. Therefore, the observed discrepancies between both effects result largely from the system's location, not from direct user decisions. The lack of full consistency between *NPV* and emission reduction is, therefore, not due to conflicting operational objectives, but rather to the overlapping influence of controllable and uncontrollable parameters. The final effect is a result of user decisions and external conditions.

4. Discussion

The results of the analysis confirmed that the use of XGBoost models combined with SHAP analysis is an effective tool for identifying key variables determining the financial and environmental performance of a shower heat recovery system operating under unbalanced flow conditions. By quantifying the impact of individual input variables on *NPV* and R_{GHG}, this approach can provide a basis for transparent system optimization [8]. It allows not only for identifying the most important variables but also for understanding their impact in various shower system operation scenarios.

The global SHAP analysis showed that for both dependent variables considered, variables related to the intensity of shower use, i.e., shower length (l_s) and mixed water flow rate (q), significantly impact the forecast result. These parameters directly influence the amount of tap water used and, therefore, the amount of recoverable thermal energy. Local analysis of individual shower system scenarios confirmed that increasing water consumption in the shower system not only increases the potential for GHG emission reduction but also translates into increased expected financial savings. This convergence suggests that, in many cases, improving the environmental performance is correlated with economic attractiveness.

However, it is important to remember the variables that were not included in both models. In the case of GHG emission reduction, the greenhouse gas emission intensity of electricity generation (e_{GHG}) and the rate of its decline over the subsequent years of vertical SHE use play a significant role. These variables determine the "environmental value" of each unit of saved energy. On the other hand, the level and dynamics of energy price changes, and to a lesser extent, the discount rate, are crucial for financial profitability. This means that the environmental effects of drain water heat recovery strongly depend on the structure of the energy system, while the financial effects depend on market conditions. The observed differences in the mechanisms shaping the net present value and potential GHG emission reduction demonstrate that maximizing environmental benefits will not, in many cases, equate to maximizing financial benefits, particularly in the case of electricity production in low-emission systems and at relatively low energy prices.

Interpreting the SHAP analysis results in a practical context, it can be concluded that the application of a vertical SHE is most economically and environmentally beneficial under conditions of intensive shower use. The consistency analysis results indicate that, despite differences in the model structures, common operational and technical variables exhibit consistent effects on both predicted variables. In particular, parameters related to the intensity of shower system use, such as shower length (l_s) and mixed water flow rate (q), simultaneously increase both the *NPV* and the potential reduction in greenhouse gas emission. This means that within the common part of the feature space, the financial and environmental effects are determined by converging physical mechanisms related to the amount of recovered energy. Electricity prices and their rate of increase over time also play a significant role in the investment profitability. Under conditions of high energy prices, the financial savings achieved will be the greatest, resulting in an increase in the *NPV*. The environmental effect, however, will be most visible in countries with the highest emission intensity of energy used for water heating, where the potential for GHG emission reduction will be the greatest. On the other hand, in countries that, thanks to conscious energy policies, have eliminated fossil fuels and replaced them with renewable sources and nuclear energy, the environmental impact of using vertical SHEs will be limited. Furthermore, reducing the amount of water used limits the amount of recoverable thermal energy, which impacts both the environmental and financial benefits. This means that the greatest benefits from these systems can be achieved in buildings with high and regular water consumption per shower, and in conditions of relatively high electricity prices and high emissions from their generation.

However, when considering the results of the analysis, it is important to remember the limitations of the adopted research methodology. The dataset used was synthetic in nature. In real-world operating conditions, greater data variability and the presence of random factors can lead to reduced accuracy of predictive models. Therefore, the results should be interpreted as an assessment of potential relationships between variables rather than as direct forecasts for actual installations.

Another significant limitation was that the analysis was based on an electric DHW heater, which significantly determined the results. For natural gas-powered devices, different results can be expected for both the financial and environmental performance of the tested solution. On the one hand, a lower natural gas price may lead to lower projected financial savings, and thus a reduction in *NPV*. Eurostat statistics [37] indicate that in the first half of 2025, the price of natural gas for households in the EU ranged from €0.0307 per kWh (Hungary) to €0.2128 per kWh (Sweden). The maximum price of natural gas was, therefore, almost half that of electricity. On the other hand, greenhouse gas emissions from natural gas combustion are typically lower than those from electricity generation in systems based on a high-emission energy mix. This may result in limited emission reduction potential. It should be noted, however, that in systems with very low emissions, using electricity to heat DHW may be more environmentally beneficial than burning natural gas. Data from the European Commission [38] indicate that the GHG emission factor for natural gas is approximately 0.20 kgCO2e/kWh. In countries with lower e_{GHG} values, the use of SHE could contribute to greater reductions in greenhouse gas emissions when used in conjunction with a gas DHW heater.

It should also be emphasized that the results of SHAP analysis are dependent on the assumed ranges of input variables. Feature importance reflects the influence of a variable within the analyzed dataset, not its universal significance. This means that changing the ranges of input variable values can lead to a change in their relative importance in the model. This is particularly true for variables with a wide range of values, such as shower length. Their high position in the importance hierarchy does not always result from their

actual importance. It may also be a consequence of a greater influence on the variability of the results. Therefore, the obtained variable rankings should be interpreted in the context of the assumed ranges of input variables. With different shower usage scenarios or with changed environmental or financial parameters, the hierarchy of importance of individual variables may change.

It is also important to note that the analysis focused on one specific type of shower heat exchanger and a specific system configuration, which limits the possibility of directly generalizing the obtained results to all solutions used in practice. For other SHE geometries, the absolute values of the achieved environmental and financial effects may be slightly different. However, the identified relationships, particularly those concerning the direction of the influence of individual input variables, are more universal and can be applied to other types of SHEs heating water supplied to the shower mixing valve.

The identified relationships should be considered in the context of the growing demand for energy in various sectors, as societal development and the functioning of a modern economy are largely dependent on access to energy, which should be both reliable, safe, and economically affordable [39]. It should be noted that one of the most energy-intensive areas of municipal infrastructure is the water and sewage sector. This is due, among other things, to growing requirements for water quality, climate change, and the occurrence of extreme events [40]. The need to ensure high system reliability is also important. In this context, water losses are a significant problem [41], which necessitates the collection, treatment, and transportation of additional volumes of water, increasing total energy consumption. In such conditions, the utilization of thermal energy carried by wastewater becomes particularly important, especially since, as Arsenyeva et al. [42] noted, even a few percent of the heat demand can be met through heat recovery from wastewater. The possibilities of heat recovery from wastewater are not limited to single-family homes. This technology demonstrates potential applications in many other facilities, such as multi-family buildings, hotels, and industrial facilities, where the amount of available waste energy can be significantly higher. The literature provides recommendations for the application of wastewater heat recovery systems in facilities with high hot water consumption. These may include hotels, for example, where decisions regarding the location of the heat recovery system should, in addition to energy demand and heat recovery potential, also consider the region's tourism potential [43]. Heat recovery from sanitary appliances other than showers is also justified. For example, Zanganeh et al. [44] emphasized the importance of heat recovery in commercial dishwashers. It is, therefore, clear that the range of possible applications of heat recovery technology from wastewater, primarily greywater, is much broader than that described in this paper.

This wide variety of heat recovery system configurations and operating conditions demonstrates that the use of predictive models combined with SHAP analysis can be a valuable tool in future research, enabling the identification of key parameters determining both the energy efficiency, environmental performance, and economic efficiency of various wastewater heat recovery systems. These studies should consider not only small local installations but also systems based on heat pumps [45]. Particular emphasis should be placed on hybrid systems combining various renewable and waste energy sources, such as wastewater and air heat pumps, as well as solar collectors [46]. Considering heat storage systems [47] would also be beneficial, as such a solution could further increase the flexibility of wastewater heat recovery systems and enable better adjustment to fluctuating demand. Integrating wastewater heat recovery systems with other technologies can increase both the energy and environmental efficiency as well as financial viability. For this reason, it is also worth examining available forms of support. As noted by Ogarek et al. [48], taking

Poland as an example, the fastest-growing renewable energy sector in this region is the one receiving the highest subsidies.

Future research should also consider the development of heat recovery technology from wastewater, including greywater. Technologies used in other energy sectors could provide inspiration for new SHE solutions. For example, Ahmad and Alsalmah [49] proposed a two-pipe solar-assisted heat exchanger. The development of such technologies defines the direction in which modern energy production is heading. These are hybrid solutions, combining various energy-harvesting mechanisms. The research described in this paper suggests that even for more complex systems for heat recovery from drain water, an approach based on SHAP analysis could be a useful tool supporting their design and optimization.

Integrating the heat recovery system under consideration with broader building energy management strategies may also be an interesting direction for further research, as Li et al. [50] noted that demand-side flexibility depends on the interaction between a number of parameters that determine the building's energy profile. Although the demonstrated vertical SHE application affects only the energy demand for DHW heating, its significance can be considered in the broader context of building energy performance.

The results can also be considered in the broader context of achieving sustainable development objectives and global climate goals. Previous research indicates that modernizing and adapting existing systems to new environmental requirements is a crucial element of the transition to more sustainable energy systems [51]. Undoubtedly, SHEs also meet this requirement, contributing to rational resource management, increasing the energy efficiency of buildings, and reducing greenhouse gas emissions. Such solutions are also consistent with the concept of a circular economy, which strives to maximize the use of energy already present in the system [52]. The development and optimization of wastewater heat recovery technologies can also support the implementation of selected sustainable development goals (SDGs). Therefore, it is hoped that the integration of sustainable energy saving techniques with modern analytical methods and predictive modeling will be an important element of the transformation towards a more environmentally friendly and resilient energy future, which is particularly important given the growing exposure to the effects of climate change [53].

5. Conclusions

The analysis demonstrated that heating the water supplied to the shower mixing valve using a vertical heat exchanger enables efficient heat recovery from drain water. For the considered range of input parameter variability, *NPVs* ranged from −€1381 to €52,168. Meanwhile, the greenhouse gas emission reduction over the 15-year operation period ranged from 61 $kgCO_2e$ to 37,207 $kgCO_2e$. Using predictive modeling in conjunction with SHAP analysis, it was possible to identify key parameters influencing the financial and environmental impacts of this solution, as well as assess the consistency between these effects. It was also possible to determine the relative importance of individual input variables influencing the project's net present value and potential greenhouse gas emission reduction. The global SHAP analysis was supplemented with local analysis for selected cases, allowing for a better understanding of how individual input variables influence the predictions of both models. Key findings from these analyses include:

1. Greenhouse gas emission intensity of electricity generation and shower length are among the most important variables shaping the potential GHG emission reduction.
2. Annual change in GHG emission intensity and mixed water flow rate also have a significant impact on environmental effects.

3. In the case of financial effects, in addition to water consumption per shower, the price of electricity and its dynamics over the entire operational life of the heat recovery installation are also crucial.
4. The direction of the impact of individual operating parameters on the projected greenhouse gas emission reduction and net present value is consistent. However, differences in the relative importance of individual variables can be noted, as confirmed by local analysis, indicating certain changes in the impact hierarchy depending on the scenario analyzed.

It should be noted, however, that the results are subject to certain limitations resulting from the model assumptions and the scope of the analyzed data. The analysis was conducted for specific technical and operational conditions of the drain water heat recovery system. Other methods of connecting the shower heat exchanger, as well as other SHE models, were not considered. Furthermore, the predictive models considered a limited number of parameters, meaning that in real-world conditions, other factors, such as the variability of water consumption profiles in the building, may also influence the system's efficiency. Another limitation may be that the local analysis was based on selected characteristic cases, which, while providing a better understanding of the model's operation, do not reflect the full variability of all possible operating scenarios.

It is also important to note the technical limitations and potential implementation risks of vertical SHEs, particularly in existing buildings. These limitations may result from local conditions, variability in operating parameters, and the need for integration with existing building systems. In each case, they may impact the actual financial and environmental performance of the solution.

Future research would benefit from conducting analyses combining predictive modeling with interpretation tools. It is also worthwhile to expand the scope of analyses to include other configurations of drain water heat recovery systems, as well as solutions used in other areas of water and sewage infrastructure. Future research could also include a larger number of scenarios, allowing for a more comprehensive assessment of the impact of variability in individual parameters on the system's financial efficiency and its potential to reduce greenhouse gas emissions.

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Abbreviations

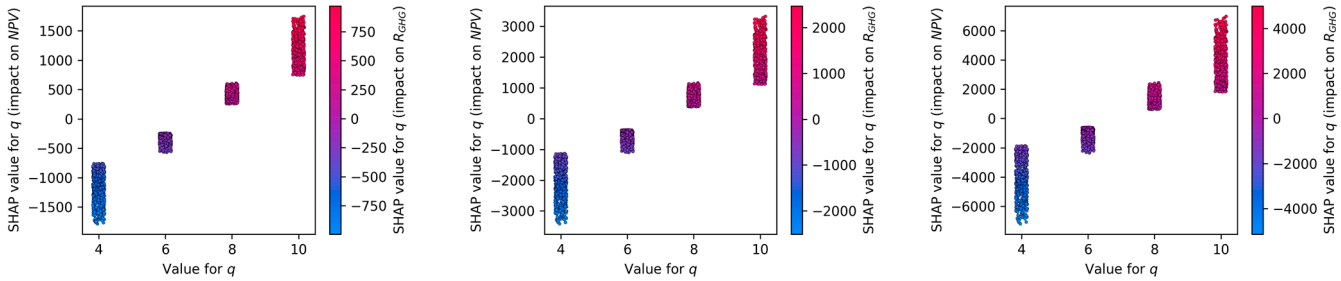
The following abbreviations are used in this manuscript:

CO_2	carbon dioxide
DHW	domestic hot water
EU	European Union

GHG	greenhouse gas
MAE	mean absolute error
NPV	net present value
RMSE	root mean square error
SDG	Sustainable Development Goal
SHAP	SHapley Additive Explanations
SHE	shower heat exchanger
SMV	shower mixing valve

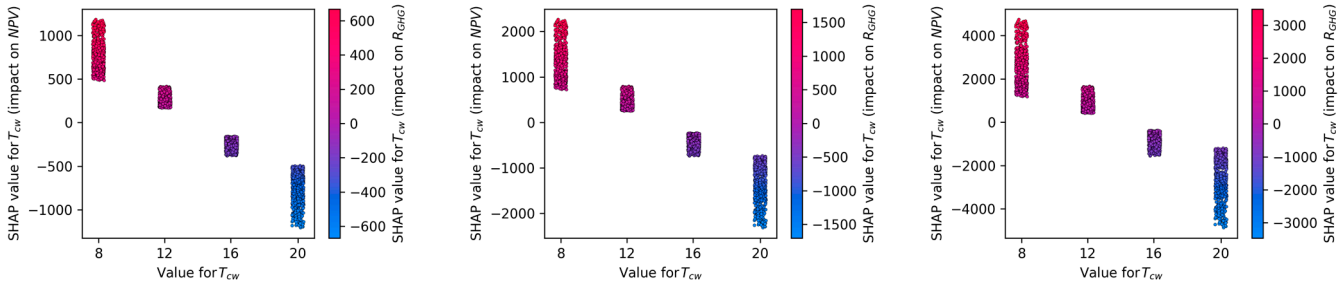
Appendix A

Figures A1–A5 present SHAP-based comparisons of the impact of selected variables on *NPV* and R_{GHG}.



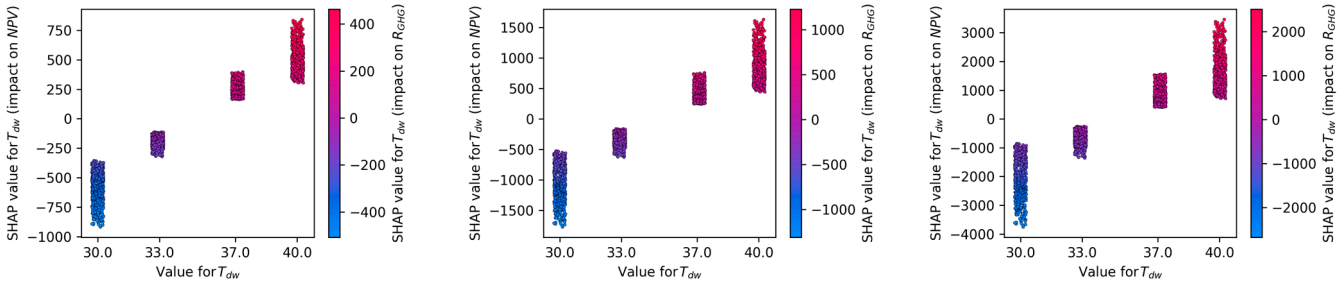
(**a**) (**b**) (**c**)

Figure A1. SHAP-based comparison of the impact of mixed water flow rate (q) on *NPV* and R_{GHG}: (**a**) minimum; (**b**) median; (**c**) maximum.



(**a**) (**b**) (**c**)

Figure A2. SHAP-based comparison of the impact of cold water temperature (T_{cw}) on *NPV* and R_{GHG}: (**a**) minimum; (**b**) median; (**c**) maximum.



(**a**) (**b**) (**c**)

Figure A3. SHAP-based comparison of the impact of drain water temperature (T_{dw}) on *NPV* and R_{GHG}: (**a**) minimum; (**b**) median; (**c**) maximum.

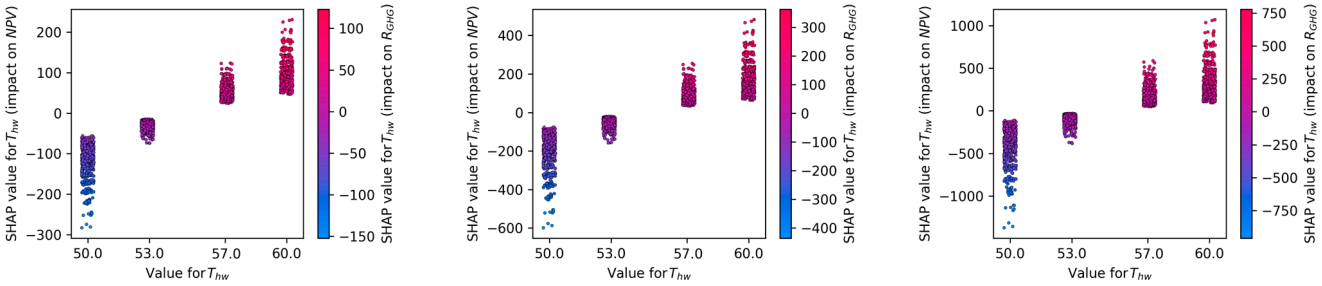


Figure A4. SHAP-based comparison of the impact of DHW temperature (T_{hw}) on *NPV* and R_{GHG}: (**a**) minimum; (**b**) median; (**c**) maximum.

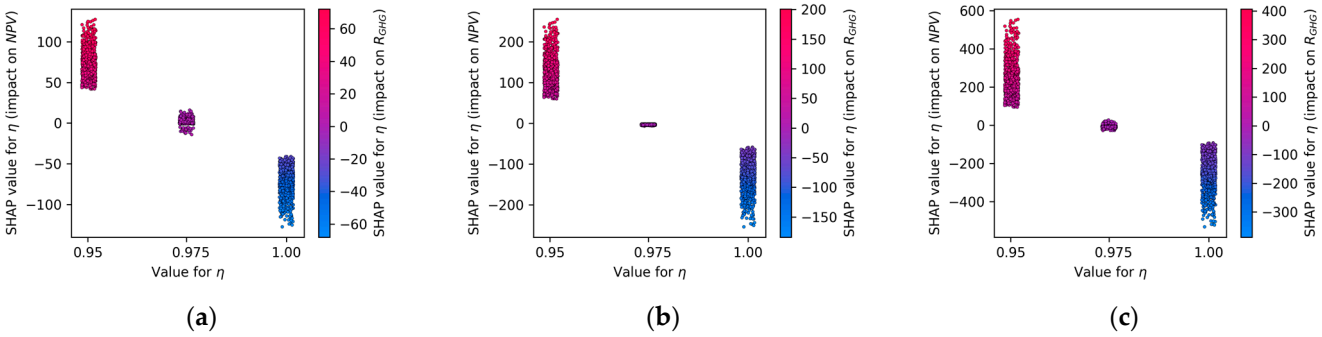


Figure A5. SHAP-based comparison of the impact of DHW heater efficiency (η) on *NPV* and R_{GHG}: (**a**) minimum; (**b**) median; (**c**) maximum.

References

1. Hall, R.J.; Kenway, S.; Memon, F.A.; O'Brien, K.R. Trade-offs between total and peak energy consumption due to plumbing layouts in Australian and UK domestic hot water systems. *J. Clean. Prod.* **2025**, *518*, 145941. [CrossRef]
2. Voznyak, O.; Dudkiewicz, E.; Laska, M.; Antypov, I.; Spodyniuk, N.; Sukholova, I.; Savchenko, O. A New Approach to the Economic Evaluation of Thermomodernization: Annual Assessment Based on the Example of Production Space. *Energies* **2024**, *17*, 2105. [CrossRef]
3. Hall, R.J.; Kenway, S.; O'Brien, K.R.; Memon, F.A. Quantification of residential water-related energy needs cohesion, validation and global representation to unlock efficiency gains. *Renew. Sustain. Energy Rev.* **2025**, *207*, 114906. [CrossRef]
4. Bednarz, K.; Stec, A.; Słyś, D. Research Trends in Renewable Energy Sources in Academic Infrastructure: A Bibliometric Analysis. *Energies* **2025**, *18*, 5812. [CrossRef]
5. Enayatollahi, R.; Appleby, A. Development of a wastewater heat recovery unit for residential buildings in New Zealand. *IOP Conf. Ser. Earth Environ. Sci.* **2025**, *1500*, 012059. [CrossRef]
6. Kaewluan, S.; Unsomsri, N.; Wiriyasart, S. Thermal Performance and Energy Consumption of Air Conditioning Systems with Heat Exchangers for Water Heater Efficiency Improvement. *ES Energy Environ.* **2025**, *29*, 1749. [CrossRef]
7. Tauseef, M.; Sharqawy, M.F. Thermal and Hydraulic Performance Analysis of a Waste Heat Recovery Device for Domestic Furnace Exhaust Gases. *Green Energy Environ. Technol.* **2026**, *5*, 1–20. [CrossRef]
8. Li, Y.; Zhang, H.; Shen, X.; Qu, K. Interpretable machine learning for predicting and optimizing residential building performance in cold regions. *Energy Build.* **2025**, *347*, 116321. [CrossRef]
9. Piotrowska, B.; Słyś, D. Variant analysis of financial and energy efficiency of the heat recovery system and domestic hot water preparation for a single-family building: The case of Poland. *J. Build. Eng.* **2023**, *65*, 105769. [CrossRef]
10. Silva, E.; Ferreira, V.; Cunha, J.; Monteiro, E. CFD Analysis on the Performance of Twisted Tapes in Horizontal Heat Exchangers for Shower Water Heat Recovery. *J. Heat Mass Transf. Res.* **2025**, *12*, 137–150. [CrossRef]
11. Forero, J.D.; Vigoya, M.F.; Casseres, D.M. Analysis of a Waste Heat Recovery System from Hot Drainage Water Using a Heat Recovery Concentric Tube Heat Exchanger Through CFD Simulation. *Int. Rev. Mech. Eng.* **2025**, *19*, 318–326. [CrossRef]
12. Kowalik, R.; Sidło, W. Drain water heat recovery for domestic hot water in polish residential buildings: Energy, economic and environmental assessment. *Desalin. Water Treat.* **2025**, *324*, 101475. [CrossRef]
13. Piotrowska, B.; Słyś, D. Analysis of the Life Cycle Cost of a Heat Recovery System from Greywater Using a Vertical "Tube-in-Tube" Heat Exchanger: Case Study of Poland. *Resources* **2023**, *12*, 100. [CrossRef]

14. Stec, A.; Piotrowska, B.; Słyś, D. Greywater as an undervalued tool for energy efficiency enhancement and decarbonizing the construction sector: A case study of a dormitory in Poland. *Energy Build.* **2025**, *330*, 115337. [CrossRef]
15. Stec, A.; Pochwat, K. Assessment of the efficiency of shower wastewater heat exchangers using machine learning-based methods. *J. Build. Eng.* **2025**, *103*, 112062. [CrossRef]
16. Purghel, D.M.; Teodosiu, C.I. Numerical Study on Shower Water Heat Recovery. *IOP Conf. Ser. Earth Environ. Sci.* **2025**, *1546*, 012025. [CrossRef]
17. Krishnan, E.N.; Muneeshwaran, M.; Rendall, J.; Brechtl, J.; Nawaz, K. Experimental investigation on heat transfer performance of drain water heat recovery heat exchangers. *Energy Build.* **2025**, *346*, 116213. [CrossRef]
18. Zhang, X.; Rhee, K.N.; Jung, G.J.; Kim, C. Exploring energy efficiency and savings potential of a horizontal domestic drain water heat recovery system in high-rise apartment buildings. *Energy Build.* **2024**, *325*, 115038. [CrossRef]
19. Kordana-Obuch, S.; Piotrowska, B.; Starzec, M. Management of waste heat in residential buildings: Predictive modelling and sensitivity analysis of variables characterising shower heat exchanger conditions. *Energy* **2025**, *318*, 134743. [CrossRef]
20. Ali, S.; Faraj, J.; Khaled, M. Heat recovery from hot water drainage: CFD simulation, energy efficiency and exergoeconomic analysis of concentric tube heat exchangers. *J. Build. Eng.* **2024**, *98*, 111034. [CrossRef]
21. Dudkiewicz, E.; Ludwińska, A. Family Dwelling House Localization in Poland as a Factor Influencing the Economic Effect of Rainwater Harvesting System with Underground Tank. *Sustainability* **2023**, *15*, 10687. [CrossRef]
22. Karimi, M.; Heidarigoujani, H.; Jahangiri, M.; Anaraki, M.T.; Janaki, D.M. Heating the Future: Solar Hot Water Collectors for Energy-Efficient Homes in Sweden. *Energy Eng.* **2026**, *123*, 6. [CrossRef]
23. Electricity Price Statistics. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Electricity_price_statistics (accessed on 17 December 2025).
24. Electricity Prices for Household Consumers—Bi-Annual Data. Available online: https://ec.europa.eu/eurostat/databrowser/view/nrg_pc_204/default/table?lang=en (accessed on 17 December 2025).
25. Commission Notice on Current State Aid Recovery Interest Rates and Reference/Discount Rates Applicable as from 1 January 2026 (Published in Accordance with Article 10 of Commission Regulation (EC) No 794/2004). Available online: https://eur-lex.europa.eu/eli/C/2025/6782/oj/eng (accessed on 7 January 2026).
26. Greenhouse Gas Emission Intensity of Electricity Generation in Europe. Available online: https://www.eea.europa.eu/en/analysis/indicators/greenhouse-gas-emission-intensity-of-1 (accessed on 17 December 2025).
27. Antosz, K.; Kozłowski, E.; Sęp, J.; Prucnal, S. Application of Machine Learning to the Prediction of Surface Roughness in the Milling Process on the Basis of Sensor Signals. *Materials* **2025**, *18*, 148. [CrossRef]
28. Mądziel, M. Investigating Real-world Emissions from Liquefied Petroleum Gas-fueled Vehicles: A Modeling Approach that Utilizes Portable Emissions Measurement Systems. *Open Transp. J.* **2025**, *19*, e26671212367963. [CrossRef]
29. Xu, Z.; Zhou, X.; Wang, Y. The implementation of machine learning models for predicting CO_2 emission in carbon capture and storage systems. *Sustain. Comput. Inform. Syst.* **2026**, *49*, 101264. [CrossRef]
30. Zhang, T.; Zhu, W.; Wu, Y.; Wu, Z.; Zhang, C.; Hu, X. An explainable financial risk early warning model based on the DS-XGBoost model. *Financ. Res. Lett.* **2023**, *56*, 104045. [CrossRef]
31. Liu, J.; Uglanov, D.A.; Kedam, N.; Zheng, G.; Shimanov, A.A.; Shimanova, A.B.; Lian, Z. Machine learning prediction of thermal–hydraulic (j–f) characteristics in compact heat exchangers with six fin configurations. *Appl. Therm. Eng.* **2025**, *280*, 128491. [CrossRef]
32. Piotrowska, B.; Kordana-Obuch, S.; Starzec, M. Using domestic drain water as affordable and clean energy: Predictive modeling and sensitivity analysis of a horizontal heat exchanger. *Energy* **2025**, *341*, 139326. [CrossRef]
33. Piotrowska, B. Modeling, optimization and sensitivity analysis of integrated photovoltaic, wind turbine, battery storage and drain water heat recovery systems. *Energy* **2026**, *346*, 140191. [CrossRef]
34. Cui, X.; Lee, M.; Koo, C.; Hong, T. Energy consumption prediction and household feature analysis for different residential building types using machine learning and SHAP: Toward energy-efficient buildings. *Energy Build.* **2024**, *309*, 113997. [CrossRef]
35. Ponce-Bobadilla, A.V.; Schmitt, V.; Maier, C.S.; Mensing, S.; Stodtmann, S. Practical guide to SHAP analysis: Explaining supervised machine learning model predictions in drug development. *Clin. Transl. Sci.* **2024**, *17*, e70056. [CrossRef]
36. Yılan, Y.; Beykent, A. Day-Ahead Electricity Price Forecasting Using the XGBoost Algorithm: An Application to the Turkish Electricity Market. *Comput. Mater. Contin.* **2025**, *86*, 1–16. [CrossRef]
37. Natural Gas Price Statistics. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Natural_gas_price_statistics (accessed on 30 March 2026).
38. GHG Emission Factors for Local Energy Use. Available online: https://data.jrc.ec.europa.eu/dataset/72fac2b2-aa63-4dc1-ade3-4e56b37e4b7c (accessed on 30 March 2026).
39. Słyś, D.; Stec, A.; Bednarz, K.; Ogarek, P.; Zeleňáková, M. Managing and Optimizing Hybrid Distributed Energy Systems: A Bibliometric Mapping of Current Knowledge and Strategies. *Energies* **2025**, *18*, 2497. [CrossRef]

40. Fisher, P.M.J.; Smith, D. The water industry and the decarbonisation of cities: A comprehensive review in the context of Cop26. *PLoS Water* **2022**, *1*, e0000023. [CrossRef]
41. Rożnowski, M.; Żywiec, J.; Szpak, D.; Tchórzewska-Cieślak, B. The Problem of Water Losses in the Visegrad Group (V4) Countries: Challenges and Opportunities. *Water* **2026**, *18*, 640. [CrossRef]
42. Arsenyeva, O.; Biletskyi, I.; Plankovskyy, S.; Kapustenko, P.; Tsegelnyk, Y.; Teliura, N. Heat Recovery Systems From Sewage: The Current State and Development Prospects. In *Sustainable Development and the Evolution of Civil Engineering*, 1st ed.; Neves Lousada, S.A., Ed.; IGI Global Scientific Publishing: Hershey, PA, USA, 2025; pp. 69–106. [CrossRef]
43. Hosseini Dehshiri, S.S.; Hosseini Dehshiri, S.J.; Mostafaeipour, A. Waste heat recovery systems integrated in hotels: An uncertain and reliable planning. *Appl. Therm. Eng.* **2025**, *281*, 128653. [CrossRef]
44. Zanganeh, J.; Seyfaee, A.; Gates, G.; Moghtaderi, B. Thermal Management and Energy Recovery in Commercial Dishwashers: A Theoretical and Experimental Study. *Energies* **2025**, *18*, 2338. [CrossRef]
45. Song, J.; Zhang, Y.; Ma, Z.; Zhang, H. Research progress and application prospect of wastewater heat pump technology in recent decade: A review. *Clean Energy* **2025**, *9*, 123–147. [CrossRef]
46. Ma, C.; Yang, Y.; Jiang, Y.; Liu, K. Control Optimization of Multi-Energy System in Residential Heating and Domestic Hot Water Application. In *Proceedings of the 12th International Conference on Cold Climate HVAC & Energy, CCHVAC 2025; Environmental Science and Engineering*; Ni, L., Wang, P., Li, J., Liu, Y., Eds.; Springer: Singapore, 2025; Volume 1, pp. 351–360. [CrossRef]
47. Amanowicz, Ł.; Turski, M. PCM-Filled Capsules (RT44HC) for Heat Storage—Laboratory Scale Pilot Study. *Energies* **2025**, *18*, 345. [CrossRef]
48. Ogarek, P.; Stec, A.; Słyś, D. Technical and economic analysis of an autonomous hybrid photovoltaic-hydrogen energy system for academic buildings with the focus on energy Independence—A case study for Poland. *Appl. Energy* **2025**, *392*, 125985. [CrossRef]
49. Ahmad, S.; Alsalmah, H.A. Numerical and artificial intelligent analysis of double pipe heat exchanger exposed to solar irradiation for sustainable energy solutions. *Results Eng.* **2025**, *27*, 105994. [CrossRef]
50. Li, W.; Sui, W.; Cheng, L.; Ji, Y.; Guo, Y.; Zhu, J. Quantifying seasonal demand-side flexibility in residential air conditioning under diverse control strategies. *Energy Build.* **2026**, *352*, 116764. [CrossRef]
51. Ciupek, B.; Frąckowiak, A. Review of Thermal Calculation Methods for Boilers—Perspectives on Thermal Optimization for Improving Ecological Parameters. *Energies* **2024**, *17*, 6380. [CrossRef]
52. Serrano-Arévalo, T.I.; Ramírez-Márquez, C.; Ponce-Ortega, J.M. Comprehensive management of energy carriers: A circular economy perspective. *Curr. Opin. Chem. Eng.* **2026**, *51*, 101224. [CrossRef]
53. Borowski, P.F.; Bandala, E.R.; Lubańska, A.; Stein, E. The Effects and Challenges of Climate Change on the Food-Energy-Water Nexus—Poland as a Case Study. In *Optimization in the Agri-Food Supply Chain: Recent Studies*; Koubaa, M., Ammar, M.H., Dhouib, D., Mnejja, S., Eds.; Wiley: Hoboken, NJ, USA, 2024; pp. 17–40. [CrossRef]

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