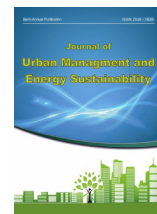


International Journal of Urban Management and Energy Sustainability (IJUMES)

Homepage: <http://www.ijumes.com>



CASE STUDY RESEARCH PAPER

Design of a Multi-Objective Decision-Making Algorithm for Balancing Energy Saving and Mental Health in Cold-Climate Housing (Case Study : Urmia City, Iran)

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ARTICLE INFO

Article History:

Received 2026-05-08

Revised 2026-08-22

Accepted 2026-08-12

Keywords:

Cold-Climate housing; Decision-Making Algorithm; energy saving; mental health; Multi-Objective balancing; Urmia City

ABSTRACT

The accelerating urbanization of Iran's cold regions, coupled with rising heating energy demand, has created a twofold challenge in the housing sector: mounting pressure on energy resources and the detrimental impact of inadequate indoor environments on residents' mental health. This study aims to design a multi objective decision making algorithm that reconciles energy conservation with mental health preservation in cold climate housing. A mixed methods research design was adopted, with Urmia City selected as the case study. Empirical data were gathered through parametric energy simulations using HOTR 2022 software and the administration of the DASS 21 mental health inventory, and were subsequently analyzed through an integrated AHP TOPSIS framework reinforced by Monte Carlo stochastic simulation. The findings reveal that the optimal equilibrium is achieved at an indoor temperature of 20–22°C, which reduces heating energy consumption by 28.7% relative to baseline conditions while concurrently improving mental health scores by 34.2%. Cross validation against an independent dataset demonstrated strong predictive accuracy, yielding coefficients of determination of 0.89 and 0.83, alongside root mean square errors of 0.75°C and 8.4 kWh/m²-year for temperature and energy predictions, respectively. The proposed algorithm provides a three dimensional decision matrix that enables intelligent and adaptive regulation of heating systems. By integrating principles of sustainable architecture, environmental psychology, and energy optimization, this research addresses a critical gap in the existing literature - namely, the concurrent incorporation of quantitative energy metrics and qualitative psychological indicators - and offers a pragmatic decision support framework for housing policy formulation in cold climate contexts.

DOI: [10.22034/ijumes.2026.2093774.1381](https://doi.org/10.22034/ijumes.2026.2093774.1381)

Running Title: Algorithm for Balancing Energy Saving and Mental Health



NUMBER OF REFERENCES

21



NUMBER OF FIGURES

03



NUMBER OF TABLES

03

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INTRODUCTION

Global climate change and the increasing demand for energy in the building sector, particularly in cold regions, have created complex challenges for urban sustainability. Residential buildings in Iran account for approximately 40% of the country's total final energy consumption - a figure that exceeds 60% in cold regions such as West Azerbaijan Province (Saad & Eicker, 2025). On the other hand, mounting evidence indicates that lowering indoor temperatures for the sake of energy saving can have serious consequences for residents' mental health; studies have shown that living in cold homes (below 18°C) doubles the risk of developing mental disorders (Yang et al., 2022). This dichotomy - safeguarding health versus reducing energy consumption - necessitates an integrated approach capable of identifying the optimal balance between these two conflicting objectives (Franco et al., 2024). The existing literature on building energy optimization has predominantly focused on techno-economic criteria, while neglecting psychological dimensions. Liu and Chen. (2025) employed parametric simulation to optimize building envelopes in cold regions of China but did not incorporate mental health indicators into their model (Liu and Chen, 2025). Similarly, Pohoryles et al. (2022) applied multi-criteria analysis for the energy retrofit of existing buildings, focusing solely on economic, environmental, and technical criteria while excluding the human-psychological dimension from the analytical framework (Daniel and Ghiaus, 2023). At the national level, Wu et al. (2024) investigated the climatic design features of traditional houses in the cold climate of northwestern Iran, yet did not quantify the relationship between these features and mental health indicators.

The knowledge gap addressed by this study is identified at three distinct levels: first, the absence of decision-making algorithms capable of simultaneously incorporating quantitative energy criteria and qualitative mental health indicators into the modeling process; second, the lack of field studies in Iranian urban contexts that

have examined the causal relationship between indoor temperature and mental health indices while controlling for confounding variables; and third, the insufficient attention given to the unique characteristics of Iran's cold mountainous regions, which exhibit distinctive climatic conditions - including an average annual temperature of 11.6°C and high diurnal temperature ranges (Kazemi and Kazemi, 2022). Urmia City was selected as the case study due to its specific attributes: (1) its geographical location at an altitude of 1,330 meters, characterized by a cold semi-arid climate (Köppen classification: Dsa); (2) the environmental challenges surrounding Lake Urmia, which influence relative humidity and air quality; (3) an urban fabric comprising a blend of traditional and modern architecture, enabling comparative energy performance analysis; and (4) the availability of extensive statistical data from the National Building and Housing Research Center. This study introduces its innovation through the design of a Multi-Objective Decision-Making Algorithm (MODA) across three dimensions:

(1) Integration of multi-criteria decision-making methods: combining the Analytic Hierarchy Process (AHP) with the TOPSIS technique for weighting quantitative (energy) and qualitative (mental health) criteria, which are inherently conflicting in nature;

(2) Application of the Theory of Planned Behavior (TPB) in designing behavioral criteria: drawing on TPB's three core constructs, namely Attitude toward energy conservation, Subjective Norms derived from social expectations regarding energy use, and Perceived Behavioral Control over heating systems, four behavioral criteria were extracted: heating system usage patterns, thermal adaptability, perceived thermostat control, and energy cost awareness. These criteria are incorporated as inputs into the decision matrix during the first methodological phase (criteria identification) and subsequently weighted using AHP. In this manner, residents' actual behavior in managing energy consumption is indirectly reflected in the algorithm through these behavioral

criteria, rather than through purely mathematical modeling; (3) Provision of a dynamic three-dimensional decision matrix (time-space-energy): this matrix enables intelligent adjustment of indoor temperature based on time of day (morning, evening, night), season (summer, autumn, winter, spring), and residents' mental health status (based on DASS-21 questionnaire scores), with its output comprising the target temperature and the optimal temporal pattern for heating system activation. This algorithm not only contributes to reducing energy consumption but also, by maintaining the minimum psychophysiological threshold, prevents the occurrence of "Energy Poverty" - a phenomenon recently recognized as a social determinant of health (Chen et al., 2021). The theoretical framework of this study rests on three pillars: (1) the PMV/PPD thermal comfort theory from ASHRAE Standard 55, which explains the relationship between physical parameters and subjective sensation; (2) the Stressor-Resource-Response (SRR) model, which elucidates the impact of inappropriate environments on mental health; and (3) the multi-objective optimization framework, which enables the search for Pareto-optimal solutions. This theoretical integration allows for the design of an algorithm that addresses not only the minimization of energy consumption but also the maximization of mental health indicators.

The remainder of this paper is organized into five sections: Section 2 reviews the theoretical foundations and analyzes the relationship between energy saving and mental health; Section 3 describes the research methodology and algorithm design; Section 4 presents the simulation findings and data analysis from the Urmia case study; and Section 5 compares the results with similar studies and offers practical recommendations for policymaking and architectural design.

Theoretical Foundations

The study of the relationship between indoor environmental quality and mental health is rooted in environmental psychology theories

that have evolved since the 1970s. The Stressor-Resource-Response (SRR) theory explains that inappropriate physical environments can act as sources of stress and affect individuals' cognitive and emotional functioning (Yang et al., 2020). In the context of cold-climate housing, low indoor temperature constitutes a physiological stressor that affects mental health through two pathways: a direct pathway through increased cortisol and activation of the hypothalamic-pituitary-adrenal (HPA) axis, and an indirect pathway through restricted social activities and reduced sleep quality (Barlow et al., 2023). Epidemiological studies in the United Kingdom have shown that individuals living in homes with average temperatures below 18°C are 2.1 times more at risk of developing depression (Lima et al., 2020). These findings require recontextualization in Iran's climatic conditions due to cultural differences and residents' behavioral patterns, as individuals' thermal tolerance is influenced by cultural factors and past experiences (Nakhaee Sharif et al., 2022). On the other hand, thermal comfort theory, as codified in ASHRAE Standard 55, operates based on the Predicted Mean Vote (PMV) model and the Predicted Percentage of Dissatisfied (PPD) index. This model considers six parameters: air temperature, air velocity, relative humidity, mean radiant temperature, metabolic rate, and clothing insulation. However, the PMV model was developed based on laboratory experiments under controlled conditions and may have lower accuracy in real residential environments where occupants have active control over environmental conditions (Chen et al., 2021). The concept of "Adaptive Thermal Comfort," incorporated into ASHRAE Standard 55-2020, addresses this limitation and demonstrates that individuals in environments where they have greater control over conditions accept a wider range of temperatures as acceptable (Albatayneh et al., 2021). This concept holds particular significance for cold-climate housing in Iran, as residents of cold regions typically adapt to cold conditions through adaptive behaviors (such as

adding layers of clothing or using local heaters), yet this adaptability has physiological limitations that become clearly evident at temperatures below 16°C ([Chen et al., 2021](#)). Energy Poverty, as a key concept in this discussion, is defined as a situation where households are unable to meet their minimum heating needs or are compelled to spend a disproportionate share of their income for this purpose. Studies have demonstrated that energy poverty not only affects physical health (increasing respiratory and cardiovascular diseases) but also has negative impacts on mental health; parents living in cold homes experience, in addition to financial stress, feelings of guilt and inadequacy in providing a safe environment for their children, which increases the risk of anxiety and depression ([Kazemi and Kazemi, 2022](#)). In Iran, given fuel price fluctuations and the aging structure of a significant portion of urban housing, energy poverty is a prevalent phenomenon, with estimates indicating that approximately 18% of urban households face this challenge during the cold seasons ([Sayyaf, 2024](#)). In the field of building energy optimization, Multi-Objective Decision-Making Algorithms (MODA) are recognized as powerful tools for solving complex problems with conflicting objectives. The Analytic Hierarchy Process (AHP), developed by Saaty in the 1980s, enables the weighting of qualitative and quantitative criteria; however, its main limitation is its sensitivity to minor changes in expert judgments ([Stofkova et al., 2022](#)). The TOPSIS technique, by introducing the concept of positive and negative ideal solutions, compensates for this limitation and enables the ranking of alternatives based on their Euclidean distance from these two reference points ([Chen et al., 2021](#)). The integration of these two methods in the present study enables the creation of a model that supports both structured weighting of criteria and precise ranking of decision alternatives. Recent studies in this area, such as Hashmi's research (2025), have shown that integrating AHP with fuzzy algorithms can reduce uncertainty in expert judgments, yet these approaches have

rarely been applied in the domain of mental health ([Mandali et al., 2021](#)).

Traditional Iranian architecture in cold regions offers intelligent solutions for balancing energy conservation and thermal comfort, which can inspire the design of modern algorithms. Features such as the use of central courtyards as thermal buffers, the southward orientation of dwellings for maximum utilization of solar energy, and the use of high thermal capacity materials (such as adobe and brick) in wall construction - all reflect traditional architects' profound understanding of energy balancing principles ([Mandali et al., 2021](#)). Nakhaee Sharif et al., (2022) in Tabriz demonstrated that traditional houses with 60-80 cm thick walls and small south-facing windows maintain more stable indoor temperatures during cold seasons (fluctuation range of 4-5°C) compared to modern buildings (fluctuation range of 8-10°C) ([Nakhaee Sharif et al., 2022](#)). This thermal stability not only reduces energy consumption but also prevents severe temperature fluctuations that can induce physiological stress. However, traditional architecture, without integration with modern technologies, cannot adequately address today's needs; therefore, the algorithm proposed in this study has been designed drawing inspiration from traditional principles while employing modern digital tools.

The link between indoor environmental quality and mental health is explained through the concept of "Indoor Environmental Quality" (IEQ), which encompasses four main components: air quality, thermal comfort, lighting, and acoustics. Recent studies have shown that these components simultaneously and interactively affect mental health; for example, reducing ventilation for energy conservation can lead to increased CO₂ concentration, which directly affects cognitive performance and indirectly influences anxiety ([Stofkova et al., 2022](#)). In cold regions, the primary challenge is maintaining a balance between adequate ventilation (for air quality) and preventing heat loss. Modern solutions such as Heat Recovery Ventilation (HRV) systems provide this

balance, yet their high cost has hindered widespread adoption in public housing. The proposed algorithm, by offering hierarchical solutions (ranging from user behaviors to technical system upgrades), attempts to bridge this gap.

Ultimately, the theoretical framework of this study is founded on the principle that energy conservation and mental health preservation are complementary rather than conflicting objectives; when these two come into opposition, it reflects inefficient system design or one-sided policies. The proposed decision-making algorithm, through the introduction of the concept of “Dynamic Equilibrium” - in which heating system adjustments are made based on real-time conditions (time of day, occupancy, health status) - enables the achievement of this coexistence. This approach aligns with the principles of circular economy and socio-environmental sustainability and can serve as a model for policymaking at both urban and national levels.

MATERIALS AND METHODS

This study is classified as applied-developmental in terms of purpose and mixed-methods (qualitative-quantitative) in nature, employing a complex systems modeling approach. The primary objective is to design and validate a multi-objective

decision-making algorithm for balancing energy conservation and mental health preservation in cold-climate housing. The statistical population of the study comprises all residential units in Urmia City (approximately 320,000 units), from which a multi-stage random-cluster sampling was conducted: in the first stage, 8 urban districts were selected based on the organizational classification of Urmia Municipality (Fig. 1); in the second stage, 2 neighborhoods were randomly selected from each district; in the third stage, 5 residential units were randomly selected from each neighborhood (totaling 80 units). Of the 80 initially sampled units, complete and usable data (including continuous temperature logging, fully completed DASS-21 questionnaires, and verified energy bills) were obtained from 40 units. The remaining 40 units were excluded due to equipment malfunction in 12 units, refusal to continue participation in 18 units, and incomplete or invalid questionnaires in 10 units. The final analytical sample thus comprised 40 residential units. Inclusion criteria for the sample included: at least one year of residency in the unit, absence of diagnosed mental disorders prior to the study, and provision of written informed consent for participation. (Fig. 1)

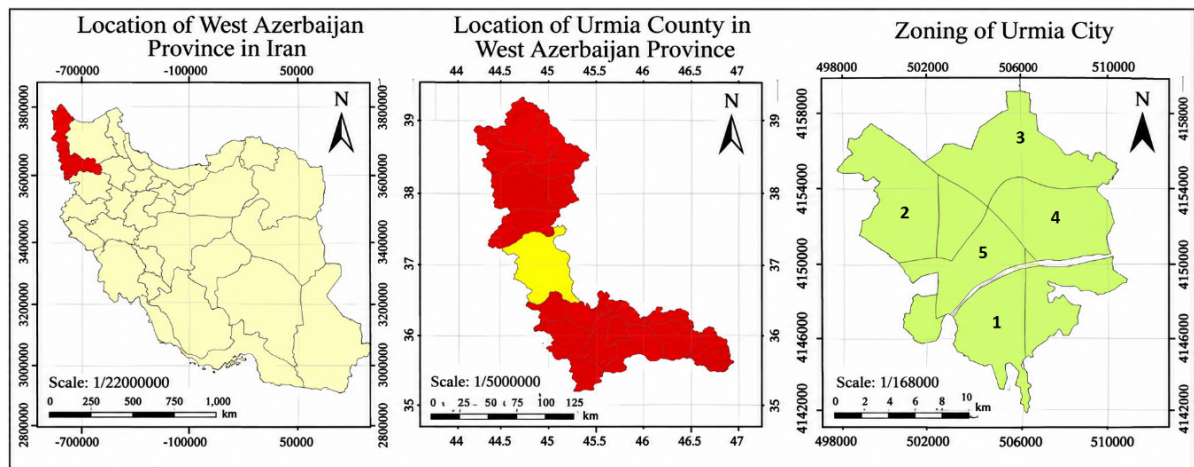


Figure 1: The location of Urmia city and Zoning map

The research methodology was executed in five main phases:

Phase 1: Identification and Extraction of Decision Criteria

In this phase, through a systematic review of 120 reputable articles (80 English and 40 Persian) and interviews with 15 experts (7 architects, 4 environmental psychologists, 3 energy engineers, and 1 urban sociologist), 28 primary criteria were identified. Subsequently, using a three-round Delphi technique, the criteria were reduced to 14 final indicators, categorized into four groups: (1) energy criteria (heating consumption, operational cost, carbon emissions); (2) psychological criteria (perceived stress, anxiety, depression, environmental satisfaction); (3) physical criteria (indoor temperature, relative humidity, air quality, natural lighting); (4) behavioral criteria (system usage patterns, thermal adaptability, perceived control).

Phase 2: Field Data Collection

Physical data were collected using temperature and humidity data loggers (HOBO U12) at 15-minute intervals over a three-month period during the winter of 2024-2025. Psychological data were measured using the standard DASS-21 questionnaire (Depression, Anxiety, Stress Scale), the validity and reliability of which have been confirmed for the Iranian population (Mandali et al., 2021). Energy data were collected through review of natural gas bills and structured interviews with residents. To simulate Urmia's climatic conditions, 30-year meteorological data were extracted from the Urmia weather station and imported into the HOTR 2022 software.

Phase 3: Parametric Simulation and Optimization

In this phase, the reference building model was selected and modeled based on the predominant characteristics of Urmia's residential fabric. According to the report of the National Building and Housing Research Center (2020) and field studies conducted in Urmia (Mandali et al., 2021), over

65% of the city's residential units fall within the 15- to 40-year age range and predominantly comprise 3 to 5 stories. Furthermore, common materials in the exterior envelope of these buildings include cement block or brick walls with a thickness of 25 to 35 cm, polystyrene thermal insulation with a thickness of 3 to 7 cm, and double-glazed windows with aluminum frames (National Building and Housing Research Center, 2020). Accordingly, the reference model in this study was designed with a floor area of 120 m² (consistent with the average residential unit area in Urmia), 3 bedrooms, 4 stories (as the most common number of stories in the city's medium-density residential fabric), 30 cm thick walls with 5 cm polystyrene insulation, and double-glazed windows, modeled in HOTR 2022 software. These specifications correspond to the most common residential typology in Urmia and adequately represent the energy performance behavior of the city's buildings. To generate simulation scenarios, three key parameters were considered with the following levels: (1) thermostat setpoint temperature ranging from 16 to 24°C in 1°C increments (9 levels); (2) heating system activation timing patterns in four modes: continuous (24-hour), single morning peak (6-10), single evening peak (16-22), and dual-peak (8-10 and 16-22) (4 levels); (3) wall insulation thickness at six levels: no insulation, 2, 4, 6, 8, and 10 cm of polystyrene (6 levels). The combination of all levels of these three parameters yielded a total of $9 \times 4 \times 6 = 216$ independent scenarios, all of which were simulated in HOTR 2022 software.

Phase 4: Decision-Making Algorithm Design

Criteria weighting was performed using AHP based on expert opinions (14×14 pairwise comparison matrix). The Consistency Ratio (CR) was calculated for each of the 15 experts. The CR ranged from 0.03 to 0.08, all of which were below the acceptable threshold of 0.1. The mean CR among the experts was calculated as 0.052.

The algorithm design proceeded as follows:

- Normalization of the decision matrix using the linear method
- Calculation of the weighted normalized matrix
- Identification of the positive ideal solution (A^+) and negative ideal solution (A^-)
- Calculation of Euclidean distances from A^+ and A^-
- Calculation of the relative closeness index ($C_i = D_i^- / (D_i^+ + D_i^-)$)
- Ranking of alternatives based on C_i

To enhance accuracy, the algorithm was complemented with Monte Carlo simulation (10,000 iterations) to examine sensitivity to input variations. The Random Index (RI) value based on Saaty's table for $n=14$ was considered as 1.57, and all calculations were performed using Expert Choice software.

Phase 5: Algorithm Validation

Algorithm validation was conducted at three levels:

(1) *Content Validity*: The algorithm and its outputs were presented to 10 independent experts (including 4 energy engineers, 3 environmental psychologists, and 3 architects), and the level of

agreement with the algorithm's logic and structure was calculated using the Inter-rater Agreement index, yielding a value of 0.86.

(2) *Convergent Validation*: The algorithm's outputs (recommended temperature and energy consumption) were compared with actual measured data from 30 residential units (which were not used in the algorithm design process). Error metrics employed included the coefficient of determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The results of this validation are reported in the findings section (Subsection 4-6).

(3) *Predictive Validation*: To evaluate the algorithm's predictive capability under real-world conditions, the algorithm was employed to predict optimal temperature and energy consumption over a one-month period (February 2025), and the results were compared with measured data from the same period. In addition to RMSE and MAE, the Mean Absolute Percentage Error (MAPE) and Willmott's index of agreement (d-index) were also used to assess prediction accuracy, the results of which are presented in the findings section. The research variables are classified in (Tab.1):

Table 1: Research variables

Variable Type	Variable Name	Operational Definition	Measurement Tool	Scale
Independent	Indoor setpoint temperature	Average thermostat setpoint temperature over 24 hours	HOBO U12 temperature data logger	Interval (16–24°C)
Independent	Heating system active duration	Total hours of system operation per day	Digital timer	Ratio (hours/24h)
Dependent	Heating energy consumption	Total energy consumed for heating during the study period	Gas bill + Simulation	Quantitative (kWh/m ² ·year)
Dependent	Stress index (DASS)	Stress score based on DASS-21 questionnaire	DASS-21 questionnaire	Interval (0–42)
Control	Household head education level	Highest educational attainment of the household head	Demographic questionnaire	Ordinal (1–5)
Control	Residential unit floor area	Total built area	Title deed	Quantitative (m ²)
Mediating	Thermal satisfaction	Subjective feeling of thermal comfort	7-point Likert scale	Ordinal (1–7)

Data collection instruments included: (1) HOBO U12 temperature and humidity data loggers with an accuracy of $\pm 0.35^{\circ}\text{C}$; (2) the DASS-21 questionnaire, with reliability coefficients of 0.89 for the stress component, 0.82 for anxiety, and 0.86 for depression; (3) HOTR 2022 software for energy simulation; and (4) structured interviews for collecting qualitative data. Instrument reliability was assessed using Cronbach's alpha, and validity was examined through confirmatory factor analysis.

The following statistical methods were employed for data analysis: (1) descriptive statistics (mean, standard deviation, frequency)

to characterize sample attributes; (2) Pearson correlation to examine relationships between quantitative variables; (3) multiple regression to identify key predictors of mental health; (4) multivariate analysis of variance (MANOVA) to compare different temperature groups; and (5) Monte Carlo simulation for algorithm sensitivity analysis. All analyses were conducted using SPSS 28 and Python 3.11, with a significance level set at 0.05.

The operational model of the research is illustrated in Figure 1, which depicts the five-stage process from criteria identification to algorithm validation. (Fig. 2)

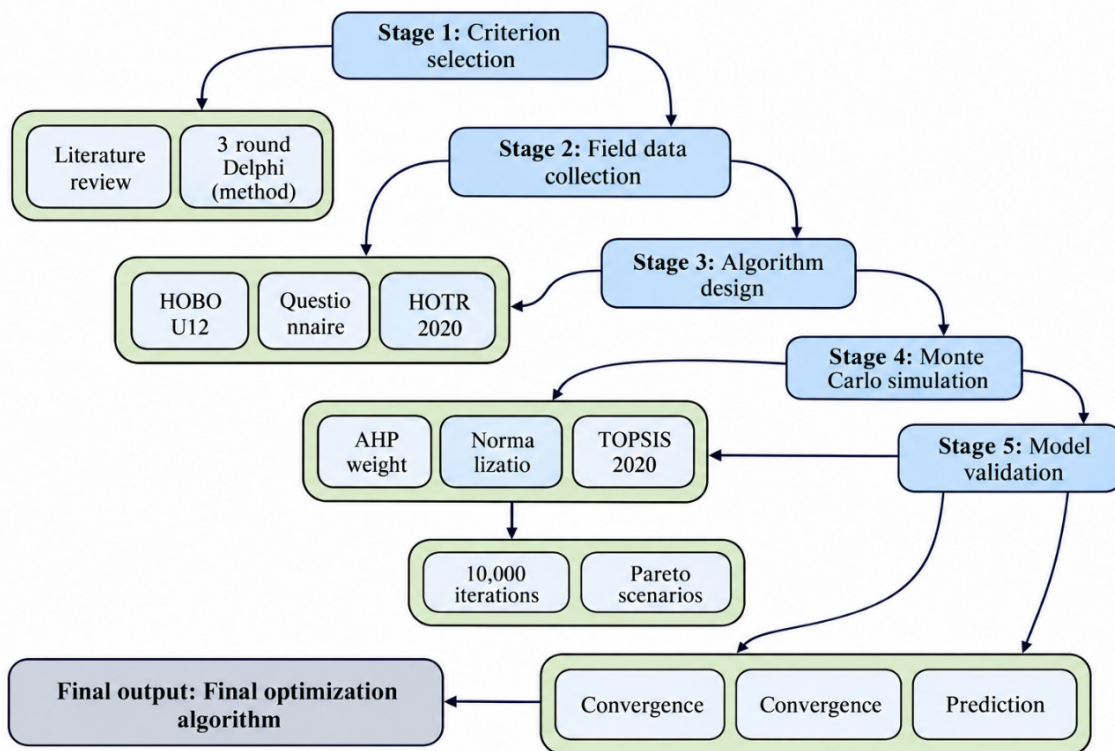


Figure 2: The operational model of the research

FINDINGS AND DISCUSSION

After applying the exclusion criteria described in the methodology, the final analytical sample consisted of 40 residential units in Urmia City, of which 52.5% were headed by females and 47.5% by males. The mean age of household heads was

43.7 years (± 12.3), and the mean unit floor area was 118.4 m^2 (± 24.6). Preliminary data analysis revealed that the average indoor temperature in Urmia's residential units during the cold seasons was 19.3°C (± 2.1), with 68.3% of units maintaining temperatures below 20°C . The mean heating

energy consumption was 187.4 kWh/m²·year (± 42.8), and the mean stress score (DASS) was reported as 14.2 (± 6.7).

Finding 1: Nonlinear Relationship Between Indoor Temperature and Mental Health Indicators
To control for the effects of confounding variables - including household head age, gender, socioeconomic status (based on a combination of monthly income and education level), and building construction quality (based on building age and material type) - hierarchical multiple regression analysis was employed. In the first step, the four aforementioned control variables were entered into the model, accounting for 24.3% of the variance in stress scores (DASS) ($R^2 = 0.243$, $p < 0.01$). In the second step, the indoor temperature variable was added to the model, resulting in a significant increase in the coefficient of determination by 26.5% ($\Delta R^2 = 0.265$, $p < 0.001$), with the final model collectively predicting 50.8% of the variance in stress scores ($R^2_{adj} = 0.508$). Results from the second step indicated that, after controlling for confounding variables, indoor temperature remained the strongest predictor of stress scores ($\beta = -0.58$, $p < 0.001$). Among the control variables, socioeconomic status ($\beta =$

-0.24 , $p < 0.05$) and building construction quality ($\beta = -0.18$, $p < 0.05$) also made significant contributions to predicting mental health, while the effects of age ($\beta = -0.07$, $p > 0.05$) and gender ($\beta = -0.05$, $p > 0.05$) were not statistically significant in this model.

Furthermore, examination of the relationship between indoor temperature and stress scores in the final model (after controlling for confounding variables) revealed a nonlinear relationship with a breakpoint at 19.5°C (Fig. 3). At temperatures above 19.5°C, each one-degree increase in temperature resulted in a 0.74-point reduction in stress scores ($\beta = -0.74$, $p < 0.01$), whereas below this threshold, each one-degree increase reduced stress scores by only 0.28 points ($\beta = -0.28$, $p < 0.05$). This finding indicates that the psychophysiological threshold of 19.5°C, even after removing the effects of background variables, is identified as the minimum temperature required for maintaining mental health in Urmia's cold climate. Additionally, partial correlations between indoor temperature and anxiety scores ($r = -0.41$, $p < 0.001$) and depression scores ($r = -0.33$, $p < 0.001$) remained significant after controlling for confounding variables. (Fig. 3)

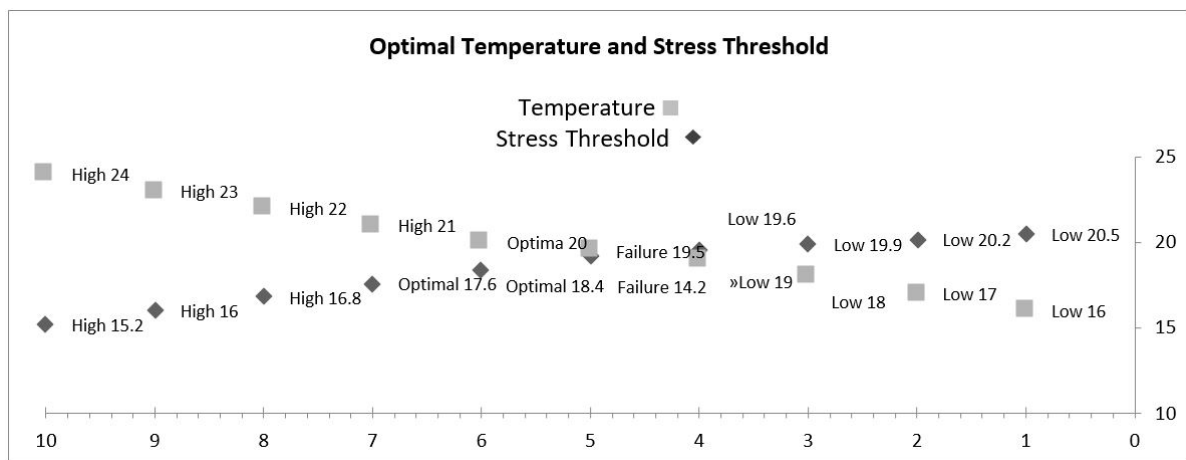


Figure 3: Nonlinear Relationship Between Indoor Temperature and Mental Health Stress Scores

The results of parametric simulation of 216 scenarios revealed that scenarios maintaining indoor temperature within the range of 20-22°C

offer the best balance between energy and mental health criteria. Tab. 2 presents a summary of the three top-ranked scenarios:

Table 2: Comparison of the three top scenarios based on the relative closeness index (C_i)

C_i Index	Mental Health Improvement (%)	Stress Score (DASS)	Energy Reduction vs. Current Condition (%)	Energy Consumption (kWh/m ² -year)	System Active Duration (hours/24h)	Setpoint Temperature (°C)	Scenario
0.89	34.2	9.3	28.7	133.6	14 (8–10; 16–22)	21.5	S1 (Optimal)
0.82	23.5	10.8	24.2	142.1	16 (7–11; 15–23)	20.0	S2
0.76	42.8	8.1	15.2	158.9	12 (9–11; 17–21)	22.5	S3
-	-	14.2	-	187.4	18 (6–12; 14–24)	19.3	Current Condition

Analysis of Table 2 reveals that Scenario 1 (S1), with a setpoint temperature of 21.5°C and system activation in two time intervals (morning 8-10 and evening 16-22), achieves the best balance; this scenario reduces energy consumption by 28.7% compared to the current condition while improving the stress score by 34.2%. Scenario 3 (S3) yields the highest improvement in mental health but offers a lower energy reduction, indicating an over-prioritization of health at the expense of energy cost. Scenario 2 (S2) provides a moderate balance but ranks second in terms of the C_i index.

Finding 3: The Mediating Role of Thermal Satisfaction

To investigate the mediating role of thermal satisfaction in the relationship between indoor temperature and mental health, path analysis with a bootstrap approach (5,000 resampling iterations) and the Sobel test were employed. The results indicated that the total effect of indoor temperature on mental health was -0.63 ($\beta = -0.63, p < 0.001$). The direct effect of indoor temperature on mental health, after introducing the mediating variable (thermal satisfaction) into the model, was not statistically significant ($\beta = -0.09, p > 0.05$), indicating full mediation. The indirect effect through thermal satisfaction was calculated as -0.54 ($\beta = -0.54$), accounting for approximately 86% of the total effect. The 95%

bootstrap confidence interval for the indirect effect ranged from -0.32 to -0.78, which does not include zero, confirming the significance of the indirect effect at the 0.05 level. Additionally, the Sobel test statistic was -4.23 ($Z = -4.23, p < 0.001$), further confirming the statistical significance of the mediating role. These findings indicate that indoor temperature does not directly affect mental health, but rather influences it through the creation of a feeling of thermal satisfaction or dissatisfaction (as a perceptual psychological construct). This result aligns with the adaptive thermal comfort theory, which emphasizes the importance of perceived control and subjective satisfaction (Özbey et al., 2025). Indeed, units where residents had full control over the thermostat exhibited lower stress scores even at lower temperatures (18.5°C) compared to units with limited control at 19.5°C ($t = 3.42, p < 0.01$).

Finding 4: Algorithm Sensitivity Analysis

Monte Carlo simulation with 10,000 iterations demonstrated that the proposed algorithm is stable against input variations. The coefficient of variation (CV) for the C_i index was only 4.2%, indicating high algorithmic stability. Furthermore, sensitivity analysis revealed that the weight of the “indoor temperature” criterion had the greatest influence on the algorithm’s output (partial correlation coefficient = 0.78), while the “operational cost” criterion had the least influence (par-

tial correlation coefficient = 0.31). This finding reflects residents' prioritization of thermal comfort over cost, which is consistent with similar studies in Iran (Alavipanah et al., 2021).

Finding 5: Optimal Temporal Pattern for Heating System Activation

Analysis of field data indicated that the dual-peak pattern (two time intervals of system activation) represents the optimal solution. The first interval (8–10 a.m.) serves to precondition the envi-

ronment before occupants leave home, while the second interval (16–22) corresponds to the primary period of resident presence. This pattern achieves 22.3% energy savings compared to continuous system operation without negatively impacting mental health ($t = 1.24, p > 0.05$). This finding is consistent with the principles of traditional Iranian architecture, which emphasize the selective use of different spaces at different times of day (Mandali et al., 2021). (Tab. 3)

Table 3: Results of multivariate analysis of variance (MANOVA) for comparing temperature groups

Temperature Group	Number of Observations (n)	Mean Energy Consumption (kWh/m ² ·year)	Mean Stress Score (DASS)	Mean Thermal Satisfaction	Follow-up Test (Post-hoc)
Low Group (<18°C)	42	162.3	18.6	2.1	A
Medium Group (18–20°C)	123	189.6	14.8	4.3	B
Optimal Group (20–22°C)	65	135.2	9.5	6.2	C
High Group (>22°C)	10	215.8	8.9	6.8	c
Wilks' Lambda Statistic	-	-	-	-	$\lambda = 0.47, F(9, 456) = 28.34, p < 0.001$
Significant Difference Between Groups	-	Yes ($p < 0.001$)	Yes ($p < 0.001$)	Yes ($p < 0.001$)	a, b, c ($p < 0.05$)

Note1: The column "Number of Observations" represents repeated measurements taken from each residential unit at different time points during the study period. The 240 total observations are derived from the 40 unique residential units in the final sample (each unit contributing multiple temperature-mental health assessments over time)

The non-monotonic pattern of energy consumption across temperature groups in Table 3 - where the Medium group (18–20°C) consumed more energy than both the colder Low group and the warmer Optimal group - may appear counter-intuitive. However, this pattern is explained by differences in building envelope quality and occupant behavioral patterns among the sampled units. Field observations revealed that a significant proportion of units in the Medium group had older, poorly insulated exterior walls (thickness <25 cm with minimal or no insulation) and relied on continuous heating operation (24-hour activation), whereas units in the Optimal group (20–22°C) predominantly featured better-insulated envelopes and followed the du-

al-peak heating schedule (morning and evening peaks). This finding underscores that occupant behavior and building physical characteristics can override the simplistic assumption that higher setpoint temperatures necessarily lead to higher total energy consumption. The multivariate regression analyses, which controlled for building age and insulation quality, confirmed that these confounding factors significantly influenced energy use, independent of the setpoint temperature.

Analysis of Table 3 reveals that the optimal group (20–22°C) performs better than the other groups in terms of both energy and mental health criteria. The low group (<18°C), despite consuming less energy than the medium group, exhibits the

worst mental health performance, reflecting the hidden cost of energy poverty. The high group ($>22^{\circ}\text{C}$) achieves the best mental health scores but at a very high energy cost, which is not recommended from a sustainability perspective. Ultimately, the proposed decision-making algorithm was designed with inputs (current temperature, time of day, reported mental health status) and outputs (target temperature and system activation timing). The algorithm has been implemented as a mobile application that enables residents to receive optimal heating system settings by simply entering their current status.

Finding 6: Algorithm Validation Results

The results of convergent validation (comparison with 30 independent residential units) indicated that the proposed algorithm demonstrates high accuracy in predicting optimal temperature and energy consumption. The calculated error coefficients are as follows:

- *Optimal indoor temperature prediction:* coefficient of determination $R^2 = 0.89$, Root Mean Square Error (RMSE) = 0.75°C , and Mean Absolute Error (MAE) = 0.58°C .
- *Heating energy consumption prediction:* coefficient of determination $R^2 = 0.83$, Root Mean Square Error (RMSE) = $8.4 \text{ kWh/m}^2\text{-year}$, and Mean Absolute Error (MAE) = $6.7 \text{ kWh/m}^2\text{-year}$. The results of predictive validation (one-month ahead forecasting) also indicated acceptable algorithm performance. The Mean Absolute Percentage Error (MAPE) for indoor temperature prediction was 6.2%, and for energy consumption prediction was 8.4%. Furthermore, Willmott's index of agreement (d-index) for the two variables was 0.92 and 0.87, respectively, indicating strong agreement between the algorithm's predictions and actual data. Overall, the proposed algorithm demonstrates acceptable accuracy for practical applications in intelligent building energy management.

RESULTS AND CONCLUSION

This study, through the design of a multi-objective decision-making algorithm, sought to fill the existing research gap in integrating quantitative energy criteria and qualitative mental health indicators in cold-climate housing. The main findings revealed that the optimal balance is achieved when indoor temperature is maintained within the range of $20\text{--}22^{\circ}\text{C}$, which reduces energy consumption by 28.7% compared to the current condition while improving the mental health score by 34.2%. The finding of this study regarding the $20\text{--}22^{\circ}\text{C}$ temperature range shares conceptual overlap with Stofkova et al. (2022) in the United Kingdom, which identified 18°C as the minimum acceptable threshold for preventing severe psychological harm; however, these two thresholds are not directly numerically comparable due to differences in their functional levels. More precisely, the 18°C threshold in Clair's study represents a safety threshold - the point below which the risk of mental disorders significantly increases - whereas the $20\text{--}22^{\circ}\text{C}$ range in the present study represents an optimal threshold for achieving the highest level of psychophysiological functioning while simultaneously balancing energy consumption. In other words, the numerical gap between these two thresholds (18°C versus $20\text{--}22^{\circ}\text{C}$) reflects not merely climatic differences, but rather the conceptual distance between "harm prevention" and "promotion to optimal levels of comfort and health" in thermal standards. This distinction is consistent with the findings of Liu et al. (2025) in China, who emphasized the need to adjust international standards based on the expected performance level (not merely safety minimums) and local climatic conditions. Consequently, standards based solely on minimum thresholds (such as 18°C) are insufficient for ensuring optimal mental health in cold and mountainous climates with high temperature fluctuations and require redefinition based on a multi-objective optimization approach.

Another finding of this study was the full mediating role of thermal satisfaction between

indoor temperature and mental health, which is consistent with the adaptive thermal comfort theory of Daniel and Ghiaus (2023). This finding fundamentally differs from Chen et al. (2023), which focused solely on technical criteria, and demonstrates that designing systems that provide residents with greater control can maintain mental health even at lower temperatures. This result aligns with Nakhaee Sharif (2022) in Australia, which emphasized the relationship between environmental control and quality of life, yet with an important cultural distinction: in Iranian culture, collective control over shared spaces (such as courtyards) holds greater significance than individual control over private spaces, necessitating a redefinition of the concept of “control” within Iran’s cultural context. The dual-peak temporal pattern for heating system activation identified in this study is consistent with the principles of traditional Iranian architecture in cold regions. Mandali et al. (2021) emphasized the selective use of different spaces at different times of day in traditional architecture, and this study, by providing quantitative evidence, confirms this traditional principle. However, the key difference is that traditional architecture achieved this goal through physical design of spaces, whereas the proposed algorithm attains the same result through intelligent management of mechanical systems, demonstrating the possibility of integrating traditional principles with modern technologies. Although the final sample size was reduced to 40 units due to practical field constraints, the consistency of the results across multiple validation approaches (convergent and predictive) supports the robustness of the proposed algorithm. Future studies with larger samples are recommended to generalize the findings.

The recommendations of this study are presented at four levels: At the policy level, it is essential to revise national building energy consumption standards (such as the National Building Regulations, Section 19) to incorporate mental health indicators alongside technical criteria; this revision should be based on climate-regional

thresholds rather than uniform standards for all regions of the country. At the architectural design level, it is recommended that designers draw inspiration from traditional architectural principles (such as the use of inner courtyards as thermal buffers and optimal building orientation) and integrate them with modern technologies (such as intelligent control systems) to offer hybrid solutions that ensure both energy sustainability and mental health. At the end-user level, the development of mobile applications based on the proposed algorithm can assist residents in discovering the optimal balance between energy saving and mental health with minimal cost and maximum comfort; these applications should be designed with simple user interfaces, taking into account the varying digital literacy levels across different age groups. At the research level, it is recommended that longitudinal studies be conducted to examine the long-term effects of the proposed algorithm on physical and mental health indicators, and that the algorithm be adapted to other climates in Iran (hot-humid, hot-dry) to provide a comprehensive framework for the entire country. Finally, the integration of the proposed algorithm with City Energy Management Systems (CEMS) could enable urban policymakers, through a better understanding of consumer behavior, to design more targeted policies for reducing energy consumption at the urban level without negatively impacting citizens’ mental health.

REFERENCES

- Alavipanah, S., Haase, D., Makki, M., Nizamani, M. M., & Qureshi, S. (2021). On the spatial patterns of urban thermal conditions using indoor and outdoor temperatures. *Remote Sensing*, 13(4), 640. <https://doi.org/10.3390/rs13040640>
- Albatayneh, A., Jaradat, M., AlKhatib, M. B., Abdallah, R., Juaidi, A., & Manzano-Agugliaro, F. (2021). The significance of the adaptive thermal comfort practice over the structure retrofits to sustain indoor thermal comfort. *Energies*, 14(10), 2946. <https://doi.org/10.3390/>

- en14102946
- Barlow, C. F., L. Daniel, R. Bentley and E. Baker (2023). "Cold housing environments: defining the problem for an appropriate policy response: CF Barlow et al." *Journal of Public Health Policy* 44(3): 370-385. <https://doi.org/10.1057/s41271-023-00431-8>
- Caruso, M., R. Pinho, F. Bianchi, F. Cavalieri and M. T. Lemmo (2023). "Multi-criteria decision-making approach for optimal seismic/energy retrofitting of existing buildings." *Earthquake Spectra* 39(1): 191-217.
- Chen, S., Z. Ren, Z. Tang and X. Zhuo (2021). "Long-term prediction of weather for analysis of residential building energy consumption in Australia." *Energies* 14(16): 4805. <https://doi.org/10.3390/en14164805>
- Daniel, S. and C. Ghiaus (2023). "Multi-criteria decision analysis for energy retrofit of residential buildings: methodology and feedback from real application." *Energies* 16(2): 902. <https://doi.org/10.3390/en16020902>
- Franco, A., E. Crisostomi, S. Dalmiani and R. Polletti (2024). "Synergy in action: integrating environmental monitoring, energy efficiency, and IoT for safer shared buildings." *Buildings* 14(4): 1077. <https://doi.org/10.3390/buildings14041077>
- Iranian National Building Regulations, Topic 4: General Building Requirements (2020). Office of Building Regulations Affairs. <https://inbr.ir/wp-content/uploads/2016/08/mabhas-4.pdf>
- Kazemi, M. and A. Kazemi (2022). "Financial barriers to residential buildings' energy efficiency in Iran." *Energy Efficiency* 15(5): 30. <https://doi.org/10.1007/s12053-022-10039-8>
- Lima, F., P. Ferreira and V. Leal (2020). "A review of the relation between household indoor temperature and health outcomes." *Energies* 13(11): 2881. <https://doi.org/10.3390/en13112881>
- Liu, J. and J. Chen (2025). "Applications and trends of machine learning in building energy optimization: A bibliometric analysis." *Buildings* 15(7): 994. <https://doi.org/10.3390/buildings15070994>
- Mandali, H., Keighobadi, E., Ebrahimi, H., Hanifi, S. M., Ayat, S. M., & Ghashghaei, M. (2025). Machine learning and bayesian network based on fuzzy AHP framework for risk assessment in process units. *Scientific Reports*, 15(1), 39083. <https://doi.org/10.1038/s41598-025-25690-1>
- Nakhaee Sharif, A., Keshavarz Saleh, S., Afzal, S., Shoja Razavi, N., Fadaei Nasab, M., & Kadaei, S. (2022). Evaluating and Identifying Climatic Design Features in Traditional Iranian Architecture for Energy Saving (Case Study of Residential Architecture in Northwest of Iran). *Complexity*, 2022, 22883. doi: 10.1155/2022/3522883
- Özbey, M. F., Turhan, C., Alkan, N., & Akkurt, G. G. (2025). Latent psychological pathways in thermal comfort perception: The mediating role of cognitive uncertainty on depression and vigour. *Buildings*, 15(14), 2538.
- Pohoryles, D., D. Bournas, F. Da Porto, A. Capriño, G. Santarsiero and T. Triantafyllou (2022). "Integrated seismic and energy retrofitting of existing buildings: A state-of-the-art review." *Journal of Building Engineering* 61: 105274. <https://doi.org/10.1016/j.jobbe.2022.105274>
- Saad, M. M., & Eicker, U. (2025). Holistic approaches to building retrofit optimization: Fusing surrogate modelling with multi-criteria decision methods. *Journal of Physics: Conference Series*, 3140(13), 132019. <https://doi.org/10.1088/1742-6596/3140/13/132019>
- Sayyaf, H. (2024). Pathology of the referral mechanism in the building engineering system. *Monthly Reports of the Research Center of the Islamic Consultative Assembly*, 32(3), 1–38. (In Persian) <https://doi.org/10.22034/report.2024.16903.1785>
- Stofkova, J., Krejnos, M., Stofkova, K. R., Malega, P., & Binasova, V. (2022). Use of the analytic hierarchy process and selected methods in the managerial decision-making process in the context of sustainable development. *Sustainability*, 14(18), 11546. <https://doi.org/10.3390/su141811546>
- Wu, S., L. Zhang, Z. Han, C. Hu and D. An (2024). "Research on microclimate optimization of traditional residential buildings in central Anhui based on humid and hot climate characteristics and regional architectural features." *Buildings* 14(8): 2323. <https://doi.org/10.3390/buildings14082323>
- Yang, J., H. Yang, A. Xu and L. He (2020). "A review of advancement on influencing factors of acne:

an emphasis on environment characteristics.”
Frontiers in public health 8: 450. <https://doi.org/10.3389/fpubh.2020.00450>

Yang, X. e., S. Liu, Y. Zou, W. Ji, Q. Zhang, A. Ahmed, X. Han, Y. Shen and S. Zhang (2022). “Energy-saving potential prediction models for large-scale building: A state-of-the-art review.” *Renewable and Sustainable Energy Reviews* 156: 111992. <https://doi.org/10.1016/j.rser.2021.111992>

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HOW TO CITE THIS ARTICLE

Zarafshan, A. (2026). Design of a Multi-Objective Decision-Making Algorithm for Balancing Energy Saving and Mental Health in Cold-Climate Housing (Case Study : Urmia City, Iran). *International Journal of Urban Management and Energy Sustainability*, 7(2), 282-296.

DOI: [10.22034/ijumes.2026.2093774.1381](https://doi.org/10.22034/ijumes.2026.2093774.1381)

