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Assessing the effects of urban building energy retrofits on energy consumption, pollutant emissions, and economic performance using urban building energy modeling (UBEM)

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Abstract

Rising energy consumption in the building sector is a key driver of urban energy demand and associated environmental pressures. Managing this trend requires effective evaluation and optimization strategies. This study develops an integrated framework that combines urban building energy modeling (UBEM) with the requirements of Iran's National Building Regulations (Section 19) to assess energy performance, environmental impacts, and economic indicators simultaneously for Qazvin's residential, commercial, and office buildings. We adopted a prototype-based UBEM approach and calibrated the model using actual energy consumption data, achieving a CV(RMSE) of 3.4% and a MAPE of 3.3%. Results show that implementing a comprehensive optimization scenario reduces energy consumption in the prototype building by 46.5%. When extrapolated to similar building typologies across the city, annual energy savings range between 648 and 792 GWh. This translates to absolute annual emission reductions of 125,000 tons of CO_2, 390 tons of SO_2, 390 tons of NOx, and 96 tons of PM2.5. A one-way sensitivity analysis indicates that the building envelope's heat transfer coefficient (U-value) has the greatest influence on urban energy consumption, while energy carrier prices most significantly affect the net present value (NPV). The results indicated that the proposed framework could be used in the assessment of energy, environmental, and economic outcomes of urban building retrofit scenarios simultaneously.

Keywords

Energy optimization
net present value (NPV)
pollutant emissions
prototype building
Section 19 of the Iranian National Building Regulations
sensitivity analysis

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1. Introduction

As urbanization expands and building floor area grows, the building sector has become one of the largest energy consumers and a major source of pollutant emissions (UNEP & GlobalABC, 2024). Reducing buildings' energy consumption can lower operational costs, improve urban air quality, and strengthen energy security (IEA, 2024; Kong et al., 2023). A city is a complex, interconnected system shaped by energy and material flows, infrastructure, human activities, and the built environment. Consequently, changes in one component can affect the performance of other components (Zhang, 2013; Zhang et al., 2015). In this context, buildings are the physical and, in many respects, fundamental component of this system, while also representing one of its major centers of energy demand (Salvalai et al., 2024). The interplay among physical and technical characteristics, building use and operational patterns, climatic and environmental conditions, and the energy supply system shapes building energy performance (Boccalatte et al., 2020). Consequently, changes in existing buildings' energy performance extend beyond a mere shift in energy demand. The surrounding environment influences such changes, contributes to pollutant emissions, and can also affect environment-related costs (Xu et al., 2018). These interdependencies within a complex urban system shift building energy from an isolated issue to an integral component of overall urban system performance. Accordingly, it is essential to begin with an assessment of the energy performance of existing buildings at the individual-building scale, followed by an examination at the urban scale, and ultimately to establish the analytical foundations required to inform urban planning and intervention while maintaining a clear alignment with their objectives (Johari et al., 2020; Ang et al., 2020).

Within the framework of complex systems, urban building energy modeling (UBEM) is an analytical tool that enables quantitative assessment from individual components at the micro level to the city scale, providing a basis for examining the relationship between existing buildings and their energy demand. UBEM approaches can be classified by the degree of data aggregation and how buildings are represented. Two principal approaches can be distinguished in this field: bottom-up and top-down modeling. In bottom-up approaches, representative buildings or building archetypes/prototypes represent the urban building stock. More specifically, the bottom-up approach is particularly useful when detailed data are limited, and the analysis needs to be less computationally demanding. However, the reliability of the resulting estimates depends largely on the quality of the building typology and on how well the selected archetypes represent the actual building stock (Reinhart & Cerezo Davila, 2016; Shen & Wang, 2024). By contrast, top-down approaches estimate building energy consumption based on aggregated data and statistical relationships established at the macro scale. Within this framework, however, representing physical details at the individual-building level, as well as assessing and developing building-scale intervention scenarios, is inherently more limited (Reinhart & Cerezo Davila, 2016).

Given the nature of UBEM, several analytical capabilities can be identified: 1) extending the analysis from an individual building to groups of buildings; 2) estimating energy performance at scales beyond the individual building; and 3) assessing the effects of interventions under different optimization scenarios (Johari et al., 2020; Ang et al., 2020). Nevertheless, UBEM models capture only one component of the urban system within the broader context of building energy analysis. In other words, translating model outputs into urban-scale decisions requires establishing appropriate linkages with other urban components and accounting for the resulting impacts on the city's various subsystems (Ali et al., 2020).

If this systems perspective is adopted, Chapter 19 of the Iranian National Building Regulations can be seen as a regulatory intervention that manages energy through systematic requirements governing building design and operation. However, its implications extend beyond the building itself and can also influence the urban environment. Chapter 19 explicitly sets requirements for the building envelope, mechanical and electrical systems, performance indicators, and reducing building energy demand and consumption (Ministry of Roads and Urban Development, 2020). The scope of such intervention can further extend to other dimensions, including building energy demand, pollutant emissions, and the associated costs, with implications for health and well-being (IEA, 2024; Johari et al., 2020). Consequently, studies addressing Chapter 19 have largely focused on either compliance with its requirements or building energy performance (Arab, 2020; Kazemi, 2017; Kazemi Pouran et al., 2020). This line of inquiry, with its direct emphasis on Chapter 19 or building energy performance, has tended to focus on a single component of the broader urban system without adequately considering its

relationships and interactions with the urban environment. Accordingly, urban systems research on Chapter 19 and energy efficiency has given comparatively limited attention to the three interrelated dimensions of energy, environment, and economy.

Accordingly, a more accurate, in-depth, and comprehensive assessment of building energy performance is possible only when the issue is first examined at the urban scale. Second, the analysis should provide a more comprehensive picture of the implications of a regulatory intervention, rather than limiting the assessment to individual components at the system's micro level. Third, the analysis should move beyond changes in energy consumption to capture their environmental implications. Moreover, when the analysis also considers economic effects, it can trace a chain of impacts from changes in energy consumption to changes in emissions and, subsequently, to the associated environmental costs. At the same time, examining the intervention's economic effects can help assess its economic feasibility. This argument rests on three dimensions – energy performance, environmental implications, and economic assessment –which can serve as a complementary analytical framework alongside analyses that address these aspects individually. A critical review of the literature and previous research will demonstrate how earlier studies have addressed these three dimensions and the extent to which they have established connections among them.

2. Theoretical and empirical background

To review the relevant literature, it is presented in two sections: a) the development of building energy modeling; and b) Chapter 19 of the Iranian National Building Regulations. Each section is examined separately.

2.1. Literature on the development of building energy modeling

A review of the literature on the development of building energy modeling at the urban scale points to several major developments, including broader access to spatial data resources, greater automation in the generation and application of diverse models, and a shift from modeling individual buildings toward urban-scale applications (Reinhart & Cerezo Davila, 2016; Chen et al., 2017). This evolution has also included incorporating various development scenarios (Ang et al., 2020). Among these approaches, urban building energy modeling (UBEM) is a practical modeling framework for estimating energy demand, evaluating carbon reduction strategies, supporting urban design and planning, and analyzing intervention scenarios (Ang et al., 2020; Shu & Zhao, 2023). In this context, Chen et al. (2017) developed CityBES to facilitate energy and cost savings through automated model generation. Using urban-scale data, they generated EnergyPlus models for 940 office and commercial buildings in San Francisco and used them to develop and evaluate retrofit scenarios. Zhang et al. (2022) expanded an urban building energy model for 59,332 buildings in Changsha by integrating GIS data, clustering techniques, and building archetypes. Their study demonstrated how to apply this modeling framework to assess energy-saving interventions at the urban scale. Abolhassani et al. (2022) developed a UBEM for Montreal by integrating CityGML, automated archetype selection, and EnergyPlus. They emphasized how building operational characteristics influence district-scale energy demand. Building on this line of research, UBEM has also been integrated with electricity grid models to examine the effects of large-scale retrofit scenarios for the existing building stock, not only in terms of energy performance but also in terms of impacts on other infrastructure systems (Johari et al., 2024). However, developing an urban-scale model is challenging. Limited access to geometric and non-geometric data, determining building operational characteristics and system specifications, and validating and calibrating many buildings are key challenges in this type of modeling (Wang et al., 2022). Under these conditions, a common solution is to classify the existing buildings into distinct types and use representative buildings for modeling. This approach, known as bottom-up modeling, can substantially reduce the computational burden. However, the reliability of such models depends on how building types are defined, the quality of the input data, and the calibration process, all of which require particular attention (Shen & Wang, 2024). UBEM has moved from single buildings to whole cities. This shift helps assess retrofit scenarios at scale. But the reliability of extrapolated results still hinges on building typologies and input data. Better scale does not automatically mean better assessment. Energy, emissions, and economics often remain separate. A truly integrated framework is still missing.

2.2. Chapter 19 of the Iranian National Building Regulations

Chapter 19 of the Iranian National Building Regulations provides requirements for energy conservation and improved building energy performance. In this context, studies have gradually assessed various aspects, from technical compliance to simulation and impact evaluation. Fayaz and Kari (2009) compared Chapter 19 with several international standards, evaluated Iranian residential buildings, and outlined its capabilities and limitations. Kordjamshidi (2020) evaluated 384 residential units in Babolsar across eight building types and extended the assessment to the study area's housing typology. The study showed differences in the thermal performance of the various building types relative to Chapter 19 requirements. Similarly, Soltaninejad et al. (2021) modeled an educational building in Kerman. Based on the data, the buildings were classified by the level of energy savings achieved under national building regulations and their environmental implications. Tavakolan et al. (2022) investigated integrating simulation with indicators such as discounted payback period and the effects of energy pricing policies.

This body of research has mainly focused on technical issues. Although other dimensions, particularly economic and environmental considerations, have gradually been incorporated, most research has remained focused on individual buildings or, at most, a limited number of buildings. Comparatively little attention has been given to the urban system as an integrated whole, considering its various dimensions from the perspective of building energy performance. By contrast, international research has increasingly moved beyond one-dimensional assessments toward integrated approaches, with some studies also incorporating environmental and economic implications into their analyses. For example, Suppa and Ballerini (2023) show that, while retrofit scenarios address energy consumption and emissions, they also link these considerations to intervention costs and economic returns. In a UBEM study, Luo et al. (2025) examined multiple dimensions, including multi-objective optimization and uncertainty analysis, as well as retrofit scenarios based on energy consumption, carbon emissions, and life-cycle costs. A more recent study adopted a similar approach but extended the analysis to the district scale (Suppa et al., 2026). This does not mean that multidimensional analyses are absent from domestic research; however, such integrated assessments have generally remained limited to groups of buildings and have rarely extended beyond the building-portfolio scale. For example, Tavakolan et al. (2022) integrated energy and economic retrofitting indicators at the individual-building scale. In another study, Mostafazadeh et al. (2023) examined retrofitting a residential building in Tehran, considering not only energy performance but also CO_2 emissions, life-cycle costs, and thermal comfort. A literature review therefore indicates that international research is moving toward integrating energy, environmental, and economic dimensions at larger scales, particularly at the urban scale. In contrast, this trend and the corresponding integrated studies in the domestic literature remain more limited and have focused predominantly on individual buildings, with relatively little attention given to the city scale. More specifically, despite numerous studies on UBEM and building energy performance assessment, frameworks that link building energy regulations to quantified urban-scale impacts across the three dimensions of energy, environment, and economy remain limited.

The literature review indicates that building energy modeling has expanded in scale and integrated multiple dimensions, incorporating urban system aspects and focusing on the implications of energy performance. Recent studies have increasingly addressed the urban scale and, in some cases, introduced additional dimensions, such as social considerations, into their scenarios, extending the analysis beyond individual buildings to neighborhoods and urban structures (Excell et al., 2024). At the same time, issues such as life-cycle considerations and the linkage between energy consumption and environmental impacts have received considerable attention in a substantial body of research (Li & Feng, 2025). Domestic studies also include examples of integrating energy considerations with economic factors, emissions, and thermal comfort. However, they differ from international studies in the scale and scope of the dimensions examined (Tavakolan et al., 2022). What matters here is not merely the inclusion of different dimensions, such as economic or environmental considerations. Rather, the fundamental issue is the lack of continuity in the analysis across scales, on the one hand, and the assessment of these dimensions as interdependent and influenced by scale, on the other. Although the country has an established regulatory framework and legal requirements for intervention, a significant gap remains in translating these requirements into scenarios that can be assessed at the urban scale while

integrating different dimensions. Accordingly, the research gap is the lack of a systematic linkage among regulations, energy performance, environmental impacts, and economic considerations at the urban building-stock scale. More specifically, there is a lack of a framework capable of modeling the requirements of Chapter 19 as measurable scenarios at the urban-building scale, quantifying the gap between existing performance and the performance required by the regulation, and ultimately assessing the consequences of this gap along the chain of energy consumption, emissions, and economic impacts.

To address this gap, this study establishes Chapter 19 as the intervention framework. It uses archetype-based UBEM to assess it quantitatively across the existing building stock. Accordingly, residential, commercial, and office buildings in Qazvin are modeled by building typology, and the gap between the existing condition and a scenario compliant with Chapter 19 requirements is modeled and quantitatively assessed. The resulting outcomes are evaluated and analyzed from three perspectives: energy performance, emissions impacts, and the economic feasibility of implementing the optimization scenario.

Accordingly, by employing a building-typology approach and archetype-based modeling, the present study seeks to address the following three questions:

1. What is the quantitative gap between current energy-use intensity and the implementation of Chapter 19 requirements in residential, commercial, and office buildings?
2. What additional pollutant burden does this gap impose on the city, and what associated external costs does it generate?
3. How do changes in economic conditions affect the economic feasibility of a scenario compliant with Chapter 19, and what role can financial incentives play in improving its economic attractiveness?

3. Research method

3.1 Research framework

The study's statistical population comprises urban residential, commercial, and office buildings, based on statistical data from the Municipality of Qazvin and the Qazvin Province Construction Engineering Organization. To address data limitations, we adopted a building-typology approach. The buildings were classified into three main groups based on three criteria: a) building use (residential, commercial, and office); b) construction period (from 2006 onward); and c) number of floors. We then used geometric characteristics, building envelope, and building systems to assess within-type homogeneity and select representative buildings. For each group, we selected several sample buildings most similar to their respective groups in terms of geometry, structure, and systems. The technical specifications of the primary representative buildings – medium-scale buildings with five floors and a floor area of more than 600 m^2 for residential use, two floors and a floor area of more than 400 m2 for commercial use, and four floors and a floor area of more than 200 m2 for office use – were used as the basis for the simulations.

To select representative buildings from each typology, we used a composite criterion combining the geometric mean and the highest frequency. First, we identified the most frequent ranges of floor area, number of floors, and construction year for each typology. We then selected the building whose characteristics most closely matched the geometric mean of these parameters as the representative building. This method ensures statistical representativeness through the highest-frequency values and centrality within the data distribution through the geometric mean, and it is also consistent with the standard approach proposed by Tardioli et al. (2018).

The present study was conducted in four operational stages: 1) collecting technical, climatic, and building energy consumption data for urban buildings in Qazvin; 2) developing and calibrating the prototype energy model using DesignBuilder/EnergyPlus in accordance with ASHRAE Guideline 14 (ASHRAE, 2020); 3) defining baseline and Chapter 19 retrofit scenarios; and 4) conducting an integrated assessment of energy savings, reductions in pollutant emissions (CO2, SO2, NOx, and PM2.5), and economic indicators, including the payback period (PP), net present value (NPV), and internal rate of return (IRR). This framework is based on a prototype-based urban building energy modeling (UBEM) approach.

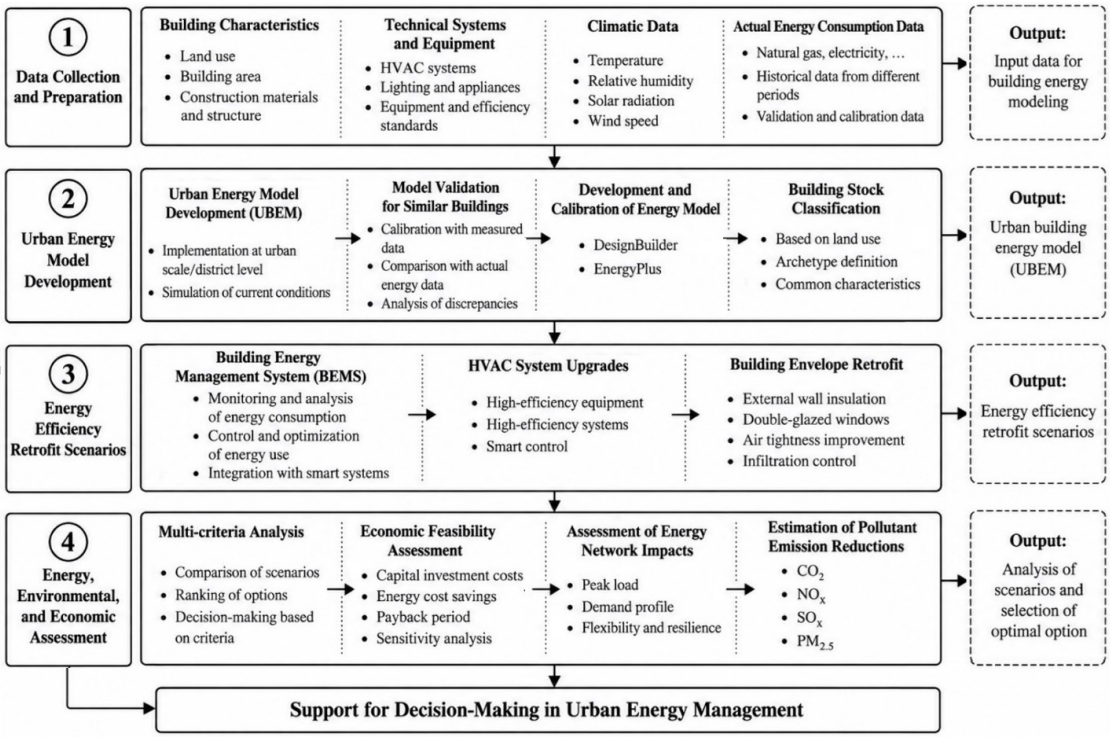


Figure 1. Proposed UBEM-based framework for the integrated assessment of the energy, environmental, and economic performance of urban buildings

3.2. Case study and development of the urban building energy model (UBEM)

Qazvin has a cold semi-arid climate (BSk). Given the limited availability of detailed building-level data in this study, we adopted a prototype-based UBEM approach. First, a representative building was selected and calibrated for each of the three building-use types, and the results were then extrapolated to buildings of the same type (residential, commercial, and office). The input data included geometric characteristics, envelope materials, HVAC systems, building age, occupancy and operation patterns, building services systems (cooling and heating), and energy consumption data for residential, commercial, and office buildings in Qazvin. Given the relevant literature and the lack of detailed data at the individual-building scale, the prototype-based UBEM approach was selected for the modeling process. The buildings were then classified into homogeneous types based on their use, construction period, number of floors, envelope characteristics, and building services systems. For each type, we then selected a representative building based on the frequency of its characteristics and its proximity to the type's central values. We then ran simulations and extrapolated results only to buildings within the same typological range. Accordingly, the urban-scale estimates presented in this study represent the performance of the target group of homogeneous buildings. In practice, directly modeling every individual building in the city is not feasible.

Table 1. Structural and physical characteristics of building types in Qazvin City

Heating/cooling system	Thermal envelope characteristics	Predominant building age (years)	Number of floors range	Average floor area range (m^2)	Estimated total number of buildings	Share of floor area (%)	Type code	Building use
Wall-mounted boiler/ split air conditioner	Brick clay block walls; standard triple-glazed windows with poor U-values	2006 to Present	4-5	600	1092	65%	T-Res	Residential
Centralized split/ chiller systems	Large glazed façades; moderate insulation	2006 to Present	1-2	400	504	15%	T-COM	Commercial
Vapor-compression chiller/ central boiler	Glass/stone façade; uninsulated, with poor U-values	2006 to Present	3-4	200	504	20%	T-OFF	Office

The statistical population comprises all building permits issued in Qazvin from 2006 to the present (approximately 20 years). Based on aggregated statistics from Qazvin Municipality and the Qazvin Province Construction Engineering Organization, the average approved floor area over this period was estimated at approximately 1.7 million m2. Selecting this extended period, rather than a single year, allows the model to capture fluctuations between periods of construction activity and stagnation, providing a basis for representing future construction trends in the city. Consequently, the generalized results reflect the weighted-average performance of buildings in the city over the past two decades. The building samples used for model calibration were selected from projects constructed between 2006 and the present to capture variations in construction practices, ranging from traditional to semi-modern methods.

3.3 Energy model calibration

The energy model was developed using DesignBuilder 7.0.2 with the EnergyPlus 9.1 simulation engine (Crawley et al., 2001). Calibration was performed against actual 12-month electricity and natural gas consumption data in accordance with ASHRAE Guideline 14 (ASHRAE, 2020), using the NMBE (Equation 1) and CV(RMSE) (Equation 2) indices. For calibrated models at the monthly time scale, acceptable ranges are NMBE < 5% and CV(RMSE) < 15%, respectively (ASHRAE, 2020; Oraiopoulos & Howard, 2022). Equation (1) presents and calculates the normalized mean bias error (NMBE):

$$NMBE(\%) = \frac{\sum_{i=1}^{n}(M_i - S_i)}{(n-p)\ddot{M}} * 100$$

where:

M_i = measured energy consumption in period i

S_i = simulated energy consumption in period i

$\bar{M}$ = mean of the measured energy consumption values

n = number of data points used for calibration

p = number of adjusted model parameters

Equation (2): coefficient of variation of the root mean square error (CV(RMSE))

$$\mathrm{CV(RMSE)}(\%) = \frac{\sqrt{\frac{\sum_{i=1}^{n}(M_i - S_i)^2}{\mathrm{n-p}}}}{\ddot{M}} \times 100$$

Based on the model calibration and validation data (Table 1), the NMBE was 0.82%, while the CV(RMSE) value was 3.4%. These values are well below the acceptance thresholds recommended by ASHRAE Guideline 14. The calibration used 12 months of actual electricity and natural gas consumption data from the representative buildings. The resulting NMBE = 0.82% and CV(RMSE) = 3.4% values fall within the acceptance criteria in ASHRAE Guideline 14. These results confirm the model›s validity at the scale of the representative buildings and over the calibration period. Nevertheless, independent, disaggregated data are not available for all buildings across the city. Therefore, do not interpret the calibration as validation of the city-scale estimates.

3.4. Design of energy optimization scenarios

The research questions highlight a gap between the current state and Chapter 19›s requirements. Accordingly, two main scenarios were defined: a baseline scenario representing the current state without any optimization measures, and a second scenario involving full implementation of Chapter 19. The latter includes improved building-envelope insulation, triple-glazed Low-E windows, condensing boilers, high-efficiency cooling systems, LED lighting, and an energy management system. These measures are based primarily on previous studies in cold climates (Asadi et al., 2012; Ma et al., 2012; Sadineni et al., 2011) and align with Chapter 19 of the National Building Regulations (National Building Regulations Office, 2025). Accordingly, the resulting energy savings will be calculated using Equation (3).

$$Energy\ Saving\ \% = \frac{Energy_{\ Base} - E_{Scenario}}{E_{Base}} * 100$$

EBase = annual energy consumption of the building under the baseline scenario

EScenario = annual energy consumption of the building under the optimization scenario

For each scenario, in addition to energy consumption, environmental pollutant emissions and economic indicators were evaluated. The results were then compared with those of the baseline scenario.

To assess the effects of the optimization scenario, an enhanced scenario based on Chapter 19 (Fifth Edition) was defined. The values of the envelope and building services parameters were specified in accordance with the requirements for the relevant building groups, as detailed below:

External walls: thermal insulation with a heat transfer coefficient of U = 0.38 W/m².k, in accordance with the requirements for Building Group 1 specified in the tables of Chapter 19.

Ceilings and roofs: installation of thermal insulation with U = 0.25 W/m2.k
Windows: triple-glazed low-E windows with UPVC frames, U = 1.8 W/m².k, and SHGC = 0.4
Heating system (HVAC): replacement of the existing heating boiler with a condensing boiler with an efficiency of 94%, and a vapor-compression chiller with COP = 3.2
Lighting and energy management system: use of LED lighting and smart lighting control (BEMS)

Table 3. Alignment of optimization measures with the specific provisions of Chapter 19 of the National Building Regulations

Optimization measure	Relevant provision of chapter 19	Standard value (chapter 19)	Existing value (baseline condition)	Improvement
Insulation of external walls	Clause 19-4-1-1 (envelope requirements table)	U<= 0.38 W/M2K	U~1.20 W/M2.K	68% reduction in heat transfer
Replacement of windows with triple-glazed low-E windows	Clause 19-4-1-3	U<=1.8 W/M2K & SHGC<=0.4	U~3.5W/M2.K	49% reduction in heat transfer
Replacement of the boiler with a condensing boiler	Clause 19-6-2-1	Efficiency (LHV) ≥ 94%	Efficiency ≈ 75%	25% increase in efficiency
Use of a high-efficiency vapor-compression chiller	Clause 19-6-3-2	COP>=3.2	COP ≈ 2.5	28% increase in efficiency
LED lighting system + BEMS	Clause 19-10-1-1	Power density ≤ 6 W/m²	Power density ≈ 12 W/m²	50% reduction in lighting energy consumption

Table 4. Classification of the energy optimization scenarios used in the study

Scenario	Strategy type	Primary objective
Baseline	Current condition	Basis for comparison
Passive scenarios	Improvement of the building thermal envelope	Reduction in heating and cooling loads
Active scenarios	Upgrading HVAC and lighting systems	Improvement in energy efficiency
Renewable energy and energy management scenarios	Use of advanced technologies and energy consumption control	Reduction in energy consumption and pollutant emissions
Integrated scenario	Simultaneous implementation of the selected measures	Achieving maximum energy savings

3.5. Energy, environmental, and economic assessment of the optimization scenarios

Based on electricity and natural gas consumption data and localized emission factors, emissions of CO_2, SO_2, NOx, and PM2.5 were calculated (Table 5). Electricity emission factors were obtained from Peyvandi et al. (2023), while natural gas emission factors were obtained from the IPCC (2022). In addition, the external cost approach and the impact pathway approach were used to value the reduction in pollutant emissions economically, based on the CE Delft (2024) and EEA (2024) reports. The economic indicators, including the payback period (PB), net present value (NPV), and internal rate of return (IRR), were calculated using a 10% discount rate over 10 years (Blank & Tarquin, 2018; Copiello et al., 2017; Fregonara & Ferrando, 2023), as presented in Equations (4), (5), and (6).

CO_2,Electricity = EElectricity × EFElectricity
CO_2,Gas = EGas × EFGas
CO_2,Total = CO_2,Electricity + CO_2,Gas
In these equations:
EElectricity: annual electricity consumption of the building
EGas: annual natural gas consumption of the building
EFElectricity: electricity-related carbon dioxide emission factor
EFGas: natural gas-related carbon dioxide emission factor
CO_2,Electricity: CO_2 emissions resulting from electricity consumption
CO_2,Gas: CO_2 emissions resulting from natural gas consumption
CO_2,Total: total carbon dioxide emissions

To assess the economic feasibility of implementing the scenarios, we estimated each measure's initial implementation cost and the annual energy cost savings. Three economic indicators (the payback period (PB), net present value (NPV), and internal rate of return (IRR)) were subsequently calculated to evaluate the economic performance of the scenarios (Blank & Tarquin, 2018). Finally, Equation (7) was used to calculate the payback period as the ratio of the initial investment cost to the annual energy cost savings.

Equation (7): payback period

PB = I / S

where:

I: initial implementation cost of the optimization scenario

S: annual energy cost savings

To evaluate economic performance over the operating period, the net present value (NPV) is calculated from the annual cash flows and the discount rate, as in Equation (8).

Equation (8): net present value (NPV)

$$NPV = \sum_{t=1}^{n} \frac{CF_t}{(1+r)} - I$$

In this equation:

CF_t: net cash flow in year t

r: discount rate

t: time period of the economic analysis

n: length of the economic analysis period

I: initial investment

To assess the profitability of the investment, the internal rate of return (IRR) was used. It was determined by calculating the discount rate that sets the net present value (NPV) equal to zero, in accordance with Equation (9).

Equation (9): internal rate of return (IRR)

$$\sum_{t=1}^{n} \frac{CF_t}{(1+IRR)^t} - I = 0$$

In this equation:

CF_t: net cash flow in year t

IRR: internal Rate of Return of the project

t: time period of the economic analysis

n: length of the economic analysis period

I: initial investment

The literature reports social discount rates ranging from 7.3% to 15% for developing countries. In this study, we adopted a 10% discount rate as the baseline for the economic assessment, reflecting Iran's economic conditions, inflation rate, and interest rates on infrastructure project financing (Turan & Gurluk, 2024; Mostafazadeh et al., 2023). To align with previous economic assessments of building retrofit projects, we assumed a 10-year project lifetime for the NPV calculation (Fregonara & Ferrando, 2023; Copiello et al., 2017). Annual maintenance and equipment replacement costs were assumed to be 2% of the initial investment cost. We also performed a sensitivity analysis around the 10% discount rate to examine uncertainty in the results. Emission factors for electricity and natural gas were taken from established national and international studies. For electricity, the CO2 emission factor was set at 0.623 t CO2/MWh, based on the emission intensity of Iran's thermal power plants reported by Peyvandi et al. (2023). We obtained the emission factors for SO2, NOx, and PM2.5 from Nazari et al. (2010) and updated national studies, including Peyvandi et al. (2023). For natural gas, we used the default emission factors provided by the IPCC (2022), with consideration of the fuel characteristics used in Iran (Table 3).

We valued reductions in pollutant emissions using the external cost approach. Under this approach, the external costs of CO2, SOX, NOX, and PM2.5 were determined using the CE Delft (2024) guidelines and the European Commission's report on external costs (European Commission, 2019), applying adjustment factors to reflect conditions in Iran. For CO2, we considered an external cost range of €100 to €164 per ton, and we calculated the external costs of local pollutants using the impact pathway approach, CAFE reference values, and updated EEA (2024) data.

$$EC_j = \Delta E_j \times UC_j$$

where:

* ED_i: Economic value of avoided damages attributable to pollutant i

* ΔE_i: reduction in emissions of pollutant i relative to the baseline scenario

* EC_i: unit external cost of pollutant i, expressed in euros per tonne

The total environmental benefit was then calculated as the sum of the avoided damage values for the four pollutants.

Table 5. Emission factors and external environmental costs

Pollutant	Electricity emission factor (kg/MWh)	Natural gas emission factor (kg/GJ)	External cost (€/tonne)	Source
CO_2	623	56.1	164-100	Peyvandi et al. (2023); CE Delft (2024); European Commission (2019)
SO_2	2.15	0.005	6000-2000	Nazari et al. (2010); EEA (2024); CE Delft (2024)
NOx	1.78	0.048	7500-2500	Nazari et al. (2010); EEA (2024); CE Delft (2024)
$PM_{2.5}$	0.47	0.0015	50000-15000	EEA (2024); CE Delft (2024); WHO (2023)

3.6. Sensitivity analysis and parameter variation ranges

A one-at-a-time sensitivity analysis was conducted for three key parameters (building-envelope U-value, energy carrier prices, and the electricity CO2 emission factor), with a range of ±20% changes compared to the baseline value (Table 10), and two influential parameters, the discount rate and project useful life (Table 11) (Luo et al., 2025; Fennell et al., 2025). These analyses aimed to assess the robustness of results for urban energy consumption, CO_2 reductions, and NPV under uncertainty in the input parameters, as well as to examine the effects of the discount rate and project lifetime under a pessimistic scenario. Sensitivity analysis was used to examine how uncertainties in input parameters affect results and to assess the robustness of urban energy models (Tian, 2024; Wang et al., 2025). In the one-at-a-time approach, one parameter is varied at each step while all other parameters are kept at their baseline values. Within this framework, the effects of changes in the U-value on energy consumption, the electricity emission factor on CO2 emissions, and energy prices on NPV were examined. For the economic analysis, discount rates of 10%, 15%, and 20% were considered, while project lifetimes of 8, 10, and 15 years were evaluated. The sensitivity of each output was determined by comparing the value obtained under each scenario with the corresponding baseline value. The direction and magnitude of change in each output were then used to identify the parameters with the greatest influence and assess the robustness of the results. This analysis was conducted independently of calibrating and validating the representative building energy model. It was used solely to assess the results' sensitivity to the input assumptions.

4. Results

4.1. Validation of the representative building energy model

Table 6 presents the validation results of the representative building energy model, evaluated by comparing the post-calibration simulation results with the actual energy consumption data. Based on these data, the NMBE was below 1%, while the CV(RMSE) and MAPE were 3.4% and 3.3%, respectively. The error in estimating carbon dioxide emissions was also less than 2%. These results indicate a good agreement between the model and the actual data. Accordingly, the calibrated model was considered sufficiently reliable to serve as the basis for developing the urban energy model and evaluating the optimization scenarios.

Table 6. Validation results for the representative building energy model

Index	Value	Acceptance Range	Source
NMBE (%)	1>	<5%	ASHRAE (2020); Oraiopoulos & Howard (2022)
CV(RMSE) (%)	3.4	<15%	
MAPE (%)	3.3	-	
RMSE (kWh/year)	7900	-	
CO_2 Emission estimation error (%)	2>		

4.2. Results of the urban energy model under the baseline scenario

The model results show clear differences in energy consumption patterns across building uses. Commercial buildings had the highest annual energy use intensity, at 220 kWh/m^2 (Table 7). Office and

residential buildings were estimated at 200 and 180 kWh/m², respectively. In residential buildings, heating accounted for 45% of total energy use. In commercial buildings, cooling and lighting were the main end uses, accounting for 35% and 25% of total energy consumption, respectively. For office buildings, heating, cooling, and lighting accounted for 35%, 30%, and 20% of total energy use, respectively.

An assessment of the physical characteristics of the buildings indicates that thermal insulation is generally poor in residential and office buildings, while it is moderate in commercial buildings. This is one factor contributing to the high level of energy consumption under current conditions.

Table 7. Results of the urban energy model under the baseline scenario

Building use	Energy Use Intensity (kWh/m²·year)	Heating (%)	Cooling (%)	Lighting (%)	Equipment efficiency	Insulation quality
Residential	180	45	28	12	Low	Poor
Commercial	220	27	35	25	Moderate	Moderate
Office	200	35	30	20	Moderate	Poor

To determine which technical measures contributed most to reducing energy consumption, we calculated each measure's contribution to total energy savings. The results were as follows: 1) improving the building envelope insulation, 42%; 2) upgrading the heating and cooling (HVAC) systems, 31%; 3) replacing conventional lighting with LED lighting, 15%; and 4) implementing a building energy management system (BEMS), 12%.

4.3. Changes in pollutant emissions under the optimization scenario

Implementing the optimization scenario reduced energy consumption and lowered pollutant emissions associated with electricity and natural gas use. As a result, emissions of all pollutants considered in the analysis decreased relative to the baseline condition. This finding highlights the direct link between improved building energy performance and reduced urban pollution. In terms of mass, carbon dioxide (CO2) showed the largest reduction among the pollutants examined. Emissions of SO2, NOx, and PM2.5 also decreased substantially (Table 8).

Table 8. Annual reduction in pollutant emissions under the optimization scenario (baseline, optimization, and reduction)

Pollutant	Baseline emissions (tons/year)	Emissions under the optimization scenario (tons/year)	Absolute reduction (tons/year)	Relative reduction (%)
CO_2	420000	295000	125000	29.8
SO_2	1450	1060	390	26.9
NO_x	1200	810	390	32.5
$PM_{2.5}$	320	224	96	30

The largest absolute reduction was in CO_2 emissions, at 125,000 tons. More importantly, from a health-impact perspective, the 30% reduction in PM2.5, 32.5% reduction in NOx, and 26.9% reduction in SO2 emissions are particularly significant. Although accurately assessing atmospheric pollutant concentrations requires air-dispersion modeling, a 30% reduction in source mass emissions of PM2.5 and NOx represents an important step toward achieving the World Health Organization (WHO) air-quality targets at the urban scale. Based on external cost coefficients reported by Delft University of Technology and the EEA 2024 report, the annual economic value of reducing local pollutants, excluding CO2, was estimated at approximately IRR 3.073 billion (EEA, 2024; CE Delft, 2024). A substantial share of this value comes from reduced healthcare costs and gains in labor productivity. This finding directly addresses the research question concerning the "health costs associated with the implementation gap in Chapter 19."

4.4. Validation of the results at the urban scale

The results obtained for the representative building within the prototype-based UBEM framework were extrapolated to residential, office, and commercial buildings across Qazvin to assess scalability. The model's validity at the representative-building level was confirmed using actual energy consumption data and the NMBE, CV(RMSE), and MAPE metrics, in accordance with the criteria specified in ASHRAE Guideline 14. Although the Qazvin Province energy balance for 2022 is available in aggregate form, it does not break down energy consumption by residential, commercial, and office uses. Moreover, the reported figures cover the entire province, not Qazvin city alone.

Table 9. Summary of model validation at different levels

Validation level	Assessment basis	Status
Prototype building	Actual energy consumption data	Completed
Model calibration	NMBE، CV(RMSE)، MAPE	Compliant with ASHRAE Guideline 14
Urban-scale extrapolation	Prototype-based UBEM method	Completed
Direct validation of the entire urban area	Aggregated actual data	Not available

4.5. Sensitivity and uncertainty analysis

This section examined three key parameters: the building-envelope heat transfer coefficient (U-value), energy carrier prices, and the CO2 emission factor for electricity. To assess the robustness of the results, we assumed a ±20% variation range relative to the baseline value for each parameter and evaluated its effects on urban energy consumption, CO2 emission reductions, and net present value (NPV).

The results, with all other parameters held constant, showed that urban energy consumption was most sensitive to changes in the U-value. A 20% improvement in the building envelope's thermal performance reduced energy consumption by about 10%. NPV was also most strongly dependent on energy carrier prices, with a 20% decrease in energy prices resulting in an approximately 28% reduction in NPV. Despite these variations, the NPV remained positive under all conditions, indicating the economic robustness of the integrated optimization scenario. Accordingly, the results showed that changes in CO2 emissions were approximately linear and proportional to changes in the electricity emission factor.

In addition to the three key parameters described above, the one-way sensitivity analysis included two influential parameters. The results obtained from this analysis can also provide evidence of the economic robustness of the integrated optimization scenario. These two parameters were evaluated in accordance with Table 11.

Table 10. Results of the one-way sensitivity analysis for key parameters

Parameter	Changes	Urban energy consumption (GWh/year)	CO_2 Reduction (ton/year)	NPV (billion IRR)
Baseline	0 %	720	125000	21012
U-value	- 20 %	648	137500	23500
U-value	+ 20 %	792	112000	18500
Energy price	- 20 %	720	125000	15200
Energy price	+ 20 %	720	125000	26800
CO_2 emission factor	- 20 %	720	100000	21012
CO_2 emission factor	+ 20 %	720	150000	21012

Table 11. Results of the one-way sensitivity analysis of the discount rate and project service life on NPV

Analysis variable	Baseline value	Range of variation	Corresponding NPV (billion rials)	Change relative to baseline
Discount rate (baseline)	10 %	---	21012	---
Discount rate (pessimistic)	10 to 15%	15 %	17500	- 16.7 %
Discount rate (highly pessimistic)	10 to 20 %	20 %	12100	- 42.4 %
Timelife (baseline)	10 years	---	21012	---
Timelife (optimistic)	10 to 15 years	15 years	27300	+ 29.9 %
Timelife (pessimistic)	8 to 10 years	8 years	18200	- 13.4 %

* Other parameters were held constant at their baseline values. Even under the most pessimistic conditions (a discount rate of 20% and a time life of 8 years), the NPV remains positive.

Assessment of the role of financial incentives under the economic conditions of the scenario

The sensitivity analysis shows that, under the most unfavorable economic conditions, represented by a 20% reduction in energy carrier prices, the payback period increases from 0.75 to 0.94 years. At the same time, NPV decreases by 28% but remains positive at 15.200 billion rials. Although NPV remains positive in all scenarios at a 10% discount rate, this assumption does not fully reflect Iran's economic conditions. Persistent inflation above 30%, bank lending rates of about 20–25%, and economic uncertainties, including large fluctuations in energy carrier prices and sudden exchange-rate changes, mean that construction-sector investors generally expect a minimum hurdle rate of around 25–30%. The sensitivity analysis presented in Table 10 shows that increasing the discount rate to 20% reduces NPV by about 42%, from 21.012 to 12.100 billion rials. Under these conditions, the project may not be sufficiently attractive to conservative investors without financial support at a 15–20% discount rate. Such incentives can help bridge the gap between the assumed social discount rate of 10% and the market return investors expect, estimated at 25–30%. Based on these findings, and in line with the approaches reported by Copiello et al. (2017) and Mostafazadeh et al. (2023), a minimum financial incentive equivalent to 15–20% of the initial investment cost, estimated at approximately 410–550 billion rials, could reduce investment risk and improve the economic attractiveness of the project under conditions of stagnant prices. This level of support could also provide a stronger financial incentive to implement Chapter 19's requirements fully.

This study's findings show that changes in energy prices have the greatest effect on the economic indicator NPV. Even under the most unfavorable condition, a 20% reduction in energy prices, the optimization scenario still yields a positive NPV. Improving the thermal performance of the building envelope (U-value) also reduces energy consumption and provides considerable environmental benefits. The one-way sensitivity analysis further shows that the main findings, including energy savings of 648–792 GWh and a positive NPV, remain reasonably robust to plausible changes in the input parameters.

5. Discussion

In line with the study objectives, the findings revealed a substantial performance gap between the existing condition of the buildings examined and the scenario defined by the requirements of Chapter 19. The approximately 46.5% reduction in energy consumption under the integrated scenario indicates that much of this gap relates to the performance of the building envelope and energy systems. This suggests that simultaneous interventions in passive and active components, together with energy-use management, offer greater potential for reducing energy demand than individual measures (Ang et al., 2020). The reduction calculated in this study broadly aligns with the findings of international UBEM studies. These studies also show that integrated interventions in the building envelope and energy systems have greater potential to reduce energy demand at the urban-building scale than individual measures (Suppa & Ballarini, 2023; Luo et al., 2025). Nevertheless, differences in climate, building characteristics, and the combination of retrofit measures can affect the magnitude of the resulting energy savings.

The results indicate that the estimated urban energy savings of 648–792 GWh per year come from

extrapolating results from representative buildings to the target building stock. Therefore, this result should be interpreted as a scenario-based estimate rather than direct validation of the entire city (Shen & Wang, 2024). The energy reduction achieved in this study is consistent with the findings of some UBEM and deep-building-retrofit studies. This consistency suggests that integrated retrofit packages can substantially reduce energy consumption in buildings with poor envelope performance and relatively inefficient energy systems. Accordingly, the energy savings obtained in this study fall within the range reported in previous building-retrofit studies. However, the magnitude can vary considerably depending on the depth of intervention, building characteristics, and combination of measures adopted (Fregonara et al., 2017).

In this study, the NPV was calculated using a 10% discount rate. However, under Iran's inflationary economic conditions, investors generally expect a minimum hurdle rate of around 25–30%. Increasing the discount rate to 20% reduces the NPV to approximately 12,000 billion rials (Table 10). Therefore, financial incentives of 15–20% are proposed not to cover project costs, but to compensate for systemic risk, the risk of future declines in energy carrier prices, and conservative investors' reluctance to undertake the investment. The economic assessment of energy-retrofit projects is sensitive to assumptions such as the discount rate, energy prices, and the assessment period. Any change in these parameters can therefore significantly affect the financial assessment results (Fregonara et al., 2017).

From an environmental perspective, reducing energy consumption also reduces emissions of CO2, SO2, NOx, and PM2.5. This finding suggests a direct link between improved building energy performance and reduced urban pollutant burden. Unlike previous studies that focused mainly on CO2, this study considers multiple local pollutants simultaneously, allowing a more comprehensive assessment of the environmental implications of source-level emission reductions. This approach is also consistent with recent developments in UBEM, which increasingly rely on multiple environmental indicators (Kong et al., 2023; Salvalai et al., 2024).

The discount rate, project lifetime, and uncertainty in input data directly affect the economic assessment of energy optimization projects (Tavakolan et al., 2022). The calculations are based on social discount rates reported for developing countries (7.3–15%) (Turan & Gurluk, 2024), the country's economic conditions, particularly high inflation, and conservative assumptions for calculating NPV, including a 10% discount rate and a Timelife of 10 years.

The one-way sensitivity analysis covered five key parameters: U-value, energy prices, the CO2 emission factor for electricity, the discount rate (10%, 15%, and 20%), and the project Timelife (10, 15, and 20 years). The results show that even under the most pessimistic condition (a 20% discount rate and a project Timelife of 8, 10, or 15 years), the integrated scenario still yields a positive NPV. The results also indicate that urban energy consumption is most sensitive to the U-value. A 20% improvement in the building envelope's thermal performance reduces energy consumption by about 10%. The findings further highlight the importance of building-envelope thermal performance, consistent with results reported in independent studies. Yun et al. (2024), for example, showed that variations in the actual U-values of existing buildings can significantly affect estimates of the energy-saving potential of retrofits (Wang et al., 2022; Yun et al., 2024). Despite these changes, the NPV remained positive under all conditions, ranging from 15,200 to 26,800 billion rials. Based on the sensitivity analysis, a 20% reduction in energy prices would increase the payback period to 0.94 years. Under these conditions, financial incentives equivalent to 15–20% of the initial investment cost (410–550 billion rials) would be needed to keep the project economically attractive. Previous studies have also highlighted the importance of complementary economic mechanisms in decision-making for building energy retrofits (Mostafazadeh et al., 2023). As expected, the sensitivity analysis showed that the economic viability of the optimization scenario is sensitive to energy prices and the discount rate. Although the NPV remains positive across the scenarios examined, a higher expected rate of return or lower energy prices could reduce the investment's relative attractiveness. Based on this finding, a 15–20% financial incentive could be considered under a support scenario to reduce investment risk and improve economic attractiveness. However, this should not be interpreted as a definitive or universal threshold for implementing Chapter 19 requirements.

The results indicate that the UBEM model depends heavily on the quality of the input data. Therefore, uncertainty in the input parameters may affect the results and scenario rankings (Ali et al., 2021). The sensitivity analysis confirmed that the main findings regarding energy savings and the economic feasibility of the selected scenario remain stable under

reasonable variations in the input parameters.

Because citywide data on the existing urban building stock (residential, commercial, and office buildings) are unavailable, validating the model only at the representative-building level is one of this study's main limitations. This study did not examine the institutional framework or the roles of responsible bodies, such as the municipality, the Construction Engineering Organization, and the Ministry of Energy, in implementing Chapter 19. This issue is particularly important when addressing the policy-related research question. Developing a policy model for regulatory and incentive mechanisms could therefore be a potential topic for future research. Previous studies indicate that occupant behavior, urban microclimate, and long-term climate change can affect model outputs (Boccalatte et al., 2020), but the present study did not examine these factors. Future research could focus on developing dynamic models, incorporating measured data, and integrating data from smart building systems. Future research should also assess how well these data can improve the accuracy of UBEM models (Salvalai et al., 2024; Li & Feng, 2025).

6. Conclusion

This study used a prototype-based urban building energy modeling approach to develop an integrated framework for simultaneously assessing the technical, environmental, and economic performance of urban buildings with residential, commercial, and office uses in Qazvin. The findings showed a substantial performance gap between the existing building stock and Chapter 19 requirements, and that implementing a scenario consistent with its technical requirements could reduce energy consumption by 46.5%, corresponding to an estimated reduction of 648–792 GWh per year at the city scale. Under the optimization scenario, annual emissions of CO2, SO2, NOx, and PM2.5 were reduced from 420,000, 1,450, 1,200, and 320 tons to 295,000, 1,060, 810, and 224 tons, respectively. This corresponds to absolute annual reductions of 125,000, 390, 390, and 96 tons, respectively. The economic value of the reductions in pollutants other than CO2 was estimated at 3.073 billion rials. These results indicate a direct potential reduction in health-related external costs under the impact pathway approach, while also showing the potential to reduce pollutant emissions at their source. However, accurately assessing atmospheric pollutant concentrations requires atmospheric dispersion modeling, which was beyond this study's scope. Overall, the sensitivity analysis showed that, under a 20% reduction in energy prices, financial incentives equivalent to at least 15–20% of the initial investment cost (410–550 billion rials) could be considered as a support scenario to reduce investment risk and maintain the economic attractiveness of implementing the scenario consistent with Chapter 19. Given that a 20% reduction in energy prices decreases the NPV by 28%, establishing a financial incentive fund to cover 15–20% of retrofit costs for urban residential, commercial, and office buildings, based on the actual energy savings achieved, could be an effective policy measure. Moreover, because improving U-Value has the greatest impact (10% reduction in consumption), measures that improve the thermal performance of the building envelope could be prioritized in retrofit planning. Establishing an integrated database of buildings' technical and performance characteristics to calibrate and continuously monitor UBEM models could also substantially improve model accuracy and reliability. This study did not examine the institutional framework or mechanisms for reforming the regulatory system governing the implementation of Chapter 19, which future research could address.

Authors' Contributions

All authors have contributed equally.

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During the preparation of this manuscript, the authors used Deep Seek Ver 4.5 solely to assist with spelling and grammar corrections, improve linguistic clarity and readability, assist in preparing the research methodology diagram, and check language consistency between the Persian and English versions of the text. The authors reviewed all content and take full responsibility for the scientific content, data, analyses, findings, and final version of the manuscript.

Conflict of Interest

The authors declare that they have no financial or non-financial competing interests that could have influenced the research, interpretation of the results, or publication of this article.

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