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IJCE is a peer-reviewed journal that offers open access to all interested readers. This journal follows a double-anonymized review process. Also, this journal adheres to the guidelines set by the Committee on Publication Ethics (COPE) and upholds the highest ethical standards in compliance with relevant ethical laws.

Message from the Editor-in-Chief

It is both an honor and a privilege to serve as the Editor-in-Chief of The Interdisciplinary Journal of Civil Engineering. This journal was founded with the vision of establishing a distinguished forum for the dissemination of high-quality research and the exchange of transformative ideas in the field of civil engineering. By fostering an interdisciplinary perspective, we aim to bridge diverse areas of expertise through promoting collaboration across academic and professional communities, addressing the complex challenges that define our rapidly evolving world.

Our mission is to advance the frontiers of civil engineering through scholarly rigor, innovation, and a persistent commitment to excellence. Each contribution to this journal represents a collective pursuit of knowledge that transcends conventional boundaries, driving progress toward sustainable, resilient, and future-ready infrastructures. I extend my sincere gratitude to our authors, reviewers, and the editorial team for their close collaboration and to our readers for their continued engagement in shaping the future of our discipline.

Dr. Nemat Hassani

Editor-in-Chief

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Application of Pressure-Sensitive Gas Fuses for Automatic Flow Cutoff in Earthquake-Induced Pipeline Damages

Authors:

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Abstract

With the development of natural gas distribution networks in over 80% of urban and rural areas of Iran and considering the country's location in the seismically active Alp-Himalaya belt, the country's lifeline infrastructure, especially gas infrastructure, is vulnerable to earthquakeinduced damage. Gas leaks and post-earthquake fires are among the very critical secondary hazards and pose serious threats to public safety and infrastructure resilience. In this context, gas fuses—functionally equivalent to Excess Flow Valves (EFVs)—are introduced as passive and pressure-sensitive safety mechanisms designed to automatically shut off the gas flow in case of a pipe failure or leak. This study evaluates the operational performance and applicability of such fuses in the Iranian gas distribution network. To conduct this evaluation, a dedicated testing platform was created to simulate normal conditions and incidents in scenarios that include normal consumption, limited leaks, and complete pipe failures. The tests were designed to assess the fuse's response to sudden pressure drops, the fuse's ability to detect abnormal and critical flow conditions, and its ability to automatically restore gas flow after system stabilization. This reversible capability allows the fuse to resume service after the failure has been resolved without manual intervention. The findings indicate that gas flow fuses operate as a completely passive system, requiring no external energy source, and also provide the capability to restore gas flow after a fault. This preliminary study confirms the feasibility of using gas fuses (EFVs) as a practical solution to enhance the seismic resilience of gas distribution systems.

Keywords: Excess Flow Valve (EFV), Earthquake, Gas Distribution Network, Automatic Shutoff, Gas Fuse

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1. Introduction

With the rapid expansion of urban and rural gas distribution networks in Iran, ensuring the security of this vital infrastructure against natural disasters—especially earthquakes—has become a major concern in crisis management and urban planning. Global experience shows that one of the deadly secondary effects of earthquakes is the failure or leakage of gas pipelines, which leads to explosions and fires in densely populated areas. Recent numerical simulations of local gas distribution networks have shown that in densely populated residential areas, permanent ground changes or earthquake-induced damage to joints and branch connections can quickly lead to gas leaks and consequently to ignition and fires (Zhu et al., 2022). These findings underscore the critical importance of proactive gas flow control in urban environments.

Analysis of past urban gas incidents has shown that a significant portion of earthquake-related damage is due to delays in shutting off the gas supply. Current safety systems are often controlled manually or electrically. However, post-earthquake conditions often involve power outages, blocked access routes, and critical disruptions that make human intervention difficult. In such conditions, even a short delay can turn into uncontrollable fires or explosions. Therefore, there is an undeniable need for a passive rapid response system—independent of electricity and operator intervention—that can automatically shut off the gas flow in response to sudden leaks or abnormal pressure drops (Li et al., 2021).

In Iran, within the framework of the project "Vulnerability Studies and Strengthening the Security of the Tehran Province Gas Network Against Earthquakes," conducted in 2003 in collaboration with the University of Water and Power Industry (Shahid Abbaspour) and the Osaka Gas Company of Japan, the evaluation of gas shut-off valves as a safety mechanism based on pressure drop detection in urban gas systems was proposed. This initiative aimed to evaluate the ability of such fuses to cut off gas flow under abnormal conditions and automatically restore it after stabilization, and it was included in the project stakeholders' action plan.

In this study, the performance of a gas shut-off fuse designed to respond to pressure drops in simulated critical conditions is evaluated using a laboratory-scale device developed by researchers. The analysis focuses on evaluating the performance of these fuses for leak detection, rapid gas flow cessation, and restoration after system stabilization. The main objective of this research is to evaluate the feasibility of using a passive and energy-independent safety component as an effective measure to enhance the seismic resilience of urban gas distribution networks.

2. Literature Review

In recent decades, with the increase in urban density and the expansion of urban gas networks, the seismic vulnerability of urban areas in this field of urban services has similarly increased. Researchers have focused on developing rapid response systems to detect gas leaks and prevent explosions after earthquakes. One of the main objectives of this research has been the development of equipment and algorithms capable of detecting abnormal flow conditions and automatically shutting off gas or other energy-carrying fluids. These systems often operate based on principles similar to pressure-sensitive mechanisms, such as excess flow valves (EFVs).

In an experimental study, a completely mechanical gas shut-off fuse that works without any external energy source was designed and analyzed. This device includes a pressure-sensitive sliding element that, when exposed to an excessive flow beyond the threshold, compresses a central spring and moves to a closed position, blocking the gas flow. Using FSI (fluid-structure Interaction) simulations and laboratory-scale tests, they confirmed a response time of less than 0.3 seconds and complete closure under variable flow conditions (Lee et al., 2021).

In another study, a dual protective system that used a seismic sensor and a pressure transducer to detect seismic movement and sudden pressure drops was developed. The system included a logic controller and a solenoid valve that would automatically activate in the event of detecting abnormal conditions. Designed for immediate response without human intervention, the device successfully cut off power and gas in less than five seconds (Rahnam Sohan et al., 2022; Mamdoohi et al., 2013).

An intelligent gas leak detection system using an MQ3 semiconductor sensor, a microcontroller, and a solenoid valve connected to a relay was designed. When detecting a flammable gas concentration above a threshold, the system issued an audio-visual alarm, displayed the leak status on an LCD screen, and cut off the gas flow through a solenoid. Experimental tests showed detection and shutdown response times between 2 and 3 seconds under controlled leak conditions (Harry et al., 2024).

In another study, a fuzzy logic-based control algorithm dedicated to regulating gas consumption was developed (e.g., Ahadi et al., 2018; Mahpour et al., 2022). The system received inputs such as pressure, flow rate, and consumption rate, and based on fuzzy inference rules, determined whether to maintain, reduce, or cut off the gas flow. Simulations in MATLAB showed that the system was effective in identifying irregular behaviors and responding appropriately under fluctuating conditions (Dayev, 2024).

In a technical paper, a mechanical relief valve used in automotive lubrication systems was introduced. This valve operated using a pressure-sensitive piston that, when exposed to a pressure differential above a specified threshold, compressed a spring and redirected the flow

to a bypass line. Although this device is designed for fluid systems, its mechanical logic aligns with the operational principles of EFVs (Nugent, 1968).

Another engineering study evaluated the performance of a mechanical spring valve designed to respond to sudden pressure drops. This device included a pressure diaphragm and a piston with a spring that remained open under normal flow conditions. In the event of a rapid pressure drop, the spring closes the valve to stop the flow. Although this mechanism was not specifically developed for gas distribution systems, its passive and pressure-sensitive behavior is consistent with the concepts of EFV (Coskun & Pehlivan, 2021).

Despite extensive efforts to design flow control systems, most existing studies have focused on sectors other than the infrastructure of urban yard arteries, such as automotive applications or turbines, or are heavily dependent on an external factor like electronic power and energy sources. To date, the performance of a completely passive, mechanical, resettable, and energy-independent flow cutoff system for automatic gas flow interruption in emergency conditions in residential gas networks has not been comprehensively studied. Therefore, this research addresses this gap by experimentally evaluating the performance of a gas shut-off fuse under simulated seismic scenarios in urban gas distribution systems.

3. Methodology

In this section, the data collection procedure and the gathered information are described. Moreover, the experimental setup and the method used in this study are explained.

3.1. EFV Operation Mechanism and Test Apparatus Configuration

The operation of the excess flow valve (EFV) is based on the principle of automatically interrupting the gas flow when the volumetric flow rate exceeds a predetermined threshold. This threshold corresponds to the maximum flow rate expected under normal consumption conditions. If a sudden surge in flow occurs—typically resulting from a downstream pipe rupture due to seismic activity or mechanical failure—the EFV is triggered and closes, thereby immediately stopping the gas supply to prevent potential hazards such as explosion or fire.

Following the closure, if the pressure between the upstream and downstream sides of the valve gradually equalizes (indicating that the leak or rupture has been resolved or isolated), the valve automatically resets and allows gas flow to resume. This passive mechanism, which requires no external energy, renders the EFV particularly suitable for earthquake-prone gas distribution networks, where secondary hazards are a major safety concern.

To conduct the experiments, a custom-made test apparatus was designed and fabricated. The main components of the system include a set of control valves and excess flow valves (EFVs), two flow meters with maximum capacities of 40 m³/h and 60 m³/h, and two pressure gauges

with upper limits of 100 psi and 2 psi. The apparatus also contains a leakage measurement assembly composed of aluminum and plastic tubes, along with a graduated cylinder. A compressor is used to supply the required pressure and flow rate during the tests. In addition, four EFVs with flow capacities of 1.6 m³/h, 2.5 m³/h, 4 m³/h, and 6 m³/h were installed in the system for performance evaluation. Figure 1 provides an overview of the developed experimental apparatus.



Figure 1. View of the fabricated apparatus for gas fuse testing

3.2. Operating Procedure of the Test Apparatus

The experimental procedure starts with compressed air supplied by a compressor. This air first passes through a pressure regulator, where both the pressure and flow rate are adjusted according to the specific needs of the test. The regulated airflow is then directed through one of two flow meters, chosen based on the expected flow capacity of the excess flow valve (EFV) being tested.

After measurement, the airflow enters the selected EFV. Each EFV is connected to a separate outlet line, allowing its performance to be evaluated independently.

Downstream of each EFV, two control valves are installed. The first valve simulates normal consumption conditions by maintaining the nominal flow rate (VN¹) and is also used later for leakage measurement. The second valve is used to create a sudden, high-flow condition—similar to what might happen if the downstream pipeline were to rupture. This setup makes it possible to assess how the EFV behaves under both standard operating conditions and emergency scenarios.

-

¹ Nominal Flow Rate

3.3. EFV Function and Leakage Measurement Procedure

The excess flow valves (EFVs) used in this study are designed to automatically shut off the gas flow when the flow rate exceeds a predefined threshold. This excessive flow can result either from unusually high gas consumption or from a rupture in the downstream pipeline.

To restore the gas flow, the pressure on both the upstream and downstream sides of the EFV must become equal. In other words, after the valve has been triggered, the downstream issue—whether due to overconsumption or a pipe break—must be resolved. The small amount of leakage permitted by the EFV allows the pressure to gradually equalize, which eventually leads to the valve reopening automatically.

To replicate this behavior during testing, a control valve is placed immediately downstream of the EFV. Closing this valve causes the pressure to equalize within a few seconds, enabling the EFV to reset and resume gas flow.

For measuring leakage, the outlet valve is connected to a flexible hose that leads to a graduated cylinder. The leakage flow is directed beneath the cylinder using a metal connector, and the resulting drop in the water level inside the cylinder is used to determine the leakage rate. Figures 2 and 3 illustrate the experimental setup and the leakage measurement system.



Figure 2. The EFV testing setup integrated with the leakage measurement unit



Figure 3. EFV mounted with a transparent plexiglass pipe for monitoring flow cut-off behavior

4. Experimental Evaluation of EFV Performance under Various Flow Conditions

The experimental scenarios described in this study are deliberately designed to reflect the most common types of damage observed in urban gas distribution systems following earthquakes. Earthquake-induced damages typically fall into several major categories: (1) full rupture of service pipes due to intense ground shaking or permanent ground deformation, (2) partial disconnection or joint loosening at threaded or mechanical connections—especially in older infrastructures, (3) pressure regulator malfunction or overload caused by rapid pressure fluctuations, and (4) residual microleakages due to material fatigue or undetected cracks. Each scenario tested in this study corresponds to one or more of these real-world conditions.

The first scenario starts with a normal gas flow and then introduces a sudden increase in flow rate. This setup is meant to simulate what happens when a service pipe suddenly breaks—an event commonly reported during seismic events due to pipe-soil interaction or unanchored service connections. The second scenario, focused on leakage measurement after EFV activation, replicates the case of partially compromised connections or microfractures that result in slow but dangerous gas leakage—conditions often linked to aging infrastructure and cumulative stress. The third scenario, high-pressure testing, models a system response under regulator failure or overpressure situations, which are frequently reported after earthquakes due to system depressurization or upstream valve failures.

By designing the laboratory tests to match actual damage patterns observed in seismic assessments of cities such as Tehran, this study offers a practical and technically sound perspective on how EFVs perform in realistic scenarios. These test conditions are intentionally

selected to go beyond idealized laboratory environments and better represent the unpredictable and dynamic behavior of gas networks following an earthquake.

To systematically evaluate how excess flow valves (EFVs) respond to real-world conditions, three distinct test scenarios were developed. These include steady-state flow with sudden rupture simulation, post-activation leakage analysis, and performance assessment under elevated pressure. Detailed procedures and corresponding findings for each scenario are presented in Sections 4.1 through 4.3.

4.1. Shut-off Flow Rate Test at 0.25 psi and Flow Regulation Based on EFV Label Specifications

In this first test, we tried to recreate what happens when a gas pipe suddenly breaks—something that often occurs during an earthquake. This kind of break causes the gas flow to increase sharply. To simulate this, we used compressed air, passed it through a pressure regulator, and then sent it into the EFVs. Because the valves had different flow capacities, two flow meters with different ranges were used to properly measure and control the flow. By adjusting the valves placed after the EFVs, we could create both normal flow and sudden high-flow situations to see how the valves would react.

Although the pressure was intended to remain steady at 0.25 psi, small fluctuations were consistently recorded, ranging from about 0.2 to 0.55 psi. These variations were mostly due to minor inconsistencies in the regulator's performance and slight instability in the airflow supply.

To make sure the findings were reliable and reproducible, the test was repeated roughly 170 times for each type of EFV. The full breakdown of measured values and technical analysis for this scenario is presented in Section 5.1.

4.2. Gas Leakage Measurement Test After Flow Shut-off

In this part of the experiment, we checked how much gas might still leak through the EFV after it had shut off the flow. To create this condition, we used a control valve installed downstream of the EFV to simulate low-consumption situations. This setup helped the EFV stay in its closed position, making it possible to measure the small amount of gas that could still pass through—similar to what might happen in real-life gas pipelines after damage.

To measure the leakage, we used a simple and effective method. A flexible hose was connected to the outlet of the EFV, and the other end of the hose was placed into a container of water. As gas leaked through the closed valve, it traveled through the hose and formed bubbles in the water. We then positioned a graduated cylinder upside down in the water to collect the gas bubbles. The rising gas displaced the water in the cylinder, and this allowed us to measure the amount of leaked gas by tracking the volume of water pushed out over time.

This approach made it easy to see and record even very small leaks. Each EFV model was tested one by one using this setup, so we could compare how much gas leaked from each type. The same conditions were kept for all tests to ensure the results could be fairly compared.

The complete results and interpretation of this leakage test are provided in Section 5.2.

4.3. Performance Evaluation of Excess Flow Valves Under Elevated Pressure Conditions

This part of the study covers the third test scenario introduced earlier in Section 4, focusing on how EFVs behave when exposed to high gas pressure. The same shut-off and leakage tests described in Sections 4.1 and 4.2 were repeated here, but under elevated pressure, to see if the valves still worked the same and whether they could reopen after shutting off.

Two common installation setups were used to reflect real conditions. In the first setup, the EFV was installed without any pressure regulator downstream. Compressed gas was slowly added, and the flow was increased past the valve's rated capacity. This helped us check how the valve shuts off the flow when pressure isn't controlled.

In the second setup, the EFV was placed before a pressure regulator, and the inlet pressure was kept at 80 psi. The regulator helped stabilize flow on the downstream side, so we could watch how the pressure difference on both sides of the valve affected its behavior when flow started.

All EFV models were tested under both setups to make sure results were consistent and comparable, and so we could study the effect of pressure in a fair way. The complete results and performance analysis under these elevated pressure conditions are presented in the next Section.

Technical Notes and Recommended Measures for Downstream Pressure Conditions:

Based on the performance charts in the manufacturer's catalog (see Figure 4), excess flow valves (EFVs) are designed to work reliably at a minimum pressure of 35 millibars. But in our experiments, the pressure measured right after the regulator—just downstream of the EFV—was only about 17.5 millibars. That's noticeably lower than the recommended level, which means the conditions during testing were quite different from what the valve was originally designed and tested for. Because of this low pressure, there's a real chance that the EFVs might not work as expected—especially when it comes to automatically restoring the gas flow after it's been shut off.

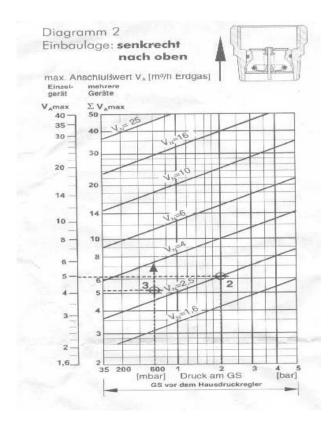


Figure 4. Performance Charts from the Manufacturer Catalog for EFV Operation

To address this issue and enable the re-establishment of gas flow after EFV activation in low-pressure systems, the following two configurations are proposed:

- 1. Install a shut-off valve at a short distance downstream of the EFV: This arrangement allows for direct manual control of the downstream pressure, facilitating pressure equalization across the valve.
- 2. Install two valves upstream of the EFV: One valve serves as the main shut-off control, while the second is used to purge the residual gas trapped between the EFV and the shut-off valve. This setup helps reduce the pressure differential across the EFV, thereby enabling the valve to reopen and restore flow.

5. Results

The results of these studies indicate that all excess flow valves (EFVs) provided flow rates at 0.25 psi that matched their labeled nominal capacities, and in most cases, flow cessation occurred when the flow rate was approximately 70% higher than the nominal value. Among the tested excess flow valves, the 1.6 cubic meter per hour model showed a reduction in leakage after repeated tests and was able to resume gas flow after a delay. The 2.5 cubic meter per hour model performed similarly to the samples but with significant improvements in leak control and reliable self-regulating capabilities, making it the most effective sample among those tested. In contrast, the 4 cubic meter per hour model showed no measurable leakage but did not

restore flow to the circuit after the flow was interrupted. The 6 cubic meter per hour model exhibited erratic leakage behavior and did not succeed in resuming flow after being shut off in any instance.

To present the findings in a more structured and accurate manner, the results have been categorized based on the three experimental scenarios defined in the previous section. In the following subsections, the outcomes of each scenario are analyzed and reported separately.

5.1. Shut-off Flow Results Under Simulated Pipe Rupture Conditions

In this test, we gradually increased the gas flow rate at a pressure close to 0.25 psi to see how each EFV model would react. The expectation was that the valves would shut off automatically once the flow went well beyond their nominal capacity. As the results showed, all the tested valves reliably stopped the flow when it reached about 69% to 72% higher than their labeled rating.

Tables 1 to 4 show the minimum, maximum, and average flow rates and activation pressures recorded for the four EFV models—1.6, 2.5, 4, and 6 m³/h. Each model was tested around 170 times to make sure the data was consistent and reliable.

Table 1. Experimental Results of the 1.6 m³/h Excess Flow Valve (EFV)

EFV Series	Excess		Flow Rate	e		Pressure		No. of
	Flow	Min	Max	Avg	Min	Max	Avg	- Repetitions
	for	(m^3/h)	(m^3/h)	(m^3/h)	(psi)	(psi)	(psi)	
	Shut-							
	off (%)							
First Series	72%	2.17	2.21	2.20	0.25	0.55	0.40	156
EFV								
Second	72%	2.17	2.21	2.20	0.25	0.55	0.40	156
Series EFV								

Table 2. Test Results for 2.5 m³/h EFV

EFV Series	Excess		Flow Rate	•		Pressure		No. of
	Flow	Min	Max	Avg	Min	Max	Avg	- Repetitions
	for	(m^3/h)	(m^3/h)	(m^3/h)	(psi)	(psi)	(psi)	
	Shut-							
	off (%)							
First Series	69%	3.47	3.87	3.63	0.25	0.55	0.40	156
EFV								
Second	69%	3.47	3.87	3.63	0.25	0.55	0.40	156
Series EFV								

Table 3. Test Results for 4 m³/h EFV

EFV Series	Excess		Flow Rate	2		Pressure		No. of
	Flow	Min	Max	Avg	Min	Max	Avg	Repetitions
	for	(m^3/h)	(m^3/h)	(m^3/h)	(psi)	(psi)	(psi)	
	Shut-							
	off (%)							
First Series	69%	5.60	5.84	5.82	0.25	0.55	0.40	156
EFV								
Second Series EFV	69%	5.60	5.84	5.82	0.25	0.55	0.40	156

Table 4. Test Results for 6 m³/h EFV

EFV Series	Excess		Flow Rate			Pressure		No. of
	Flow	Min	Max	Avg	Min	Max	Avg	Repetitions
	for	(m^3/h)	(m^3/h)	(m^3/h)	(psi)	(psi)	(psi)	
	Shut-							
	off (%)							
First Series	69%	8.46	9.06	8.72	0.25	0.55	0.40	156
EFV								
Second Series	69%	8.46	9.06	8.72	0.25	0.55	0.40	156
EFV								

Figure 5 illustrates the average flow rate at which each valve is activated. The values—2.21, 3.87, 5.84, and 9.06 m³/h—correspond to the tested models in the same order and were based on repeated test cycles.

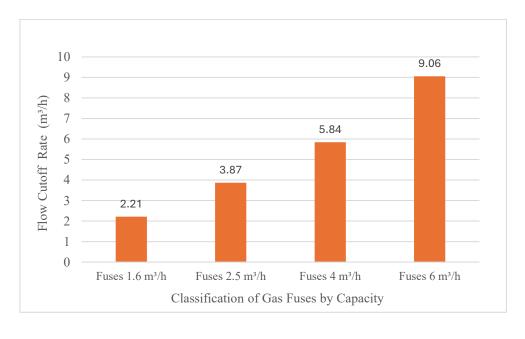


Figure 5. Comparison of Maximum Flow Cutoff Rates in Different Fuses at 0.25 psi Pressure

These measured values show that, on average, each EFV triggered well above its nominal flow capacity, highlighting their built-in tolerance for short-term surges. This means the results reflect how the valves really behave in a controlled setting—not just what their labels say.

When looking at the data trend, a clear pattern appears: the higher the nominal capacity of the valve, the higher the flow rate needed to shut it off. This trend, also seen in Tables 1–4 and Figure 5, shows that the valves are designed in a way that lets them allows extra flow just before activation. From a safety perspective, this kind of behavior gives important clues about how EFVs would work in real-world emergencies like earthquakes.

Figure 6 presents a combined chart showing both the maximum cutoff flow rates and the peak activation pressures for all four EFV models. This dual-parameter view helps compare the flow and pressure behavior of each valve in one visual.

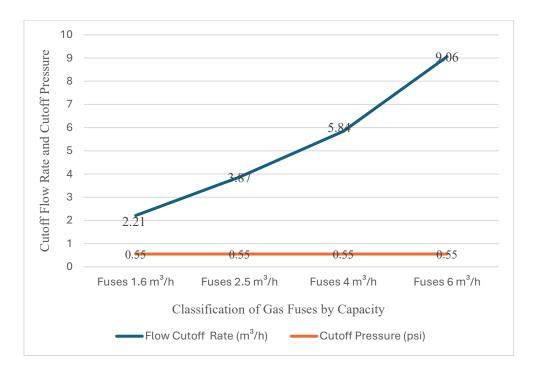


Figure 6. Correlation Between Maximum Flow Rate and Maximum Cutoff Pressure in Different Fuses

As seen in the figure, the cutoff flow rate increases with valve capacity, ranging from 2.21 to 9.06 m³/h. In contrast, the activation pressure remains constant at 0.55 psi across all models. This indicates that while the flow response depends on the mechanical structure of each valve, the pressure threshold is fixed and independent of capacity.

This consistent pressure behavior confirms the valves are engineered to react reliably to pressure surges regardless of their size. Together with the variation in cutoff flow, this reinforces the reliability and mechanical integrity of these EFVs under sudden flow increase conditions—especially during low-pressure disturbances such as seismic events.

Overall, the results confirm that EFVs can respond effectively to sudden flow surges caused by pipe ruptures, which makes them a strong option for improving gas network safety in seismic zones.

5.2. Leakage Performance After Shut-off

The leakage tests provided important insights into how well each Excess Flow Valve (EFV) model limited gas flow once the valve had shut off. As shown in Tables 5 through 8, each model was tested multiple times under the same conditions. The results revealed noticeable differences in leakage behavior among the valves.

Table 5. Measured Leakage Values across Repeated Tests for the 1.6 m³/h Excess Flow Valve

Test No.	1	2	3	4	78	79	80	81	153	154	155	156
First Series EFV	-	-	-	-	0.26	0.26	0.17	0.15	0	0.12	0.146	0.09
Second Series EFV	1.8	0.226	0.124	0.166	0.22	0.18	0.13	0.09	0.09	0.16	0.13	0.1

Table 6. Measured Leakage Values across Repeated Tests for the 2.5 m³/h Excess Flow Valve

Test No.	1	2	3	4	78	79	80	81	153	154	155	156
First	-	-	-	-	1.645	1.323	1.287	1.148	1.17	2.546	1.02	1.07
Series												
EFV												
Second	0.247	0.122	0.202	0.16	0.091	0.241	0.243	0.219	0.427	0.143	0.262	0.333
Series												
EFV												

Table 7. Measured Leakage Values across Repeated Tests for the 4 m³/h Excess Flow Valve

Test No.	1	2	3	4	78	79	80	81	153	154	155
First Series EFV	-	-	-	-	0	0	0	0	0	0	0
Second Series EFV	0.179	0.0685	0.148	0.0867	0.0592	0.0574	0.061	0	0	0	0

Table 8. Measured Leakage Values across Repeated Tests for the 6 m³/h Excess Flow Valve

Test No.	1	2	3	4	78	79	80	81	153	154	155	156
First Series EFV	-	0	0	0	0	0	0	0	0	0	0	0
Second Series EFV	=	2	1.9369	1.037	0	0.0326	0.0484	0.171	0	0	0	0

The z.6 and 2.5 m³/h models initially showed moderate leakage, but the rate gradually decreased with more test repetitions. This trend was likely caused by improved internal sealing or mechanical stabilization after repeated activations. In contrast, the 4 m³/h valve showed no

measurable leakage in any of the tests, indicating a highly effective sealing design and consistent performance. The 6 m³/h model, however, showed variable results with no clear stability in leakage rate.

Table 9 and Figure 7 only show the average leakage rate for each EFV model, measured in micrometers cubed per second ($\mu m^3/s$).

 1.6 m³/h EFV
 2.5 m³/h EFV
 4 m³/h EFV
 6 m³/h EFV

 First Series EFV
 1.2376
 0
 0
 0

 Second Series EFV
 0.1526
 0.204
 0.055
 0.046

Table 9. Average Measured Leakage Rate for Different EFV Types

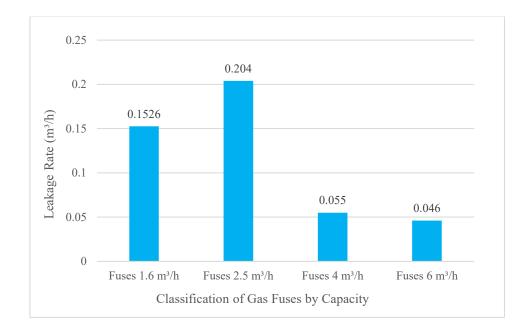


Figure 7. Average Gas Leakage in Different Fuses

In this comparison, the 1.6 and 2.5 m³/h models had relatively high average leakage, while the 4 m³/h valve had a near-zero leakage rate across all test cycles. For the 6 m³/h model, however, its performance cannot be reliably assessed based on Table 9 or Figure 7 alone, because of the high variability in its data details that can only be seen in Tables 5 through 8.

These results make it clear that a valve's ability to control leakage depends on more than just its size. Things like how it's built, how well its internal components are designed, and how it performs under stress all play a role. That's why, when choosing EFVs for gas networks—especially in places where safety really matters—it's not enough to look only at the rated flow capacity. It's just as important to know how the valve behaves over time, how reliable it is after repeated use, and whether it might still allow small amounts of gas to leak through under low-flow conditions.

Taken together, the findings in this section support what earlier safety studies have shown about Tehran's gas infrastructure: threaded joints and service lines are some of the most vulnerable points during an earthquake. Since upgrading the entire system would be expensive and technically difficult, using EFVs—especially models that show stable, low-leakage performance—can be a smart and affordable way to strengthen the safety of these high-risk areas.

5.3. EFV Shut-off and Reopening Behavior Under High Pressure

The performance of all EFV models was also tested under elevated pressure conditions (80 psi) to better understand how pressure influences their behavior. The tests were carried out using two different setups, as described earlier in Section 4.3.

In the first setup, where no pressure regulator was used, all EFVs successfully shut off the gas flow once the rate exceeded about 70% above their nominal capacity—similar to how they behaved under low-pressure conditions. However, after the valves were activated, none of them reopened. The reason was the high pressure difference across the valve, which made it difficult to balance the forces needed for automatic reset.

In the second setup, with the EFV placed upstream of a pressure regulator, two outcomes were observed. In some tests, the valve closed almost immediately after flow started. In others, the downstream flow went far beyond the EFV's rated capacity before activation. For example, the 2.5 m³/h model allowed flow to reach about 11 m³/h before shutting off. Although this is still considered acceptable in terms of safety, it shows that the pressure regulator changes how the valve responds. Similar to the first setup, none of the valves reopened after shut-off in this configuration either.

Overall, these results suggest that EFVs still do a good job shutting off the flow when pressure gets too high. However, reopening the valve after it shuts off seems to be a challenge in these conditions. Also, where the valve is placed—especially in relation to components like pressure regulators—can change how and when it reacts. These findings show how important it is to think carefully about pressure changes and how the system is set up when using EFVs in high-pressure parts of a gas network.

6. Conclusion

Given the development of urbanization and the increasing density of cities against natural disasters such as earthquakes, strengthening the resilience of urban infrastructure systems, including urban gas distribution infrastructure, has become one of the critical priorities. Considering the high costs, complexity, and operational limitations of extensive renovations of urban gas infrastructure or the development of remote shut-off systems, the use of excess flow valves (EFVs) is considered a practical and immediate method for risk reduction.

This study demonstrated that EFVs can effectively shut off gas flow during sudden surges caused by simulated pipeline failures, even at both low and high pressures. Among the tested models, the 2.5 m³/h EFV showed the most stable leakage control and consistent self-resetting behavior, making it a strong candidate for real-world deployment. In contrast, the 6 m³/h valve exhibited erratic performance, particularly under low-pressure conditions.

The experiments also revealed that EFV reopening is limited under elevated pressure due to an imbalance across the valve—especially when no mechanisms are in place to equalize pressure. This was further influenced by the valve's location in the system, such as whether it was placed before or after the regulator.

These hands-on results—gathered from more than 170 test cycles for each valve—highlight just how important it is to think carefully about where and how EFVs are installed. The layout of the system and how pressure behaves across different parts both play a big role in how well these valves perform in practice.

The combination of passive operation, self-contained response mechanisms, and simple deployment makes EFVs a compelling and scalable option for reinforcing gas network safety in seismic environments. Still, before they can be widely used, it's important to test them in different real-world situations. Doing so will help fine-tune how they're chosen and installed—and ensure they work well outside the lab too.

7. Recommendations

Based on the results of this study and the known weaknesses in the urban gas system, especially in high-risk areas, the following points are suggested for practical and short-term action:

Install EFVs after the regulator:

These valves worked well with low-pressure gas after the regulator. They can stop gas in case of big leaks, like when a pipe is broken, a valve is opened to the air, or something gets disconnected during an earthquake. Using EFVs based on the gas meter size can help reduce gas leakage inside damaged buildings.

Use EFVs at the riser, after the main shut-off valve:

Even though there isn't enough test data for high-pressure conditions before the regulator, installing EFVs right after the meter shut-off valve (meter-stop valve) could help protect against leaks from damaged joints. It's technically better to place the EFV before the shut-off valve, but that's harder to do while gas is flowing. After the valve is easier and safer.

The 2.5 m³/h model is the most reliable:

Among the models tested, the 2.5 m³/h EFV worked the best in both stopping and restarting the gas flow. This model is a good choice for pilot testing and early installations.

Start with a pilot project:

Running a pilot project in a real neighborhood will help gather more useful information—like how gas quality or different usage types affect performance. Based on that, the company can work with manufacturers to improve any weak points.

Choose the right pilot location:

Places with a higher risk of damage, like older homes with risers under roof edges or near walls, should be chosen first. For example, District 17 in Tehran could be a good area to start.

Compare the cost to other systems:

The cost of using EFVs should be compared to other options like remote shut-off systems or smart meters. If the price can be lowered—especially with local production—EFVs could be a more affordable solution for many homes.

Use EFVs as part of a bigger plan:

For long-term earthquake safety, EFVs can be part of a full protection system:

- o Remote shut-off for big stations and main lines
- Automatic shut-off at local stations
- EFVs can be installed at service lines, either before or after the shut-off valve, depending on the setup.
- Pressure regulators
- o Smart meters in the future
- o Small EFVs at each appliance or burner point

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Proposing an Integrated Conceptual Framework for Implementing Spatial Data Infrastructure by Systematically Reviewing and Analyzing SDI Maturity Models

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Abstract

This study deals with the absence of a uniform global scale for spatial data infrastructure (SDI) maturity assessment and presents a five-layer holographic conceptual framework derived from a systematic literature review and evaluation of metadata. The literature review identified key maturity models—NGDA², ANZLIC³, INSPIRE⁴, SDIOGI⁵, and hierarchical perspectives (Building Block and Umbrella)—alongside metadata standards ISO 19115/19139, FGDC⁶, Dublin Core, and GEMET. The methodology comprises four phases: First, selecting twenty seminal articles from Web of Science, IEEE Xplore, and ScienceDirect; second, screening studies via inclusion/exclusion criteria; third, extracting and coding dimensions and indicators into detailed tables; and then conducting a comparative matrix synthesis. Based on a systematic review of SDI maturation models, we identified five core dimensions - organizational, political, technical, qualities, and human resources - common across a leading framework. We integrated these into a new five-layer hollow conceptual framework, centered on quality and continuous improvement to drive adaptive, feedback-driven maturation. By utilizing established best practices and international standards (e.g., Inspire, ISO 19115), this entirely conceptual model requires no field data and offers athletes and decision makers a pragmatic tool for strategic planning and results monitoring. It establishes a universal goal for SDI maturity assessment and paves the way for future empirical validation across different contexts.

Keywords: Maturity Assessment, Conceptual Framework, Metadata Standards, Continuous Improvement

- 2. National Geospatial Data Assets
- 3. Australia and New Zealand Land Information Council
- 4. Infrastructure for Spatial Information in Europe
- 5. Spatial Data Infrastructure On-Going Improvement
- 6. Federal Geographic Data Committee

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1. Introduction

In recent years, Spatial Data Infrastructures (SDIs) have emerged as the backbone for managing and sharing geospatial information across interdisciplinary projects. Numerous maturity models—such as the NGDA framework in the United States, ANZLIC in Australia, and INSPIRE standards in Europe—have been proposed to assess the capabilities and developmental stages of SDIs. However, these models work largely isolated - each with their own dimensions, indicators, and evaluation methods - reflecting distinct geographical contexts and institutional structures. This fragmentation inhibits intersections of maturity assessments among countries and organizations and excludes the establishment of a uniform global benchmark index for SDI maturity. Furthermore, the spread of different models not only generates confusion among researchers and decision makers but also complicates the practical distribution, design, and improvement of SDIs. The absence of a comprehensive, comparative evaluation of these models further hides their respective limitations and strengths, and prevents systematic aggregation and adoption of best practice. Consequently, there is a compelling need for a systematic, comparative study that critically examines existing frameworks and proposes an integrated model to evaluate the SDI maturity on a global scale.

The importance of evaluating the SDI maturity can be understood through both international and regional frameworks. Internationally, the EU's Inspire initiative has established standards to ensure interoperability and seamless data exchange between member states. In North America, the NGDA framework aims to spread federal geospatial computer practices to states and local units. Regular programs such as ANZLIC in Australia and the UN Geos have shown that maturity assessments can quickly identify and correct structural deficiencies. Despite these initiatives, an absence of a universally approved scale that addresses the different requirements and mandates of these frameworks and the connection of SDI projects. Therefore, the development of an integrated framework for SDI maturity assessment is important - not only to harmonize processes at both global and regional levels, but also to speed up decisions and reduce development and maintenance costs for geospatial infrastructure.

The primary aim of this study is to develop an integrated framework for assessing the maturity of Spatial Data Infrastructures on a global scale. The specific objectives are:

- 1. To review and categorize existing SDI maturity models in the literature—including the NGDA, ANZLIC, INSPIRE frameworks, and other established approaches—without any primary data collection.
- 2. To conduct a theoretical analysis of each model's dimensions and characteristics from a structural and conceptual standpoint, identifying strengths and limitations based solely on documented sources.
- 3. To develop a conceptual taxonomy of SDI maturity components, detailing key dimensions and their conceptual interrelations through a systematic literature study.
- 4. To design an integrated conceptual framework for SDI maturity assessment grounded entirely in theoretical principles and documented best practices, with no requirement for practical implementation or local datasets.

5. To provide scholarly guidance and research recommendations for applying the conceptual framework in future studies and for advancing maturity models, emphasizing theoretical rigor and qualitative research methodology.

2. Literature Review

SDI is the relevant set of technologies, policies, and organizational arrangements that facilitate access to spatial data and their usability. The term Spatial Data Infrastructure (SDI), while seemingly self-explanatory, is actually a complex concept that has attracted various definitions. For instance, the Global Spatial Data Infrastructure (GSDI) Association has stated that SDIs provide a foundation for the discovery, evaluation, and application of spatial data. The definition of GSDI includes geographic data, metadata, framework, services, clearinghouse, standards, partnerships, education, and communication (Parida & Tripathi, 2018). In this context, "infrastructure" refers to a reliable and supportive environment, akin to a road or telecommunications network, that facilitates access to geographic information through a minimum set of standard procedures, protocols, and specifications. SDI should be more than just a single dataset or database; it encompasses geographic data and attributes, sufficient documentation (metadata), tools for discovering, visualizing, and evaluating data (catalogs and web mapping), and a means of accessing geographic data. To be functional, an SDI must include the necessary organizational arrangements for its coordination and management at local, regional, national, and/or supranational scales. Researchers have identified several key components common to all SDI implementations: people, access networks, policies, technical standards, and data sets (Figure 1). SDI provides an environment where people and systems can interact with technology to use, manage, and produce geographic data (Gomes et al., 2024).

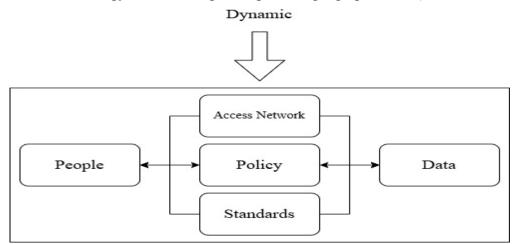


Figure 1. Components of SDI (Ian Williamson et. al.,2003)

A spatial data infrastructure (SDI) can work at various interconnected levels, including global, regional, national, state, local, and business. These levels represent a hierarchy where spatial data and related services are administered and shared, often with addictions and interactions between them. For example, local datasets can contribute to a national SDI, which in turn can match regional or global standards and initiatives. Similarly, Corporate SDIs can operate within and contribute to wider national or even international frameworks (Oliveira et al., 2015).

Following the examination of the SDI structure, the discussion now turns to the tools that can integrate different levels or enable interaction among SDIs at the same level. The evaluation and assessment of a Spatial Data Infrastructure (SDI) are vital for understanding its efficiency, identifying areas for improvement, and demonstrating its value to stakeholders. This process involves defining clear goals, establishing relevant performance indicators, and using appropriate calculations to measure SDI's performance against these goals. Evaluation helps to measure influence, find strengths and weaknesses, inform decisions, strengthen accountability, and promote SDI sustainability. Performance indicators are quantitative and are assessed through calculations such as data availability and quality, use and effect of SDI, and its sustainability and governance. The selection of indicators and metrics depends on the specific goals and maturity of the SDI, and their regular calculation provides valuable insights for ongoing development and enhancement (Mahpour et al, 2022; Maphale & Smit, 2021). Various approaches have been proposed for modeling SDI development. Some of these models include the umbrella view, the building block view, and the generative view. These perspectives offer hierarchical approaches, both top-down and bottom-up, for modeling the development of an SDI.

Having examined the structure and evaluation of SDIs, we now turn to maturity models, which provide staged frameworks for assessing and developing SDI capabilities.

2.1. Existing Maturity Models

- 1. NGDA Framework (USA): Defines five maturity stages—Preparation, Service Development, Partnership, Integration, and Sustenance—emphasizing federal-state collaboration.
- 2. ANZLIC Model (Australia/New Zealand): Outlines six maturity levels addressing structural, procedural, and institutional aspects, from initial data awareness to automation and innovation.
- 3. INSPIRE Compliance (EU): Lacks a formal maturity scale but uses technical, metadata, and service requirements to gauge member states' alignment with the INSPIRE Directive.
- 4. SDIOGI (SDI Ongoing Improvement): A cyclical approach based on the Theory of Constraints, focusing on identifying and resolving bottlenecks while evaluating performance and continuous improvement.
- 5. Building Block and Umbrella Views: Provide hierarchical top-down and bottom-up perspectives for SDI development, either by component layers or all-encompassing umbrella systems.

2.2. Metadata

Geospatial metadata must adhere to international standards to ensure interoperability and discoverability. Principal standards include ISO 19115 for metadata structure and content, ISO 19139 for its XML implementation, the U.S. FGDC standard, Dublin Core for general data

cataloging, and GEMET as a multilingual environmental thesaurus. These standards establish a uniform framework for defining mandatory fields, formats, and shared vocabularies (Cooper et al., 2025; Yoo & Kim, 2021).

Despite the dissemination of maturity models and robust meta standards, there is no integrated conceptual structure that consolidates the main dimensions and indicators for a uniform global evaluation of SDI maturity. In addition, existing evaluations usually depend on practical implementations and local data sets, while systematic theoretical and comparative studies remain scarce. This fragmentation complicates the model options and the evaluation methodology for researchers and decision makers and emphasizes the need for a theoretically rooted structure based only on the literature review and best practices to evaluate the maturity of SDI globally.

3. Methodology

This study uses a systematic literature review that includes four primary phases: (1) Identification and collection of peer-reviewed articles on SDI maturation models and metadata standards from leading databases; (2) Screening and application of inclusion/exclusion criteria to ensure relevance and quality; (3) Systematic extraction and conceptual coding of each model's dimensions and indicators; and (4) comparative analysis that leads to the synthesis of an integrated conceptual framework. This completely theoretical process requires neither field data nor complex empirical analysis, and chairs exclusively on documented sources and scientific evaluation. The complete workflow for these steps is depicted in Figure 2.

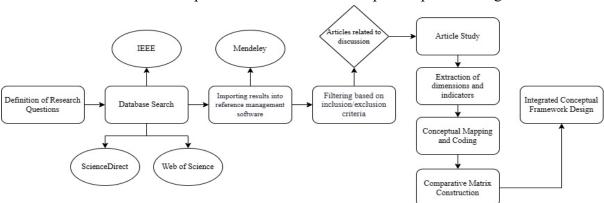


Figure 2. Workflow of research methodology

First, research questions and keyword combinations are formulated based on the study's objectives and identified gaps. Selected databases include Web of Science, IEEE Xplore, and ScienceDirect. Initial results are imported into a reference manager (e.g., Mendeley), and titles and abstracts are independently reviewed by two researchers to minimize bias and maximize accuracy.

To guarantee the quality and relevance of sources, the following criteria are defined:

- Inclusion Criteria:
 - 1. Peer-reviewed journal articles or reputable conference proceedings.

- 2. Primary focus on SDI maturity models or infrastructure evaluation.
- 3. Specification of dimensions, indicators, or theoretical frameworks for maturity assessment.
- 4. English-language publications from 2010 onward.

• Exclusion Criteria:

- 1. Descriptive articles lacking a clear evaluation model or framework.
- 2. Case studies with limited field data and no broad theoretical contribution.
- 3. Conference abstracts without full-text availability.
- 4. Sources without an accessible full text.

Following two screening rounds (title/abstract and full text), approximately 20 studies were selected for final analysis.

Each selected study is meticulously reviewed to extract reported dimensions and indicators. The process entails:

- 1. Extraction Template: A table with columns for "Model Name," "Dimension," "Indicator," "Definition," and "Reference" is established.
- 2. Independent Coding: Two researchers independently code each article and populate the template.
- 3. Reconciliation Phase: Discrepancies between coders are resolved through discussion, referencing original texts.
- 4. Conceptual Coding: Similar dimensions and indicators are grouped into conceptual categories (e.g., "Organizational Structure," "Technical Processes," "Institutional Interactions").
- 5. Matrix Construction: A comparative matrix is generated to display which dimensions and indicators each maturity model covers.

This descriptive, theory-driven methodology obviates the need for local data collection or processing, providing a robust foundation for designing the integrated conceptual framework.

4. Results

4.1. Comparative Analysis

As part of a systematic review of Spatial Data Infrastructure (SDI) maturity models, this section presents a comprehensive analysis of prior studies in the field. Table 1 offers a structured summary of key research, detailing information such as authors, publication year, core focus, applied SDI maturity framework, and methodology of each study. This review is designed to identify common patterns, strengths, and limitations in existing models, as well as to uncover research holes in the literature. Selected studies were curated based on criteria including explicit focus on SDI maturity, geographical diversity, and methodological innovation. The comparative analysis of these frameworks establishes a critical basis for developing the integrated conceptual model proposed in the subsequent parts of this article.

Table 1. An overview of the 20 selected studies, detailing each article's authorship, publication year, examined SDI maturity frameworks, and study type

		examined SDI maturity frameworks, and	Framework or	tyme of
No	Authors/Year	Title	rramework or maturity model	type of study
1	(Ilić, 2009)	Global Spatial Data Infrastructure	GSDI	Conceptual
2	(Oliveira et al., 2015)	Building a Thematic Spatial Data Infrastructure and Situation-Awareness for Global Events	GSDI	Usage
3	(She et al., 2019)	Bridging open source tools and Geoportals for interactive spatial data analytics	Architectural Framework	Usage
4	(Akingbemisilu, 2024)	A Critical Evaluation of Government Role in Spatial Data Infrastructures for Healthcare Decision-Making	NSDI / CGDI / UNSDI / INSPIRE	Experimental
5	(Sjoukema et al., 2017)	Evolving Spatial Data Infrastructures and the Role of Adaptive Governance	NSDI	Experimental
6	(Çalikoğlu & Łuczak, 2024)	Multidimensional assessment of SDI and HDI using TOPSIS and bilinear ordering	Sustainable Development Index / INSPIRE	Conceptual
7	(Parida & Tripathi, 2018)	Odisha Spatial Data Infrastructure (OSDI) – Its Data Model, Metadata and Sharing Policy	GSDI / NSDI	Usage
8	(Izdebski, 2018)	Analysis of the cadastral data published in the Polish Spatial Data Infrastructure	NSDI	Conceptual
9	(Chipatiso, 2023)	Analyzing the nexus between Spatial Data Infrastructure Development and e-Government	NSDI / SDI Development	Review
10	(Maphale & Smit, 2021)	A Theoretical Proposition for Spatial Data Infrastructure On-Going Improvement	SDIOGI	Review
11	(Kalantari Oskouei et al., 2019)	An analysis of the national spatial data infrastructure of Iran	NSDI	Conceptual
12	(Yoo & Kim, 2021)	Strategic Analysis for Governance Development of the National Spatial Data Infrastructure Portal in Korea	NSDI / NSDIP	Review
13	(Cooper et al., 2025)	Geospatial data quality training for the South African Spatial Data Infrastructure – Lessons learnt from training geospatial data custodians	NSDI / SASDI	Review
14	(Wetzel et al., 2024)	Spatial data infrastructure components to provide regional climate information services	SDI Development	Review
15	(Ran & Nedovic- Budic, 2024)	Online Decision Support Infrastructures for Integrating Spatial Planning and Flood Risk Management Policies	SDI Development	Conceptual
16	(Hill et al., 2024)	An integrated geospatial data model for active travel infrastructure	SDI Development	Conceptual
17	(Ahmad et al., 2024)	A Review of Pakistan's National Spatial Data Infrastructure Using Multiple Assessment Frameworks	NSDI	Review
18	(Ukueku et al., 2025)	Improving HIV case finding using spatial data infrastructures in Anambra State, Nigeria: a pre-post intervention study	NSDI	Experimental

No	Authors/ Year	Title	Framework or	type of
110	114411015/ 1041		maturity model	study
	(Zwirowicz-	Spatial Data Infrastructure and Mobile Big		
19	Rutkowska &	Data for Urban Planning Based on the Example	NSDI / PSDI	Usage
	Michalik, 2024)	of Mikolajki Town in Poland		
20	(Gomes et al.,	Brazil Data Cube Workflow Engine, a tool for	CDI Davalammant	Componentival
20	2024)	big Earth observation data processing	SDI Development	Conceptual

Following the systematic review of prior studies in Table 1, the next step involves identifying and categorizing the core dimensions and indicators that define SDI maturity models. Table 2 provides a structured presentation of the most critical components extracted from prominent maturity models, including technical, governance, institutional, human, and infrastructural criteria. This table not only offers a framework for understanding each model's specific focus on distinct aspects of SDI but also establishes an analytical foundation for their systematic comparison in Table 3. By conducting a comparative examination of these dimensions, overlaps, divergences, and conceptual gaps among the models can be elucidated. Such insights significantly contribute to the development of the proposed integrated framework, ensuring broader and more balanced coverage of SDI maturity elements.

Table 2. Outlines the core dimensions and specific indicators identified for each SDI maturity model, mapping how each framework assesses key aspects of infrastructure development

No	Model	Dimension	Indicator
1	GSDI	Organizational	Existence of a governance body
2	GSDI	Technical	Availability of catalog services
4	NSDI	Policy	Presence of national metadata policy
5	NSDI	Institutional	Stakeholder partnership mechanisms
6	SDI Readiness	Human Resources	Staff training programs in SDI
7	GSDI	Data Quality	Metadata completeness rate
10	SDIOGI	Continuous Improvement	Frequency of maturity reassessments
16	SDI Dev.	Technical Processes	Use of standard OGC web services
17	NSDI	Policy	Clarity of data sharing regulations
20	SDI Dev.	Workflow Automation	Implementation of the data cube
			engine

By building on the structural insight from Table 2, it is important to organize these important dimensions within a conceptual framework and analyze their context. Table 3 categorizes systematically related dimensions in thematic clusters (e.g., "data management", "technical abilities", and "institutional integration"), which enables a deeper understanding of model convergence and divergence. By illustrating how indicators are distributed over conceptual categories, this table clarifies the mechanisms that operate SDI maturity and establishes a basis for identifying areas that require reinforcement or further development in the proposed model. Such structured analysis acts as a critical step in transforming fragmented findings into a continuous and actionable framework.

Table 3. Taxonomy of SDI Maturity Dimensions	Table 3.	Taxonomy	of SDI	Maturity	Dimensions
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Conceptual Category	Associated Dimensions			
Organizational	Governance body; Stakeholder engagement			
Technical	Catalog services; Web service standards			
Policy	Metadata policy; Data sharing regulations			
Institutional	Partnership mechanisms; Management roles			
Continuous Improvement	Reassessment frequency; Feedback loops			
Data Quality	Completeness; Accuracy			
Human Resources	Training programs; Expertise levels			
Workflow Automation	Pipeline tools; Engine implementations			

The conceptual classification in Table 3 reveals that the common dimensions across SDI maturity models can be organized into eight primary groups (organization, technical, policy, institutional, continuous improvement, data quality, human resources, and workflow automation). This categorization not only reflects the diversity of domains influencing spatial infrastructure maturity but also uncovers recurring patterns in existing literature. For example, the stated emphasis on technical criteria and data quality emphasizes the strategic priority of robust infrastructure and reliable data, while the focus on continuous improvement and automation emphasizes the need for SDI adaptation to technological advances. Such a structured analysis promotes a comprehensive understanding of the interaction between critical dimensions and development priorities, which is central to creating the proposed integrated framework with improved context and practical relevance.

Table 4. Presence of Dimensions in Each Maturity Model. Columns are

Org.: Organizational, Tech.: Technical, Policy: Policy, Inst.: Institutional, CI: Continuous Improvement, DQ:

Data Quality, HR: Human Resources, WA: Workflow Automation

	•	J ,		,				
Model	Org.	Tech.	Policy	Inst.	CI	DQ	HR	WA
GSDI	✓	✓	✓	✓	_	✓	_	_
NSDI	\checkmark	_	\checkmark	\checkmark	_	_	_	_
SDI Readiness	_	_	✓	_	_	_	✓	_
SDIOGI	_	_	_	_	\checkmark	_	_	_
SDI Dev.	_	✓	_	-	_	_	_	✓

Table 4 offers a comprehensive overview of dimension coverage across various SDI maturity models, mapping the analytical focus and scope of each framework. The results highlight that macro-level models such as GSDI and NSDI, by simultaneously addressing dimensions like *organizational*, *policy*, and *institutional*, exhibit a holistic and multi-faceted structure. This reflects the necessity for cross-sectoral alignment in SDI development. In contrast, specialized models such as SDIOGI and SDI Development predominantly concentrate on one or two specific dimensions (e.g., *workflow automation* or *continuous improvement*), demonstrating a targeted approach to addressing operational challenges at micro-level implementation. The disparity in coverage not only reveals methodological gaps between macro and micro models

but also justifies the integration of their strengths into the proposed framework. This analysis provides an empirical basis for prioritizing dimensions in the design of an integrated model, ensuring a balanced synthesis of strategic breadth and operational specificity.

In this section, we first conducted a systematic critical evaluation of existing SDI maturity frameworks and prior studies through Table 1, incorporating peer-reviewed revisions to enhance methodological robustness. Subsequently, Table 2 enabled the systematic extraction of core dimensions and indicators, revealing foundational elements across models. These dimensions were then clustered into eight conceptually and operationally coherent groups in Table 3, grounded in theoretical and practical synergies. The analytical process culminated in Table 4, which delineates the granular coverage of each conceptual group across maturity models, facilitating a structured comparative assessment. Collectively, this hierarchical analysis—integrating methodological rigor and conceptual insights—provides the scaffolding for designing the integrated conceptual framework elaborated in the following section.

4.2. Integrated Conceptual Framework

To address the identified gaps and consolidate the finest dimensions and indicators from various maturity models, we propose an integrated conceptual framework comprising five interrelated layers: (1) Governance & Policy, (2) Organizational & Institutional, (3) Technical & Infrastructure, (4) Quality & Continuous Improvement, and (5) Human Resources & Automation. These layers are arranged holographically¹—each functioning autonomously while simultaneously contributing to the whole.

Governance & Policy Layer

Encompasses metadata standards (ISO 19115/19139, FGDC, Dublin Core), legal regulations, and strategic policies. Its purpose is to establish a formal foundation for SDI processes and oversight. Key indicators include the existence of a national metadata policy, clarity of data-sharing regulations, and compliance with international directives (INSPIRE, GSDI).

Organizational & Institutional Layer

Drawn from the NGDA and ANZLIC frameworks, this layer focuses on management structures, inter-agency collaboration, and stakeholder engagement mechanisms. Indicators include the presence of a dedicated governance body, coordinating committees, and public—private partnership arrangements.

Technical & Infrastructure Layer

Based on GSDI and SDI Development perspectives, it covers catalog services (CSW/WMS/WFS), service-oriented architectures, and data workflow automation. Essential metrics include API availability, OGC standards compliance, and data source integration capabilities.

Quality & Continuous Improvement Layer

¹ From the perspective of social and philosophical sciences, holographic refers to views that emphasize the internal connection of components and see the "whole in the component" (The Web of Life, n.d.).

Inspired by the SDIOGI model, this layer is responsible for ongoing maturity monitoring. It defines metrics such as metadata completeness rates, periodic reassessment cycles, and feedback loop mechanisms to ensure the framework adapts to evolving requirements and technologies.

Human Resources & Automation Layer

Integrates human capacity indicators (training programs, expertise levels) and automation tools (batch processing, data pipeline engines). This layer ensures teams possess the necessary skills and that processes are executed automatically.

Figure 3 presents a holographic, five-team conceptualization of our integrated SDI maturity frame, with each concentric ring that works autonomously, but still contributes to the whole. In the core, the quality and continuous improvement layer (yellow) defines the feedback-driven calculations-metadata completeness rates, periodic re-evaluation intervals, and two-way feedback looping-which continuously evaluates and delineates the infrastructure. Enclosing this are human resources and automation layers (light green), which ensure that trained personnel and automated workflows can quickly implement quality insights. The technical and infrastructure ring (TEAL) provides OGC-compatible catalog and web services (CSW, WMS, WFS), API connection, and service-oriented architecture that forms the basis for data access and workflow automation. The organizational and institutional team (blue) establishes governing bodies, coordination committees, and stakeholder partnerships to translate technical abilities into coordinated action. Finally, the outermost governance and policy ring (ROS) codifies national and international metadata policy (e.g., inspires compliance, ISO 19115), legal regulations, and strategic directives that guide the total SDI goals. Between each adjacent layer symbolizes two-way arrows continuously exchanging information and iterative adaptation, ensuring that political adjustments, organizational changes, technical upgrades, and improvements to human-automation live back in the central quality engine and circulate in the entire system.

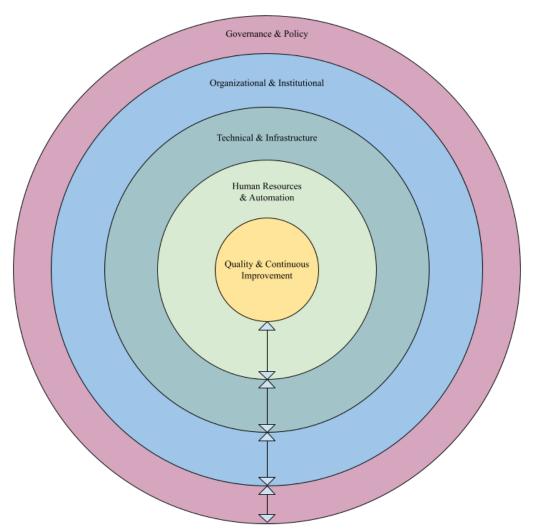


Figure 3. The holographic, five-layer SDI maturity framework

By adopting this framework, SDI researchers and managers can comprehensively and systematically assess infrastructure maturity, pinpoint weaknesses, and design strategic development roadmaps. Moreover, this purely conceptual model—requiring neither local data nor initial implementation—enables long-term planning and establishes a universal standard for global SDI maturity assessment.

5. Conclusion

By synthesizing a systematic review of SDI maturity models with metadata standards, this study proposes an integrated conceptual framework composed of five holographic layers: Governance & Policy, Organizational & Institutional, Technical & Infrastructure, Quality & Continuous Improvement, and Human Resources & Automation. This innovative structure maintains alignment with international criteria (INSPIRE, GSDI) while charting clear pathways for policy revision, inter-agency coordination, and ongoing enhancement. At the Governance & Policy layer, continuous development and periodic revision of national metadata policies are emphasized, ensuring a robust legal foundation and harmonization with global directives. The Organizational & Institutional layer promotes optimized organizational capacities through tailored public-private partnership mechanisms and clearly defined coordination bodies. The Technical & Infrastructure layer reinforces data accessibility and flexibility by prioritizing OGC-compliant web services and automated data workflows. The Quality & Continuous Improvement layer, armed with periodic reassessment metrics and bidirectional feedback channels, safeguards the framework's adaptability to emerging requirements. Finally, the Human Resources & Automation layer, through targeted training programs and advanced automation tools, ensures that SDI teams remain skilled and processes stay efficient. Without reliance on field data or intricate empirical analyses, this framework acts as a powerful tool for managers and policymakers, enabling strategic planning and establishing a global evaluation standard for SDI maturity. Implementing this model will allow organizations to systematically identify weaknesses, set development priorities, and guarantee that spatial data infrastructures progress toward sustainability and innovation.

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Economic Valuation of Industrial Water Toward Water Reallocation and Environmental Restoration in Zayandeh-Rood Basin, Iran

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Abstract

The Zayandeh-Rood basin is one of the regions with high socio-economic importance in Iran, which at the same time has faced the problems of scarcity of water resources. excessive exploitation of water resources in the Zayandeh-Rood River basin, the largest permanent river in Central Iran, has supported significant socio-economic development in the basin, but at the same time, it has caused a severe reduction in the ecological flow of the river and a rapid fall in the groundwater table. This has caused catastrophic subsidence in the Isfahan aquifer, destroyed local ecosystems, and resulted in the complete drying of the terminal lagoon (Gawkhoni). As long as cheap water is provided to the economic sectors of the basin regardless of its economic value, and the overexploitation of the basin's water resources is not adjusted by reallocation, no improvement in the environmental conditions of the basin will be expected. Industries, which are one of the major users of water in the Zayandeh Rood basin, have paid an average of less than 2 percent of the economic value of water as the water price during the study period. Considering that the price elasticity of demand for industrial water is high, and the cost paid for water in the relevant industries has been significantly lower than the economic value of water in these industries. Therefore, adopting the policy of reforming the water pricing system in this sector can lead to substitution between different water qualities, including recycling, and pave the way for environmental restoration and reallocation of water in the basin.

Keywords: Economic Valuation, Environmental Restoration, Water Reallocation, Water Scarcity

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1. Introduction

Water resources have faced a severe shortage due to the increase in demand caused by various factors such as population growth, increasing urbanization and industrialization, along with the improvement of living standards. Climate change and uncertainties related to it have also added to the deterioration of this issue (Saquib et al., 2022; Seidenfaden et al., 2021). The pollution of water sources caused by the discharge of urban, industrial, and agricultural sewage has also become another threat to the water supply (du Plessis, 2022; Bashir et al., 2020). According to the Falkenmark water stress index, Iran's water resources are unfortunately in a critical condition (Moridi, 2017). The negative water balance of groundwater due to excessive withdrawal from aquifers, transfer of surface water, and drought has caused severe water stress in Iran's wetlands (Neysiani et al., 2022).

Estimating the economic values of increasingly scarce water resources may be an important step to facilitate efficient economic adaptation (Hurd et al. 2004). The economic value of water resources generally refers to the added value of benefits that can be measured in available currencies and generated per unit of water withdrawn from natural storage space (Ma & Zhao, 2019). The general idea in the economic valuation of water is to identify the value of water in its competitive uses so that decision makers can better understand and communicate the values and trade-offs between different uses. Valuation also supports more transparent and informed decision-making about water allocation and use(Ostrom, 1990). Water is one of the main consumables in production processes, especially in the manufacturing industry. Lack of knowledge about the economic value of water may increase the scarcity problems of this resource and can even cause problems in the management of economic processes. In most developing countries, the price paid for water in different sectors of water consumption, including production processes, does not necessarily reflect water scarcities in catchments or reflect the costs of water extraction, transportation, and treatment (Revollo-Fernández et al., 2018). The limitation of water resources in Iran and the problems facing the supply of new water sources have increased the importance of this input in the production process (Tahamipour Zarandi et al., 2020). As Ghobadi & Moridi (2022) have stated, the conditions for water value-based pricing are available for industrial uses. Water saving methods should include pricing as well as properly implemented environmental fines (Tabieh et al., 2022). Population growth and increased prosperity have led to increased demand for water. However, social and political transformation processes, as well as policy regulations leading to new water-saving technologies and improvements, are countering this development by slowing down and even reducing domestic and industrial water use globally(Flörke et al., 2013). In Iran, it is also necessary to take effective measures aimed at improving water conservation and reducing the effects of water scarcity, especially in areas that are facing water crisis (e.g., Mamdoohi et al., 2013). On the other hand, investments in water supply, storage, and transfer facilities, intersectoral competition for water, are all water management problems that involve choices about how to combine water with other resources to obtain the greatest public return from a scarce resource(Varian 2010). Economic valuation of water is very necessary and

important for making effective decisions. Policymakers consider the economic valuation of water as a means to shape policies and developments related to water (Australian Water Partnership, 2016).

The Zayandeh-Rood basin is one of the regions with high socio-economic importance in the country, which at the same time has faced the problems of scarcity of water resources. The manufacturing industry has a special importance in the economic activity dynamics of the basin (Arjroodi et al., 2019). In addition, these industries have a significant share of the output value of the country's manufacturing industry. Therefore, the attention of the government and industries has been directed to the options of extracting water from new sources and especially from non-conventional sources of water, including water transfer from the Persian Gulf and the Sea of Oman, and water reuse projects. In this study, the monetary value of water in the manufacturing industry in Isfahan province, which also provides the possibility of comparing different values of water in different industries. Determining the economic value of water in the industries of Isfahan province not only provides the possibility of proper and efficient management of water in the province, but especially it can help to clarify the economic considerations of plans for the use of non-conventional resources, including the transfer of water from the Persian Gulf and the Sea of Oman, and the water reuse in these industries. On the other hand, considering that there is relatively little international literature on the calculations of the economic value of industrial water for developing countries that are facing problems of water resource scarcity. In Iran, these studies have mostly been conducted to investigate the economic value of water in domestic and agricultural uses, and the expansion of these studies to the industry sector has been very limited. Therefore, in this context, this article intends to partially fill the existing study gap by estimating the value of water for the manufacturing industry in a region that is under relative water stress, along with economicsocial development.

In addition, this study has tried to reveal the role of reforming the pricing system in water reallocation and environmental restoration by comparing the economic value of water with the price paid by industries for water. Therefore, this study, which estimates the economic value of water in regional industries, has been done as the first step in creating a proper economic view of the value of water use in this basin. As Ward & Michelsen (2002) state, information on the economic value of water enables decision makers to make informed decisions about the development, conservation, allocation, and use of water when growing demands for all uses are made in the face of increased scarcity. It is obvious that in order to obtain a more complete set of information, it is necessary to value water in other sectors of water consumption in the Zayandeh-Rood river basin, including agriculture, urban, and ecosystem services.

Because of the limited role that markets play in water allocation, competitive market prices on which to base water resource allocation decisions are usually not available. Because of this, economists have developed techniques to measure the economic value associated with priceless natural resources. The theoretical foundations of non-market economic valuation of natural resources are well developed (e.g., Freeman 2014). Advances in methods for estimating economic benefits in real cases have also progressed well. Some areas of water valuation have

received less attention. Especially for intermediate goods or products derived from water. Water valuation is based on the normative framework of neoclassical welfare economics and is an application of cost-benefit analysis (Johansson 1993; Richard et al. 2004). Since the way of valuing water in each specific case is different depending on the specific characteristics of the situation (such as the use of water and the place of use) and according to the desired decision, therefore, several methods have been invented in the economic valuation of water. In this regard, many efforts have been made to introduce economic valuation methods of water. Gibbons (1986) uses the water consumption approach as the basis of his classification and for this purpose, considers seven specific categories of water consumption. According to this classification of water uses and the usual methods of water valuation in the fields of urban, irrigation, industrial, navigation and water transportation, recreational and aesthetic, pollutant absorption, and hydroelectric power plants have been investigated. According to Ward & Michelson (2002), water economic valuation methods can be used as market and managed prices, changes in net income due to water consumption when water is an intermediate good, and measuring efficiency, such as increased productivity based on increased water consumption.

Young & Loomis (2014) have also compiled an explanation about the methods of determining the economic value of water. They present methods of economic valuation of water in the form of different categories, considering different aspects and fields. Therefore, water economic valuation approaches can be classified according to the quantification techniques used. Most of the water evaluation methods are divided into two general categories, which differ in mathematical methods and the type of data used in the valuation process. One group includes inductive methods that use inductive logic, such as statistical or econometric methods, to derive generalizations from individual observations. Another group includes deductive methods that use logical processes to reason from general premises to specific conclusions. In sum, there is no single economic value for water, and each method is useful in certain circumstances. Examples of studies in the field of industrial water valuation are mentioned below:

Wang and Lal (2002) have determined the economic value of water for different branches of Chinese industry. In this work, the Cobb-Douglas cost function is used to estimate water price elasticity and water value. According to research findings, the economic value of water in Chinese industries has varied from 0.05 to 26.8 Chinese yuan per cubic meter of water.

Renzetti & Dupont (2003), using the data of 1981, 1986, and 1991 of Canadian manufacturing companies, estimated the final shadow value of water in Canadian industries. Based on the results, the average value is 0.046 dollars per cubic meter of water.

Kumar (2006) conducted a study using a linear programming approach on a sample of 92 companies over three years. The results show that the average shadow price of water is 7.21 rupees per cubic meter, and the derived price elasticity of water demand is high, averaging - 1.11. This suggests that water charges may be an effective tool for water conservation.

Nahman & De Lange (2012), Using data and information from annual reports and sustainability reports of 58 companies, it has estimated the economic value of water in South African industries. According to the results, the average economic value of water in the investigated

industries is equal to 369.10 South African Rand (equivalent to 21.44 US dollars) per cubic meter of water. It goes on to explain that, for example, this is the maximum amount companies are (in theory) willing to pay for an additional cubic meter of water.

Ku & Yoo (2012) state that a sustainable water supply is very important for manufacturing companies, because industrial water is used for various purposes as one of the important inputs in the production process. Despite the importance of industrial water use and the increasing demand for industrial water, relatively few studies have been conducted on industrial water consumption in Korea. In this work, the marginal productivity approach is used to estimate the economic value of water in the Korean manufacturing industry, and it uses data from 53,912 factories in Korea in 2003. This study estimates the final production value and industrial water output elasticity using the Cobb-Douglas production function and the Translog production function. Estimated values vary by sector, ranging from a high of 13,760 KRW per cubic meter of water in the transportation equipment sector to a low of 428 KRW per cubic meter of water in the instrumentation sector. This research states that the findings provide the possibility of drafting future water pricing scenarios by the Korean government based on the available estimated value information.

Rodríguez-Tapia et al. (2021) conducted a study on the manufacturing industry in Mexico. The applied method includes estimating the marginal productivity of water from the translog production function. The information comes from the 2014 Economic and Industrial Census, which reports data on 476,753 economic units across the country. The results show that one cubic meter of water used in the Mexican manufacturing industry creates an added value equal to 7.8 dollars

Around the world, less research has been done on the economic value of water in industrial uses than in agriculture and domestic use, and there are only a handful of studies in this field in Iran. In the study conducted by Tahamipour Zarandi (2017), the production function method and the residual method were used. In this research, the purpose of which was to determine the economic value of water in the chemical industries of Iran, the economic value of water using the production function method was estimated as 36697 Rials, and using the residual method, it was equal to 35867 Rials per cubic meter of water. And he states that this value is far from the current price of water and thus, the price paid for water in the country's chemical industries is much lower than the economic value of water in this part of the industry.

Tahamipour Zarandi et al. (2020) have devoted their research to determining the economic value of water in Iran's industry. In this research, which used the residual method, the weighted average of the economic value of water during the period of 2004-2013 was equal to 87347 Rials per cubic meter of water.

Mousavi et al. (2021), in a study that they conducted in order to determine the economic value of water in environmental, agricultural, and industrial uses in the Urmia lake basin, used the residual method to estimate the economic value of water in industry. This study has estimated the economic value of water in industrial use in 2018 as 33342 Rials per cubic meter of water. Among the previous works in the field of industrial water valuation in the Zayandeh-Rood basin, we can refer to the studies of Yekom Consulting Engineers (2013) based on industry

data in the period of 2001-2006 that estimated the average economic value of water in the industrial sector of the Gawkhoni basin. In another study published in the Inter3 report (2013) to estimate the economic value of water in the industry sector of the Zayandeh-Rood basin, the generalization of global works was used, and the calculations were not done in a region-specific manner and separately by industry branches.

In this way, the work of economic valuation of industrial water for the Zayandeh-Rood basin using statistical data of the industry in the period of 2002-2019 using the residual method for the whole industry of Isfahan province, and also by separating the four two-digit ISIC codes, for the first time by This study has been conducted and has no previous history. In addition, none of the previous studies on the economic valuation of industrial water for the Zayandeh-Rood basin have compared the resulting value with the price paid by industries for water. In this study, for the first time, an attempt has been made to reveal the potential of reforming the pricing system in environmental restoration of the Zayandeh-Rood Basin by comparing the economic value of water with the price paid by industries for water.

2. Methodology

2.1. Case study

Zayandeh Rood River is the largest permanent river in Central Iran, which has supported significant socio-economic development in the basin. But at the same time, over-extraction from water resources in the Zayandeh-Rood river basin has caused a severe reduction in the ecological flow of the river and a rapid fall in the groundwater table (Abou Zaki et al., 2020). This has caused the pronounced subsidence in the Isfahan aquifer (Beni et al., 2024; Sorkhabi et al., 2022), destroyed local ecosystems, and resulted in the complete drying of the terminal lagoon (Gawkhoni) (Hekmatpanah et al., 2012). Fig. 1 depicts the location of the Zayandeh-Rood basin and Isfahan city.



Figure 1. Location of the Zayandeh-Rood basin and Isfahan city

The methods of determining the economic value of water as a production input can be classified into two categories: parametric and non-parametric methods. One of the non-parametric methods for determining the economic value of water that has been used in various studies is the residual method (Young & Loomis, 2014). In this study, due to the limitation of data, among the various methods for measuring the economic value of water, the residual method has been used, which will be briefly explained below. With the data that is available in the Statistical Centre of Iran on industrial workshops in the form of a time series for a maximum period of eighteen years in each branch of industry, it is not possible to estimate the production function correctly. In addition, due to the difference in the industries of Isfahan province in terms of the nature of production, it is not possible to consider them as competitors in water consumption in a mathematical programming model, so this method is also out of the scope of selection. Regarding other methods, it should be noted that the method of observations of water market transactions is used in countries that have a water market, which does not match the conditions of this research. The value-added method greatly exaggerates the value of water and is not suitable for this task. The alternative cost method is used only when the value of water cannot be easily estimated using other methods. Therefore, the residual method has been used in this research. This method was used in various studies to determine the economic value of water, such as Lowe et al. (2022), Rodrigues et al. (2021), Tehamipour Zarandi et al. (2020), and LIU et al. (2019). The residual method is applied to estimate the value of water when it is used as an input or an intermediate good of production. The residual value approach actually measures average value because it is based on measures of the total value of production and the total cost of non-water inputs.

In the practical model of applying the residual method using the available data of the Statistical Centre of Iran on industrial workshops of 10 or more workers during the period of 2002 -2019, in the first stage, all intermediate costs except water cost are deducted from the output value until the added value that includes the cost of water is obtained. Then the amounts of service compensation, operating surplus, depreciation, and net tax are calculated, and their sum is deducted from the added value. In this way, the total value of water is calculated. Finally, by dividing the total value of water by the amount of water consumed, the value of each unit of water will be obtained. The data related to compensation for the services of employees and net tax were extracted from the data of the Statistical Centre of Iran on industrial workshops of 10 or more workers during the period of 2002 -2019. Depreciation is calculated according to Article 151 of the Direct Taxes Law and based on the descending method equal to 12% of the book value of capital formation per year. To calculate the operating surplus, the share of the operating surplus from the added value for each code and for the whole industry of Isfahan province was extracted from the input-output table of 2015, and the operating surplus was calculated according to the obtained share.

Thus, in this research, to determine the economic value of water in the industries of Isfahan province, the residual valuation method has been used for the whole industry of Isfahan

province, as well as for 4 two-digit ISIC codes, including codes 19(manufacture of coke and refined petroleum products), 20(manufacture of chemicals and chemical products), 23(manufacture of other non-metallic mineral products) and 24(manufacture of basic metals), which are the major consumers of industrial water.

3. Results and Discussion

The production value of the industrial sector of Isfahan Province in 2019 has crossed the border of 2300 trillion Rials. Figure 2 presents the share of selected codes in the production of added value in Isfahan province based on average values during the period from 2002 to 2019. The share of the 4 selected codes was about 78% of the total production value of the industry sector of Isfahan province, and the share of the added value of the 4 selected codes was 73% of the total added value of the industry of Isfahan province. In addition, these 4 selected codes have consumed about 85% of the total water in the industrial sector of Isfahan province. Figure 3 presents the share of water consumption in the industrial sectors of Isfahan province.

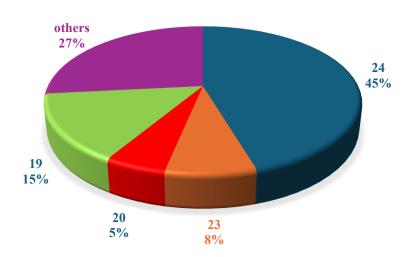


Figure 2. Added value in different industrial sectors of Isfahan province

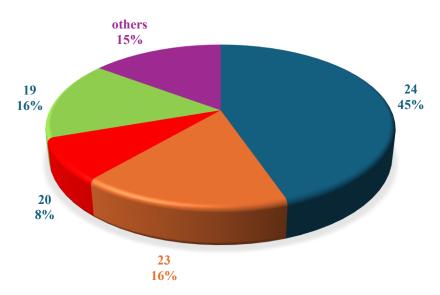


Figure 3. Water consumption in different industrial sectors of Isfahan province

In Figure 4, input value, output value, added value, and water cost of 4 selected codes compared to the whole industry of Isfahan province, based on the average values during the period from 2002 to 2019, are displayed.

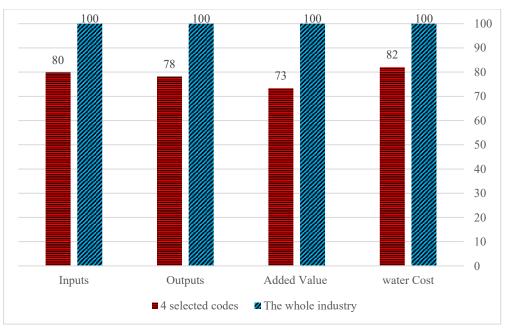


Figure 4. Comparison of input value, output value, added value and water cost of 4 selected codes with the whole industry of Isfahan province

In this work, the economic value of water in the industry of the province and in 4 selected codes in the period from 2002 to 2019 was calculated using the residual method. The Producer Price Index (PPI) can be used to remove the effect of inflation by serving as a deflator for other economic data or as a basis for adjustments. Therefore, in order to eliminate the effect of inflation and create a perspective based on the current value of water in large industries in the

basin, the Rial value of water was adjusted using the Producer Price Index (PPI) of the industrial sector in manufactured products for April 2025. Accordingly, during the study period, the average current value of water per cubic meter of water in the entire industry of Isfahan province was 6,648,818 Rials, in code 19 (Manufacture of coke and refined petroleum products) 7,411,597 Rials, in code 20 (Manufacture of chemicals and chemical products) 3,245,207 Rials, in code 23 (Manufacture of other non-metallic mineral products) 2,960,888 Rials, and in code 24 (manufacture of basic metals) 8,732,424 Rials. The adjusted Rial values of water based on the April 2025 PPI for the total industry sectors and for the four selected codes are shown in Figure 5.

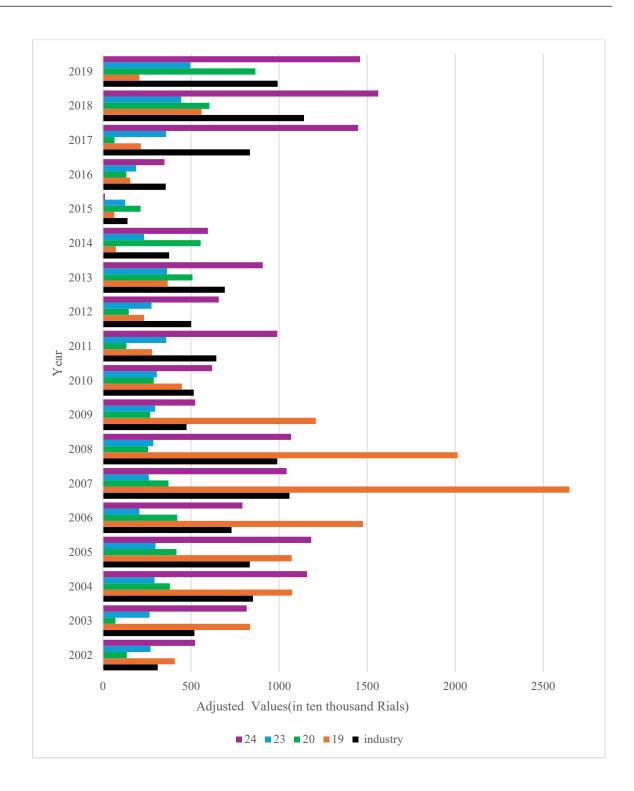


Figure 5. Adjusted economic value of water in the industry of the province and 4 selected codes

The cost paid for water in the production process of the industry of Isfahan province during the period from 2002 to 2019 was between 0.05 and 0.25% of the total production costs of the industry, and on average, less than 0.2% of the total production costs. In addition, in this research, the economic value of water in industries was also examined and compared with the cost paid for water during the study period, and the relevant results are given in Table 1.

Accordingly, the ratio of the cost paid for water in the industrial production process of Isfahan province to the value of water during the study period ranged from less than 0.6 percent to 5.35 percent, and the average ratio of the cost paid for water to the value of water during the period was 1.87 percent.

Table 1. The ratio of water cost to water value in the industry sector

	The factor of water cost to water value in the industry sector
Year	The ratio of water cost to water value (percentage)
2002	1.58
2003	1.10
2004	0.78
2005	0.61
2006	0.74
2007	0.96
2008	0.92
2009	2.32
2010	1.94
2011	1.85
2012	4.50
2013	1.74
2014	1.85
2015	5.35
2016	3.62
2017	0.68
2018	2.33
2019	0.79

In addition, in this work, the value of water in each sector and the share of each sector in value-added production, and the share of each sector in the total water consumption in the production process for 2019 were compared. The results are shown in Figure 6. Therefore, the most efficient sector among the 4 selected codes is code 24 (manufacture of basic metals), and at the same time, this sector is the largest water consumer in all the industries of the Zayandeh-Rood basin, which consumes almost half of the industrial water in the basin. Therefore, one of the sectors It is noteworthy that reforming the water pricing system can help to improve water consumption in the basin.

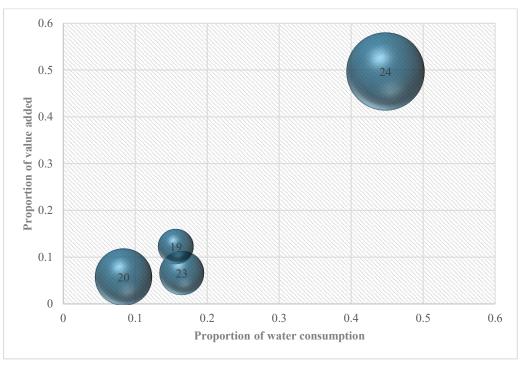


Figure 6. The water value, water consumption, and added value in 4 selected codes

4. Conclusion

In this research, in order to estimate the economic value of water, the residual method was used for the whole industry of Isfahan province and also for 4 two-digit ISIC codes that constitute the most water-consuming industries in Isfahan province. The reason for using this method is the limitation of available data, because the available information is very general and does not provide the necessary multiplicity for the possibility of fitting the production functions with sufficient reliability. In this way, by using the residual method and using the data of the Statistical Centre of Iran on industrial companies of 10 or more employees during the period of 2002 -2019, the work of estimating the economic value of water in the industries of Isfahan province was carried out. Due to the relatively high inflation rate in Iran during the period under review, in order to eliminate the effect of inflation and create a perspective based on the current value of water in large industries in the basin, the Rial value of water was adjusted using the Producer Price Index (PPI) of the industrial sector in manufactured products for April 2025. According to the findings of the research, the average current economic value of water for each cubic meter of water in the whole industry of Isfahan province is equal to 6,648,818 Rials, in code 19 (manufacture of coke and refined petroleum products) equal to 7,411,597 Rials, in code 20 (manufacture of chemicals and chemical products) was equal to 3,245,207 Rials, in code 23 (manufacture of other non-metallic mineral products) it was equal to 2,960,888 Rials, and in code 24 (manufacture of basic metals) it was equal to 8,732,424 Rials. Based on the results, according to the value of water in each industry code, the share of each sector in value-added production, and the share of each sector in the total water consumption in the production process for 2019, it was determined that the most efficient sector among the 4 selected codes is code 24 (manufacture of basic metals).

During the time period examined in this research, which is related to the period from 2002 to 2019, the ratio of the cost paid for water to the total cost of production in the whole industry of Isfahan province was between 0.05 and 0.25%. This figure for the whole industry of Isfahan province was equal to 0.145 percent on average, which shows that the cost of water has a very small share in the production cost of these industries. This is despite the fact that the economic value of water in these industries has been much higher than the cost paid for water. The results of the research showed that the average ratio of payment for water to the value of water during the mentioned period was equal to 1.87 %. In other words, during the mentioned period (2002) to 2019), industries have paid less than 2% of the economic value of water as water cost. This indicates the need to reform the water pricing system for industrial uses. Price signals can encourage conservation of water resources and help increase the efficiency of water use. Price elasticity of demand for industrial water is significantly higher than for residential consumption. This suggests that industrial demand for water is potentially more sensitive to price and may therefore indicate opportunities for substitution between different water qualities, including recycling (Worthington, 2010). As long as cheap water is provided to the economic sectors of the basin regardless of its economic value, and the overexploitation of the basin's water resources is not adjusted by reallocation, no improvement in the environmental conditions of the basin will be expected.

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The Application of Artificial Intelligence and Deep Learning in Extracting Agricultural Parcel Boundaries and Its Role in Enhancing Spatial Data Infrastructure (SDI)

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Abstract

Accurate delineation of agricultural land parcels is a key requirement for implementing precision agriculture, natural resource management, and the development of Spatial Data Infrastructures (SDI). Considering the diversity of planting patterns, vegetation changes, and challenges such as occlusions and manual interpretation methods lack sufficient efficacy. In recent years, deep learning models have emerged as innovative solutions for extracting parcel boundaries from satellite imagery and spatial data due to their high capability in extracting complex features and processing large-scale data. This study aims to investigate the role of deep learning models in accurately delineating agricultural land parcel boundaries based on the analysis of satellite images and spatial data within the framework of Spatial Data Infrastructure (SDI). The study focuses on analyzing various deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs). These models are evaluated from the perspectives of technical structure, input data types, performance metrics, and adaptability to operational challenges in precision agriculture. For comparative analysis, a set of recent studies and selected models is reviewed regarding accuracy, limitations, and compatibility with real-world conditions such as heterogeneous landscapes and scarce labeled data. The results indicate that CNN-based models perform well in processing satellite imagery but have limitations in capturing contextual dependencies, which can be improved by combining them with RNNs. Additionally, GAN models are effective in augmenting training data and generating synthetic images. The findings of this study can serve as a foundation for developing more intelligent and hybrid models in future SDI and smart agriculture systems.

Keywords: Deep Learning, Satellite Imagery, Smart Agriculture, Convolutional Neural Networks (CNN), Spatial Data Infrastructure (SDI)

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1. Introduction

In recent years, with significant advancements in information technologies and geographic tools, the use of Geographic Information Systems (GIS) and Spatial Data Infrastructure (SDI) in agriculture has become a fundamental pillar in resource management and agricultural development. One of the fundamental issues in this field is the precise delineation of agricultural land parcels, which plays a vital role in proper water resource planning, optimal resource allocation, and increasing agricultural productivity. Traditional methods for parcel boundary delineation, such as field surveying and processing of aerial photographs and satellite images, are often time-consuming, costly, and may not achieve the desired accuracy under certain conditions.

In this context, advanced machine learning techniques, particularly deep learning, have created a paradigm shift in this domain. Deep learning models, due to their capability to process complex data and hidden patterns in satellite imagery, artificial intelligence, and sophisticated simulations, enable more accurate identification and delineation of land parcel boundaries. These techniques are especially valuable in precision agriculture, where the need for accurate and timely data analysis is critical. They can enhance accuracy and efficiency in boundary delineation and agricultural resource management. This article examines the application of deep learning in delineating agricultural land parcels within the framework of Spatial Data Infrastructure (SDI), analyzing the challenges and benefits of using this technology to improve accuracy and agricultural productivity.

Accurate delineation of agricultural land parcel boundaries plays a crucial role in smart agriculture, water resource management, and land optimization. This process provides essential information for precision agriculture and helps farmers optimize resource consumption and increase crop yield (Dawn et al., 2023). However, traditional methods such as field surveying and the processing of aerial photographs and conventional satellite images face various challenges.

While field surveying is effective in some cases, it is time-consuming, expensive, and limited to recording fine details of parcel boundaries (Bennett et al., 2020). Additionally, conventional image processing methods, such as Object-Based Image Analysis (OBIA), heavily depend on segmentation techniques and often lack sufficient accuracy for extracting agricultural parcel boundaries (Xia et al., 2018).

Processing satellite images encounters multiple challenges affecting analysis accuracy and model performance. Key challenges include spatial and temporal variability of data, atmospheric conditions such as cloud cover or fog, varying resolution of images from different sensors, and noise and measurement errors. Furthermore, the large volume of data requires powerful storage, processing, and analysis capabilities, which can be time-consuming and costly without proper infrastructure. Accurate interpretation of features in heterogeneous areas or densely vegetated regions also presents a significant challenge in agricultural, natural

resource, or disaster management applications. Moreover, the need for labeled data to train machine learning models is another common limitation in this field.

Artificial intelligence and deep learning have made significant advances in increasing the accuracy (e.g., Haery et al., 2024) and reducing the cost of delineating agricultural parcel boundaries. For example, models such as U-Net and RCF¹ have been used to extract hard and soft edges, respectively, enabling more precise identification of agricultural parcels (Xia et al., 2018). These methods leverage deep learning capabilities to better interpret images and extract boundaries.

Additionally, accurate delineation of agricultural parcel boundaries is key to monitoring crop health and growth. Inaccurate boundary delineation can lead to mixing data from adjacent fields in remote sensing analyses, such as vegetation indices (e.g., NDVI²), resulting in unreliable outcomes. This can negatively impact management decisions like irrigation scheduling (e.g., Mahpour and Shafaati, 2024), fertilization, or harvesting. Therefore, precise boundary extraction is a fundamental step in effective precision agriculture and intelligent crop monitoring. AI-based solutions have improved crop monitoring accuracy and health assessment by 30 to 50 percent and enhanced resource-based decision-making (Hoque & Padhiary, 2024). Deep learning models such as YOLOv5³ have demonstrated successful performance in identifying and classifying agricultural products (Ram et al., 2023).

Overall, although traditional methods have limitations in accurate parcel boundary delineation, artificial intelligence and deep learning offer promising solutions. These technologies not only improve accuracy but also reduce time and costs, contributing to the optimization of smart agriculture.

2. Literature Review

Convolutional Neural Networks (CNNs) have demonstrated remarkable success in processing satellite images for various tasks, including land boundary detection. CNNs excel at extracting high-level features from images, making them particularly effective for spatial data analysis. In the field of remote sensing, CNNs have shown strong capabilities in feature representation, leading to improved scene classification of satellite imagery (Liu et al., 2019).

Compared to other deep learning models, CNNs have both advantages and limitations. While CNNs are effective at processing local regions of images, they lack the ability to capture long-range contextual dependencies across different image areas (Zuo et al., 2016). Recurrent Neural Networks (RNNs), on the other hand, are designed to capture sequential dependencies and can be useful for encoding spatial dependencies in satellite imagery (Zuo et al., 2015; Zuo et al., 2016). The combination of CNNs and RNNs, often referred to as Convolutional Recurrent

² Normalized Difference Vegetation Index

¹ Richer Convolutional Features

³ You Only Look Once Version 5

Neural Networks (C-RNNs), has proven successful in learning spatial dependencies between image regions and enhancing feature discrimination within image representations (Zuo et al., 2015; Zuo et al., 2016).

Generative Adversarial Networks (GANs) offer a different approach to satellite image analysis. Although GANs have not been directly compared with CNNs for land boundary detection, they have been explored in remote sensing applications to overcome challenges related to limited data availability (Logan et al., 2021). GANs can generate synthetic satellite images that potentially augment training datasets and improve model performance in scenarios with scarce data.

In summary, while CNNs perform well in processing satellite images for tasks such as land boundary detection, combining them with other deep learning models like RNNs can yield better results by capturing both local and contextual information. The choice of model depends on the specific task requirements, available data, and computational resources. Future research may focus on developing hybrid models that leverage the strengths of multiple architectures to optimize performance in satellite image analysis (Teixeira et al., 2023).

This section provides a comparative review of deep learning models presented in recent studies related to agricultural land segmentation. The focus is on evaluating the strengths, limitations, and real-world adaptability of these models, particularly in heterogeneous landscapes, noisy backgrounds, and limited labeled data scenarios. Table 1 summarizes the key characteristics of these models.

Table 1. Review of recent studies on deep learning methods for land parcel and vegetation segmentation from remote sensing images.

Article	Model	Strengths	Weaknesses	Real-World Compatibility	Reference
Local refinement mechanism for improved plant leaf segmentation in cluttered backgrounds	U-Net-based model with local refinement mechanism	High accuracy in leaf segmentation in greenhouses; use of Gaussian and High-Boost filters	Sensitive to image blur and occlusion; requires precise labeled data	Performs well in greenhouse conditions; needs improvement for field conditions	Ma et al., 2023
Development of Semantic Maps of Vegetation Cover from UAV Images to Support Planning and Management in Fine-Grained Fire- Prone Landscapes	CNNs for shrub detection	Ability to detect vegetation cover in heterogeneous landscapes	Performance depends on the quality of labeled data	General capability in complex landscapes, but sensitive to input data quality	Trenčanová et al., 2022
Enabling Multi-Part Plant Segmentation with Instance-Level	Weakly supervised learning and	Addresses object overlap issues; uses semi-	Time-consuming multi-part	Suitable for low- labeled data areas;	Mukhamadiev et al., 2023

Article	Model	Strengths	Weaknesses	Real-World Compatibility	Reference
Augmentation Using Weak Annotations	pseudo- labeling	automatic labeling	labeling requires semi-labeled data	needs further optimization	
Improved random forest classification model combined with the C5.0 algorithm for vegetation feature analysis in nonagricultural environments	Object-based Random Forest for forest classification	94.02% accuracy on aerial data; strong in vegetation discrimination	Designed for forests, not specific agricultural lands	Performs well in diverse vegetation cover landscapes	Wang, 2024
Improvement in Land Cover and Crop Classification based on Temporal Features Learning from Sentinel-2 Data Using Recurrent- Convolutional Neural Network (R- CNN)	CNN + RNN hybrid (Pixel R-CNN)	96.5% accuracy in crop classification using Sentinel-2 data	Focuses on crop classification, not boundary segmentation	Compatible with multi-temporal satellite images	Mazzia et al., 2019
A Futuristic Deep Learning Framework Approach for Land Use-Land Cover Classification Using Remote Sensing Imagery	Multi-spectral bands, topography, and texture fusion	89.43% accuracy in land use mapping	Not specifically designed for land parcel boundary detection	Capable of working with diverse data sources	Nijhawan et al., 2018
Deep Learning for Feature-Level Data Fusion: Higher Resolution Reconstruction of Historical Landsat Archive	GAN for spatial resolution enhancement	Improves the resolution of historical Landsat data to Sentinel-2 quality	Focused on image reconstruction, not segmentation	Enhances input data quality for downstream models	Chen et al., 2021
Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data	Self- supervised learning combined with CNN	Detects crop types from Landsat-8 and Sentinel-1A data	Suitable for crop classification, not boundary segmentation	Performs well on multisensor data	Kussul et al., 2017
Convolutional Neural Networks enable efficient, accurate, and fine- grained segmentation of plant species and	Analysis of high- resolution RGB UAV images	High accuracy in identifying specific plant species	Requires UAV data, which can be limited	Suitable for precise local-scale vegetation mapping	Kattenborn et al., 2019

Article	Model	Strengths	Weaknesses	Real-World Compatibility	Reference
communities from					
high-resolution UAV					
imagery					

According to the table above, some models, such as the U-Net-based approach with local refinement, achieve precise leaf segmentation under greenhouse conditions (Ma et al., 2023). CNNs have shown good capability in detecting vegetation in heterogeneous landscapes (Trenčanová et al., 2022). Weakly supervised learning models are effective in overcoming object overlap challenges and reducing the need for fully labeled data (Mukhamadiev et al., 2023). Object-based Random Forest models also achieve high accuracy in forest classification (Wang, 2024).

On the other hand, limitations are evident in these studies. For example, some models perform poorly under image blur or occlusion conditions (Ma et al., 2023). Lack of sufficient labeled data reduces model accuracy, especially for tasks requiring multi-part or semi-automatic labeling ((Mukhamadiev et al., 2023), (Trenčanová et al., 2022)). Models like Pixel R-CNN, while successful in crop classification, are not specifically designed for agricultural land boundary delineation (Mazzia et al., 2019). Another challenge is adapting to complex landscapes and diverse vegetation covers. Although some models show general robustness, there remains a need for improvement to handle real-world heterogeneous data effectively ((Wang, 2024), (Kattenborn et al., 2019)).

Although the reviewed models have made significant advances in vegetation cover classification and agricultural land use mapping, most of them are not specifically designed for the delineation of agricultural plot boundaries. This gap highlights the need to develop models explicitly aimed at parcel boundary detection. Additionally, applying techniques such as weakly supervised learning, image super-resolution (Chen et al., 2021), and multimodal data fusion could enhance model performance under real-world conditions.

3. Theoretical Framework

Based on the butterfly model of Spatial Data Infrastructure (SDI), the agricultural cadastre is considered the primary source of spatial and descriptive data related to agricultural land parcels. These data include field boundaries, types and intensity of land use, ownership, and land use classifications. When integrated within the SDI framework, these data can be combined with other layers such as topographic maps, climate data, water resources, and agricultural infrastructure, thereby providing a unified platform for analysis, decision-making, and policymaking (Williamson et al., 2010).

Within this model, SDI acts as a bridge between cadastral data and land management systems. Through this infrastructure, the spatially enabled government can deliver various services such

as land use planning, resource management, facilitation of public services, and monitoring of sustainable development based on geospatial data. Therefore, the agricultural cadastre is not only a tool for registering and maintaining parcel information, but within the SDI framework, it becomes a key instrument for sustainable agricultural development, more efficient resource utilization, and improved land governance.

Given the need for spatial data processing and analysis in agricultural cadastre, particularly in the automated delineation of parcel boundaries, the application of emerging technologies such as Artificial Intelligence (AI) and Deep Learning becomes crucial. These technologies are foundational to advancements in precision agriculture, especially in delineating field boundaries.

AI refers to the development of computer systems capable of performing tasks that typically require human intelligence (Sharma, 2021). In agriculture, AI is used for a range of applications, including disease detection, plant classification, and smart irrigation (Ünal, 2020).

Deep Learning, a subfield of AI, uses artificial neural networks to uncover hidden patterns in unlabeled and unstructured data without human intervention (Ünal, 2020). Among these, Convolutional Neural Networks (CNNs) have shown remarkable ability in analyzing agricultural images obtained from satellites, aerial vehicles, and ground-based cameras (El Sakka et al., 2024).

Accurate delineation of field boundaries is critical for precision agriculture, as it enables farmers to optimize resource management, enhance crop health, and increase productivity (El Sakka et al., 2024), (Kujawa & Niedbała, 2021)). The significance of these technologies in precision farming lies in their ability to process vast amounts of data collected throughout the growing season, support decision-making systems, and optimize various aspects of agriculture (Wang, 2024). These technologies help develop smart agricultural systems that make agriculture more efficient and effective by utilizing advanced information technologies (Ünal, 2020). These capabilities are especially important in addressing global challenges such as population growth and limited agricultural land expansion (Sharma, 2021).

Therefore, AI, deep learning, and field boundary delineation are key components of precision agriculture, enabling farmers to make data-driven decisions, optimize resource use, and enhance overall productivity. As these technologies advance, their role in addressing food security challenges and promoting sustainable agriculture is expected to grow increasingly prominent ((Glady et al., 2024), (Padhiary & Kumar, 2025)).

This study's theoretical framework focuses on three major model categories, each with specific theoretical and technical foundations for spatial and image data analysis:

3.1. Convolutional Neural Networks (CNNs)

CNNs utilize architectures inspired by human vision and extract spatial and spectral features from images using convolutional layers. They are particularly effective in identifying objects,

boundaries, and complex patterns in satellite imagery. Architectures such as U-Net, SegNet, and 2D/3D CNNs have proven highly effective for pixel-wise classification and delineation of agricultural features.

CNNs have emerged as powerful tools in satellite image analysis for agricultural applications, playing a critical role in accurate boundary detection of land parcels. They have demonstrated exceptional performance in analyzing images from satellites, UAVs, and terrestrial cameras (El Sakka et al., 2024). By leveraging vegetation indices and multispectral imagery, CNNs enhance analytical capabilities and contribute to improved agricultural outcomes. Notably, hybrid 3D-2D CNN models have shown superior performance in extracting spatial and spectral features from high-resolution satellite images, achieving up to 95.6% classification accuracy for land cover, outperforming traditional machine learning algorithms such as SVM and RF (Saralioglu & Gungor, 2022).

Interestingly, although very deep CNNs are structurally complex and require extensive training data, some studies have proposed efficient and lightweight architectures that outperform well-known models like GoogleNet and SqueezeNet in classifying wetland areas (Jamali et al., 2021).

Consequently, CNNs—especially 3D/2D models and optimized architectures—are among the most effective tools for satellite image analysis in agricultural applications. These models outperform traditional methods in accurately identifying field boundaries by extracting high-resolution spatial and spectral features. Integrating CNNs with techniques such as data augmentation, transfer learning, and multimodal fusion further enhances their performance in tasks like crop classification and land use mapping (Teixeira et al., 2023).

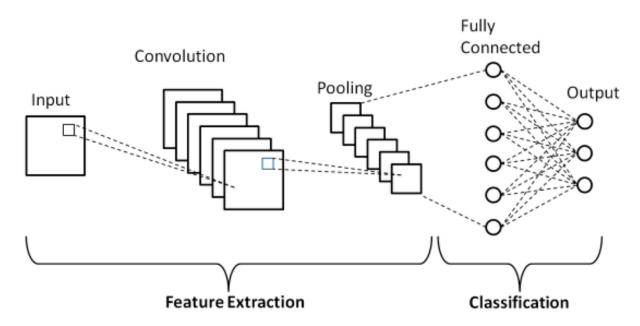


Figure 1. Basic structure of a convolutional neural network (CNN) for analyzing satellite images in precision agriculture. Adapted from (Phung & Rhee, 2019)

The basic CNN architecture image includes convolution, pooling, and fully connected layers designed to extract local features from images. CNNs, with their high ability to extract spatial features from satellite images, are an effective tool for identifying and determining agricultural land boundaries. Studies have shown that the use of CNNs in this field has higher accuracy than traditional methods.

3.2. Recurrent Neural Networks (RNNs)

RNNs are designed for processing sequential data such as text, speech, or time series. Their key feature is the ability to retain previous information through feedback loops, allowing them to model temporal dependencies in data. These networks are widely used in applications like machine translation, speech recognition, and sentiment analysis.

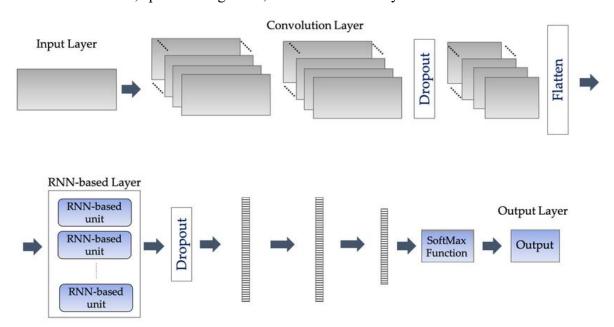


Figure 2. CNN-RNN Hybrid Architecture. Adapted from (Mekruksavanich & Jitpattanakul, 2021)

The architecture of the combined CNN-RNN model illustrates the integration of two types of neural networks: Convolutional Neural Networks (CNNs) for extracting spatial features from imagery, and Recurrent Neural Networks (RNNs) for modeling temporal dependencies within the data. In this framework, the CNN component initially extracts spatial representations from satellite images, which are subsequently processed by the RNN to capture temporal dynamics.

In the context of precision agriculture, delineating agricultural parcel boundaries is of critical importance. Multitemporal satellite imagery enables the observation of land cover changes over time. The hybrid CNN-RNN architecture leverages the spatial feature extraction capabilities of CNNs and the temporal modeling capabilities of RNNs, facilitating more accurate and stable boundary detection of agricultural fields.

Consequently, the application of CNN-RNN hybrid architectures in satellite image analysis for agricultural parcel boundary extraction significantly enhances both the accuracy and efficiency of the process by jointly exploiting spatial and temporal information.

3.3. Generative Adversarial Networks (GANs)

GANs consist of two distinct neural networks: a generator that produces new data and a discriminator that attempts to distinguish real from generated data. Through this adversarial process, the quality of the generated data improves significantly. GANs are widely used for realistic image generation, data augmentation, and style transfer.

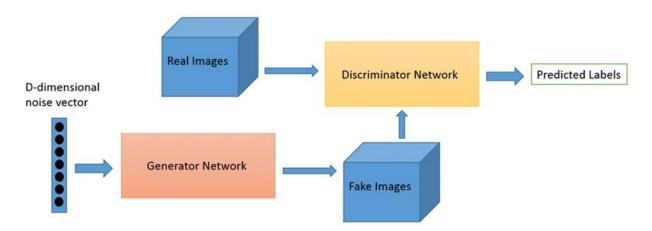


Figure 3. General Architecture of a Generative Adversarial Network (GAN). Adapted from (Alqahtani et al., 2019)

GANs can generate realistic synthetic images, which expand the training dataset—especially useful when real data is scarce. This capability contributes to improving the accuracy of boundary delineation models in agricultural land monitoring.

3.4. Deep Learning Strategies for Agricultural Parcel Boundary Delineation

Deep learning models, spatial data, and satellite imagery act synergistically to improve the accuracy and efficiency of agricultural field boundary detection. Research in this domain can be categorized into four main strategies:

1. Complex Feature Extraction Using CNNs

CNNs, due to their hierarchical structure, can detect spatial and spectral patterns at various levels. This makes them highly effective in delineating fine boundaries of land parcels. However, they may struggle with long-range dependencies and non-local contextual relations—especially in landscapes with similar vegetation types belonging to different parcels. Combining CNNs with LSTM or attention mechanisms can address these limitations and enhance boundary delineation performance ((Adegun et al., 2023), (Teixeira et al., 2023), (Zhang et al., 2020)).

2. Multi-Branch Architectures for Complex Image Analysis

Multi-branch architectures use separate pathways to analyze local, contextual, and textural features, enabling them to better model the complexity of agricultural imagery (Khan & Basalamah, 2023). These models process data at multiple scales and effectively extract boundaries despite object overlap and varying shapes. Fusion mechanisms using attention improve accuracy significantly, especially in noisy or cluttered backgrounds.

3. Multimodal Approaches Using Diverse Data

Integrating various data types (spectral, spatial, biophysical, climatic) provides a more comprehensive view of agricultural landscapes. Such data, often from different sources and resolutions, pose challenges like alignment and spectral matching. Success in this domain relies on models' ability to extract meaningful features from heterogeneous data while minimizing noise and redundancy (Alipour et al., 2023).

4. Accuracy Enhancement Through Attention and Residual Structures

Models using attention mechanisms and residual structures—such as RAANet⁴—achieve high accuracy in land use classification from remote sensing data (Liu et al., 2022). These techniques enable the model to focus adaptively on important regions, improving classification while reducing network complexity. Despite their computational demands, such models are particularly effective in analyzing noisy or asymmetric agricultural plots.

Integrating deep learning models with data-centric frameworks like SDI offers new pathways for developing automated systems in the agricultural cadastre. This contributes significantly to advancing precision agriculture and optimizing land management.

4. Research Methodology

This study is a review and analytical research conducted to examine the role and effectiveness of deep learning models in delineating the boundaries of agricultural land parcels based on satellite imagery analysis and geospatial data, within the framework of Spatial Data Infrastructure (SDI). Drawing on credible scientific sources, the research aims to analyze and explain the application of modern deep learning architectures in land parcel boundary extraction and their contribution to smart agriculture development.

The methodology adopts a descriptive-analytical approach using library and documentary resources. The main focus is on theoretical analysis of the structure of deep learning models, their advantages, limitations, types of input data, performance indicators, and accuracy levels in applications related to precision agriculture and land management. The study particularly examines models such as Convolutional Neural Networks (CNNs), multi-branch frameworks, and models equipped with attention mechanisms.

⁴ Residual ASPP with Attention Net

The research process began with the collection of scientific sources, including peer-reviewed journal articles, technical reports, and empirical findings from prior studies. The selected models were then comparatively analyzed based on criteria such as technical structure, type of data used, relevance to boundary delineation, and performance evaluation metrics. Comparative tables were used to summarize key characteristics and illustrate the differences and similarities among the models.

Three widely used deep learning models for delineating agricultural field boundaries are analyzed in this study:

- Convolutional Neural Networks (CNNs)
- Recurrent Neural Networks (RNNs)
- Generative Adversarial Networks (GANs)

These models were selected based on criteria such as reported accuracy, adaptability to various conditions, availability of training data, and scalability. Due to their broad applicability, successful performance in remote sensing tasks, and interoperability with other architectures, these models were chosen as the central focus of this analysis. In the following sections of the paper, they are examined in the context of the theoretical framework and their integration with SDI.

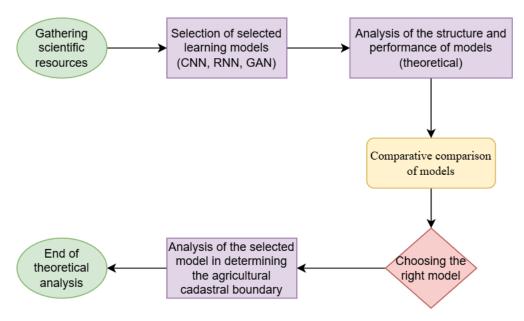


Figure 4. Illustration of the overall workflow of the study, from literature collection to theoretical analysis of SDI and the selected deep learning models.

CNNs have demonstrated remarkable success in satellite image processing tasks, including land boundary detection. They possess strong capabilities for extracting high-level spatial features, making them particularly effective for geospatial data analysis (Liu et al., 2019). In

remote sensing, CNNs have shown robust performance in object representation and have improved scene classification accuracy (Liu et al., 2019).

However, compared to other deep learning models, CNNs have both strengths and limitations. While CNNs are effective in processing local image regions, they often lack the ability to capture contextual dependencies between different parts of the image (Zuo et al., 2015). This is where RNNs can complement CNNs. Designed to learn sequential dependencies, RNNs can be beneficial for encoding spatial relationships in satellite imagery. The integration of CNNs and RNNs, known as Convolutional Recurrent Neural Networks (C-RNNs), has proven successful in learning spatial dependencies across image regions, enhancing object segmentation and boundary detection ((Zuo et al., 2015),(Zuo et al., 2016)).

GANs, on the other hand, offer a different approach to satellite image analysis. Although not directly compared with CNNs for land boundary detection, GANs have been explored in remote sensing to address limited data availability (Logan et al., 2021). GANs are capable of generating synthetic satellite images, potentially expanding training datasets and improving model performance in scenarios where labeled data are scarce.

In conclusion, while CNNs are effective in processing satellite images for boundary detection tasks, their combination with other deep learning architectures, such as RNNs, can yield improved outcomes by capturing both local and contextual information. Model selection should be tailored to the specific task requirements, data availability, and computational resources. Future research may focus on developing hybrid models that leverage the strengths of multiple architectures to optimize satellite image analysis (Teixeira et al., 2023).

Throughout this study, credible academic sources were reviewed to evaluate deep learning models in terms of structure, analytical capabilities, limitations, and suitability for geospatial data in smart agriculture. The findings provide valuable guidance for future research aimed at designing efficient and integrated models within the SDI framework and intelligent agricultural systems.

5. Results

5.1. Analysis of Core Deep Learning Models

Table 1 compares three main deep learning models—Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Generative Adversarial Network (GAN)—in terms of their strengths, limitations, and compatibility with real-world conditions for delineating agricultural land parcel boundaries using satellite imagery and geospatial data:

Table 2. Comparative analysis of CNN, RNN, and GAN deep learning models in terms of strengths, limitations, and real-world applicability for agricultural parcel boundary delineation

Deep Learning Model	Strengths	Limitations	Compatibility with Real-World Conditions
CNN (Convolutional Neural Network)	- High accuracy in extracting spatial and local features from satellite images- Strong performance in precise classification and boundary detection- Stable results with high-resolution data	- Inability to capture contextual and sequential dependencies across image regions- Reduced accuracy when dealing with heterogeneous and variable data- High dependency on labeled datasets	- Suitable for environments with high-quality and relatively uniform data- Less effective for diverse datasets or time-series data
RNN (Recurrent Neural Network)	- Captures temporal and contextual dependencies in sequential and time-series data-Enhances spatiotemporal analysis in satellite imagery- A complementary approach to CNN limitations	- Requires large and well- ordered sequential datasets- High computational complexity and training time- Sensitive to noise and disordered data	- Suitable for applications involving temporally and spatially sequenced data- Less effective in environments with limited or unstructured data
GAN (Generative Adversarial Network)	- Generates realistic synthetic data to augment training datasets- Reduces reliance on labeled data by increasing data diversity- Can improve the quality of hybrid models	- Complex training process requiring careful parameter tuning- Risk of generating unrealistic or inconsistent data if not properly trained- Indirect application in boundary extraction (mainly for data augmentation)	- Effective under conditions of data scarcity, enhancing model generalization- Requires strong computational resources and careful model supervision

5.2. Evaluation of Hybrid Models

Hybrid models, such as C-RNN and CNN-GAN combinations, have also been analyzed for their ability to improve accuracy under diverse conditions, including variations in vegetation types, parcel sizes, and data quality. Results suggest that hybrid models can reduce reliance on labeled data and provide more accurate performance in complex and heterogeneous environments.

5.3. Data Quality and Study Reliability

Given the nature of this study, which is based on a systematic review and comparative analysis of credible research in the field of agricultural parcel delineation using deep learning algorithms, the evaluation and validation process is analytical and grounded in scientific criteria.

The datasets used in the analyzed studies are mainly derived from reputable remote sensing sources such as Sentinel-2, Landsat-8, and high-resolution imagery, contributing to the credibility of the findings. Consequently, the results of this review provide a reliable foundation

for developing intelligent models within Spatial Data Infrastructure (SDI) frameworks for precision agriculture applications.

5.4. Proposed Analytical Framework

By identifying the strengths and limitations of the reviewed models, this study offers an analytical framework for selecting the most appropriate algorithm based on data conditions, land type, and specific goals in agricultural land management systems. This framework may serve as a foundation for future research on the development of localized models within SDI-based smart agriculture environments.

6. Conclusion

In recent years, the application of deep learning in analyzing satellite imagery, especially for the precise delineation of agricultural field boundaries, has witnessed significant growth. Challenges such as landscape heterogeneity, variability in cropping patterns, and the scarcity of labeled data have highlighted the limitations of traditional methods. In response, advanced deep learning models offer promising solutions to overcome these barriers.

Among various approaches, three major deep learning architectures have received the most attention:

Convolutional Neural Networks (CNNs)

Recurrent Neural Networks (RNNs)

Generative Adversarial Networks (GANs)

The following table (Table 2) presents a comprehensive comparison of these architectures, clarifying their strengths, weaknesses, and specialized applications in the context of agricultural remote sensing and boundary extraction.

The combination of spatial data, satellite imagery, and advanced deep learning techniques leads to improved accuracy and efficiency in delineating agricultural land boundaries. This synergy enhances feature extraction, enables better handling of complex landscapes, supports effective data integration, and ultimately yields more reliable results in mapping and monitoring agricultural areas.

Table 3. Comparative Analysis of Deep Learning Models (CNN, RNN, and GAN) in Agricultural Land
Parcel Boundary Delineation Using Satellite Imagery and Geospatial Data

Feature / Criterion	CNN (Convolutional Neural Network)	RNN (Recurrent Neural Network)	GAN (Generative Adversarial Network)
Appropriate Input	Images, especially 2D imagery	Sequential and time-series	Image data, suitable for
Data	such as satellite data	data with temporal dependencies	generating synthetic and augmented data

Feature Extraction Capability	High-level and local feature extraction (e.g., edges, textures)	Temporal and contextual dependency encoding between sequential data	Generation of new data samples similar to real data; data augmentation
Contextual Dependency Modeling	Limited to local features only	Strong; capable of capturing long-term and contextual dependencies	Capable of generating diverse data, but not designed for dependency modeling
Primary Application in Remote Sensing	Scene classification, land boundary extraction, spatial data analysis	Complementary to CNN for modeling spatial/temporal dependencies	Augmentation of training data, generation of high-fidelity synthetic imagery
Limitations	Inability to model extended dependencies within images	Requires structured sequential data; complex training	Challenging training and convergence require quality initial data
Role in Hybrid Architectures	Foundation of image processing; core feature extractor	Complementary component for contextual encoding; enhances CNN models	Enhances data diversity; supports robust training of other models
Implementation in Precision Agriculture	Accurate boundary delineation, vegetation classification, and texture analysis	Temporal-spatial change analysis, contextual encoding across land units	Data synthesis to mitigate the limited labeled samples in agricultural datasets
Computational Requirements	Medium to high (depending on network depth)	High (depending on sequence length and network complexity)	Very high (due to simultaneous training of generator and discriminator)
Future Development Potential	Enhancement via integration with RNNs and other networks	Development of CNN-RNN hybrid models for improved spatial encoding	Advancement of more stable and spatially-aware GAN models for geospatial data

In this study, the roles and applications of deep learning algorithms—specifically CNNs, RNNs, and GANs—in delineating the boundaries of agricultural land parcels using satellite imagery and geospatial data were reviewed. The findings from reviewed studies show that, especially when used in combination, these models have significantly improved boundary detection accuracy compared to traditional and even classical machine learning approaches.

Integrating these models within the Spatial Data Infrastructure (SDI) framework facilitates smart agriculture optimization, land and water resource management, and data-driven planning. Moreover, combining deep learning models with spatial databases can contribute to the development of intelligent decision-support systems in agriculture.

Overall, this research indicates that the development of hybrid, multi-architecture models using multi-source data provides an effective pathway to address current challenges in agricultural boundary delineation within the SDI environment. Future studies are encouraged to focus on lightweight, cost-effective hybrid models that are adaptable to diverse and localized spatial data. Such research directions could significantly contribute to the advancement of smart agricultural infrastructure and sustainable natural resource management.

Based on the comparative analysis, CNNs demonstrate strong performance in extracting local spatial features from satellite imagery, especially in accurately classifying objects and identifying field boundaries. However, their inability to capture global or sequential dependencies across image regions limits their interpretive capacity. RNNs, designed specifically to handle sequential and contextual relationships, effectively address this limitation. The combination of CNN and RNN (i.e., C-RNN) can significantly enhance the accuracy of feature identification in complex and heterogeneous landscapes.

On the other hand, while GANs are not directly designed for boundary extraction, they play a crucial role in augmenting training datasets by generating highly realistic synthetic images. This improves the performance of deep learning models by compensating for the lack of labeled training data.

In conclusion, no single model can be considered the optimal choice in all scenarios, as model selection depends on data characteristics, task requirements, and available computational resources. However, for the specific task of delineating agricultural boundaries using satellite imagery, C-RNN models—combining the spatial strength of CNNs with the contextual awareness of RNNs—stand out as a balanced and effective approach. In parallel, the use of GANs as a complementary tool for training data enhancement can further boost the performance of such hybrid models.

Thus, a forward-looking strategy in this domain involves the development and implementation of multi-stage, hybrid models that integrate deep learning, data generation, and advanced geospatial analysis into a unified framework.

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Integration of UAV Photogrammetric Data and SDSS: An Innovative Approach for Environmental Hazard Management in Iran

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Abstract

The increasing frequency of environmental hazards such as floods, landslides, earthquakes, and wildfires has highlighted the need for innovative risk management solutions, particularly in countries with diverse climates like Iran. This study aims to explore the potential for integrating UAV-based photogrammetry technology with Spatial Decision Support Systems (SDSS) to improve environmental hazard management processes. The methodology is both review-based and analytical, involving a systematic review of reputable domestic and international scientific sources from 2015 to 2023, and a comparative analysis of the application of these technologies in Iran and other countries. Findings show that integrating precise UAV data with the analytical capacities of SDSS can play a significant role in the stages of hazard identification, prediction, and impact mitigation. This combination, leveraging machine learning algorithms, significantly enhances real-time analysis capabilities, crisis scenario modeling, and prioritization of high-risk areas. However, challenges such as high costs, legal restrictions on UAV flights, and a shortage of skilled personnel remain significant barriers to practical implementation in Iran. Ultimately, the study emphasizes the necessity of developing localized frameworks, specialized training, and supportive policies to effectively utilize these technologies.

Keywords: UAV, Spatial Decision Support Systems (SDSS), Machine Learning, Risk Management

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1. Introduction

Environmental hazards, including floods, earthquakes, landslides, wildfires, and climate change, pose increasing threats to human communities, infrastructure, and natural ecosystems. According to a United Nations report, natural disasters over the past two decades have caused damages exceeding \$1.5 trillion and affected more than 1.3 billion people (UNDRR, 2020). These hazards not only lead to economic and human losses but also threaten environmental sustainability through intensified climate change and the degradation of natural resources. In Iran, its geographical location along the Alpine-Himalayan seismic belt, diverse climate conditions, and increasing pressure on natural resources make it one of the world's high-risk regions (Zare et al., 2019). For example, the devastating floods of 2019 in Golestan, Lorestan, and Khuzestan provinces caused widespread damage to infrastructure and agriculture, emphasizing the urgent need for advanced tools to manage such hazards (Rahimi et al., 2020).

Effective environmental hazard management requires the collection of accurate data, advanced spatial analysis, and evidence-based decision-making. In recent decades, geospatial technologies such as photogrammetry and Spatial Decision Support Systems (SDSS) have attracted attention due to their ability to process complex data and provide practical solutions (Keenan & Jankowski, 2019). Photogrammetry, a method for extracting 3D information from 2D images, enables high-quality data collection from remote or hazardous areas through UAVs (Gomez & Purdie, 2016). This technology helps identify hazard-prone areas and assess damage by producing accurate 3D models. On the other hand, SDSS, using Geographic Information Systems (GIS) and spatial analysis, facilitates data-driven decision-making for planning and emergency response (Singh et al., 2023). Integrating these two technologies can lead to unified frameworks for hazard management, where UAV data serve as inputs for SDSS analyses.

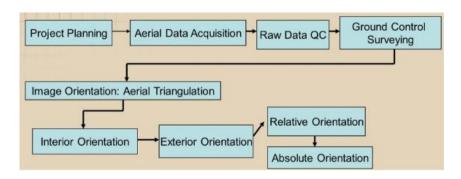


Figure 1. Photogrammetry process (generating imagery or digital elevation models)

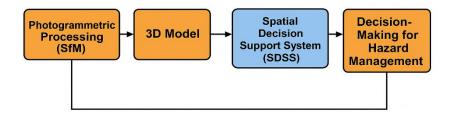


Figure 2. Conceptual process of integrating UAV photogrammetric data with SDSS in environmental hazard management

Despite recent advances, integrating photogrammetry and SDSS in environmental hazard management still faces scientific challenges and gaps. Many existing studies focus on the separate application of these technologies, but integrated frameworks that utilize both simultaneously—especially in disaster management—remain limited (Ekiyama et al., 2020). In Iran, this scientific gap is even more pronounced due to the lack of localized studies that consider the country's unique geographical, climatic, and infrastructural conditions (Hosseini et al., 2018). For example, while UAV data has been used in assessing the damage from the Bam and Kermanshah earthquakes, the absence of an integrated SDSS for analyzing this data has reduced the overall efficiency of these technologies (Zare et al., 2019; Hosseini et al., 2018). Furthermore, practical challenges such as high equipment costs, lack of technical expertise, and legal restrictions on UAV flights have limited widespread adoption of these technologies in developing countries like Iran (Mohammadi et al., 2021).

In recent years, the development of machine learning and artificial intelligence algorithms has significantly enhanced the capability to analyze complex and large-scale UAV data. Algorithms such as Random Forest, Support Vector Machine, and Artificial Neural Networks have enabled accurate land use classification, detection of environmental changes, and hazard prediction (Zhu et al., 2017; Li et al., 2020). Integrating these algorithms with SDSS can lead to smarter decision-making and faster crisis response. Additionally, the development of advanced multispectral and thermal sensors on UAVs has improved the ability to detect thermal hotspots, vegetation cover changes, and early signs of landslides or wildfires (Colomina & Molina, 2014). These advancements not only improve the accuracy of input data for SDSS but also enable real-time modeling for critical scenarios. Consequently, there is an increasing need for data-driven frameworks capable of operationally integrating the analytical capabilities of UAVs and SDSS, particularly in countries like Iran with diverse geography and climate.

The importance of this integration is amplified in Iran due to the diversity and intensity of environmental hazards. Frequent earthquakes, seasonal floods, wildfires in the Zagros region, and landslides in the Central Alborz are only some of the challenges that demand innovative solutions (Yousefi et al., 2022). These technologies can assist by generating precise maps and predictive analyses, thus contributing to damage reduction, improved crisis response, and protection of fragile ecosystems. However, the lack of operational frameworks for integration and the absence of international collaboration for knowledge transfer remain key barriers

(USDA, 2018). This study aims to explore the potential of integrating photogrammetry and SDSS and to offer solutions for overcoming these challenges.

In addition to the increasing technological possibilities, public policy and community engagement play an essential role in the successful integration of UAV and SDSS in environmental management. For instance, Japan's disaster risk reduction framework emphasizes community participation alongside advanced geospatial technologies (Okazaki & Nakasu, 2015). Similarly, integrating citizen-generated data through mobile platforms with SDSS could complement UAV data, creating hybrid models for rapid assessment. These participatory approaches enhance situational awareness, particularly in developing countries where governmental response capacities may be limited.

Research Questions:

- 1. How can photogrammetry and SDSS be effectively integrated into environmental hazard management?
- 2. What are the challenges and opportunities associated with UAV data usage in Iran?
- 3. How can these technologies be utilized for managing specific hazards in Iran, such as floods and earthquakes?

2. Literature Review

In recent decades, the increasing intensity and frequency of environmental hazards such as floods, droughts, landslides, and forest fires have prompted researchers and policymakers to seek accurate and technological solutions for monitoring, analyzing, and managing these phenomena. One of the most significant developments in this area is the emergence of UAV (drone) technology and its widespread application in remote sensing and photogrammetry. These tools, capable of capturing high-resolution spatial data, have rapidly replaced many traditional methods and enabled more accessible high-precision mapping, 3D modeling, and environmental index extraction (Gomez & Purdie, 2016).

On the other hand, Spatial Decision Support Systems (SDSS), with their capabilities for multicriteria analysis, scenario modeling, and integration of spatial and temporal data, have emerged as effective tools in natural resource management and response to environmental crises. Various studies have shown that integrating UAV data with the analytical capabilities of SDSS can make the decision-making process more accurate, faster, and evidence-based (Shi et al., 2019; Baghestani et al., 2025)

For instance, a project at West Virginia University aimed to use UAV data in designing decision-support models for assessing environmental hazards. The results demonstrated a significant improvement in the accuracy of predictions and spatial analyses (West Virginia University, 2023). In another study, Srivastava et al. (2022) utilized UAV-based photogrammetry to monitor forest biophysical parameters such as tree height and canopy

density, and their findings confirmed the high accuracy of this technology in environmental studies.

Additionally, Rahman et al. (2023) used UAV data to estimate the population of Sumatran elephants, showing that this method is an effective and low-cost alternative to traditional endangered species census techniques. In agriculture, the use of SDSS alongside multispectral UAV data led to optimized water usage and increased crop productivity (Shi et al., 2019).

Recent studies have highlighted the application of UAV-based photogrammetry in post-disaster urban planning. For example, in the aftermath of the 2020 Beirut explosion, UAVs were employed to rapidly assess damage and plan for infrastructure recovery (Hosseini et al., 2021). Moreover, in flood-prone regions of Bangladesh, community-based UAV deployment strategies have shown that local pilots, trained with minimal investment, can gather critical geospatial data. This approach reduces dependency on external expertise and fosters resilience at the community level (Ahmed et al., 2020).

Furthermore, integration of UAV data into cloud-based SDSS platforms, such as Google Earth Engine or ArcGIS Online, enables collaborative data sharing among agencies, enhancing coordination during emergency response. These tools are especially useful in multi-agency contexts where timely data access is critical.

Collectively, these studies underscore the importance of integrating modern technologies such as UAV photogrammetry and spatial decision support systems in the sustainable management of environmental hazards, providing a scientific foundation for the present research.

3. Methodology

This research adopts a review-based approach, aiming to analyze scientific and practical resources related to the topic. Sources were selected from reputable scientific databases such as Springer, PubMed, ScienceDirect, and Civilica (for Persian resources). Selection criteria included:

- Direct relevance to photogrammetry, SDSS, or UAV data.
- Focus on environmental hazard management or related fields like disaster and natural resource management.
- Scientific credibility (published in reputable journals or by recognized institutions).
- Inclusion of localized studies in Iran to ensure relevance to national conditions.
- Recency (sources mostly post-2015).

To ensure comprehensiveness, a mix of scientific articles, project reports, and expert web pages was reviewed. Ultimately, 20 key sources were selected for their coverage of both global and local aspects of the subject. The analysis was conducted qualitatively and comparatively to identify strengths, weaknesses, and research gaps.

4. Results and Discussion

4.1. Capabilities of UAV Photogrammetry in Disaster Monitoring and Assessment

One of the key advantages of UAV-based photogrammetry is its ability to produce high-precision 3D maps. Using techniques like Structure from Motion (SfM), it generates highly detailed 3D models of terrain features (Westoby et al., 2012; Gomez & Purdie, 2016). These models are especially valuable for identifying high-risk areas such as unstable slopes and low-lying flood-prone zones. In Iran, this technology has been used in earthquake-affected areas like Kermanshah for precise damage mapping (Hosseini et al., 2018).

Moreover, UAV data can generate spatiotemporal time series, revealing gradual trends such as soil erosion, landslides, and unauthorized construction. This information can be highly effective in prioritizing recovery and relief actions.

4.2. Role of Spatial Decision Support Systems (SDSS) in Analysis and Decision-Making

SDSS integrates spatial data, analytical tools, and decision-support models to facilitate complex crisis scenario analysis (Jankowski & Nyerges, 2001). Within SDSS, multi-criteria decision-making methods like AHP and fuzzy analysis are used to prioritize high-risk areas. For instance, Rahimi et al. (2020) used SDSS in the Gorganrud watershed to provide more accurate flood forecasts. This tool can combine indicators such as slope, rainfall patterns, vegetation type, and population density in models that support critical decision-making.

4.3. Synergy Between Photogrammetry and SDSS in Environmental Hazard Management

Combining UAV data with SDSS capabilities leads to powerful systems for hazard identification, prediction, and mitigation. This integration can utilize real-time data to forecast future crisis scenarios (Singh et al., 2023). The successful experiences of countries like Japan and Indonesia in concurrently using these technologies highlight their effectiveness in improving disaster response (Ekiyama et al., 2020). In Iran, the joint application of these technologies has been proposed for earthquake assessment in Bam and wildfire monitoring in the Zagros region (Mohammadi et al., 2021; Zare et al., 2019).

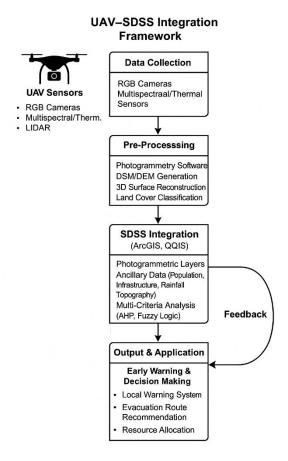


Figure 3. Conceptual Model of UAV-SDSS Integration Framework in Environmental Hazard Management

4.4. International Case Studies in UAV and SDSS Integration

Several countries have successfully implemented integrated UAV-SDSS systems for disaster management. In Indonesia, UAVs are now used as a standard tool for early detection of volcanic activity around Mount Merapi. The real-time imagery is fed into a centralized SDSS platform that models potential lava flow and affected population zones (Nugroho et al., 2022).

In the U.S., the Federal Emergency Management Agency (FEMA) uses UAV-SDSS integration for flood mapping and evacuation route optimization, with cloud-based access provided to local responders. In Turkey, the AFAD (Disaster and Emergency Management Authority) uses machine learning-enhanced UAV-SDSS platforms to predict landslide risks in mountainous regions (Korkmaz & Gokceoglu, 2019).

Table 1. Applications, Challenges, and Opportunities of Photogrammetry and SDSS in Environmental Hazard Management

Technology	Application	Advantages	Challenges	Future Opportunities
Photogrammetry	Earthquake and flood mapping	High accuracy; access to hard-to- reach areas	High cost; weather condition impact	Early warning systems
SDSS	Flood prediction, wildfire management	Advanced spatial analysis	Lack of technical expertise; need for accurate data	Integration with artificial intelligence

4.5. Main Challenges in the Implementation of These Technologies in Iran

The implementation process of these technologies is accompanied by challenges such as high costs for purchasing UAVs, specialized software, and computing infrastructure (González et al., 2020). In addition, legal restrictions on UAV flights in certain areas constitute one of the main obstacles to their development (Mohammadi et al., 2021). The lack of skilled human resources is another serious challenge that limits the effective use of these technologies. Under adverse weather conditions or in areas with dense vegetation, the accuracy of photogrammetric data decreases (Bichou et al., 2019).

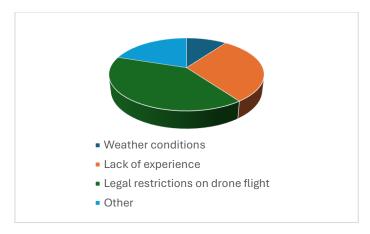


Figure 4. Percentage Distribution of the Main Challenges in the Implementation of UAV and SDSS

Technologies in Environmental Hazard Management in Iran

4.6. Emerging Opportunities Through the Integration of Novel Technologies

Advancements such as multispectral and thermal sensors on UAVs have increased the capability to identify thermal hotspots, changes in vegetation cover, and early signs of crises (Colomina & Molina, 2014). Additionally, machine learning algorithms such as Random Forest, SVM, and CNN have enabled the automated analysis of large-scale UAV data (Zhu et al., 2017; Li et al., 2020). Integrating these algorithms with SDSS can operationalize early warning systems, real-time monitoring, and behavioral prediction for critical environments in Iran.

5. Conclusion

This research has shown that integrating UAV-based photogrammetry with Spatial Decision Support Systems (SDSS) offers an innovative and efficient approach for managing environmental hazards. By generating highly accurate 3D maps and advanced spatial analyses, these technologies enable the rapid identification of high-risk areas, hazard prediction, and the formulation of protective plans. In Iran, which faces numerous challenges such as floods, earthquakes, and wildfires, these tools can play a key role in reducing both human and financial losses. For example, the use of UAV data in assessing earthquake damage in affected regions and managing wildfires in vulnerable areas demonstrates the high potential of these technologies under local conditions.

However, challenges such as high equipment costs, a shortage of technical expertise, and legal restrictions on UAV flights remain significant obstacles. Overcoming these challenges requires investment in the development of cost-effective technologies, training of specialists, and reform of existing regulations. This study emphasizes the need to establish integrated frameworks for the effective use of these technologies. Ultimately, the integration of photogrammetry and SDSS not only supports sustainable environmental hazard management but also, by strengthening early warning systems and protecting ecosystems, paves the way for a safer future for communities—especially in high-risk areas such as Iran.

In addition to the key findings of this study, it is important to situate these results within an international perspective. Countries such as Japan, Indonesia, and the United States have demonstrated the successful integration of UAV and SDSS through structured regulatory frameworks, strong institutional capacity, and active public-private partnerships (Ekiyama et al., 2020). In comparison, Iran's use of these technologies remains primarily exploratory and limited to academic or pilot-level applications.

A critical observation is the absence of real-world experimental testing of UAV-SDSS integration in Iran's hazard-prone regions. To validate the conceptual models discussed, pilot projects should be conducted in vulnerable zones such as the Gorganrud floodplain, Kermanshah earthquake-prone zones, or Zagros wildfire corridors. These field trials would provide valuable feedback for refining operational models and tailoring decision-support tools to local realities.

Moreover, the current frameworks often focus heavily on geospatial data and overlook sociodemographic factors that are crucial in effective disaster response. Including population density, access to infrastructure, age distribution, and economic vulnerability in SDSS layers can significantly improve the accuracy and fairness of hazard mitigation planning.

From a governance perspective, the institutionalization of UAV-SDSS systems requires the formation of interdisciplinary expert teams, capacity-building programs, and the establishment of centralized environmental intelligence platforms. These systems should be connected with real-time data repositories, integrate citizen reports, and support multi-agency coordination.

Therefore, future research should prioritize the development of hybrid models that integrate remote sensing data, ground-level information, and artificial intelligence into adaptive, predictive, and participatory systems for disaster risk management.

Recommendations:

To better utilize these technologies, the following recommendations are proposed:

- 1. **Develop cost-effective technologies:** Design more affordable UAVs and software to improve access for developing countries like Iran.
- 2. **Training and capacity building:** Organize training courses for specialists in photogrammetry, SDSS, and UAV data processing.
- 3. **Formulate supportive regulations:** Facilitate UAV flight regulations for environmental applications and disaster management.

4. Future Research:

- Conduct case studies in various regions of Iran, such as northern watershed basins or seismically active areas.
- Explore the application of artificial intelligence in analyzing UAV data for hazard prediction.
- 5. **International Collaborations:** Leverage global experiences, such as USDA projects, to develop localized technologies.

Future Opportunities:

The integration of UAV-based photogrammetry and SDSS is poised for further expansion through convergence with other emerging technologies and innovative governance models. The following opportunities highlight the future direction of these systems in environmental hazard management, especially within the Iranian context:

1. Integration with Internet of Things (IoT):

The deployment of sensor networks (e.g., river gauges, weather stations, seismic sensors) in combination with UAVs and SDSS can create smart, interconnected early warning systems. These IoT-enabled platforms can automatically trigger UAV flights upon detecting anomalies, such as sudden rises in water level or seismic activity, allowing real-time data collection and rapid modeling.

2. Use of Cloud Computing and Edge AI:

Cloud-based platforms like Google Earth Engine or Amazon Web Services allow for large-scale, collaborative analysis of UAV data. In parallel, Edge AI – running machine learning models directly on UAVs – reduces reliance on internet connectivity and enables real-time decision-making in remote or rural disaster zones (Zhu et al., 2017).

3. Participatory Disaster Mapping:

Engaging local communities through mobile apps that collect geo-tagged photos and field observations complements UAV imagery. Combining citizen science with SDSS can strengthen situational awareness and accelerate emergency responses, particularly in low-resource settings (Ahmed et al., 2020).

4. Automated Multi-Hazard Prediction Systems:

By combining meteorological, hydrological, geological, and remote sensing data, next-generation SDSS can simulate multi-hazard interactions, such as landslides triggered by earthquakes or floods following dam failures. UAV-derived high-resolution terrain models improve the spatial accuracy of these simulations.

5. Customized Early Warning Systems for Rural Areas:

In rural and high-risk zones like the Zagros and Alborz regions, localized UAV-SDSS frameworks can provide targeted alerts via SMS, local radio, or community centers. These alerts can be tailored based on terrain, accessibility, population density, and infrastructure vulnerability.

6. Climate Change Adaptation and Monitoring:

Long-term UAV monitoring allows the tracking of ecosystem degradation, glacier retreat, desertification, and coastline shifts. These data sets, integrated into SDSS, support national adaptation planning and international reporting obligations (e.g., for the Paris Agreement).

7. National-Level Environmental Intelligence Platforms:

By integrating data from satellites, UAVs, IoT sensors, and public reports, Iran could develop a centralized, AI-powered "Environmental Intelligence Platform" that continuously monitors hazards, forecasts risks, and advises policymakers in real-time.

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Values, Beliefs, and Norms in Modal Shift: The Role of Environmental Attitudes Under Demand Management Policies

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Abstract

This study examines how individuals' values, beliefs, and norms influence their responses to demand management policies targeting private vehicle use. Specifically, it investigates the impact of these latent variables on shifts in travel mode choice from private cars to public transit under a zonal pricing policy. A comprehensive survey was administered to 500 residents of Tehran's "air pollution control zone". Findings indicate that individuals with stronger environmental concerns and biospheric values were more likely to switch to public transit following the implementation of zonal pricing, whereas those with more pronounced hedonic values continued to rely on private vehicles both before and after the policy. Socioeconomic characteristics were also found to be significant. Individuals holding either a high school diploma or a master's degree were more inclined to use public transit after providing the scenarios. Trip purpose influenced travel behavior, with those traveling for personal errands or shopping more likely to use private vehicles regardless of the policy. Overall, the results suggest that zonal pricing, as a demand management strategy during periods of environmental concern, can be an effective tool for reducing private vehicle use, particularly when accounting for the interplay between environmental values, socioeconomic factors, and travel purposes.

Keywords: Environmental Concerns, Modal Shift, Transportation Demand Management, Tehran, Value-Belief-Norm

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1. Introduction

Rapid urban development has intensified challenges in transporting people and goods, with growing complexities in meeting mobility needs. Urban expansion has increased travel demand, often outpacing the capacity of existing transportation infrastructure. In recent decades, community livability has declined and economic growth has been hindered due to the uncontrolled rise in motorized vehicle use, leading to traffic congestion, environmental degradation, and other associated threats (De Vos, 2016).

Transportation demand management (TDM) has emerged as a key strategy to enhance the efficiency of urban transport systems by discouraging unnecessary private vehicle use and promoting healthier, more efficient, and environmentally sustainable alternatives, such as public transit and non-motorized modes (Mahpour and Saeedi Shahrivar, 2022). Within TDM, pricing policies can target specific areas, facilities, network links, or employ mixed approaches (Lindsey, 2003). Evidence suggests that measures such as improved traffic conditions, enhanced environmental quality, and better public transport performance can increase public acceptance of congestion pricing, particularly when implemented transparently (Ahadi et al., 2018; Glavic et al., 2017; Cipriani et al., 2018).

Improving environmental quality is directly related to shifts in public attitudes and behaviors toward sustainability. Greater engagement with environmental issues can foster the adoption of cleaner, more sustainable transport modes and reduce reliance on private vehicles (Gkargkavouzi et al., 2019). Previous studies indicate that individuals with stronger environmental values view the damage caused by vehicle use as a moral concern and are more willing to support policies aimed at reducing car dependence (Jakovcevic and Steg, 2013). These moral considerations, which can encourage lower vehicle use and promote better environmental conditions, are referred to as environmentally friendly behaviors (Miller et al., 2014).

In the present study, the variables of the value-belief-norm (VBN) theory, which are based on environmentally friendly activities, values, and beliefs (Stern, 2000), were applied as latent variables to assess individuals' environmental attitudes toward reducing private vehicle use. The present study also incorporates socioeconomic characteristics and travel-related factors. This approach was applied in a case study evaluating the effectiveness of a zonal pricing policy as a transportation demand management measure in Tehran, Iran.

2. Literature Review

The most recent report issued by the International Energy Agency (IEA) indicated that the level of carbon dioxide pollutant emitted by combusting fuel reached 31.86 Gtons in 2018, around 27% of which was related to the transportation sector (Akbari et al., 2020). Grelier and Engineer introduced motorized vehicles as the origin for 72% of the surface pollution caused by the transportation sector in Europe during 2015 (Grelier and Engineer, 2018). Tehran is no exception: a report released in 2019 by the Tehran Air Quality Control company revealed that

only 29 days (8%) were considered "clean" in the metropolis during that year (Mahpour et al., 2024).

The share of mobile and stationary sources in pollutant creation, and consequently air pollution, was 83% and 17%, respectively. Since personal vehicles produce the central part of the pollutants caused by the transportation sector, mode choice for traveling can be considered environmentally friendly behavior due to its potential effect on the environment, the health and the quality of life of individuals (Van der Werff and Steg, 2016). Thus, the level of valuing the environment by individuals, and their willingness to enhance environmental conditions, can be assessed in the structures called environmentally friendly attitudes.

In the present study, environmentally friendly attitudes and behaviors were examined by applying VBN theory based on the theory's criteria to evaluate individuals' environmental attitudes. In addition, value orientations, including biospheric, altruistic, egoistic, and hedonic groups, were proposed in the previous research as the first part of the chain of the theory (Kiatkawsin and Han, 2017; Nordfjærn and Fallah Z, 2017; Hiratsuka et al., 2018; Unal et al., 2019). The individuals having deep concerns about environmental conditions, such as air pollution and global warming, are those with a stronger belief in biospheric value. Further, those who are deeply concerned about the needs and social welfare of other individuals believe in altruistic values more strongly than others. Both of the values mentioned above are positively related to the environmental condition (Annika and Garvill, 2003; Cleveland et al., 2005).

Along with the aforementioned values, other values are available with a stronger belief in maintaining personal benefits, the nature of which implies personal ethics and hedonism (Unal et al., 2019). These values are known as hedonic and egoistic and are negatively related to environmental ones (Steg et al., 2014b). In the structure of VBN theory, there is a branch of beliefs representing individuals' environmental concerns, which is named the new environmental paradigm (NEP) (Dunlap et al., 2000). The NEP indicates any relationship between humans and the environment in the form of a worldview on the issues. Further, it demonstrates how humans consider themselves as a part of the environment or believe in their dominance over the environment (e.g. Mahpour et al., 2022a; Mahpour et al., 2022b; Unal et al., 2019). The NEP obtained by value orientations predicts another branch of environmental beliefs, known as the awareness of consequences (AC) (Kiatkawsin and Han, 2017). AC refers to individuals' awareness regarding the effect of their behavior on the environment. Researchers found that the AC appeared for the environment through travel mode choice. Feeling the responsibility for the consequences of transportation choices led to a moral commitment. This, in turn, influenced people to be more accepting of transportation plans that included a car-use toll approach (de Groot and Steg, 2009).

Based on the results of the studies in the field of VBN theory, various cultures and beliefs in different countries significantly affect individuals' attitudes towards environmental crises. For example, a study conducted in Russia concerning the environmental attitudes and beliefs of individuals showed an indirect relationship between the acceptability of personal vehicle use

with biospheric values and NEP attitudes. However, a direct relationship was observed between individuals' altruistic values, AC of the effective behaviors on the environment, and individual support for the policy (Unal et al., 2019). Developing and performing VBN theory-related research in Argentina indicated that biospheric, altruistic, and egoistic values are indirectly related to the policies encouraging a reduction in personal vehicle use. However, there was a direct relationship between individuals' altruistic values, AC of the behaviors influencing the environment, and individual support for the policy (Jakovcevic and Steg, 2013). Based on the results of a study that evaluated individuals' environmental beliefs using VBN theory in six urban zones in Norway and transportation mode selection, environmental values and beliefs explain 58% of the variance of personal norms (Lind et al., 2015).

The promotion and development of environmentally friendly transportation was studied by examining individual values in VBN theory through structural equation modeling in Norway during 2019. This study confirmed the significant effect of environmental beliefs on the success of plans for decreasing personal car use and developing nonpolluting transportation (Nordfjærn and Rundmo, 2019). Furthermore, some studies assessed the reduction of vehicle utilization and sustainable transport development under environmental beliefs based on VBN theory criteria in other countries. The results obtained by distributing questionnaires among Chinese drivers indicated that the perceived norms and attitudes significantly affect making decisions to use personal vehicles (Mahpour et al., 2017; Mamdoohi et al., 2016).

3. Methodology

This study employed data from a comprehensive survey conducted in parts of Tehran, Iran, where zonal pricing policies are already implemented. In the present study, environmental attitudes from VBN theory, along with socioeconomic variables, were considered to identify the changes in travel mode under the zonal pricing policy in Tehran. In this regard, the results related to latent environmental variables were provided by using confirmatory factor analysis. A discrete choice model was then developed by quantifying socioeconomic variables as the latent variables. This was done in conjunction with considering the information obtained about individuals' travel modes to examine the effects of pricing policies. Figure 1 displays the VBN theory structure applied in this study (Mahpour et al., 2025a).

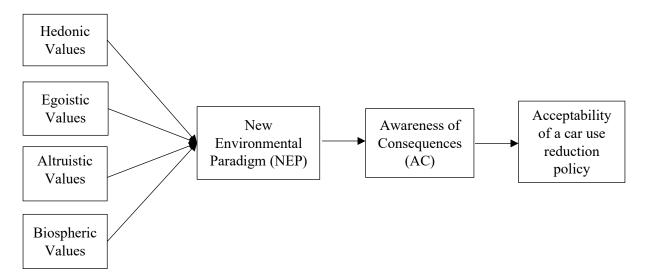


Figure 1. VBN Theory structure in the current study

After examining the results related to factor analysis and quantifying the latent environmental variables, a discrete choice model was created using multinomial logistic regression. This model was developed using environmental variables, as well as individuals' demographic and socioeconomic characteristics, and travel information.

In order to evaluate the changes in individuals' travel mode under the zonal pricing policy, the effects of each group of explanatory variables (i.e., environmental latent variables and individuals' characteristics) on dependent variables were separately examined by implementing confirmatory factor analysis and quantifying the latent variables. Figure 2 displays the final integration of models.

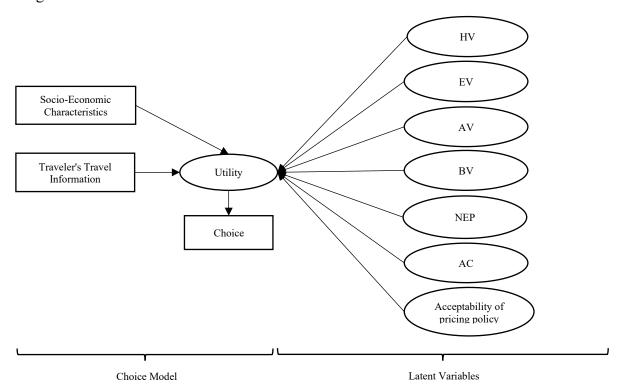


Figure 2. Latent Variable (VBN Theory) and Integrated Choice Model Framework in the current study

4. Data Collection

Tehran, with a population of around 9.1 million and an area of 700 km², consists of 22 municipal districts and 650 traffic zones. Every day, approximately 19 million travel trips are conducted, of which 52.4% are compulsory trips (Mahpour et al., 2018). The data collection occurred by distributing a questionnaire among the individuals residing in parts of Tehran known as "air pollution control zones." The traffic congestion and air pollution control zones are located in the central parts of Tehran. These zones were formerly known as the "odd-even plan." Based on the previous plan, vehicles could travel in these restricted zones according to the last number on their plate. Thus, those with even numbers could travel in the restricted zones only during even days (Saturday, Monday, and Wednesday), and those with odd numbers could travel only during odd days (Sunday, Tuesday, and Thursday). In the new plan, private vehicles are allowed to enter the zones 20 times in a season. Additionally, they must pay a certain fee for traveling within the air pollution control zone if the number exceeds the maximum of 20. The traffic congestion zone is a smaller region within the air pollution control zone, and vehicles must also pay a certain fee each time they travel within that zone. Fig. 3 represents the air pollution control and traffic congestion zones.



Figure 3. Air Pollution Control Zones (No. 1) and Traffic Congestion Zones (No. 2) in Tehran (Baghestani et al., 2025c)

The questionnaire consisted of six parts. The objectives of the study and confidentiality of information were explained to the individuals before proceeding. In the first part, two questions were asked: "Have you traveled to the traffic congestion zone in the last week?" and "Have you traveled to the air pollution control zone during the recent week?" The second part asked participants about their environmental values and attitudes. In this section, twelve values were grouped under the titles of hedonic, egoistic, biospheric, and altruistic. Participants were asked

to calculate a value orientation index by using a nine-point Likert scale ranging from 1 (strongly against my values) to 7 (strongly aligned with my interests). Additionally, fifteen NEP-related phrases referring to the individuals' attitudes and beliefs towards the environment, five questions regarding individuals' awareness of the consequences of their behavior on the environment, and five questions about the acceptability of the plan for reducing private vehicle use were provided. The latent variables, items, and their sources in the present study are presented in Table 1.

Table 1. Latent variables and indicators

Row	Latent Variable	Indicator	Items	Reference
	Hedonic Values	Hv1	1- Pleasure	
1	(HV)	Hv2		
	(111)	Hv3	3- Self-indulgence	
		Ev1	1- Social power	
	E:-4:- V-l	Ev2	2- Wealth	
2	Egoistic Values	Ev3	3- Authority	
	(EV)	Ev4	4- Influentiality	(Steg et al.,
		Ev5	5- Ambition	2014b, de
		Av1	1- Equality	Groot et al., 2008, Steg et
2	Altruistic Values	Av2	2- A world at peace	al., 2014a)
3	(AV)	Av3	3- Social justice	
	()	Av4	4- Helpfulness	
		Bv1	1- Respecting the earth	
4	Biospheric Values	Bv2	2- Unity with nature	
4	(BV)	Bv3	3- Protecting the environment	
	(21)	Bv4	4- Preventing pollution	
	New	Nep1	1- We are approaching the limit of the number of people the Earth can support.	
5	Environmental Paradigm	Nep2	2- Humans have the right to modify the natural environment to suit their needs.	(Dunlap et al., 2000)
	(NEP)	Nep3	3- When humans interfere with nature, it often produces disastrous consequences.	

Row	Row Latent Variable Indicator Nep4		Items	Reference
			4- Human ingenuity will ensure that we do NOT make the earth unlivable.	
		Nep5	5- Humans are severely abusing the environment.	
		Nep6	6- The Earth has plenty of natural resources if we just learn how to develop them.	
		Nep7	7- Plants and animals have as much right as humans to exist.	
		Nep8	8- The balance of nature is healthy enough to cope with the impacts of modern industrial nations.	
		Nep9	9- Despite our special abilities, humans are still subjected to the laws of nature.	
		Nep10	10- The so-called "ecological crisis" facing humankind has been greatly exaggerated.	
		Nep11	11- The Earth is like a spaceship with minimal room and resources	
		Nep12	12- Humans are meant to rule over the rest of nature.	
		Nep13	13- The balance of nature is very delicate and easily upset	
		Nep14	14- Humans will eventually learn enough about how nature works to be able to control it.	
		Nep15	15- If things continue on their present course, we will soon experience a major ecological catastrophe.	
		Ac1	1- Using a car causes the exhaustion of scarce resources such as oil	(Jakovcevic
6	Awareness of Consequences (AC)	Ac2	2- Using a car takes up a lot of space, resulting in less space for cyclists, pedestrians, and children.	and Steg, 2013; de Groot et al.,
		Ac3	3- Using a car is an important cause of traffic- related accidents	2008)

Row	Latent Variable	Indicator	Items	Reference
		Ac4	4- Using a car reduces the urban quality of life due to traffic noise and odor nuisance.	
		Ac5	5- The level of air pollution decreases by reducing car use	
		Acpl	1- I would protest against it	
	Acceptability	Acp2	2- I would resign myself to do it	
7	of Car Use	Acp3	3- I would accept it	(de Groot et
	Reduction Policy (ACP)	Acp4	4- I would feel that the policy was unfair to me	al., 2008)
		Acp5	5- I would agree with it	

In the third part, the respondents were requested to consider their last travel into the air quality control zone. The questions were related to travel purpose, mode, origin, and final destination. Participants were asked about average out-of-pocket costs (while not using private vehicles), as well as the existence of a travel companion, the start and end times of their travel, and the duration of their presence in the zone. The pricing scenarios were offered in the fourth part to evaluate the willingness of individuals to pay these fees for entering the air pollution control zone. In this study, the amounts set for entering the traffic congestion zone based on the different hours of the day in 2016 were applied to provide pricing limits in order to assess the sensitivity of the respondents to various fees, as well as their tendency to travel in the air pollution control zone. Then, a 10-90% increase was added to the base fees in each type of pricing to evaluate individuals' willingness to pay and enter into the air pollution control zone while increasing the level of pollutants. Therefore, sixteen pricing scenarios proposed in the different hours of the day were applied as the policy for pricing the air pollution control zone. This was done in order to examine the tendency of the individuals to pay the intended fees. Table 2 summarizes the final percentages added to the base fees of the 2016 traffic plan as pricing scenarios in this case study.

Table 2. Pricing scenarios in the present study

Type 1 (Enter from 6:30 AM-10:00 AM)	Prices (Iranian Rial)
10%	343,200ª
20%	374,400
30%	405,600

50%	468,000
Type 2 (Enter from 10:00 AM-2:00	Prices (Iranian
PM)	Rial)
10%	257,400
25%	292,500
50%	351,000
75%	409,500
Type 3 (Enter from 2:00 PM-6:00	Prices (Iranian
PM)	Rial)
10%	165,000
25%	187,500
50%	225,000
75%	262,500
100%	300,000
Weekly License (Check in at all	Prices (Iranian
hours)	Rial)
10%	1,100,000
25%	1,250,000
50%	1,500,000

^a 1 US Dollar equals approximately 900,000 Iranian Rial

In the fifth part, respondents were requested to determine the frequency of using different travel modes (more than 7 times in a week, 4-7 times in a week, 1-3 times in a week, 1-3 times in a month, 4-8 times in a year, and less than 4 times in a year). The final part of the questionnaire included questions related to socioeconomic and demographic characteristics. Table 3 provides a summary of these variables.

Table 3. Summary of socioeconomic variables in the present study (sample size= 500)

Variable	Category	Cumulative Frequency	Relative Frequency (%)
Gender	Female	213	42.6
Gender	Male	287	57.4
Age	18-24	80	16.0

Variable	Category	Cumulative Frequency	Relative Frequency (%)
	25-34	157	31.4
	35-44	135	27.0
	45-54	76	15.2
	55-64	42	8.4
	+65	10	2.0
	Middle School Degree	43	8.6
	High School Diploma	111	22.2
7.1	Associate	111	22.2
Education	Bachelor	168	33.6
	Master	58	11.6
	Doctoral	9	1.8
	Jobless	122	24.4
	Retired	26	5.2
	Government Employees	36	7.2
	Private Sector Employee	99	19.8
Occupation	Self-employed	194	38.8
	Physicians	5	1.0
	Engineer	11	2.2
	Faculty member	0	0.0
	Other	7	1.4
D : : 1:	Yes	437	87.4
Driving license	No	63	12.6
Do you have an independent	Yes	378	75.6
income?	No	122	24.4
	1	46	9.2
Household size	2	107	21.4
	3	176	35.2

Variable	Category	Cumulative Frequency	Relative Frequency (%)
	4	137	27.4
	5 and more	34	6.8
	10 million Rials	15	3.0
	10-20 million Rials	98	19.6
	20-30 million Rials	141	28.2
Monthly Income	30-40 million Rials	129	25.8
	40-50 million Rials	89	17.8
	50-100 million Rials	22	4.4
	More than 100 million Rials	6	1.2
	0	52	10.4
	1	334	66.8
Number of Cars	2	102	20.4
	3+	12	2.4
	Less than 200 million Rials	97	19.4
F 1 0 10 P:	200-500 million Rials	240	48.0
Family-Owned Car Prices	500-1000 million Rials	83	16.6
	More than 1000 million Rials	28	5.6
	Work	232	46.4
	Education	43	8.6
The Purpose of the Trip	Shopping	39	7.8
	Recreation	34	6.8
	Personal Affairs	139	27.8
	Other Purposes	13	2.6

5. Results

The latent variables considered in the present study were examined through confirmatory factor analysis using Amos 25 software (Table 4). The results obtained from the composite reliability (CR) related to the variables in the chain of VBN theory demonstrated an acceptable reliability (above 0.7). In addition, the factor loading of the criteria was significant at p < 0.001. The

results obtained from the criteria for evaluating confirmatory factor analysis are represented in Table 5, which indicates an appropriate goodness-of-fit.

 $\label{thm:condition} \textbf{Table 4. Estimated Results of Factor Analysis for Value Orientations, NEP, and AC } \\$

	Estimate	p-value	CR
Hvalue1 ← HV	1.000	-	
Hvalue2 ← HV	0.756	< 0.001	0.849
Hvalue3 ← HV	0.884	< 0.001	
Evalue1 ← EV	1.000	-	
Evalue3 ← EV	1.169	< 0.001	0.846
Evalue4 ← EV	1.201	< 0.001	
Avalue1 ← AV	1.000	-	
Avalue2 ← AV	1.202	< 0.001	0.844
Avalue3 ← AV	1.208	< 0.001	
Bvalue1 ← BV	1.000	-	
Bvalue2 ← BV	1.321	< 0.001	0.897
Bvalue3 ← BV	1.197	< 0.001	
NEP15 ← NEP	1.000	-	
NEP11 ← NEP	0.881	< 0.001	
NEP7 ← NEP	0.965	< 0.001	0.703
NEP3 ← NEP	0.945	< 0.001	
NEP5 ← NEP	0.688	< 0.001	
AC3 ← AC	1.000	-	
AC4 ← AC	1.027	< 0.001	0.833
AC5 ← AC	1.309	< 0.001	

Table 5. Evaluation of the Confirmatory Factor Analysis

Indices	CMIN/DF	RMSEA	TLI	CFI	GFI	AGFI
Acceptance Range	Between 1 and 3	≤ 0.07	≥ 0.90	≥ 0.90	≥ 0.90	≥ 0.80

Results	1.620	0.063	0.910	0.912	0.917	0.817

Table 6 presents the results of the multinomial logit model by using environmental attitudes (derived from VBN theory), individuals' characteristics, and travel mode, with three alternatives of not changing the vehicle and switching from a private car to public transit.

Table 6. Results of Multinomial Logit Model

Choice	Variable Symbol	Variable Description	Coefficie nt	Significance Level
Not Changing the Vehicle	AC	Awareness of consequences (latent variable)	-0.45	0.0000
	HV	Hedonic value (latent variable)	0.85	0.0000
	Price2	Cost per 100,000 Rials	-0.0035	0.0457
	Zttpub	Average travel time of public transportation	24.99	0.0017
	Zstart2	Starting time of the journey after 6:30=1, otherwise=0	-1.08	0.0000
	Zpurp3	Travel purpose (Shopping)=1, otherwise=0	2.96	0.0000
	Zpurp6	Travel purpose (Personal Affairs) =1, otherwise=0	1.49	0.0000
	Nveh	Ranking variable of the number of vehicles in the household	0.55	0.0015
	Vehcost	Ranking variable of the number of vehicle costs	0.75	0.0000
	Empd	Governments Employee=1, otherwise=0	-1.15	0.0000
	Nowor	Jobless=1, otherwise=0	-5.33	0.0000
	Hcar	Ranking variable of traveling using a car more than 7 times in a week or 4-7 times in a week=1, otherwise=0	2.20	0.0000
Altering from a Personal Vehicle to a Bus	CTE	Constant Number	7.64	0.0000
	NEP	NEP Statements (latent variable)	0.88	0.0000
	Zdu	Duration of stay in the zone (all combinations)	-1.01	0.0000

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Choice	Variable Symbol	Variable Description	Coefficie	Significance
			nt	Level
	Nveh1	Number of vehicles in HH (1)=1, otherwise=0	1.23	0.0000
	Vehcost3	Vehicle costs 500-1000 million Rials=1, otherwise=0	-2.05	0.0052
	Std	No income and you are a student=1.otherwise=0	4.00	0.000
	Hhs	Ranking Variable of Household Sizes	-0.24	0.0017
	Edu2	High school degree=1, otherwise=0	1.60	0.0000
	Ibus	Ranking variable of traveling using Bus 4-8 times in a year or less than 4 times in a year	-1.69	0.0000
	CTE	Constant number	7.31	0.0000
	BV	Biospheric value (latent variable)	0.32	0.0001
Altering from a Personal Vehicle to the Subway	Zend2	Ending time of the journey after 6:30=1, otherwise=0	2.78	0.0000
	Zdu4	Duration of stay in the zone more than 3 hours=1, otherwise=0	-1.06	0.0000
	Vehcost4	Vehicle costs more than 1000 million Rials=1, otherwise=0	-4.60	0.0000
	Indine	Having an independent income=1, otherwise=0	-1.10	0.0000
	Edu4	Master's degree=1, otherwise=0	0.66	0.0000
	Hsub	Ranking variable of traveling using Subway: More than 7 times in a week or 4-7 times in a week, otherwise=0	1.55	0.0000
Evaluation Criteria	$LL(\beta)$	-1015.30667		
	$ ho_c^2$	0.4016		
	$ ho_{adj}^2$	0.3967		

As shown in Table 6, the effect of travel costs associated with utilizing a personal vehicle in the air pollution control zone is negative and significant (-0.0035) in the acceptability of not changing vehicles. The issue demonstrates a decrease in the tendency to utilize private vehicles by raising the fees of the air pollution control plan. Additionally, an increase in the mean

duration of traveling by public transportation increases the probability of choosing a personal vehicle. In other words, the individuals compared the duration of travel completed by personal vehicles and public transportation and preferred to use their personal vehicles if traveling via public transportation took too long (the consequence of a lack of good public transportation coverage).

Based on the results, the influence of AC on not changing a vehicle was obtained as negative. In fact, those having such attitudes were less inclined to drive their personal vehicle. This variable indicates individuals' awareness of the environmental consequences of their activities (Unal et al., 2019, Liu et al., 2017). This demonstrates these individuals are fully aware of the environmental consequences of their personal vehicle usage, feel greater responsibility for conserving environmental resources, and attempt to obtain more information about the outcomes of their activities on the environment (Hiratsuka et al., 2018, Cools et al., 2011). The researchers believe that people's unawareness of the consequences of their actions on the environment is one of the critical issues leading to their inattention to the environment (Odeck and Kjerkreit, 2010). Improving their awareness of this topic is suggested by incentive programs such as community engagement and public advertisements (e.g., Tayarani Yousefabad et al., 2022; Tayarani Yousefabad et al., 2021).

Regarding the alternative of continuing private vehicle use, HV with a positive sign was determined as significant. This variable demonstrates hedonism and individual values, reflecting those who paid more attention to themselves and cared less about other people, as well as the environment, and their behavior is formed based on benefit-seeking. Accordingly, these persons more often used personal vehicles regardless of environmental issues.

The positive sign of BV in the alteration from personal vehicle use to buses represented the higher probability of choosing vehicles by those having such attitudes. The latent variable indicates individuals' concerns about the environment. Those who felt more responsibility for preserving environmental resources attempted to select environmentally friendly alternatives such as public transit. Those with a stronger environmental view had a better cognitive orientation towards the environment. They represent greater environmental sensitivity by considering that nature and other organisms, as a part of the larger universe, have their specific rights and values, and the environment should not be exploited as an instrumental value and profitable resource.

Based on the results of the model, the sign of NEP in altering travel modes from personal vehicles to a public transportation bus was obtained as positive, reflecting the higher environmental friendliness of buses compared to that of a personal vehicle. Thus, these respondents were more likely to choose riding the bus.

Regarding the cases in which the respondent started to work in the air pollution zone at the peak hours of the morning (6:30-10), the probability of not selecting to change the vehicle decreased because of imposing a greater cost on the individual. The probability of choosing the

metro by those who worked at these hours increased due to the congestion of the metro in the opposite direction (entering the air pollution control zone).

The possibility of selecting a personal vehicle was higher among the respondents who were traveling to the air pollution zone for shopping or taking care of personal issues. Due to the characteristics of such trips, these travelers could better organize their activities by using personal vehicles compared to public transit. These findings resonate with evidence from ridehailing studies during pandemics, where trip purposes such as shopping or mandatory activities significantly shaped adoption likelihood (Baghestani et al., 2025b).

Based on assessing the sign of Zdue (ordinal variable showing the duration of presence in the air pollution zone) and Zdu4 (dummy variable when the duration is more than three hours), the respondents' willingness to use public transit (bus and metro) decreased while spending greater time in the zone. Longer travels were usually more complex and possessed a longer chain of travel from destination to destination. Consequently, travelling with a personal vehicle was considered more appropriate than using the bus and/or metro.

In the present study, the number of personal vehicles owned by a household, as well as their approximate price and mean family expenditure, were used as an income proxy. The previous studies reported a higher tendency to use personal vehicles for higher-income individuals (Hess and Börjesson, 2016). The sign related to the number of private vehicles owned by the household (NVEH) and their approximate cost (vehcost) was determined as positive in not changing the vehicle, which is consistent with the result of other studies. Those with more income continued to use personal vehicles. Further, two dummy variables of vehcost3 (the approximate cost of household-owned cars is 500-1000 million Rials) and vehcost4 (the approximate cost of household-owned cars is above 1000 million Rials) were negative and significant in selecting between riding the bus and metro, respectively. Individuals who owned expensive vehicles were considered part of an affluent class and were less inclined to utilize public transportation, which is in line with the results of other studies (Hess and Börjesson, 2016; Baghestani et al., 2025a). Those with one personal vehicle in their household (NVEC1) (middle class) were more likely to ride the bus.

The probability of using a private vehicle by government staff and the unemployed was low, and the university students showed more willingness to utilize the bus. Additionally, the respondents who had independent incomes were less inclined to use the metro. The acceptability of riding the bus is reduced by increasing family size. Those holding diplomas and bachelor's degrees as their last educational degree were more likely to use the bus and metro, respectively (Baghestani et al., 2025a).

6. Summary and Conclusion

Travel demand management (TDM) is an effective approach to alleviate traffic congestion and reduce air pollution. Heightened awareness of air pollution's negative effects on health and well-being has amplified community concerns about environmental issues. These concerns

enhance the efficiency of TDM policies through positive public reactions, particularly during environmental crises. In this regard, this study employed four groups of variables related to individuals' values, beliefs, and norms to evaluate mode shifts from personal vehicles to public transportation (metro and bus) under zonal pricing policies. Specifically, it assessed environmental-related latent variables using Value-Belief-Norm (VBN) theory to model travelers' attitudes toward mode changes under TDM policies.

The latent variables encompassed the VBN theory chain, grounded in environmentally friendly activities, including environmental values and beliefs. These were integrated with socioeconomic variables and travel characteristics to model mode shifts under zonal pricing, as a key TDM method.

Results showed that the latent variable Awareness of Consequences (AC), representing awareness of environment-related behavior consequences, was inversely related to personal vehicle selection before and after policy implementation. Thus, precise public transportation policies in metropolitan areas, such as reducing headways, enhancing comfort, and improving access, can minimize personal vehicle use among environmentally aware individuals. Additionally, a direct relationship between Biospheric Values (BV) and the New Environmental Paradigm (NEP) index, with public transportation use, validated the study's predictions, aligning earth-centric values with clean transport adoption. Conversely, Hedonic Values (HV), focused on individual pleasures, correlated with personal vehicle use.

A direct link was also observed between personal vehicle and public transit choices and trip temporal distribution. For instance, individuals less inclined to use public transport on weekdays exhibited higher personal vehicle tendencies before and after zonal policies. Factors like long headways and irregular services likely drive this preference for personal vehicles.

These findings offer transportation decision-makers a clear perspective: developing clean transport and reducing private vehicle dependency can gain community acceptance during environmental challenges. Public perceptions and beliefs about crises can facilitate policies to curb private vehicle reliance. Zonal and road pricing policies emerged as effective tools for addressing increased travel time, environmental pollution, and congestion. Revenue from these policies can be reinvested in public transport upgrades, creating a positive feedback loop of improved service and greater public acceptance.

This study modeled individuals' environmental attitudes and socioeconomic variables, examining their distinct effects on mode changes under TDM. Future research should develop integrated models accounting for individual variability, heterogeneity, and deeper decision-making insights in other metropolitan areas. Studies targeting specific groups, such as students or sector employees, and comparing attitudes across domains, are recommended.

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