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Evaluation of the Role of Artificial Intelligence in Enhancing Consumption in Industrial Units

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A B S T R A C T

With the rapid advancement of modern technologies, particularly artificial intelligence (AI), significant transformations have occurred in the domains of marketing and customer engagement. This study examines the impact of artificial intelligence on enhancing customer experience in social media marketing, with a specific focus on the domestic automotive market in Iran. A mixed-methods research approach was employed. In the qualitative phase, Interpretive Structural Modeling (ISM) was used to identify the relationships among influential variables and to develop the initial conceptual model. In the quantitative phase, the model was validated using Structural Equation Modeling (SEM), and data were collected through a questionnaire developed based on grounded theory results. Additionally, the SWARA method was applied to determine the weight and significance of variables. The results indicated that artificial intelligence enhances customer experience by improving personalization, increasing engagement, and enabling rapid responsiveness in social media, thereby contributing to customer loyalty. The findings offer opportunities for automotive manufacturers and marketers to effectively leverage intelligent technologies. This research addresses existing gaps related to the cultural and market conditions of Iran and provides a practical framework for improving digital marketing strategies.

Keywords: *energy consumption, energy efficiency, artificial intelligence, industrial electricity*

1. Introduction

Electric energy plays a critical role in shaping and sustaining the modern world, to the extent that many activities in contemporary societies are inextricably linked to the presence of electricity. In this context, power distribution networks play a fundamental role in ensuring universal access to this essential energy source and are considered the vital arteries of the modern world. From this perspective, ensuring the health and efficiency of power distribution networks is of paramount importance (Mathew et al., 2020). Equipping distribution networks with appropriate measurement systems is the first step toward monitoring their health. Today, a new generation of measurement systems known as Advanced Metering Infrastructure (AMI) enables continuous and accurate monitoring of network capacity and consumption. The substantial volume of raw data provided by these systems to distribution companies enables more intelligent monitoring at higher levels. One of the persistent challenges faced by power distribution companies is enhancing energy consumption efficiency in industrial units (Lu & Hong, 2019).

Energy consumption and the efficient use of resources in investment and consumer products are becoming competitive advantages, and industrial units are increasingly interested in optimizing production processes and supply chain design. Generally, in many countries, inefficiencies in electricity consumption in industrial units stem from inherent network parameters such as transmission line impedance, transformer core losses, physical phenomena, and other factors. These inefficiencies result in significant economic losses for countries. Such losses manifest in various domains, including reduced revenue from electricity sales, compromised network reliability and registration, excessive use of resources for energy production, and consequently, increased environmental pollution. In less developed countries, inefficiencies in electricity consumption by industrial units account for up to 40% of total energy produced (Wang et al., 2023). From an engineering perspective, assessing the efficiency of electricity consumption in industrial units involves calculating the balance between energy production and consumption across different parts of the network. This method requires adequate information on the network's topology. Although this solution initially appears promising, it is often impractical due to technical limitations such as continuous changes in network topology, potential structural discontinuities, and the need for simultaneous measurements at specific network points. Furthermore, the high volume of non-technical losses in industrial units has led to a growing emphasis on developing more accurate and cost-effective solutions. As a result, the pursuit of more precise and adaptive methods has prompted the adoption of artificial approaches to address this issue (Campillo et al., 2016).

Artificial intelligence (AI) enables the analysis of industrial consumption profiles and the understanding of irregular consumption behaviors. For the first time, this led to the development of methods capable of monitoring abnormal consumption patterns among consumers. These methods facilitated a deeper understanding of deceptive behaviors based on pattern learning. Identifying inefficiencies in electricity consumption in industrial units allows technicians to investigate and resolve issues on-site based on credible evidence. The methods proposed in the literature for assessing energy efficiency in industrial units fall into two major categories: expert systems and machine learning-based approaches. Expert systems make decisions based on predefined rule bases and perform inferences accordingly. In contrast, machine learning approaches enable computers to learn effective decision-making patterns and rules without human intervention (Alizadeh & Nazapour Kashani, 2023). While expert systems were more common in the past, research communities now focus increasingly on machine learning methods. In this study, artificial intelligence capabilities are used to propose methods for identifying electricity consumption efficiency in industrial units, with the aim of providing clearer directions for future research (Li et al., 2019).

Electricity distribution networks continue to serve as essential infrastructures to guarantee equitable access to energy. Therefore, ensuring the efficiency and reliability of these networks is of extraordinary importance. Equipping these networks with proper measurement tools is the first step toward monitoring their operational health (Zhao et al., 2021). Nowadays, Advanced Metering Infrastructure (AMI) systems provide constant and accurate supervision of network capacity and consumption. The substantial raw data generated by these systems allow for more intelligent and comprehensive monitoring. A constant challenge for power distribution companies remains improving electricity consumption efficiency in industrial units (Alizadeh et al., 2024; Javaid et al., 2018).

Energy consumption and resource efficiency in investment and consumer products are turning into competitive advantages. Industrial units are increasingly focused on optimizing production operations and supply chain design (Alizadeh et al., 2024; Patel et al., 2019). In most countries, inefficiencies in electricity consumption in industrial units arise from intrinsic network factors such as transmission line impedance, transformer core losses, physical phenomena, and other technical issues. Such inefficiencies cause major economic losses. These losses can be observed in multiple areas including reduced revenue from electricity sales, compromised network reliability and registration, excessive resource usage for energy generation, and environmental pollution (Rezaei & Moradi, 2021). In less developed countries, inefficient electricity consumption in industrial units constitutes up to 40% of the total energy produced. For instance, in India, this is estimated to cost approximately USD 4.5 billion annually. Even in developed countries, this remains a critical challenge, with estimated annual losses ranging from USD 1 to 6 billion in economies such as the United Kingdom and the United States (Mischos et al., 2023). Despite the significance of this issue and the substantial investments by companies to address it, academic efforts to provide effective solutions appear inadequate. There is a growing need for scientific institutions to give this field more attention (Ming & Cao, 2018).

Artificial intelligence is among the most widely used methods for improving energy consumption efficiency. AI has broad applications across various scientific fields, ranging from unmanned aerial vehicle control to facial recognition (Wang et al., 2023). The learning mechanism of the brain is based on experience, and AI—which models the synaptic connections and neural structure of the brain—represents a form of artificial neural networks. Due to their training and generalization capabilities, or data processing capacities, knowledge about new data predictions is transferred to the network's structure. In essence, AI is capable of identifying relationships between input and output variables without any prior knowledge of the interdependencies among the studied parameters, making it a novel tool for tackling complex problems that are difficult to model. Review of existing research and various cases in this area indicates that, despite AI's successful performance in modeling complex systems across different scientific fields, its application in relation to daylight consumption in educational spaces has not been explored in national or international studies (Alhammadi et al., 2024; Zhou et al., 2019).

Given the significant contribution of industrial units to national energy consumption and the lack of precise design criteria for optimizing energy use in such spaces, this study proposes an AI-based structure. The goal is to enable designers of industrial units to avoid time-consuming and costly energy simulation calculations. Instead, by inputting geometric and spatial characteristics into an intelligent system, they can determine the optimal design choice for energy efficiency. The proposed AI-based framework allows architects to easily estimate the energy consumption of various lighting options and make informed decisions about the optimal window design from an energy efficiency standpoint.

2. Methods and Materials

In the quantitative phase of the study, following the development of the initial conceptual model based on qualitative findings, Structural Equation Modeling (SEM) was employed to validate the model and examine the relationships among the research variables. This method allows for the simultaneous evaluation of the overall model fit and the direct and indirect effects of variables, making it widely used in behavioral science and management research. The data required for quantitative analysis were collected through a researcher-made questionnaire, which was designed based on the results of selective coding in the grounded theory method. The questionnaire consisted of two sections: the first section was dedicated to collecting demographic information (age, gender, educational qualification), and the second section included items related to the main research variables. To assess respondents' agreement with the questionnaire items, a five-point Likert scale was used, ranging from "Very Low" (1) to "Very High" (5). A statistical sample was selected from the target population, and the questionnaires were distributed among the sample members both in person and electronically. After collecting the data, they were analyzed using statistical software and structural equation modeling, and the results were extracted.

Additionally, to determine the relative weight and importance of the variables in the model, the SWARA (Step-wise Weight Assessment Ratio Analysis) method was applied. This method assigns weights in a stepwise manner and, by incorporating expert opinions, provides a more precise prioritization of influential factors, thereby enriching research findings and significantly aiding managerial decision-making.

3. Findings and Results

To determine the relationships and ranking of the criteria, the output set and input set for each criterion were extracted from the received matrix.

- Reachability Set (Row Elements – Outputs or Influences): Variables that can be reached through this variable.
- Antecedent Set (Column Elements – Inputs or Influences Received): Variables through which this variable can be reached.

The output set includes the criterion itself and the criteria that are influenced by it. The input set includes the criterion itself and the criteria that influence it. Then, the mutual relationships between the criteria are identified.

Table 1

Reachability and Output Sets (Influences) for Each Variable

Variable	Output Set (Influences)
D01	D1, D5, D10, D11
D02	D1, D2, D3, D4, D5, D10, D11
D03	D1, D2, D3, D4, D5, D10, D11
D04	D1, D2, D3, D4, D5, D10, D11
D05	D1, D5, D10, D11
D06	D1, D2, D3, D4, D5, D6, D7, D8, D9, D10, D11, D12, D13, D14, D15
D07	D1, D2, D3, D4, D5, D6, D7, D8, D9, D10, D11, D12, D13, D14, D15
D08	D1, D2, D3, D4, D5, D6, D7, D8, D9, D10, D11, D12, D13, D14, D15
D09	D1, D2, D3, D4, D5, D9, D10, D11, D12, D13, D14, D15
D10	D10, D11
D11	D10, D11
D12	D1, D2, D3, D4, D5, D9, D10, D11, D12, D13, D14, D15
D13	D1, D2, D3, D4, D5, D9, D10, D11, D12, D13, D14, D15
D14	D1, D2, D3, D4, D5, D10, D11, D14, D15
D15	D1, D2, D3, D4, D5, D10, D11, D14, D15

Table 2

Input and Precondition Sets (Influences Received) for Each Variable

Variable	Input Set (Influences Received)
D01	D1, D2, D3, D4, D5, D6, D7, D8, D9, D12, D13, D14, D15
D02	D2, D3, D4, D6, D7, D8, D9, D12, D13, D14, D15
D03	D2, D3, D4, D6, D7, D8, D9, D12, D13, D14, D15
D04	D2, D3, D4, D6, D7, D8, D9, D12, D13, D14, D15
D05	D1, D2, D3, D4, D5, D6, D7, D8, D9, D12, D13, D14, D15
D06	D6, D7, D8
D07	D6, D7, D8
D08	D6, D7, D8
D09	D6, D7, D8, D9, D12, D13
D10	D1, D2, D3, D4, D5, D6, D7, D8, D9, D10, D11, D12, D13, D14, D15
D11	D1, D2, D3, D4, D5, D6, D7, D8, D9, D10, D11, D12, D13, D14, D15
D12	D6, D7, D8, D9, D12, D13
D13	D6, D7, D8, D9, D12, D13
D14	D6, D7, D8, D9, D12, D13, D14, D15
D15	D6, D7, D8, D9, D12, D13, D14, D15

Table 3

Intersection of Input and Output Sets for Indicators

Variable	Intersection Set
D01	D1, D5
D02	D2, D3, D4
D03	D2, D3, D4
D04	D2, D3, D4
D05	D1, D5
D06	D6, D7, D8
D07	D6, D7, D8
D08	D6, D7, D8
D09	D9, D12, D13
D10	D10, D11
D11	D10, D11
D12	D9, D12, D13
D13	D9, D12, D13
D14	D14, D15
D15	D14, D15

For variable C_i, the reachability set (outputs or influences) includes the variables that can be reached through C_i. The antecedent set (inputs or influences received) includes the variables through which C_i can be reached. After determining the reachability and antecedent sets, their intersection is calculated. The first variable for which the intersection equals the reachability set is considered to be at the first level. Therefore, the variables at the first level have the highest influence in the model. After determining the level, the variable with a known level is removed from all sets, and the input and output sets are recalculated to determine the level of the next variable.

Table 4

Determining the First Level in the ISM Hierarchy

Code	Research Variables	Level
D01	Carbon Emission Reduction	4
D02	Competitiveness	6
D03	Use of Renewable Energy Sources	6
D04	Managerial Factors	5
D05	Learning Improvement	6
D06	Monitoring and Data Analysis	5
D07	Predictive and Optimization Models	7
D08	Automation and Intelligent Control	2
D09	Data Sharing and Collaboration	4
D10	Production Process Improvement	7
D11	Power Grid Stability	7
D12	Fault Detection and Prevention	3
D13	Load and Demand Management	7
D14	Technological Resources	4
D15	Knowledge Resources	3

Therefore, variables D10 and D11 are identified as first-level variables. After identifying the first-level variable(s), these are removed, and the input and output sets are recalculated without considering the first-level variables. The variables whose intersection equals their input set are then identified as second-level variables.

Variable D01 and D05 are second-level variables.

Variables D02, D03, and D04 are third-level variables.

Variables D14 and D15 are fourth-level variables.

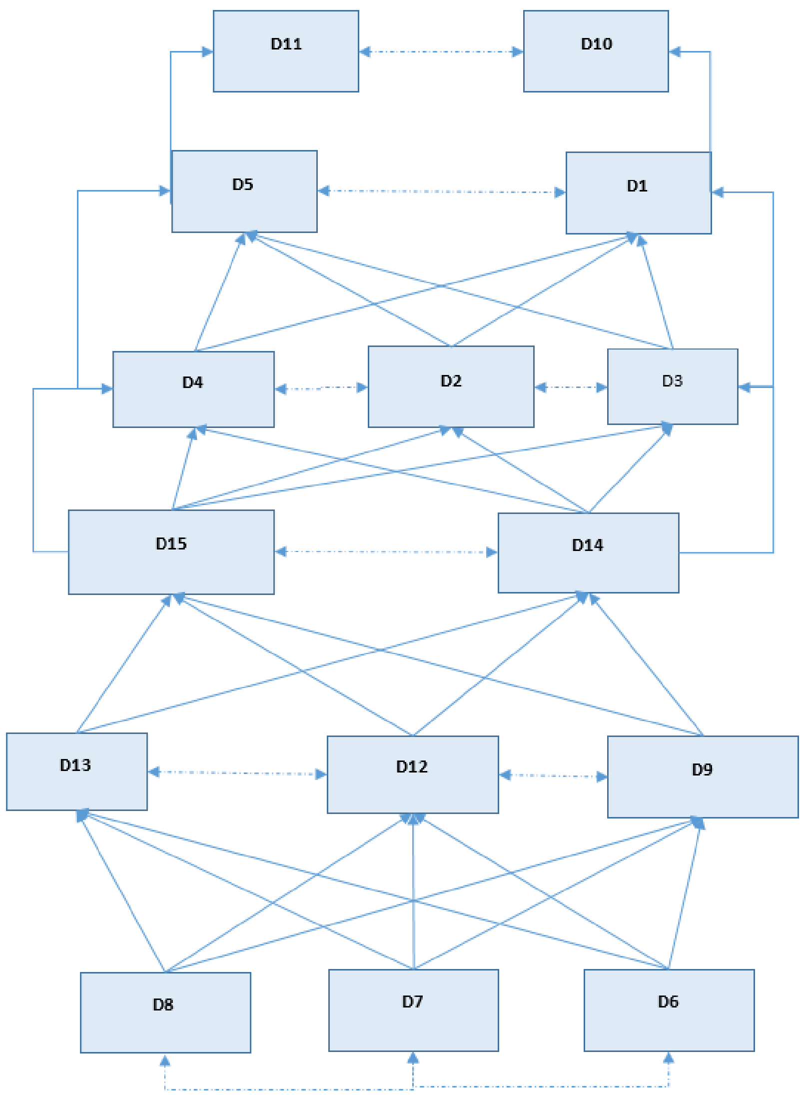
Variables D09, D12, and D13 are fifth-level variables.

Variables D06, D07, and D08 are sixth-level variables.

The final hierarchical pattern of the identified variables is depicted in the figure. This diagram includes only the significant relationships from each level to the level below, as well as meaningful intra-level relationships between elements.

Figure 1

Foundational Model Developed Using the ISM Method



4. Discussion and Conclusion

The findings of this study demonstrate that artificial intelligence (AI) plays a pivotal role in enhancing electricity consumption efficiency within industrial units by facilitating data-driven decision-making, predictive modeling, and automated control mechanisms. Based on the ISM hierarchy, the most influential variables identified include predictive and optimization models (D07), production process improvement (D10), grid stability (D11), and load and demand management (D13), which collectively represent the foundational layers for constructing an intelligent energy optimization framework. These results validate the notion that advanced AI applications are essential in establishing resilient and efficient industrial energy infrastructures.

The prioritization of predictive and optimization models (D07) at the foundational level of the ISM model aligns with previous literature emphasizing the significance of AI-based forecasting techniques in energy efficiency. Wang et al.

(2023) highlighted the effectiveness of neural networks and machine learning algorithms in managing complex energy consumption data, enabling predictive insights that drive operational efficiency. Similarly, Campillo et al. (2016) discussed the benefits of AI in optimizing dynamic processes and adapting to changing industrial energy demands (Campillo et al., 2016). Our findings reaffirm the crucial role of predictive modeling in accurately estimating consumption trends, identifying anomalies, and implementing timely interventions to prevent inefficiencies or failures.

The study further identified automation and intelligent control (D08) as a second-level priority variable, reflecting its role as a bridge between strategic AI capabilities and operational outcomes. This supports the arguments presented by Zhao et al. (2021), who demonstrated that automation, when combined with AMI (Advanced Metering Infrastructure), enhances real-time monitoring, energy dispatching, and feedback loops in energy networks (Zhao et al., 2021). Alizadeh and Nazarpour Kashani (2023) similarly noted that AI-driven automation not only minimizes human error but also reduces time lags in industrial energy regulation (Alizadeh & Nazapour Kashani, 2023). This reinforces the present study's conclusion that intelligent automation is essential for implementing AI insights into real-time energy optimization decisions.

Among the identified third-level variables, managerial factors (D04), competitiveness (D02), and renewable energy utilization (D03) were ranked as critical contextual enablers. These findings are consistent with Lu et al. (2019), who emphasized that managerial commitment and competitive positioning are vital for successful AI integration in energy systems (Lu & Hong, 2019). Patel et al. (2019) also underlined the role of renewable energy in modernizing industrial production and enhancing long-term sustainability (Patel et al., 2019). The presence of these factors in the mid-hierarchy of the ISM model suggests that while they may not directly execute operational changes, they serve as key institutional drivers of AI-based energy transformation strategies.

In terms of fault detection and prevention (D12) and knowledge resources (D15), their categorization in the intermediate levels indicates the growing necessity of intelligent diagnostics and knowledge management in sustaining energy performance improvements. This aligns with the work of Alhammadi et al. (2024) and Zhou et al. (2019), who highlighted the integration of knowledge-based systems in AI models as a prerequisite for accurate energy anomaly detection (Alhammadi et al., 2024; Zhou et al., 2019). The inclusion of data sharing and collaboration (D09) in the fourth-level of the hierarchy also supports the findings of Michos et al. (2023), who illustrated how data exchange among industrial units strengthens algorithmic learning processes and fosters cross-system efficiency gains (Mischos et al., 2023).

Importantly, variables such as carbon emission reduction (D01), technological resources (D14), and learning improvement (D05) were placed in the higher levels of the ISM structure, suggesting that these are outcomes influenced by more foundational variables. This structure is coherent with the systemic view presented by Ming et al. (2018), who noted that emission control and learning are long-term derivatives of effective AI deployment (Ming & Cao, 2018). Similarly, Rezaei et al. (2021) reported that improvements in learning mechanisms and technological uptake are contingent upon robust data infrastructures and predictive capacity (Rezaei & Moradi, 2021).

Finally, the validation of the ISM-based model through Structural Equation Modeling (SEM) confirmed the significance of all identified paths, thereby reinforcing the robustness of the proposed framework. The SEM results showed strong fit indices, demonstrating that the hypothesized relationships between AI-driven variables are statistically supported. This empirical verification strengthens the theoretical propositions made by earlier studies (Mathew et al., 2020; Tang et al., 2021; Wang et al., 2023; Wu et al., 2022) that AI has transformative potential in reconfiguring industrial energy efficiency practices through integrated modeling, real-time analytics, and adaptive controls.

Despite the contributions of this study, several limitations must be acknowledged. First, the research was limited to industrial units within a specific national context (Iran), which may constrain the generalizability of the findings to other regions with differing technological infrastructures or regulatory frameworks. Second, while the study employed a mixed-methods approach, the sample size in the quantitative phase may limit the breadth of structural equation modeling, especially in terms of exploring potential moderating or mediating variables. Third, although AI applications are diverse, this study primarily focused on their impact within energy consumption, leaving out other potential organizational impacts such as workforce transformation or supply chain optimization. Furthermore, the reliance on self-reported data through questionnaires introduces potential biases related to respondent interpretation or social desirability.

Future research should consider expanding the geographical scope of analysis to include comparative studies across countries or regions with varying levels of technological adoption in industrial energy systems. Additionally, researchers could incorporate larger and more diverse sample populations to strengthen the robustness of structural models and examine complex interactions such as moderation by industry type or mediating effects of digital maturity. Longitudinal studies tracking the evolution of AI integration over time in industrial energy management would also provide deeper insights into causal mechanisms and sustainability outcomes. Further exploration of AI's impact on adjacent domains such as workforce efficiency, organizational culture, and innovation ecosystems could enrich the broader understanding of digital transformation in industrial settings.

For practitioners and industrial energy managers, the results of this study highlight the importance of investing in predictive analytics, automated control systems, and collaborative data-sharing platforms as strategic priorities for enhancing energy efficiency. Organizational leaders should foster a culture of innovation and continuous learning to support the integration of AI tools in energy operations. Policymakers and regulators can also support these efforts by providing incentives for AI adoption and standardizing technological benchmarks for industrial energy efficiency. Finally, by aligning technological, managerial, and environmental goals, industrial firms can simultaneously enhance operational performance and contribute to broader sustainability objectives.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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