

From Values to Innovation: Behavioral Dynamics of Energy Efficiency and AI-adoption in Small and Medium-sized Enterprises

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FROM VALUES TO INNOVATION: BEHAVIORAL DYNAMICS OF ENERGY EFFICIENCY AND AI-ADOPTION IN SMALL AND MEDIUM-SIZED ENTERPRISES

Abstract

This study addresses innovation-adoption of organizations by examining the behavioral and organizational mechanisms underlying energy-efficiency practices and artificial intelligence adoption among SMEs in New York State. Integrating Value-Belief-Norm theory with Diffusion of Innovation theory, we develop and test a framework linking values, responsibility beliefs, industry norms, innovation perceptions, behavioral intentions, and organizational adoption. The findings reveal a sequential behavioral pathway in which biospheric values strengthen responsibility beliefs, which reinforce industry norms and subsequently promote energy-efficiency behaviors. Perceived benefits also significantly strengthen intentions to adopt AI for energy management. However, these intentions do not consistently translate into actual AI adoption, revealing an intention–adoption gap in the organizational implementation of emerging technologies. By integrating values-based behavioral mechanisms with innovation diffusion processes, this study extends innovation-adoption research beyond technology perceptions and intentions to account for the normative and behavioral foundations of organizational innovation. The findings further demonstrate that favorable perceptions of an innovation may be necessary but insufficient for implementation in resource-constrained organizations, highlighting the importance of distinguishing between innovation acceptance and realized organizational adoption.

Key words: Artificial intelligence; innovation adoption; small and medium-sized enterprises; organizational behavior; energy efficiency; diffusion of innovation

INTRODUCTION

This study examines the relationship among three key concepts: small and medium-sized enterprises (SMEs), energy efficiency, and artificial intelligence (AI) driven technology adoption. SMEs are the focus of this investigation due to their substantial energy consumption and their growing need for energy-related innovations to achieve sustainable operations. SMEs as for-profit organizations with fewer than 500 employees (United States International Trade

Commission, 2010) has central role in economic activity (Thurik & Wennekers, 2004; Gherghina et al., 2020) make substantial contributions to economic growth, job creation, employment, innovation, and export participation in the United States (Gherghina et al., 2020; Kongolo, 2010; Varum & Rocha, 2013; Saunila, 2020; United States International Trade Commission, 2010).

Additionally, although individual SMEs generally have relatively low energy demands and smaller carbon footprints, their collective energy consumption is considerable due to their large number (Fresner et al., 2017; Gennitsaris et al., 2023). Therefore, energy efficiency has become a critical issue for SMEs in the context of sustainable economic and environmental development. AI-driven technologies have the potential to reduce energy consumption and emissions as a key contributor to energy reduction (Zhou et al., 2024), intelligent energy management (Khan et al., 2023), smart energy systems (Cheng & Yu, 2019), and sustainable energy management (Ahmad et al., 2021).

There is still limited understanding of how SMEs consume energy (Hampton & Fawcett, 2017; Fawcett & Hampton, 2020). While the challenges faced by SMEs in adopting new technologies are well documented (Bressler et al., 2011), the underlying factors influencing technology adoption in this context remain largely understudied (Akpan et al., 2022; Enriquez et al., 2025). Therefore, the purpose of this research is to explore the behavioral dynamics shaping SMEs' approaches to energy efficiency through the adoption of advanced technologies like AI.

BACKGROUND

The role of SMEs in the United States economy has been described as the “backbone” (Office of the United States Trade Representative, 2026) and the “lifeblood” (U.S. Small Business Administration Office of Advocacy, 2019). There are approximately 36.2 million SMEs in the United States, and they make substantial contributions to economic activity. SMEs comprise 97.2% of exporters and contribute 33.0% of known export value (\$588.4 billion). They employ 45.9% of the private-sector workforce (62.3 million workers), contribute 43.5% of U.S. GDP, generate 38.7% of private-sector payroll (approximately \$3.5 trillion), and account for 35.0% of private-sector receipts (\$17.8 trillion) (U.S. Small Business Administration Office of Advocacy, 2026).

Energy efficiency is particularly important in SMEs because, although individual firms consume relatively small amounts of energy, their collective consumption is substantial (Fresner et al., 2017). Despite their significant energy use and potential for energy savings, understanding of SME energy consumption remains limited (Hampton & Fawcett, 2017; Fawcett & Hampton, 2020). Janda et al. (2014) describe this challenge as “learning from poor data,” reflecting the fact that SMEs remain understudied and often data poor.

The International Energy Agency (IEA) (2015) estimates that SMEs account for more than 13% of global energy demand and approximately one-third of industrial and service-sector energy use. In the United States, the industrial sector accounts for 35% of total energy consumption and the commercial sector for 13% (Energy Information Administration - EIA, 2025). Given that SMEs represent 99.9% of all businesses, they are estimated to account for nearly 48% of total business-sector energy consumption. These figures demonstrate that SMEs are significant energy users and should play a central role in energy-efficiency strategies.

This study is grounded in two theoretical foundations. First, the Value-Belief-Norm (VBN) theory provides a framework for understanding how energy-efficiency behaviors are shaped by values, beliefs, and personal norms (Stern et al., 1999). Although VBN theory has been widely applied to explain pro-environmental behavior across diverse populations (Whitley et al., 2018; Lebrument et al., 2025; Fornara et al., 2016; Choi et al., 2015; Ünal et al., 2019; Fauzi et al., 2024), relatively few studies have examined SMEs (Jain et al., 2024; Ketprapakorn & Kantabutra, 2019; Fatoki, 2024). This study applies VBN theory to explain how SME decision-makers’ values, beliefs, and norms relate to energy-efficiency practices.

Second, the study examines perceptions of AI adoption and innovation profiles using Diffusion of Innovation (DOI) theory (Rogers, 2003). AI, defined as the focal innovation (Acemoglu & Restrepo, 2019), is examined in relation to its adoption for energy efficiency within SMEs. DOI theory provides a framework for understanding how new technologies are perceived, spread, and adopted within a social system over time.

Decision-makers serve as key agents responsible for making and implementing decisions related to energy use and technology adoption. The VBN and DOI theories provide complementary

perspectives for understanding how decision-makers sociocultural factors, innovation understanding, and organizational contexts associate with energy-efficiency practices and AI adoption in SMEs. Therefore, this study uses survey data collected from SME decision-makers, including owners, co-owners, managers, and full-time employees responsible for organizational operations. These individuals are defined as those who play a primary role in strategic decision-making processes within SMEs (Huang, 2009; Musso & Francioni, 2012). Their behaviors are influenced by the organizational cultures in which they operate (Gao et al., 2017; Xie et al., 2021; Su et al., 2022). Prindle and Finlinson (2011) emphasize the close relationship between organizational behavior and organizational culture in the context of energy management.

METHODOLOGY

The purpose of this study is to investigate the drivers of energy-efficiency behaviors and innovation approaches in SMEs and to explain how these factors shape workplace practices and technology-adoption decisions within organizational settings. Specifically, this study addresses two research questions: (1) How do values, beliefs, and norms relate to energy-efficiency behavior in SMEs? and (2) How do perceived innovation attributes relate to SMEs' current use and future intention to use AI technologies, and what are the innovation profiles of SMEs?

The surveys were conducted in the State of New York with the approval of the Institutional Review Board (IRB) of the author's institution in August 2025. Participants who met the eligibility criteria were presented with an informed consent form at the beginning of the survey. Participants were allowed to proceed to the survey questions only after providing informed consent. An online questionnaire was administered through the Qualtrics platform. The survey was collected between September and November 2025. Data were collected using a purposive sampling technique, which enabled the researcher to reach individuals have the characteristics relevant to the research objectives (Barratt et al., 2015; Rai & Thapa, 2015).

The recruitment strategies were (1) in-person outreach, including business visits and participation in business-related events; (2) online distribution through digital platforms; and (3) email and phone outreach. Email and phone outreach proved largely ineffective. In contrast, in-person outreach and online distribution were more successful in reaching SME decision-makers.

Approximately 950 businesses were contacted through in-person outreach, including site visits and attendance at business-related events. Approximately 76% of these businesses declined to participate in the survey. A total of 303 survey entries were recorded in Qualtrics during the data-collection period, of which 155 were complete (Figure 1).

Sociocultural Measures

An adapted VBN model is employed in which personal moral norms are replaced with industry norms (Prawesh et al., 2021; Roxas, 2022), which better reflects the organizational decision-making context of SMEs. This approach is based on the idea that organizational behavior is shaped by the values (Meglino & Ravlin, 1998) and beliefs (Schein, 1985) of decision-makers, whose perceptions guide strategic choices and operational practices within organizations. The model (Figure 4) assumes that each variable in the relationship directly related the subsequent variable. Based on this assumption, 4 hypotheses were formulated. A total of 12 statements were used to assess participants' latent psychological constructs related to energy efficiency behaviors in their workplaces (Table 1). All measurement items were adopted from previous literature to ensure validity. The constructs included *biospheric values*, *egoistic values*, *energy efficiency responsibility beliefs*, and *industry norms* from sector, business, and customers. Measures for biospheric values, egoistic values, and beliefs were adapted from Stern et al. (1999), and norms were adapted from Cialdini (2003) and Whitley et al. (2016). Altruistic values were excluded due to their high correlation and conceptual overlap with biospheric values (Steg & De Groot, 2012; Sockhill et al., 2022).

H1. SME decision-makers' biospheric values (BV) are related to their energy efficiency responsibility beliefs (EERB).

Egoistic values relate to self-interest, which in a business context is highly connected to business survival, cost reduction, and competitiveness. When energy efficiency is perceived as a means to achieve economic benefits, decision-makers with strong egoistic values can develop responsibility beliefs toward energy efficiency based on its instrumental value (Ruepert et al., 2017).

H2. SME decision-makers' egoistic values (EV) are related to their energy efficiency responsibility beliefs (EERB).

Decision makers who perceive energy efficiency as an organizational responsibility are more likely to recognize, internalize, and respond to industry norms promoted by peers, competitors, and other key stakeholders. Stakeholder pressures, industry expectations, and competitive dynamics are key dynamics for internalization of environmental responsibility (Bansal & Roth, 2000).

H3. SME decision-makers' energy efficiency responsibility beliefs (EERB) are related to their industry norms (IN).

Firms adopt energy efficiency practices in response to pressures from competitors and normative pressures from customers and suppliers to maintain competitiveness and legitimacy (Lee et al., 2022). When energy efficiency is widely supported or expected within an industry, SME decision makers become more interested in adopting energy efficiency practices in order to maintain legitimacy, competitiveness, and alignment with industry standards.

H4. SME decision-makers' industry norms are related to their energy efficiency behaviors (EEB).

Validity was established by selecting items measuring biospheric values, egoistic values, and beliefs from previously validated scales reported by Stern et al. (1999). Similarly, the norm scale items were adapted from prior studies using validated measures (Cialdini, 2003; Whitley et al., 2016). Construct validity was assessed using confirmatory factor analysis (CFA), following established guidelines for measurement model evaluation (Brown & Moore, 2012). Convergent validity was supported by statistically significant standardized factor loadings exceeding 0.60, composite reliability (CR) values above the recommended threshold of 0.70, and average variance extracted (AVE) values greater than 0.50. Discriminant validity was evaluated using the Fornell–Larcker criterion, with results indicating that the square root of the AVE for each construct exceeded its correlations with other constructs. For the values scale, participants were asked to rate the importance of each item on a 5-point Likert scale, ranging from 1 (not at all important) to 5 (very important). For beliefs and norms, participants indicated their level of

agreement or disagreement using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Diffusion of Innovation Measures

This section includes 17 measurement items that represent the attributes of innovation as framed by the DOI Theory, including *relative advantage*, *compatibility*, *complexity*, *observability*, and *trialability* (Rogers, 2003). Participants rated their level of agreement using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). These 5 constructs were selected because Rogers (2003:211) identifies them as the core perceived attributes of innovations.

The proposed model includes intention and behavior as adoption outcomes (Figure 5). Complexity is treated as a separate construct, while the remaining four constructs are grouped under the category of perceived benefits. The model also assumes direct causal relationships between each variable and the subsequent variable in the causal chain. Based on these assumptions, 3 following hypotheses were formulated.

Although Rogers (2003) conceptualizes relative advantage, compatibility, observability, and trialability as distinct constructs, he acknowledges that these attributes collectively represent the perceived favorability of an innovation. Furthermore, Arts et al. (2011) emphasize that consumers tend to adopt innovations that are perceived as less complex. Tornatzky and Klein (1982) similarly argue that innovation characteristics are not necessarily perceived as independent by technology adopters. In the context of SMEs, decision-makers are therefore unlikely to evaluate each attribute separately; instead, they tend to form a holistic judgment regarding the overall usefulness of an innovation.

H5. Perceived benefits of AI are related to future AI adoption intention.

According to Rogers (2003, pp. 238–240), relative advantage, compatibility, trialability, and observability are positively associated with the rate of adoption, while complexity is negatively related to adoption. Relative advantage, compatibility, observability, and trialability contribute to participants perceived benefits of AI, thus complexity is treated as a different construct. Rogers (2003) defines complexity as the degree to which an innovation is perceived as difficult to

understand and use. Dwivedi et al. (2021) emphasize that the complexity and opacity of AI technologies increase perceived difficulty.

H6. Complexity is related to future AI adoption intention.

From the perspective of Venkatesh et al. (2003), behavioral intention is a key determinant of actual technology use. It was underlined that individuals who intend to use a technology are more likely to translate that intention into real usage behavior.

H7. Future AI adoption intention is related to AI adoption behavior.

The measurement items (Table 2) used in this study were adapted from Al-Jabri and Sohail (2012), who adapted them from previously validated scales (Tan & Teo, 2000; Lin, 2011; Poon, 2008; Fain & Roberts, 1997; Laukkanen & Cruz, 2009), thus ensuring content validity. Al-Jabri and Sohail (2012) further validated these scales through focus group discussions and pilot testing. A total of 17 items were used to measure participants' perceptions of AI adoption attributes, including relative advantage (5 items), compatibility (3 items), observability (4 items), complexity (3 items), and trialability (2 items). Although trialability was measured using only two items adapted from prior studies, it exhibited strong factor loadings and high internal consistency ($\lambda > 0.70$).

Innovation Profile Measures

In this section, innovation adoption is conceptualized as a *self-perceived innovation orientation* inspired by Rogers' (2003) DOI adopter orientations toward innovation adoption. Accordingly, the measurement instrument was designed to reflect respondents' relative alignment with different DOI-inspired adoption orientations. The *winner-takes-all procedure* (Haykin, 2009) served as an initial rule to identify cases with a clearly dominant adoption orientation. For respondents without a uniquely dominant orientation, a second-stage *dominance-based heuristic abstraction* (Puppe, 1993) was applied to preserve theoretically meaningful variation.

The innovation adoption items were adapted from Savary (2005:58) (Table 3) and were theoretically grounded in Rogers' (2003) DOI framework, thus supporting *content validity*. The

scale follows a categorical measurement logic, in which each item represents a theoretically different adoption profile rather than serving as an indicator of a single latent construct.

FINDINGS

Demographics of participants and their firm profiles are presented in Table 4 and Table 5. Participants are mainly managers (50.3%), owners (36.1%) and co-owners (9.7%). The category “other” refers to employees who hold operational management responsibilities and are involved in decision making and business practices as an employee (3.9%). Most participants were between 25 and 44 years of age (62.6%), with relatively fewer respondents in the youngest and oldest age groups. The sample was predominantly male (76.8%). In terms of education, more than two-thirds of respondents have least a bachelor’s degree, indicating a relatively high level of educational background. Participants also reported considerable work experience, with more than half (54.8%) having over 10 years of professional experience.

The largest proportion of respondents operate in buildings housing 2-5 businesses (31.6%), followed by those in single-business buildings (22.6%). This suggests that most participants conduct their operations in less densely populated commercial environments. The industry distribution of survey participants demonstrates representation across a wide range of sectors, indicating a diverse sample. The largest proportion of respondents operate in accommodation and food services (36.1%), followed by retail trade (9.0%), while several other industries including art, entertainment, and recreation, finance and insurance, and construction are also represented. The distribution of firm age indicates the mix of young and well-established businesses among the survey participants. The largest proportion of firms has been operating for 1–5 years (29.0%), suggesting a strong presence of early-stage businesses.

Participants were asked about their political orientation and their views on climate change (Figure 2). These two questions were adopted from Carlisle et al. (2025). The results indicate that most respondents identified as politically moderate, with moderates representing the largest group (38.1%). This was followed by conservatives (21.3%) and liberals (20%), while smaller proportions identified as very conservative (11.6%) or very liberal (9%). With respect to climate change, there was strong agreement that it is a serious problem. A majority of respondents either

agreed (30.3%) or strongly agreed (32.9%) with this statement. A small proportion strongly disagreed (1.3%), and 10.3% of the participants disagreed.

They were also asked on energy efficiency behavior, current and future AI adoption, and energy program awareness (Figure 3). It was asked whether businesses have implemented any energy-efficiency measures specifically related to their HVAC (heating, ventilation, and air conditioning) systems. From the 155 participants, 41 respondents (26.5%) reported using energy efficiency measures currently, while 69 participants (44.5%) indicated that they did not use any such measures. An additional 45 participants (29.0%) reported that they were unsure whether energy efficiency measures were in place.

Another question in the survey asked participants whether their businesses currently use AI in their HVAC systems. The majority of respondents indicated that they do not use AI-based HVAC technologies. Specifically, 117 participants (75.5%) reported “No,” 27 participants (17.4%) indicated that they were unsure, and only 11 participants (7.1%) reported yes, using AI.

Participants were also asked about their intentions to adopt AI-driven HVAC technologies in the future. When asked whether they would consider implementing AI-enabled HVAC systems in their workplaces, 48 participants (31.0%) indicated that they would be willing to do so, while 31 participants (20.0%) reported that they would not. A substantial proportion of respondents, 76 participants (49.0%) reported that they were undecided.

The final survey question examined participants’ awareness of New York State energy programs that support the use of technologies like AI to improve energy efficiency among SMEs (this part will be discussed in greater detail in the policy chapter). A total of 152 participants responded to this question, while 3 did not provide a response. Among those who responded, only 5 participants (3.3%) reported being aware of such programs. In contrast, 103 participants (67.8%) indicated that they were not aware of these programs, and 44 participants (28.9%) reported being unsure.

VCN Findings

The following findings are about the adopted models from the VBN and DOI theories. Reliability of the sociocultural measures was evaluated by examining the internal consistency of the items within each construct of the VBN framework. Specifically, Cronbach's alpha was used as the reliability indicator, with values of 0.70 or higher considered acceptable. The biospheric values scale demonstrated high reliability ($\alpha = 0.862$), indicating strong internal consistency among its items. Egoistic values also showed good reliability ($\alpha = 0.831$), suggesting that the indicators coherently capture the same underlying construct. The beliefs scale exhibited acceptable reliability ($\alpha = 0.739$), exceeding the recommended threshold and supporting the aggregation of these items into a single beliefs construct. Finally, the norms scale showed high internal consistency ($\alpha = 0.865$), indicating that the norms items reliably represent a common latent dimension.

CFA was used (Brown & Moore, 2012) to test whether the observed variables appropriately represent the latent constructs of the VBN theory. The CFA results indicate that all standardized factor loadings exceeded the recommended threshold of 0.60, and all were statistically significant, demonstrating an acceptable measurement model. As shown in Table 6, Cronbach's alpha and Composite Reliability (CR) values for all constructs ranged from 0.739 to 0.892, indicating satisfactory internal consistency and construct reliability. Additionally, the Average Variance Extracted (AVE) values ranged from 0.504 to 0.742, exceeding the recommended minimum criterion of 0.50 and confirming adequate convergent validity. All factor loadings were substantially above 0.50, providing further support for convergent validity. Discriminant validity (DV) was also established using the HTMT criterion. All HTMT values were below the recommended threshold of 0.85, with values ranging from 0.195 to 0.753. These findings confirm that the constructs demonstrate adequate discriminant validity and are conceptually distinct from one another.

Table 7 presents the results of the structural model. It examines the hypothesized relationships among biospheric values, egoistic values, energy efficiency responsibility beliefs, and industry norms. The behavior component in the structural model represents energy efficiency behavior and was measured through the survey question asking whether participants use energy efficiency measures or not. The results indicate that biospheric values have a significant positive relationship with energy efficiency responsibility beliefs ($\beta = 0.732$, $z = 9.075$, $p < 0.001$), which

is supporting H1. In contrast, the relationship between egoistic values and energy efficiency responsibility beliefs is positive but not statistically significant ($\beta = 0.118$, $z = 1.885$, $p = 0.059$), not supporting H2. Furthermore, energy efficiency responsibility beliefs significantly and positively relate to industrial norms ($\beta = 0.581$, $z = 3.338$, $p = 0.001$), supporting H3. Lastly, industry norms have a significant positive relationship with energy efficiency behavior ($\beta = 0.469$, $z = 3.552$, $p < 0.001$), thereby supporting H4. These findings highlight a sequential pathway in which biospheric values shape beliefs, beliefs associated with norms, and norms associated with energy efficiency behavior in SMEs workplace settings. Additionally, it suggests that energy efficiency behavior is primarily driven by environmentally oriented value motivations rather than self-interested considerations, reinforcing the importance of biospheric values within the value–belief–norm pathway.

DOI Findings

In the second model, internal consistency reliability for the DOI constructs was evaluated using Cronbach's alpha. All constructs exceeded the recommended threshold of 0.70, indicating satisfactory reliability and supporting the aggregation of items into their respective scales. Specifically, relative advantage demonstrated high reliability ($\alpha = 0.905$), reflecting strong consistency among items measuring perceived innovation benefits. Compatibility showed excellent reliability ($\alpha = 0.925$), suggesting that its indicators coherently capture the alignment of the innovation with existing values and practices. Observability also exhibited high internal consistency ($\alpha = 0.893$), exceeding the acceptable threshold and supporting its use as a single construct. Similarly, complexity demonstrated strong reliability ($\alpha = 0.871$), indicating consistent measurement of perceived difficulty associated with the innovation. Finally, trialability showed high internal consistency ($\alpha = 0.889$), suggesting that the items reliably measure opportunities to experiment with the innovation prior to adoption.

CFA was conducted (Brown & Moore, 2012) to assess whether the observed items properly represented their respective latent constructs (Table 8). The results show that all standardized factor loadings exceeded the recommended threshold of 0.70 and were statistically significant, indicating a satisfactory measurement model. Cronbach's alpha and CR values for all constructs ranged from 0.871 to 0.925, demonstrating strong internal consistency and construct reliability.

In addition, the AVE values ranged from 0.689 to 0.803, exceeding the recommended minimum value of 0.50 and confirming adequate convergent validity. These results in general indicate that the measurement model exhibits acceptable reliability and convergent validity and is suitable for further structural model analysis. Discriminant validity was assessed using the HTMT criterion. Perceived Benefits was specified as a higher-order construct comprising Relative Advantage, Compatibility, Observability, and Trialability, while Complexity was retained as a separate construct. The HTMT value between Perceived Benefits and Complexity was 0.212, which is well below the recommended threshold of 0.85. Therefore, the results provide strong evidence of discriminant validity, indicating that Perceived Benefits and Complexity are empirically distinct constructs.

The results (Table 9) indicate that perceived benefits of AI have a strong and positive relationship with intention to use AI ($\beta = 0.368$, $z = 4.455$, $p < .001$). This finding supports H1 and points out that benefit perceptions such as relative advantage, compatibility, observability, and trialability play a central role in shaping AI adoption intentions. In this study, participants who perceived greater benefits of AI were significantly more likely to express an intention to use AI. Perceived complexity of AI did not have a significant relationship with intention to use AI ($\beta = 0.067$, $z = 0.857$, $p = .392$). Therefore, H2 is not supported. It means that in the context of this study, complexity is not a decisive factor once perceived benefits are considered. Lastly, the relationship between intention to use AI and AI use behavior was positive but weak ($\beta = 0.177$, $z = 1.706$, $p = .088$) and therefore did not provide support for H3 at the 0.05 significance level. As a result, these findings suggest that SMEs' intentions to adopt AI are primarily driven by perceived benefits rather than perceived complexity, while the transition from intention to actual AI use may depend on additional external, organizational and structural factors beyond individual perceptions alone.

Innovation Profile Findings

As an initial exploratory step of the analysis for the innovation profiles, a highest-score (winner-takes-all) classification procedure (Haykin, 2009:37) was applied to examine whether any respondents demonstrated a clearly dominant self-perceived adoption orientation. When a single innovation measurement item received a uniquely highest score, the respondent was associated

with the corresponding adoption orientation for descriptive purposes. The Figure 6 shows the distribution of respondents' adopter categories. 13 respondents were classified as *Innovators*, indicating very early engagement with AI technologies. 11 respondents fell into the *Early Adopter* category, while 7 were categorized as *Early Majority*, representing individuals who show interest in AI but tend to adopt it after observing others. 3 respondents were classified as *Late Majority*, who typically delay adoption until the technology is widely accepted, and 5 respondents were identified as *Laggards*, reflecting a higher level of resistance to innovation. 3 participants did not provide a response.

The first procedure resulted in dominant orientation identification for 39 respondents, while 113 respondents demonstrated highest scores across multiple innovation categories. The observed distribution of adopter categories does not correspond to Rogers' (2003) theoretical adopter distribution; First, the data were collected using *purposive sampling* aligned with the study's objectives, rather than sampling intended to represent a general population. Second, the total sample size ($N = 155$) is relatively small. Importantly, this deviation is not a limitation but a meaningful outcome. Rogers' adopter distribution reflects population-level diffusion processes over time, whereas the present study focuses on a purposively selected group of SME decision makers. Innovation adoption was examined as a *mixed orientation* combining multiple adopter profiles. A substantial number of respondents ($n = 113$) were identified as having a mixed adopter orientation, indicating that they demonstrated traits associated with more than one adopter category.

A second-stage heuristic classification and abstraction procedure was applied (Puppe, 1993) to determine the dominant orientation of the 113 mixed-oriented participants (Figure 7). Because these respondents showed similarly high levels of agreement across multiple adopter categories, they could not be meaningfully assigned to a single profile and were initially classified as mixed oriented. To further differentiate their adoption tendencies, a dominance threshold of 0.50 was established to ensure substantive orientation differences rather than marginal variation.

The mixed-oriented participants were classified into three composite categories: (1) early innovators, (2) late innovators, and (3) balanced (Table 10). This approach follows Puppe's (1993, pp. 131–148) suggestion that constellations of related observations can be meaningfully

combined into a single conceptual classification. *Early oriented* respondents exhibited higher mean scores on the Innovator (Time_1) and Early Adopter (Time_2) items, indicating a pro-innovation orientation. *Late-oriented* respondents demonstrated higher mean scores on the Late Majority (Time_4) and Laggard (Time_5) items, reflecting a more cautious or anti-innovation orientation. *Balanced* respondents showed approximately equivalent mean scores across early and late adoption items, suggesting neither a dominant pro- nor late-adoption tendency. One respondent could not be assigned to any of these composite categories due to missing data, which prevented determination of a dominant innovation orientation. The results indicate that the innovation profiles of SME decision makers are predominantly characterized by mixed adopter orientations (n=113) rather than clear alignment with a single adopter category (n=39). Most respondents exhibited overlapping characteristics across multiple adopter categories, with a prevailing tendency toward early-oriented (n=77) and balanced (n= 30) profiles.

DISCUSSION

The discussed results are presented in two stages: (1) the behavioral and organizational patterns of energy-efficiency and AI adoption among SMEs, and (2) the theory-tested results of energy-efficiency practices and technology adoption in SMEs. The inclusion of managers, owners, co-owners, and operationally responsible employees suggests that the findings reflect the perspectives of individuals directly involved in organizational operations, energy-related decision-making, strategic planning, and technology adoption (Huang, 2009; Musso & Francioni, 2012). Since decision-makers reflect organizational culture through processes of external adaptation and internal integration (Schein, 1984), these dimensions are also evident in their approaches to energy efficiency and technology adoption. The predominance of male participants is consistent with research highlighting the underrepresentation of women in SME leadership positions (Hoobler et al., 2011; Madison et al., 2022). The sample also captured a diverse range of SMEs across multiple industries, broadening representation across organizational contexts.

Respondents generally identified with moderate political views, suggesting that the sample was not highly polarized and reflected a broad middle segment of the political spectrum. SMEs with fewer than 500 employees account for approximately 36 million businesses in the United States

and contribute substantially to economic growth, employment, innovation, and exports (Kongolo, 2010; United States International Trade Commission, 2010; Varum & Rocha, 2013; Gherghina et al., 2020; Saunila, 2020). Given their importance, politicians across ideological perspectives frequently emphasize SME contributions and seek support from SME owners (Malhotra et al., 2025).

Previous studies have documented increasing political polarization surrounding climate change in the United States (Dunlap et al., 2016; Carmichael et al., 2017). However, respondents in this study expressed strong concern about climate change, suggesting that climate awareness is widely shared regardless of political orientation. In contrast, awareness and adoption of HVAC-related energy-efficiency practices were relatively low. Only about one in four businesses reported using such measures, while many either did not use them or were uncertain whether they were implemented.

The low adoption of energy-efficiency measures may be explained by financial barriers and tenancy arrangements. High investment costs remain a major obstacle to energy-efficiency improvements in commercial buildings (Marquez et al., 2012). Furthermore, because more than 52% of commercial building space in the United States is rented, split incentives often discourage investment in energy-efficiency upgrades (Bird & Hernández, 2012). In these situations, owners bear investment costs while tenants receive most of the financial benefits, reducing incentives for both parties (White et al., 2020; Castellazzi et al., 2017).

The large proportion of respondents who were unsure whether energy-efficiency measures existed may reflect informational gaps (De Ayala et al., 2021). Previous research suggests that both building owners and tenants often have limited understanding of energy systems and associated costs (Palmer & Walls, 2015). As a result, limited knowledge of alternative technologies and energy consumption patterns remains a barrier to adoption (Marquez et al., 2012). Similarly, the large, undecided group regarding AI-enabled HVAC systems suggests that these technologies remain unfamiliar to many SMEs. The prevalence of uncertainty indicates caution rather than rejection and represents a potential market if supported by effective communication, awareness campaigns, and financial incentives. From Rogers' (2003:164) perspective, many SME decision-makers have not yet acquired sufficient knowledge about AI

applications for energy efficiency, and attitudes toward AI-enabled systems are still developing. The findings also reveal very low awareness of New York State energy policies and programs supporting technology-based energy-efficiency initiatives. This creates information asymmetry (Liu et al., 2019), potentially limiting informed technology-adoption decisions.

The current and future AI adoption for energy efficiency remains limited, reflecting the early stage of diffusion. AI adoption is not yet socially patterned, indicating that diffusion has not progressed sufficiently for systematic differences across firms or individuals to emerge. From Rogers' (2003:164) perspective, many SME decision-makers still lack adequate knowledge about AI applications for energy efficiency, and attitudes toward these technologies are still forming. The absence of significant predictors further suggests limited organizational readiness and continued uncertainty regarding AI-based energy technologies.

The findings suggest that SMEs generally demonstrate environmental values and openness toward innovation; however, the actual adoption of energy-efficiency and AI technologies remains constrained by limited knowledge, organizational barriers, and informational uncertainty. The individual and organizational patterns related to energy efficiency and technology adoption reflect 5 main findings.

1. ***Awareness & Adoption Gap:*** SMEs demonstrate higher levels of awareness and concern than actual adoption behavior.
2. ***Uncertainty Hesitation:*** Uncertainty and limited familiarity are more common barriers than direct resistance to energy and technology-related decisions.
3. ***Strategic and Pragmatic Decision-Making:*** SMEs approach innovation selectively, cautiously, and pragmatically rather than ideologically.
4. ***Incomplete Knowledge Diffusion:*** The diffusion of information regarding energy-efficiency technologies and policies remains limited among SMEs.

This section discusses the results related to energy-efficiency behavior tested with VBN theory, technology adoption tested with DOI theory, and the innovation profiles of SMEs. The VBN analysis reveals three important findings. First, the results support the sequential pathway proposed by VBN theory (Stern, 2000), linking values, beliefs, norms, and behaviors. Biospheric

values are associated with responsibility beliefs, responsibility beliefs are associated with industry norms, and norms subsequently relate to energy-efficiency behavior. Second, consistent with previous studies, biospheric values play an important role in shaping environmental responsibility beliefs (Al Mamun et al., 2022). Individuals who hold environmentally oriented values tend to develop stronger perceptions of responsibility regarding energy use and conservation.

Third, egoistic values did not show a meaningful relationship with responsibility beliefs. While previous studies often report a negative relationship between egoistic values and environmental responsibility (Steg et al., 2005; De Groot & Steg, 2007), no significant association was observed in this study. Unlike household consumers, SME decision-makers must balance economic survival, organizational continuity, and environmental concerns simultaneously. As a result, egoistic values may coexist with environmental responsibility beliefs within a pragmatic organizational context.

The DOI analysis also produced three important findings. First, perceived benefits play a central role in shaping SMEs' intentions to adopt AI technologies, consistent with Rogers' (2003) argument that perceived advantages increase adoption rates. Relative advantage, compatibility, observability, and trialability were all important in shaping AI adoption intentions, suggesting that SMEs are primarily motivated by the practical and organizational value of AI technologies. Second, perceived complexity was not significantly associated with intention to use AI, indicating that concerns about difficulty may become less important when perceived benefits are strong. Although prior studies emphasize simplicity as a facilitator of adoption (Cadarette et al., 2017) and identify complexity as a barrier (Dwivedi et al., 2021), SME decision-makers may be willing to overlook complexity when AI is viewed as useful for organizational operations and energy management. Third, intention alone was not a strong predictor of actual AI use behavior (Bhattacharjee & Sanford, 2009). This suggests that external factors such as cost, infrastructure, regulatory requirements, and organizational decision-making authority may constrain the translation of positive intentions into actual adoption (Venkatesh et al., 2003; Liang et al., 2007).

Regarding innovation profiles, SME decision-makers were predominantly characterized by early-adopter and balanced orientations. This pattern is consistent with research highlighting the

strong relationship between SMEs and innovation (Parrilli & Elola, 2012; Indrawati et al., 2020). However, SMEs appear to approach adoption strategically rather than automatically, as reflected in the relatively low level of actual AI adoption. Limited resources, uncertainty, operational risks, competition, and organizational constraints (Hanadi & Aruna, 2013) likely encourage careful evaluation of new technologies before implementation.

The divergence between the observed adopter distribution and Rogers' (2003) theoretical distribution further highlights the contextual nature of innovation adoption among SMEs. Because the study employed purposive sampling within specific commercial and energy-related settings, the findings are not intended to replicate population-level diffusion patterns. Instead, they provide insight into how SME leaders perceive and position themselves toward innovation in real organizational contexts. Overall, SMEs are willing to adopt environmentally responsible and AI-supported practices when organizational value is evident; however, implementation is often moderated by practical and structural constraints. Positive attitudes toward innovation and sustainability do not automatically translate into actual adoption behavior.

CONCLUSION

This study aimed to understand energy-efficiency behaviors and technology adoption in SMEs. The first academic implication is that the findings demonstrate the applicability of both VBN and DOI theories within SME contexts, a relatively underexplored area in energy research. The second implication is that the findings differ from some theoretical expectations in two ways: (1) the non-significant relationship between egoistic values and environmental responsibility beliefs suggests that SME decision-making may involve more pragmatic and multidimensional value structures, and (2) the gap between positive adoption intentions and actual AI use highlights the importance of incorporating organizational and structural variables into technology-adoption research. Practically, the findings suggest that SMEs may benefit from increasing awareness and education regarding energy-efficiency systems, HVAC technologies, and AI-enabled applications. SMEs may also adopt a more strategic approach by considering long-term operational and energy-management benefits rather than focusing solely on implementation costs. For policy makers, the findings highlight the need to improve communication and outreach efforts to increase SME awareness of available energy-efficiency programs. A limitation of the

study is its reliance on purposive sampling and its focus on SMEs in New York State, which may limit the generalizability of the findings. In addition, the study focused primarily on organizational decision-makers and may not fully capture employee perspectives. Future research could examine the role of organizational culture and leadership in shaping energy-efficiency behaviors and technology adoption to better understand the development of green and smart businesses.

REFERENCES

- Acemoglu, D., & Restrepo, P. (2019). The Wrong Kind of AI? Artificial Intelligence and the Future of Labor Demand. National Bureau of Economic Research (NBER Working Paper No. 25682).
- Ahmad, A. Y. A., & Alhulayil, M. (2025). Analysis of Energy Efficiency in Public Buildings Using AI. In *2025 International Conference on Business Intelligence for Technology Innovation (ICBITI)* (pp. 1-8). IEEE.
- Akpan, I. J., Udoh, E. A. P., & Adebisi, B. (2022). Small business awareness and adoption of state-of-the-art technologies in emerging and developing markets, and lessons from the COVID-19 pandemic. *Journal of Small Business & Entrepreneurship*, 34(2), 123–140. <https://doi.org/10.1080/08276331.2020.1820185>.
- Al Mamun, A., Hayat, N., Fazal, S. A., Mohiuddin, M., Masud, M. M., & Raman, R. (2022). Biospheric values, environmental responsibility, and green consumption behavior: Examining the mediating role of environmental self-identity. *Sustainability*, 14(11), 6772.
- Al-Jabri, I., & Sohail, M. S. (2012). Mobile banking adoption: Application of diffusion of innovation theory. *Journal of electronic commerce research*, 13(4), 379-391.
- Arts, J. W. C., Frambach, R. T., & Bijmolt, T. H. A. (2011). Generalizations on consumer innovation adoption: A meta-analysis on drivers of intention and behavior. *International Journal of Research in Marketing*, 28(2), 134–144. <https://doi.org/10.1016/j.ijresmar.2010.11.002>.
- Bansal, P., & Roth, K. (2000). Why companies go green: A model of ecological responsiveness. *Academy of Management Journal*, 43(4), 717–736. <https://doi.org/10.2307/1556363>.

- Barratt, M. J., Ferris, J. A., & Lenton, S. (2015). Hidden Populations, Online Purposive Sampling, and External Validity: Taking off the Blindfold. *Field Methods*, 27(1), 3–21. <https://doi.org/10.1177/1525822X14526838>.
- Bhattacharjee, A., & Sanford, C. (2009). The intention–behaviour gap in technology usage: The moderating role of attitude strength. *Behaviour & Information Technology*, 28(4), 389–401. <https://doi.org/10.1080/01449290802121230>.
- Bird, S., & Hernández, D. (2012). Policy options for the split incentive: Increasing energy efficiency for low-income renters. *Energy Policy*, 48, 506–514. <https://doi.org/10.1016/j.enpol.2012.05.053>
- Bressler, M. S., Bressler, L. A., & Bressler, M. E. (2011). A study of small business technology adoption and utilization. *Academy of Entrepreneurship Journal*, 17(2).
- Brown, T. A., & Moore, M. T. (2012). *Confirmatory factor analysis*. Handbook of structural equation modeling, 361-379.
- Carlisle, J. E., Kane, S. L., Solan, D., Bowman, M., & Joe, J. C. (2015). Public attitudes regarding large-scale solar energy development in the US. *Renewable and Sustainable Energy Reviews*, 48, 835-847.
- Carmichael, J. T., Brulle, R. J., & Huxster, J. K. (2017). The great divide: Understanding the role of media and other drivers of the partisan divide in public concern over climate change in the USA, 2001–2014. *Climatic Change*, 141(4), 599–612. <https://doi.org/10.1007/s10584-017-1908-1>.
- Castellazzi, L., Bertoldi, P., & Economidou, M. (2017). Overcoming the split incentive barrier in the building sector. Publications Office of the European Union, Luxembourg, 10, 912494.
- Cheng, L., & Yu, T. (2019). Smart dispatching for energy internet with complex cyber-physical-social systems: A parallel dispatch perspective. *International Journal of Energy Research*, 43(8), 3080–3133. <https://doi.org/10.1002/er.4384>.
- Choi, H., Jang, J., & Kandampully, J. (2015). Application of the extended VBN theory to understand consumers’ decisions about green hotels. *International Journal of Hospitality Management*, 51, 87–95. <https://doi.org/10.1016/j.ijhm.2015.08.004>.
- Cialdini, R. B. (2003). Crafting normative messages to protect the environment. *Current Directions in Psychological Science*, 12(4), 105–109. <https://doi.org/10.1111/1467-8721.01242>.

- Cialdini, R. B. (2003). Crafting normative messages to protect the environment. *Current Directions in Psychological Science*, 12(4), 105–109. <https://doi.org/10.1111/1467-8721.01242>.
- De Ayala, A., Foudi, S., Solà, M. D. M., López-Bernabé, E., & Galarraga, I. (2021). Consumers' preferences regarding energy efficiency: A qualitative analysis based on the household and services sectors in Spain. *Energy Efficiency*, 14(1), 3. <https://doi.org/10.1007/s12053-020-09921-0>.
- De Groot, J. I. M., & Steg, L. (2007). Value Orientations and Environmental Beliefs in Five Countries: Validity of an Instrument to Measure Egoistic, Altruistic and Biospheric Value Orientations. *Journal of Cross-Cultural Psychology*, 38(3), 318–332. <https://doi.org/10.1177/0022022107300278>.
- Deal, T. E., & Kennedy, A. A. (1982). Corporate cultures: The rites and rituals of corporate life: Addison-Wesley, 1982. ISBN: 0-201-10277-3. \$14.95. *Business Horizons*, 26(2), 82-85.
- Denison, D. (1990). Corporate culture and organizational. *New York: Wiley*.
- Dunlap, R. E., McCright, A. M., & Yarosh, J. H. (2016). The Political Divide on Climate Change: Partisan Polarization Widens in the U.S. *Environment: Science and Policy for Sustainable Development*, 58(5), 4–23. <https://doi.org/10.1080/00139157.2016.1208995>.
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., et al. (2021). Artificial Intelligence (AI): Multidisciplinary Perspectives on Emerging Challenges, Opportunities, and Agenda for Research, *Practice and Policy International Journal of Information Management*, 57, 101994.
- Energy Information Administration EIA (2025) April. U.S. Energy Information Administration. Monthly Energy Review, April tables.
- Enriquez, R., Han, D., Harris, R., & Reddick, C. (2025). Exploring digital access and digital engagement of senior small business owners. *Quality & Quantity*, 59(4), 3631–3647. <https://doi.org/10.1007/s11135-025-02157-z>.
- Fain, D., & Roberts, M. L. (1997). Technology vs. consumer behavior: The battle for the financial services customer. *Journal of Direct Marketing*, 11(1), 44–54. [https://doi.org/10.1002/\(SICI\)1522-7138\(199724\)11:1%253C44::AID-DIR5%253E3.0.CO;2-Z](https://doi.org/10.1002/(SICI)1522-7138(199724)11:1%253C44::AID-DIR5%253E3.0.CO;2-Z).

- Fatoki, O. (2024). Determinants of energy conservation behavior in small hospitality firms: Application of the extended value belief norm theory. *International Journal of Research in Business and Social Science* (2147- 4478), 13(6), 80–93. <https://doi.org/10.20525/ijrbs.v13i6.3386>.
- Fauzi, M. A., Hanafiah, M. H., & Kunjuraman, V. (2024). Tourists' intention to visit green hotels: Building on the theory of planned behaviour and the value-belief-norm theory. *Journal of Tourism Futures*, 10(2), 255–276. <https://doi.org/10.1108/JTF-01-2022-0008>.
- Fawcett, T., & Hampton, S. (2020). Why & how energy efficiency policy should address SMEs. *Energy Policy*, 140, 111337. <https://doi.org/10.1016/j.enpol.2020.111337>.
- Fornara, F., Pattitoni, P., Mura, M., & Strazzera, E. (2016). Predicting intention to improve household energy efficiency: The role of value-belief-norm theory, normative and informational influence, and specific attitude. *Journal of Environmental Psychology*, 45, 1–10. <https://doi.org/10.1016/j.jenvp.2015.11.001>.
- Fresner, J., Morea, F., Krenn, C., Aranda Usón, J., & Fabio Tomasi. (2017). Energy efficiency in small and medium enterprises: Lessons learned from 280 energy audits across Europe. *Journal of Cleaner Production*, 142, 1650–1660. <https://doi.org/10.1016/j.jclepro.2016.11.126>.
- Gao, L., Wang, S., Li, J., & Li, H. (2017). Application of the extended theory of planned behavior to understand individual's energy saving behavior in workplaces. *Resources, Conservation and Recycling*, 127, 107–113. <https://doi.org/10.1016/j.resconrec.2017.08.030>.
- Gennitsaris, S., Oliveira, M. C., Vris, G., Bofilios, A., Ntinou, T., Frutuoso, A. R., Queiroga, C., Giannatsis, J., Sofianopoulou, S., & Dedoussis, V. (2023). Energy Efficiency Management in Small and Medium-Sized Enterprises: Current Situation, Case Studies and Best Practices. *Sustainability*, 15(4), 3727. <https://doi.org/10.3390/su15043727>.
- Gherghina, Ștefan C., Botezatu, M. A., Hosszu, A., & Simionescu, L. N. (2020). Small and Medium-Sized Enterprises (SMEs): The Engine of Economic Growth through Investments and Innovation. *Sustainability*, 12(1), 347. <https://doi.org/10.3390/su12010347>.
- Hampton, S., & Fawcett, T. (2017). Challenges of designing and delivering effective SME energy policy. *European Council for an Energy Efficient Economy Summer Study 2017*.

- Hanadi, A., & Aruna, S. (2013). A study of factors affecting innovation adoption in SMEs. *International Journal of Innovation and Technology Management*, 10(2).
- Haykin, S. (2009). *Neural networks and learning machines*, 3/E. Pearson education India.
- Hofstede, G. (1998). Attitudes, Values and Organizational Culture: Disentangling the Concepts. *Organization Studies*, 19(3), 477–493. <https://doi.org/10.1177/017084069801900305>.
- Hoobler, J. M., Lemmon, G., & Wayne, S. J. (2011). Women's underrepresentation in upper management. *Organizational Dynamics*, 40(3), 151–156. <https://doi.org/10.1016/j.orgdyn.2011.04.001>.
- Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression*. John Wiley & Sons.
- Huang, X. (2009). Strategic decision making in Chinese SMEs. *Chinese Management Studies*, 3(2), 87–101. <https://doi.org/10.1108/17506140910963602>.
- Indrawati, N. K., Salim, U., Djawahir, A. H., & Iqbal, M. (2020). The impact of absorptive capacity and innovation on SMEs' business performance. *International Journal of Innovation Science*, 12(2), 218–232.
- International Energy Agency - IEA (2015), *Policy Pathway - Accelerating Energy Efficiency in Small and Medium-sized Enterprises 2015*, IEA, Paris <https://www.iea.org/reports/policy-pathway-accelerating-energy-efficiency-in-small-and-medium-sized-enterprises-2015>, Licence: CC BY 4.0.
- Jain, N. K., Panda, A., & Arghode, V. (2024). Tourism's circular economy: Opportunities and challenges from an integrated theoretical perspective. *Business Strategy and the Environment*, 33(7), 6172–6186. <https://doi.org/10.1002/bse.3802>.
- Janda, B. K., Bottrill, C., & Layberry, R. (2014). Learning from the “data poor”: Energy management in understudied organizations. *Journal of Property Investment & Finance*, 32(4), 424–442. <https://doi.org/10.1108/JPIF-03-2014-0018>.
- Ketprapakorn, N., & Kantabutra, S. (2019). Culture Development for Sustainable SMEs: Toward a Behavioral Theory. *Sustainability*, 11(9), 2629. <https://doi.org/10.3390/su11092629>.
- Khan, S. U., Khan, N., Ullah, F. U. M., Kim, M. J., Lee, M. Y., & Baik, S. W. (2023). Towards intelligent building energy management: AI-based framework for power consumption and

- generation forecasting. *Energy and Buildings*, 279, 112705. <https://doi.org/10.1016/j.enbuild.2022.112705>.
- Kongolo, M. (2010). Job creation versus job shedding and the role of SMEs in economic development. *African journal of business management*, 4(11), 2288.
- Laukkanen, T., & Cruz, P. (2008). Comparing consumer resistance to mobile banking in Finland and Portugal. In *International Conference on E-Business and Telecommunications* (pp. 89-98). Berlin, Heidelberg: Springer Berlin Heidelberg.
- Lebrument, N., Zumbo-Lebrument, C., & Rochette, C. (2025). Application of the VBN theory to understand residents' participation in the smart city: The case of French metropolises. *Urban Studies*, 62(5), 954–975. <https://doi.org/10.1177/00420980241269808>.
- Lee, D., Fu, Y., Zhou, D., Nie, T., & Song, Z. (2022). Is There a Missing Link? Exploring the Effects of Institutional Pressures on Environmental Performance in the Chinese Construction Industry. *International Journal of Environmental Research and Public Health*, 19(18), 11787. <https://doi.org/10.3390/ijerph191811787>.
- Liang, H., Saraf, N., Hu, Q., & Xue, Y. (2007). Assimilation of Enterprise Systems: The Effect of Institutional Pressures and the Mediating Role of Top Management1. *MIS Quarterly*, 31(1), 59–87. <https://doi.org/10.2307/25148781>.
- Lin, H. F. (2011). An empirical investigation of mobile banking adoption: The effect of innovation attributes and knowledge-based trust. *International Journal of Information Management*, 31(3), 252–260. <https://doi.org/10.1016/j.ijinfomgt.2010.07.006>.
- Liu, Y., Yao, X., & Wei, T. (2019). Energy efficiency gap and target setting: A study of information asymmetry between governments and industries in China. *China Economic Review*, 57, 101341. <https://doi.org/10.1016/j.chieco.2019.101341>.
- Madison, K., Moore, C. B., Daspit, J. J., & Nabisaalu, J. K. (2022). The influence of women on SME innovation in emerging markets. *Strategic Entrepreneurship Journal*, 16(2), 281–313. <https://doi.org/10.1002/sej.1422>.
- Malhotra, N., Margalit, Y., & Shi, S. (2025). The Politics of Small Business Owners. *British Journal of Political Science*, 55, e94. <https://doi.org/10.1017/S0007123425000274>.
- Marquez, L., McGregor, J., & Syme, M. (2012). Barriers to the adoption of energy efficiency measures for existing commercial buildings. *Victoria: CSIRO Mathematics, Informatics and Statistics*.

- Meglino, B. M., & Ravlin, E. C. (1998). Individual Values in Organizations: Concepts, Controversies, and Research. *Journal of Management*, 24(3), 351–389. <https://doi.org/10.1177/014920639802400304>.
- Musso, F., & Francioni, B. (2012). The Influence of Decision-Maker Characteristics on the International Strategic Decision-Making Process: An SME Perspective. *Procedia - Social and Behavioral Sciences*, 58, 279–288. <https://doi.org/10.1016/j.sbspro.2012.09.1002>.
- Office of the United States Trade Representative. (2026). *Trans-Pacific Partnership: Small and medium-sized enterprises chapter*. U.S. Trade Representative. Retrieved April 2026, from <https://ustr.gov/trade-agreements/free-trade-agreements/trans-pacific-partnership/tpp-chapter-chapter-negotiating-8>.
- Overbye-Thompson, H., & Hamilton, K. A. (2025). A diffusion of innovations measurement scale for reinvention, relative advantage, compatibility, complexity, trialability and observability. *PLoS One*, 20(10), e0334616.
- Palmer, K. L., & Walls, M. (2015). Does Information Provision Shrink the Energy Efficiency Gap? A Cross-City Comparison of Commercial Building Benchmarking and Disclosure Laws. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.2622692>.
- Parrilli, M. D., & Elola, A. (2012). The strength of science and technology drivers for SME innovation. *Small Business Economics*, 39(4), 897–907. <https://doi.org/10.1007/s11187-011-9319-6>.
- Pettigrew, A. M. (1979). On Studying Organizational Cultures. *Administrative Science Quarterly*, 24(4), 570. <https://doi.org/10.2307/2392363>.
- Poon, W. (2007). Users' adoption of e-banking services: The Malaysian perspective. *Journal of Business & Industrial Marketing*, 23(1), 59–69. <https://doi.org/10.1108/08858620810841498>.
- Prawesh, S., Chari, K., & Agrawal, M. (2021). Industry Norms as Predictors of IT Outsourcing Behaviors. *International Journal of Information Management*, 56, 102242. <https://doi.org/10.1016/j.ijinfomgt.2020.102242>.
- Prindle, W., & Finlinson, S. (2011). How Organizations Can Drive Behavior-Based Energy Efficiency. In *Energy, Sustainability and the Environment* (pp. 305–335). Elsevier. <https://doi.org/10.1016/B978-0-12-385136-9.10011-7>.

- Puppe, F. (1993). Heuristic Classification. In F. Puppe, *Systematic Introduction to Expert Systems* (pp. 131–148). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-77971-8_15.
- Rai, N., & Thapa, B. (2015). A study on purposive sampling method in research. Kathmandu: Kathmandu School of Law, 5(1), 8-15.
- Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). Free Press.
- Roxas, B. (2022). Eco-innovations of firms: A longitudinal analysis of the roles of industry norms and proactive environmental strategy. *Business Strategy and the Environment*, 31(1), 515–531. <https://doi.org/10.1002/bse.2907>.
- Ruepert, A. M., Keizer, K., & Steg, L. (2017). The relationship between Corporate Environmental Responsibility, employees' biospheric values and pro-environmental behavior at work. *Journal of Environmental Psychology*, 54, 65–78. <https://doi.org/10.1016/j.jenvp.2017.10.006>.
- Saunila, M. (2020). Innovation capability in SMEs: A systematic review of the literature. *Journal of Innovation & Knowledge*, 5(4), 260–265. <https://doi.org/10.1016/j.jik.2019.11.002>.
- Savery, C. A. (2005). *Innovators or laggards: surveying diffusion of innovations by public relations practitioners*. Master's thesis, University of Akron. Ohio.
- Schein, E. H. (1984). Coming to a new awareness of organizational culture. *Sloan management review*, 25(2), 3-16.
- Schein, E. H. (1985). Defining organizational culture. *Classics of organization theory*, 3(1), 490-502.
- Sockhill, N. J., Dean, A. J., Oh, R. R. Y., & Fuller, R. A. (2022). Beyond the ecocentric: Diverse values and attitudes influence engagement in pro-environmental behaviours. *People and Nature*, 4(6), 1500–1515. <https://doi.org/10.1002/pan3.10400>.
- Steg, L., & De Groot, J. I. M. (2012). Environmental values. In S. Clayton (Ed.), *The Oxford handbook of environmental and conservation psychology* (pp. 81–92). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780199733026.013.0005>.
- Steg, L., Dreijerink, L., & Abrahamse, W. (2005). Factors influencing the acceptability of energy policies: A test of VBN theory. *Journal of Environmental Psychology*, 25(4), 415–425. <https://doi.org/10.1016/j.jenvp.2005.08.003>.

- Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., & Kalof, L. (1999). A Value-Belief-Norm Theory of Support for Social Movements: The Case of Environmentalism. *Human Ecology Review*, 6(2), 81–97.
- Su, S., Li, J., Yuan, J., Tang, M., Wang, E., & Ding, Y. (2022). How can energy saving culture of a company influence energy behaviors and consumptions in its offices? A simulation and optimization model. *Journal of Building Engineering*, 58, 105011. <https://doi.org/10.1016/j.jobbe.2022.105011>.
- Tan, M., & Teo, T. S. (2000). Factors influencing the adoption of Internet banking. *Journal of the Association for information Systems*, 1(1), 1–44. <https://doi.org/10.17705/1jais.00005>.
- Thurik, R., & Wennekers, S. (2004). Entrepreneurship, small business and economic growth. *Journal of Small Business and Enterprise Development*, 11(1), 140–149. <https://doi.org/10.1108/14626000410519173>.
- Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on Engineering Management*, EM-29(1), 28–45. <https://doi.org/10.1109/TEM.1982.6447463>.
- Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on Engineering Management*, EM-29(1), 28–45. <https://doi.org/10.1109/TEM.1982.6447463>.
- U.S. Small Business Administration Office of Advocacy. (2019). *Small businesses generate 44 percent of U.S. economic activity*. U.S. Small Business Administration.
- U.S. Small Business Administration Office of Advocacy. (2026). *Frequently asked questions about small business 2026*. U.S. Small Business Administration. https://advocacy.sba.gov/wp-content/uploads/2026/02/FINAL_FAQsAboutSmallBusiness_2026_012826.pdf.
- Ünal, A. B., Steg, L., & Granskaya, J. (2019). “To support or not to support, that is the question”. Testing the VBN theory in predicting support for car use reduction policies in Russia. *Transportation Research Part A: Policy and Practice*, 119, 73–81. <https://doi.org/10.1016/j.tra.2018.10.042>.
- United States International Trade Commission (2010). Small and medium-sized enterprises: Overview of participation in US exports. *United States International Trade Commission*:

- Washington, DC, USA. (USITC Publication No. 4125).
<https://www.usitc.gov/publications/332/pub4125.pdf>.
- Varum, C. A., & Rocha, V. C. (2013). Employment and SMEs during crises. *Small Business Economics*, 40(1), 9–25. <https://doi.org/10.1007/s11187-011-9343-6>.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward A Unified View1. *MIS Quarterly*, 27(3), 425–478. <https://doi.org/10.2307/30036540>.
- White, A., Kirby, A., Debelius, H., & Duncan, J. (2020). *How Green Leasing Programs Can Help Overcome the Split Incentive*. ACEEE Summer Study Paper.
- Whitley, C. T., Takahashi, B., Zwickle, A., Besley, J. C., & Lertpratchya, A. P. (2018). Sustainability behaviors among college students: An application of the VBN theory. *Environmental Education Research*, 24(2), 245–262.
<https://doi.org/10.1080/13504622.2016.1250151>
- Xie, C., Ding, H., Zhang, H., Yuan, J., Su, S., & Tang, M. (2021). Exploring the psychological mechanism underlying the relationship between organizational interventions and employees' energy-saving behaviors. *Energy Policy*, 156, 112411. <https://doi.org/10.1016/j.enpol.2021.112411>.
- Zhou, M., Ma, L., Zhang, T., Wu, Q., Zhou, Y., & Sun, L. (2024). Artificial intelligence empowerment in China's energy landscape: Enhancing power grid investment efficiency. *Frontiers in Energy Research*, 12, 1441540. <https://doi.org/10.3389/fenrg.2024.1441540>.

AI-USE STATEMENT: ChatGPT was used for grammatical editing of this manuscript.

FIGURES

Figure 1. Survey data collection process

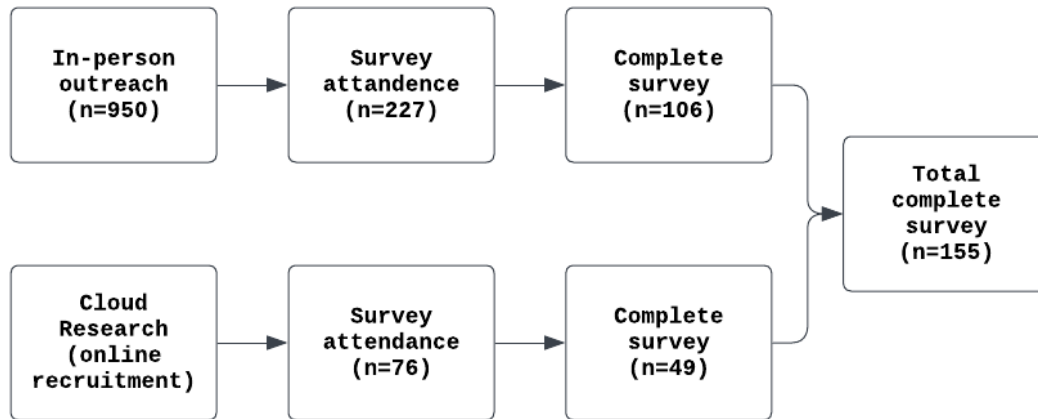


Figure 2. Political Orientation and Climate Change Attitude of the Participants

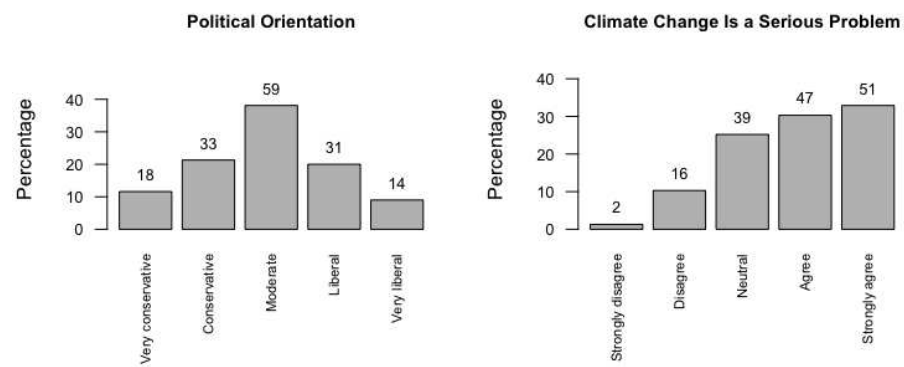


Figure 3. Distribution of energy-efficiency measures, AI use, and program awareness in New York State

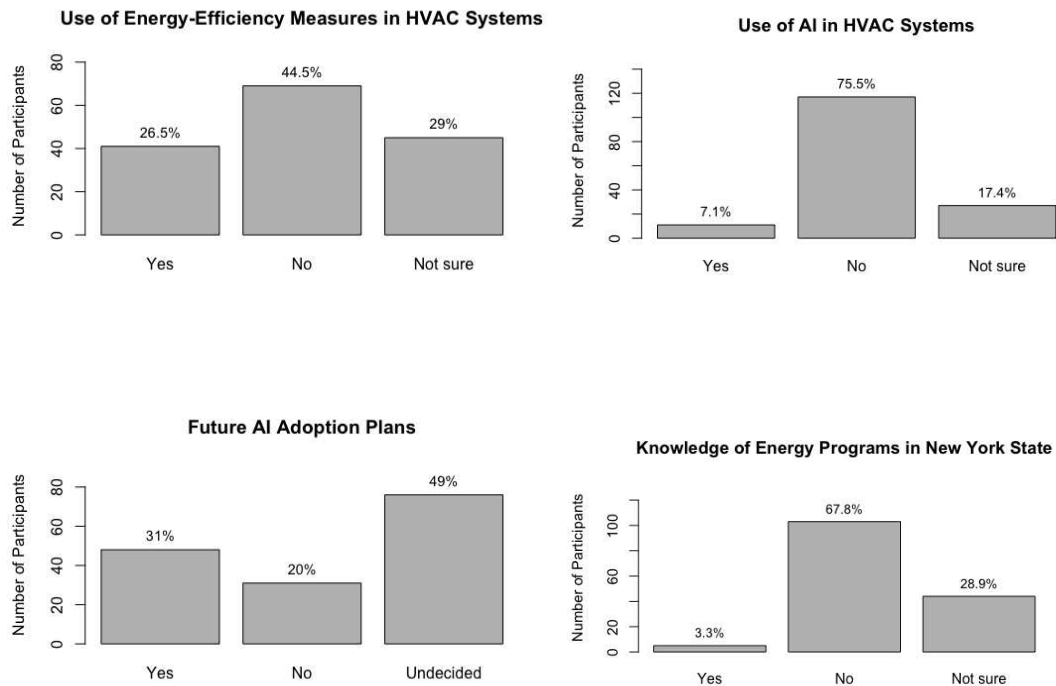


Figure 4. Proposed research model based on the VBN framework

Figure 5. Proposed research model based on the DOI framework

Figure 6. Number of the adopters

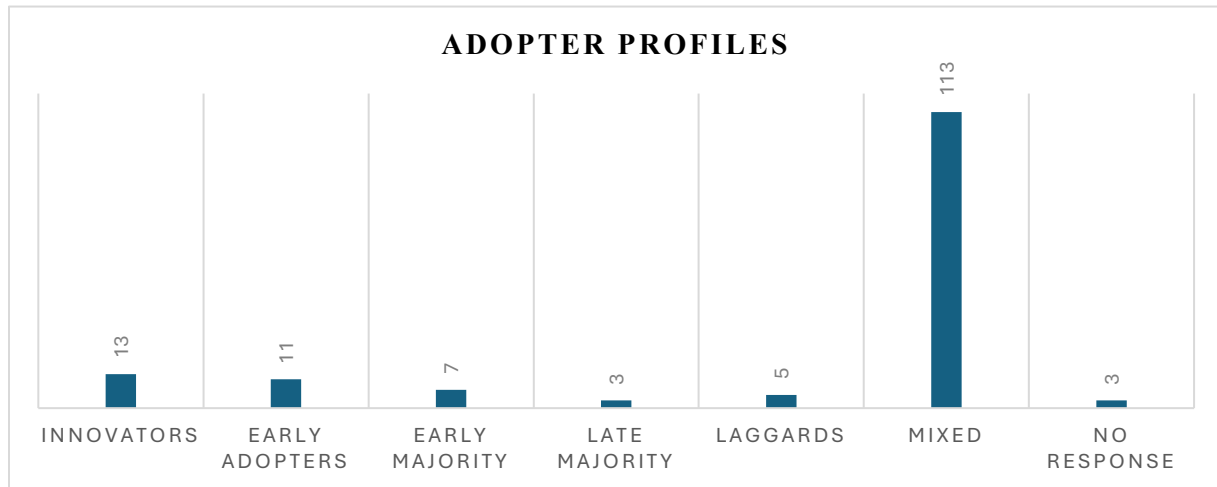
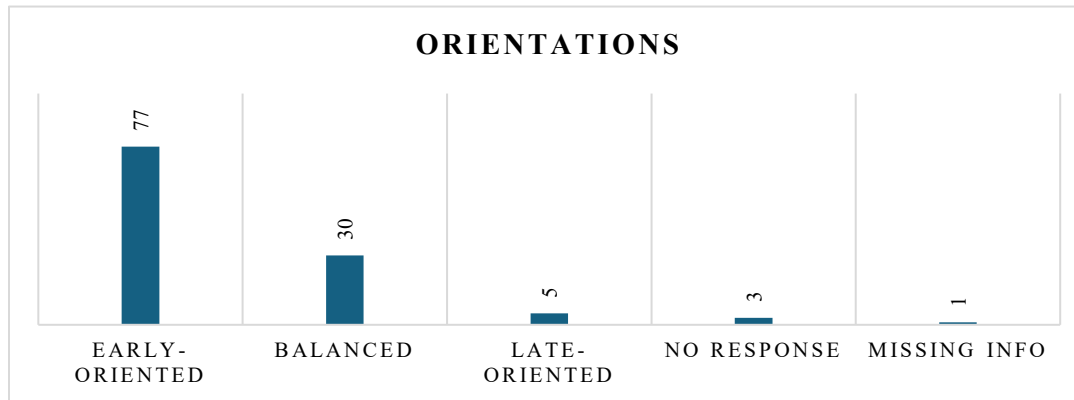


Figure 7. Classification of Mixed Orientations



TABLES

Table 1. Measurement Scale for VBN framework

Constructs	Description	Measurement Items	Sources/ Adapted from
Biospheric values	SME concern for environmental protection and resource conservation	V1-Preventing pollution, conserving natural resources, V2-Respecting the earth, harmony with other species, V3-Protecting the environment, preserving nature.	<i>Stern et al. (1999)</i>
Egoistic values	SME focus on financial gains, control, and competitiveness	V4-Social power, control over others, V5-Wealth, material possessions, money, V6-Authority, the right to lead or command.	
Energy Efficiency Responsibility Beliefs	SME beliefs on responsibility and action for improving business energy efficiency	B1-The government should take stronger action to support energy efficiency in business, B2-I feel a personal obligation to reduce my business's energy use, B3-Businesses and industry should improve energy efficiency and lower emissions.	
Industry Norms	Industry, business, and customer expectations guiding SME environmental responsibility	N1-Businesses in my industry, in general, support the importance of energy efficiency, N2-Businesses in my industry, in general, implement energy efficiency practices, N3-Our customers, in general, support the importance of energy efficiency.	<i>Cialdini (2003), Whitley et al. (2018)</i>

Table 2. Measurement Scale for DOI framework

Constructs	Description	Measurement Items	Sources/ Adapted from
Relative advantage	Advantages, usefulness, and value of AI	RA1- AI is a convenient way to improve how we operate, RA2- AI helps our business run more efficiently, RA3- AI allows us to work more effectively, RA4- AI gives us greater control over our operations, RA5- AI is useful for managing business resources,	<i>Tan & Teo (2000)</i>
Compatibility	Degree to which AI use fits with existing operations	C1-AI fits well with the way we currently operate, C2-AI is compatible with our business practices, C3-Using AI fits well with our work processes,	<i>Lin (2011)</i>
Observability	Visibility of AI benefits and outcomes	O1-The benefits of using AI are visible in our daily operations, O2-AI allows faster results compared to manual processes, O3-The outcomes of using AI can be seen quickly, O4- AI makes its impact on our business clear,	<i>Poon (2007), Fain & Roberts (1997)</i>
Trialability	Opportunity to trial AI before adoption	T1-I would like to try AI tools for at least one month, T2-I want to test AI in our business to see how it performs.	<i>Tan & Teo (2000)</i>
Complexity	Difficulty, challenges, and effort involved in using AI	CX1-Using AI requires a lot of mental effort, CX2-AI systems require technical skills, CX3-Working with AI can be frustrating or overwhelming,	<i>Tan & Teo (2000), Laukkanen & Cruz (2009)</i>

Table 3. Measurement Items for Self-perceived Innovation Orientation

Innovation Orientation	Measurement Item	Source
Innovator	Time_1. I am venturesome and eager to be the first to try new innovations	<i>Savery (2005)</i>
Early adopters	Time_2. I adopt innovations and influence others to do so	
Early majority	Time_3. I am willing to follow the lead of others in adopting innovations	
Late majority	Time_4. I go along with innovations out of necessity	
Laggards	Time_5. I am resistant to change	

Table 4. Demographic of the survey participants (N=155)

Demographic Variable	Category	Survey Participants	
		Frequency	Percent (%)
Job position	<i>Manager</i>	78	50.3
	<i>Owner</i>	56	36.1
	<i>Co-owner</i>	15	9.7
	<i>Other</i>	6	3.9
Age	<i>18-24</i>	8	5.2
	<i>25-34</i>	53	34.2
	<i>35-44</i>	44	28.4
	<i>45-54</i>	31	20.0
	<i>55-64</i>	18	11.6
	<i>65+</i>	1	0.6
Gender	<i>Male</i>	119	76.8
	<i>Female</i>	36	23.2
	<i>Non-binary/Third gender</i>	0	0.0
	<i>Prefer not to say</i>	0	0.0
	<i>Prefer to self-describe</i>	0	0.0
Education	<i>Elementary or Middle School</i>	2	1.3
	<i>High School Diploma or Equivalent</i>	24	15.5
	<i>Associate's degree</i>	17	11.0
	<i>Bachelor's Degree</i>	81	52.3
	<i>Master's Degree</i>	25	16.1
	<i>Doctoral Degree</i>	6	3.9
Work Experience	<i>Less than 1</i>	0	0.0
	<i>1-5</i>	30	19.4
	<i>6-10</i>	40	25.8
	<i>11-19</i>	32	20.6
	<i>20+ years</i>	53	34.2
Household Income (Annual)	<i>less than \$50K</i>	13	8.4
	<i>\$50K - \$100K</i>	57	36.8
	<i>\$100K - \$250K</i>	64	41.3
	<i>\$250K - \$500K</i>	18	11.6
	<i>more than \$500K</i>	3	1.9

Table 5. Firm profile (N=155)

Firm Profile Variable	Category	Survey Participants	
		Frequency	Percent (%)
Number of Businesses in the Commercial Building	<i>1</i>	35	22.6
	<i>2-5</i>	49	31.6
	<i>6-10</i>	30	19.4
	<i>11-20</i>	24	15.5
	<i>21-50</i>	10	6.5
	<i>51-100</i>	3	1.9
	<i>More than 100</i>	4	2.6
Primary Industry	<i>Accommodation and food service</i>	56	36.1
	<i>Retail Trade</i>	14	9.0
	<i>Art, entertainment, and recreation</i>	12	7.7
	<i>Finance and insurance</i>	12	7.7
	<i>Construction</i>	10	6.5
	<i>Others (renewable energy, personal services, gym, gas station, spa, engineering consultation, beauty, barber, auto repair)</i>	10	6.5
	<i>Information</i>	7	4.5
	<i>Manufacturing</i>	7	4.5
	<i>Health care and social assistance</i>	6	3.9
	<i>Professional, scientific, and technical service</i>	6	3.9
	<i>Real estate and rental and leasing</i>	5	3.2
	<i>Transportation and warehousing</i>	5	3.2
	<i>Educational services</i>	1	0.7
	<i>Management of companies and enterprises</i>	1	0.7
	<i>Mining, quarrying, and oil and gas extraction</i>	1	0.7
	<i>Utilities</i>	1	0.7
	<i>Wholesale trade</i>	1	0.7
Firm Age	<i>Less than 1</i>	4	2.6
	<i>1-5</i>	45	29.0
	<i>6-10</i>	37	23.9
	<i>11-20</i>	36	23.2
	<i>More than 20 years</i>	33	21.3
Number of Employees	<i>Only myself</i>	5	3.2
	<i>1-10</i>	70	45.2
	<i>11-50</i>	42	27.1
	<i>51-200</i>	24	15.5
	<i>201-500</i>	14	9.0
Annual Energy Expenditure	<i>less than \$5K</i>	25	16.1

	<i>\$5K - \$20K</i>	76	49.0
	<i>\$20K - \$50K</i>	37	23.9
	<i>more than \$50K</i>	16	10.3

Table 6. Factor loadings, reliability and AVE

Construct	Item	Mean	SD	Loading	CR	Cronbach's α	AVE
Biospheric Values (BV)	V1	4.327	0.737	0.808	0.874	0.862	0.699
	V2	4.348	0.699	0.810			
	V3	4.391	0.748	0.886			
Egoistic Values (EV)	V4	3.414	1.267	0.779	0.836	0.831	0.635
	V5	3.738	1.042	0.704			
	V6	3.601	1.086	0.890			
Beliefs (B)	B1	4.132	0.814	0.663	0.753	0.739	0.504
	B2	3.901	0.940	0.617			
	B3	4.162	0.788	0.871			
Norms (N)	N1	3.403	1.106	0.949	0.892	0.865	0.742
	N2	3.429	1.059	0.859			
	N3	3.589	0.866	0.705			

Table 7. Results of The Structural Model

Paths	Standardized Coefficient	Z	p
H1: Biospheric Values→ Belief	0.732	9.075	0.000***
H2: Egoistic Values →Belief	0.118	1.885	0.059
H3: Belief→Norm	0.581	3.338	0.001***
H4: Norm→Behavior	0.469	3.552	0.000***

Table 8. Factor loadings, reliability and AVE

Construct	Item	Mean	SD	Loading	CR	Cronbach's α	AVE
Relative advantage	RA1	3.722	0.953	0.884	0.918	0.905	0.696
	RA2	3.712	0.964	0.874			
	RA3	3.614	0.940	0.859			
	RA4	3.464	0.960	0.802			
	RA5	3.895	0.844	0.717			
Compatibility	C1	3.311	1.008	0.872	0.924	0.925	0.803
	C2	3.437	0.963	0.898			
	C3	3.450	0.940	0.922			
Observability	O1	3.500	0.997	0.897	0.890	0.893	0.689
	O2	3.836	0.887	0.809			
	O3	3.796	0.894	0.729			
	O4	3.550	0.900	0.857			
Complexity	CX1	3.197	1.240	0.886	0.871	0.871	0.696
	CX2	3.546	1.115	0.848			
	CX3	3.278	1.084	0.745			
Trialability	T1	3.831	0.836	0.870	0.888	0.889	0.799
	T2	3.900	0.849	0.916			

Table 9. Results of Structural Model

Paths	Standardized Coefficient	z	p
H1: Perceived Benefits of AI → Intention to Use AI	0.368	4.455	< .001
H2: Perceived Complexity of AI → Intention to Use AI	0.067	0.857	.392
H3: Intention to Use AI → AI Use Behavior	0.177	1.706	.088

Table 10. Decision Rule

Composite Category	Decision Rule
Early Innovators	$\text{Mean (Innovator + Early Adopter)} \geq \text{Mean (Late Majority + Laggard)} + 0.50$
Late Innovators	$\text{Mean (Late Majority + Laggard)} \geq \text{Mean (Innovator + Early Adopter)} + 0.50$
Balanced	Difference between early and late means < 0.50