

PUBLIC PERCEPTIONS OF AI-DRIVEN RENEWABLE ENERGY: DETERMINANTS OF SUPPORT FOR GREEN HYDROGEN APPLICATIONS

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ABSTRACT: Integrating the Technology Acceptance Model (TAM), Value–Belief–Norm (VBN) Theory, and Institutional Theory, this study develops a psycho-institutional framework to examine the governance paradox—namely, the divergence between rapid technological advancement and limited public support in the context of energy transitions. Drawing on survey data from 1,250 Taiwanese citizens and analyzed using Covariance-Based Structural Equation Modeling (CB-SEM), the proposed model exhibits an excellent fit to the data ($\chi^2/df = 1.07$; CFI = 0.998; RMSEA = 0.007). The results indicate that Artificial Intelligence Energy Cognition (AIEC) and Environmental Values (EV) exert significant effects on Support Intention (SI), with Policy Trust (PT) emerging as the most influential mediating mechanism ($\beta = 0.35$, $p < .001$). The structural model explains 24% of the variance in SI toward Green Hydrogen (GH) ($R^2 = 0.24$), suggesting that institutional credibility outweighs perceived technical utility in shaping public acceptance of radical energy technologies. Further analysis reveals a scale-dependent cognitive pattern: respondents expressed greater confidence in AI applications for macro-level system optimization ($M = 4.10$) than in autonomous AI control over localized energy equipment ($M = 3.96$). Collectively, these findings indicate that narrowing the implementation gap in AI-driven GH deployment requires transparent, accountable, and trust-based governance mechanisms, highlighting the central role of institutional design in managing societal acceptance during energy transitions.

KEYWORDS: *Green Hydrogen; Artificial Intelligence Energy Cognition; Environmental Values; Policy Trust; Support Intention*

1. INTRODUCTION

The global energy transition has reached a critical juncture. Although the decarbonization potential of Green Hydrogen (GH) is widely recognized, a persistent implementation gap remains between policy ambitions and large-scale deployment (Odenweller & Ueckerdt, 2025). In response, Artificial Intelligence (AI) has increasingly been positioned as a socio-technical instrument for optimizing grid dispatch, managing renewable intermittency, and integrating hybrid energy systems (Xiang et al., 2025).

However, as algorithmic systems evolve from decision-support tools to entities exercising autonomous decisional authority, they introduce new societal risks, most notably algorithmic opacity ("black-box" decision-making) and the amplification of systemic bias (Afroogh et al., 2024). Recent scholarship suggests that algorithmic decision-making (ADM) has the potential to fundamentally reshape the citizen–state relationship; in the absence of robust institutional trust, public concerns regarding automated bias may erode the legitimacy of algorithmic governance arrangements (Parviainen et al., 2025). Consequently, these technical limitations underscore the critical importance of institutional credibility in mediating public acceptance.

Accordingly, the diffusion of GH applications constitutes not only a techno-economic challenge but also a governance problem centered on public trust in both complex technologies and the institutions responsible for their implementation (Gordon et al., 2025).

Despite the increasing ubiquity of AI in everyday contexts—such as smartphones and algorithmic recommendation systems—its application within high-risk, NIMBY-prone (Not in My Back Yard) GH infrastructure constitutes a highly specialized cognitive domain that is markedly distinct from general digital literacy. Although prior studies have examined the role of AI explainability in shaping trust (Afroogh et al., 2024), systematic empirical investigation into the public's domain-specific cognition of AI applications in energy systems remains substantially limited (Safari et al., 2024). This gap is particularly consequential in energy policy contexts where citizens must form judgments about algorithmic systems without direct operational experience.

To address this conceptual gap, this study introduces Artificial Intelligence Energy Cognition (AIEC) as a distinct psychological construct capturing individuals' subjective understanding of, and perceived functional competence in, AI-enabled energy systems. AIEC reflects how lay citizens cognitively evaluate the capacity of AI to support complex energy functions, rather than general familiarity with digital technologies.

Unlike general digital literacy, AIEC specifically captures perceptions of algorithmic competence in stabilizing volatile renewable energy inputs and managing complex energy storage and dispatch processes (Dong & Wang, 2024). In the context of macro-level energy governance, AI-enabled decision systems often operate as credence goods, whose performance and reliability cannot be readily evaluated by lay citizens *ex ante*. As a result, individuals must rely on cognitive heuristics and institutional signals when forming judgments about such technologies.

Accordingly, AIEC functions as a critical cognitive antecedent to institutional trust, shaping whether AI-enabled energy governance arrangements are perceived as legitimate and acceptable (Ibrahim et al., 2025). This perspective highlights the theoretical necessity of situating technology acceptance frameworks—most notably the Technology Acceptance Model (TAM)—within the broader institutional and governance context of the energy transition, rather than treating acceptance as a purely individual or utilitarian decision (Davis, 1989; Venkatesh & Davis, 2000).

To address these theoretical gaps, this study advances an integrated psycho-institutional model that synthesizes the TAM with value-oriented and institutional perspectives. In high-uncertainty policy contexts such as AI-driven GH deployment, lay citizens often lack the informational capacity to form concrete awareness of consequences or clearly ascribe responsibility for technological outcomes. Under such conditions, prior research suggests that Environmental Values (EV) operate as salient heuristic cues, shaping policy support either directly or indirectly through trust-based mechanisms (Gordon et al., 2024; Palomo-Vélez et al., 2025). Accordingly, this study conceptualizes EV not merely as a moral orientation but as a psychological anchor underpinning Policy Trust (PT).

Building on this logic, the proposed framework specifies two complementary pathways. The first is a rational pathway, grounded in TAM, through which AIEC influences Support Intention (SI) via Perceived Usefulness (PU). The second is a normative-institutional pathway, informed by Institutional Theory, whereby EV reinforce trust in governing institutions, thereby mitigating perceived technological risks and enhancing SI (Palomo-Vélez et al., 2025).

The central contribution of this study lies in empirically demonstrating that PT functions as a critical mediating mechanism linking AI-related cognition and EV to public SI. In doing so, this research provides a systematic explanation for the governance paradox of “technological advancement versus social apathy.” While existing studies have predominantly examined the technical feasibility and economic efficiency of GH, the psycho-institutional processes underlying societal acceptance remain insufficiently theorized (Gordon et al., 2025; Mhlanga, 2025). By integrating AIEC, EV, and institutional trust into a unified analytical framework, this study helps bridge the persistent divide between technological optimization and social acceptance under conditions of radical technological uncertainty.

2. THEORETICAL INTEGRATION AND LITERATURE REVIEW

2.1 Addressing the Theoretical Gap: A Psycho-Institutional Synthesis

Existing scholarship on public acceptance of GH has predominantly emphasized techno-economic evaluations or isolated examinations of risk perception and community attitudes. Although research on AI in energy governance has expanded rapidly, it remains largely oriented toward technical system optimization, including load forecasting, energy storage management, and grid dispatch (Dong & Wang, 2024; Safari et al., 2024). As a result, empirical understanding of the psycho-institutional processes through which public cognition is translated into policy support remains limited.

Moreover, influential theoretical frameworks—most notably the TAM and the Value-Belief-Norm (VBN) theory—are rarely integrated within a unified analytical structure, and frequently neglect the mediating role of institutional trust in shaping public support for high-uncertainty energy technologies. To address this limitation, the present study advances a synthesized psycho-institutional framework that systematically integrates TAM, VBN, and Institutional Theory.

2.2 The Rational Pathway: TAM

The TAM posits that PU and Perceived Ease of Use (PEOU) constitute the primary cognitive determinants of behavioral intention toward technology adoption (Davis, 1989; Venkatesh & Davis, 2000). In AI-related decision contexts, prior empirical evidence consistently identifies PU as the most salient predictor of adoption and support intentions, particularly when system interaction is indirect or abstracted from end users (Ibrahim et al., 2025).

Building on this foundation, the present study theorizes that AIEC—reflecting individuals’ understanding of the functional role of AI in energy systems—enhances SI indirectly through the mediation of PU. In contrast to conventional individual-level Institutional Theory adoption settings, citizens engaged with macro-level energy policy are not required to directly operate AI systems, thereby reducing the explanatory relevance of perceived ease of use. Accordingly, PEOU was excluded from the final model to enhance theoretical parsimony and mitigate respondent cognitive burden in the survey design.

2.3 The Normative and Institutional Pathways: VBN and Institutional Theory

To explain public support for AI-driven GH, this study develops an integrated framework combining the cognitive-rational pathway of the TAM, the normative-motivational pathway of the Value–Belief–Norm (VBN) Theory, and the contextual-constraint pathway of Institutional Theory. The framework posits that EV constitute the deep normative foundation of SIs, while PT serves as a critical institutional mediator translating individual values into concrete policy support.

This study operationalizes the VBN theory primarily through EV, directly addressing reviewer feedback. This choice is justified by three sequential theoretical considerations. First, in the context of high-uncertainty technologies such as AI and GH, the public often struggles to form concrete perceptions of consequences or assign responsibility (Mehmeti et al., 2025). Under such informational ambiguity, relatively stable and abstract EV play a crucial heuristic role, guiding individuals toward initial policy preferences (Bouman et al., 2021). Capturing this foundational value-driven mechanism is therefore essential for understanding public judgment under high-tech risk conditions.

Second, although the full VBN chain (values → beliefs → norms → behavior) effectively predicts general pro-environmental behavior (Chen, 2015), for energy infrastructure policies that rely on institutional credibility, the pathway from values → PT → support is more direct and potent. Recent studies confirm that incorporating trust into this pathway can explain public support for complex energy policies as effectively—or even more effectively—than the traditional full-chain model (Gordon et al., 2025; Palomo-Vélez et al., 2025). This underscores institutional trust as a central catalyst in translating values into support intentions within energy governance.

Third, this study integrates multiple variables from TAM and Institutional Theory. Mechanically including the full VBN constructs (e.g., New ecological paradigm, NEP \ Awareness of consequences, AC \ Ascription of responsibility, AR \ Personal norm, PN) would lengthen the survey, complicate the model, and increase the risk of common method bias while reducing statistical power (Kline, 2016). Following recent simplification strategies (Al Mamun et al., 2025), we focus on the core pathway of values → PT → support, aiming to test the central theoretical mechanism using the most parsimonious constructs.

By focusing on EV and PT, this approach not only directly addresses the need for theoretical simplification under the dual conditions of high technological uncertainty and institutional dependence but also theoretically highlights the importance of transparent, equitable, and enforceable institutional design (Devine et al., 2024; Scott, 2014).

2.4 The Dual Role of AI in Energy Transition

AI offers substantial technical advantages in contemporary energy systems, particularly in load forecasting, renewable energy scheduling, and real-time grid management thereby enhancing system reliability and operational efficiency (Safari et al., 2024). However, the translation of AI-related cognition into public policy support remains socially and institutionally complex (Odenweller & Ueckerdt, 2025). Although AI’s predictive and optimization capabilities contribute to decarbonization objectives (Safari et al., 2024), their societal acceptance is not automatic.

Specifically, concerns related to algorithmic bias, limited transparency, the conceptualized “empathy gap” in automated decision-making, and the risk of excessive reliance on algorithmic outputs underscore the need for caution against uncritical techno-optimism (Afroogh et al., 2024; Odenweller & Ueckerdt, 2025). These limitations highlight why cognitive understanding alone is insufficient to secure public support, reinforcing the importance of institutional trust and value-based evaluations in governing AI-enabled energy transitions.

2.5 Synthesis: A Dual-Mediation Model

Accumulating evidence indicates that in high-uncertainty energy policy contexts, trust and transparency function as situational and context-dependent mechanisms rather than stable antecedents (Organisation for Economic Co-operation and Development [OECD], 2025). While some studies report a limited moderating role of political trust in shaping climate policy support (Devine et al., 2024), others contend that trust operates as a critical mediating mechanism in the acceptance of hydrogen-related technologies (Palomo-Vélez et al., 2025). These divergent findings underscore the need for a more integrative analytical framework capable of reconciling cognitive, normative, and institutional processes.

Accordingly, this study proposes a dual-mediation psycho-institutional model (Palomo-Vélez et al., 2025), in which AIEC influences SI through two complementary pathways: (1) a rational-cognitive pathway via PU, and (2) an institutional-trust pathway via PT, while EV affect SI both directly and indirectly via PT (Palomo-Vélez et al., 2025). By explicitly modeling these dual mediation pathways, the proposed framework addresses a critical theoretical gap concerning the role of institutional trust in translating public cognition and values into policy support within AI-driven energy transitions (Gordon et al., 2025). This integrative approach offers empirically grounded insights for the governance and implementation of GH policies under conditions of high technological uncertainty.

3. METHOD

This study adopted a theory-driven, cross-sectional survey design to investigate the psycho-institutional mechanisms underlying public support for AI-enabled GH applications among Taiwanese citizens aged 20 years and above. The core constructs—AIEC, EV, PU, PT, and SI—were specified as latent variables and operationalized using a structured and previously validated measurement instrument.

Grounded in the integration of the TAM, the Value-Belief-Norm (VBN) theory, and an institutional trust perspective, this study employed Covariance-Based Structural Equation Modeling (CB-SEM) to test the hypothesized relationships and mediation effects. CB-SEM was selected due to its suitability for theory-driven hypothesis testing and its capacity to estimate complex models involving multiple latent constructs. Although the cross-sectional design necessitates caution in making causal claims, this analytical approach enables rigorous examination of theoretically specified mechanisms underlying public support intentions.

Measurement scales were adapted from well-established sources, including Davis (1989), Stern et al. (1999), and recent institutional trust literature (e.g., Gupta, 2025). All items were contextually refined to capture respondents' perceptions of AI's functional role in hydrogen production, storage, and decision optimization, as well as their evaluations of PT. The integrated conceptual framework is presented in Figure 1, illustrating the dual mediation pathways through which AIEC and EV influence SI via PU and PT.

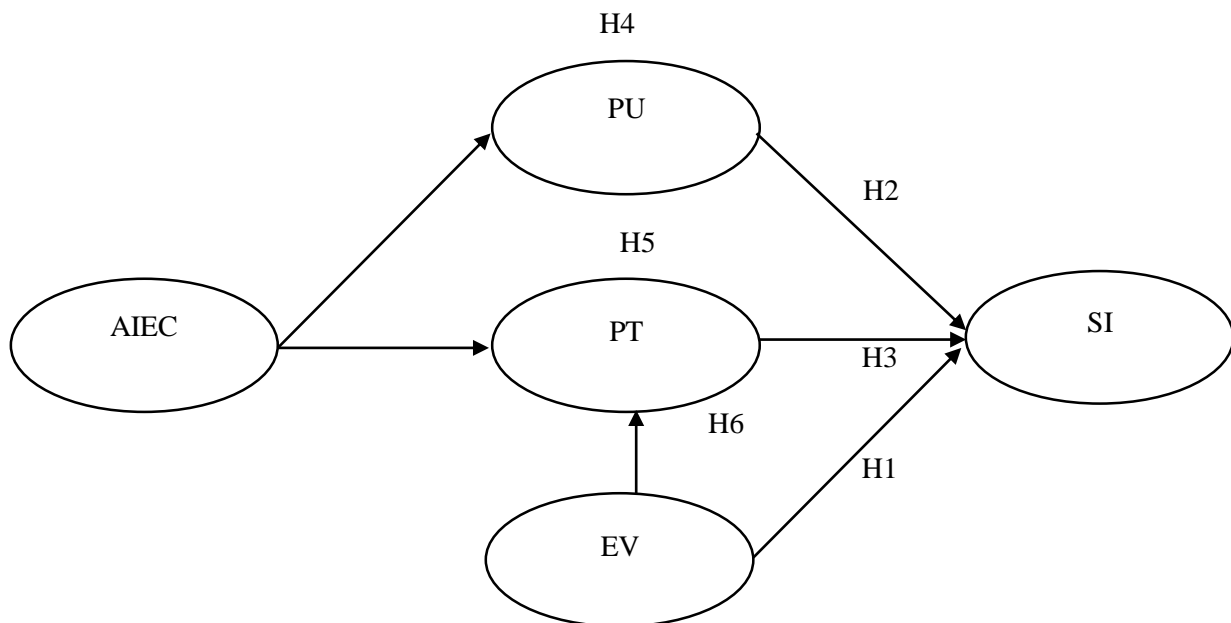


Figure 1. Research framework. Source: Authors' own work

Note. AIEC = artificial intelligence energy cognition; PU = perceived usefulness; PT = policy trust; EV = environmental values; SI = support intention.

Drawing upon the aforementioned theoretical frameworks, this study proposes a dual-mediation model. The specific hypotheses are as follows:

- **H1:** Environmental values (EV) positively predicts support intention (SI).
- **H2:** Perceived usefulness (PU) positively predicts support intention (SI).
- **H3:** Policy trust (PT) positively predicts support intention (SI).
- **H4:** Perceived usefulness (PU) mediates the relationship between artificial intelligence energy cognition (AIEC) and support intention (SI).

- **H5:** Policy trust (PT) mediates the relationship between artificial intelligence energy cognition (AIEC) and support intention (SI).
- **H6:** Policy trust (PT) mediates the relationship between environmental values (EV) and support intention (SI).

3.1 Sample and Instrumentation

Data were collected via a structured, self-administered online survey targeting Taiwanese citizens aged 20 years and above. Stratified sampling was employed to enhance population representativeness. After excluding incomplete and invalid responses, 1,250 valid questionnaires were retained, exceeding recommended thresholds for stable CB-SEM, including a minimum sample size of 200 or 10–20 observations per estimated parameter (Kline, 2016).

The sample distribution closely approximated official national demographic statistics, with deviations in gender, age, educational attainment, and regional residence maintained within $\pm 3\%$ (Ministry of the Interior, Department of Household Registration [MIHR], 2026). This demographic alignment reduced potential sampling and nonresponse biases and supported the assumption of sample independence (Bethlehem, 2010; Couper, 2017; Valliant et al., 2018).

All latent constructs were operationalized using multi-item scales adapted from established literature to ensure content validity. Minor wording adjustments were made to reflect the specific context of AI-enabled GH applications. All items were measured on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree), a response format widely adopted in energy policy and technology acceptance research to capture nuanced attitudinal variations.

Participants were recruited through targeted advertisements on Facebook and LINE, with automated quota controls applied to enhance demographic diversity and recruitment efficiency (Bethlehem, 2010; Wright, 2005). To ensure data quality, a rigorous screening procedure was implemented to exclude responses that failed attention checks, exhibited straight-lining behavior, or showed unusually short completion times indicative of speeding. The final exclusion rate remained below 5%, consistent with recommended data quality standards (Meade & Craig, 2012; Zhang & Conrad, 2014). Although post-stratification weighting (raking) was prepared to correct potential demographic imbalances, it was applied only when necessary to avoid compromising inferential validity (Kline, 2016).

3.2 Analysis Strategy and Statistical Testing

The primary analytical approach employed in this study was CB-SEM, implemented using IBM SPSS AMOS with maximum likelihood estimation (MLE). MLE was selected due to its effectiveness in estimating complex relationships among latent constructs and its robustness under conditions approximating multivariate normality.

Data distribution was evaluated in accordance with Mardia's (1970) criteria for multivariate normality. Both univariate and multivariate skewness and kurtosis were examined. The data were deemed suitable for CB-SEM, as the multivariate kurtosis statistic did not exceed the critical threshold of $p \times (p + 2)$, where p denotes the number of observed variables. To further ensure the precision of population-level inference, the margin of error (MoE) was calculated at a 95% confidence level. The resulting MoE fell within the generally accepted $\pm 3 - 5\%$ range for national survey research (Moore et al., 2017), as computed using the following formula:

$$MoE = Z \times \sqrt{\frac{p \times (1 - p)}{n}}$$

Note. where Z corresponds to the 95% confidence level, p represents the estimated population proportion, and n denotes the sample size.

To assess and mitigate potential common method bias (CMB), a dual-procedural approach was employed. First, Harman's single-factor test was conducted, with CMB considered negligible when the first unrotated factor accounted for less than 50% of the total variance. Second, a common latent factor (CLF) was incorporated into the structural equation model. The results indicated that CMB was minimal, as changes in standardized structural path coefficients remained below the conservative threshold of 0.20, and the inclusion of the CLF did not yield a significant improvement in model fit (Podsakoff et al., 2003). Furthermore, multicollinearity was assessed using tolerance values and variance inflation factors (VIF). In accordance with the stringent criteria proposed by Hair et al. (2010) and Kline (2016), multicollinearity was ruled out, as all VIF values were below 3.0 and tolerance values exceeded 0.20, thereby supporting the robustness and reliability of the estimated structural parameters.

3.3 Measurement Model and Hypothesis Testing

To ensure the rigor of the measurement model, four primary psychometric criteria were applied. First, indicator reliability was assessed by examining standardized factor loadings, with values exceeding 0.50 considered acceptable. Second, internal consistency was evaluated using Cronbach's alpha and composite reliability (CR), both of which were required to exceed the recommended threshold of 0.70 in accordance with established measurement quality guidelines (Hair et al., 2010; Nunnally &

Bernstein, 1994). Third, convergent validity was assessed using the average variance extracted (AVE), with values above 0.50 indicating adequate convergence. Fourth, discriminant validity was evaluated using the Fornell–Larcker criterion, whereby the square root of the AVE for each construct was required to exceed its highest correlation with any other construct (Fornell & Larcker, 1981).

Confirmatory factor analysis (CFA) was conducted using IBM SPSS AMOS to evaluate the overall fit of the measurement model. Consistent with the benchmarks proposed by Byrne (1998), Hu and Bentler (1999), and Kline (2016), multiple goodness-of-fit indices were employed. Specifically, χ^2/df values below 3.0 indicated excellent fit, while values below 5.0 were deemed acceptable. Comparative fit index (CFI) and Tucker–Lewis index (TLI) values greater than 0.95 reflected good model fit, with values above 0.90 considered acceptable. Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR) values below 0.05 indicated superior fit, values between 0.05 and 0.08 represented acceptable fit, and values between 0.08 and 0.10 denoted marginal but permissible fit.

CB-SEM was subsequently employed to test the hypothesized relationships. Model evaluation encompassed overall goodness-of-fit indices (χ^2/df , p , CFI, TLI, RMSEA, and SRMR), standardized path coefficients (β), corresponding significance levels, and coefficients of determination (R^2).

To enhance the inferential robustness of the mediation analysis, a non-parametric bootstrapping procedure with 5,000 resamples was implemented. Indirect effects were estimated using 95% bias-corrected confidence intervals (BC CIs), a method particularly appropriate for psychological constructs that may exhibit moderate skewness, as it does not rely on the assumption of normality of the indirect effect distribution (Preacher & Hayes, 2008; Zhao et al., 2010). Following Efron (1979), mediation effects were considered statistically significant when the 95% BC CI did not include zero. Partial mediation was inferred when both direct and indirect effects were significant, whereas full mediation was established when the indirect effect was significant and the direct effect became non-significant (Shrout & Bolger, 2002; Zhao et al., 2010).

4. RESULTS

From an initial pool of 1,300 responses, 1,250 were retained as valid after rigorous data screening, yielding a functional completion rate of 96.2%. The exclusion of 50 responses (3.8%) was necessitated by failed attention checks or incomplete entries, a rate well within the permissible 5% threshold advocated by methodological literature (Meade & Craig, 2012; Zhang & Conrad, 2014). The finalized sample ($N = 1,250$) substantially exceeds the requisite power for CB-SEM, surpassing the recommended 10–20 cases-per-parameter ratio (Kline, 2016). Preliminary diagnostics confirmed the absence of statistically significant outliers, ensuring high data integrity. Furthermore, a comparative analysis of gender, age, and regional distribution demonstrated that demographic deviations remained within $\pm 3\%$ of national census parameters (MIHR, 2026), obviating the need for post-stratification weighting and affirming the sample's representativeness.

Assessment of multivariate normality was conducted utilizing Mardia's coefficient. Given the 30 observed variables ($p = 30$), the estimated multivariate kurtosis from AMOS was -4.058, which is significantly lower than the critical theoretical threshold ($p \times (p + 2) = 960$). This indicates that the maximum likelihood (ML) estimation procedure is unlikely to be biased by non-normality. Regarding univariate normality, skewness values ranged from -0.121 to 0.071, while kurtosis values ranged from -1.048 to -1.188. These indices fall well within the conventional limits of $\pm 2\%$ for skewness and $\pm 7\%$ for kurtosis (Hair et al., 2010). Collectively, these diagnostics confirm that the dataset satisfies the distributional assumptions essential for CB-SEM.

To mitigate potential common method bias (CMB), this study employed both procedural and statistical controls. Harman's single-factor test revealed that the primary factor accounted for only 28.68% of the total variance, significantly below the 50% heuristic threshold. Further validation via the Common Latent Factor (CLF) approach demonstrated that fluctuations in standardized structural path coefficients remained below 0.20, and the change in Comparative Fit Index (ΔCFI) was negligible (< 0.01). Following Podsakoff et al. (2003), these findings confirm that CMB does not pose a substantial threat to the validity of the results. Additionally, at a 95% confidence level, the sample size yields a precision of $\pm 2.8\%$, surpassing the conventional $\pm 3 - 5\%$ range accepted in national-level survey research, thereby reinforcing the statistical power of the subsequent analyses.

$$MoE = 1.96 \times \sqrt{\frac{0.5 \times (1 - 0.5)}{1250}} = 0.0277 \Rightarrow \pm 2.8\%$$

Potential multicollinearity among the predictors was evaluated through Tolerance and Variance Inflation Factor (VIF) diagnostics. Tolerance values ranged from 0.848 to 0.891, comfortably exceeding the 0.20 threshold, while VIF values (1.123 to 1.179) remained well below the conservative cutoff of 3.0 (Hair et al., 2010; Kline, 2016). These results preclude multicollinearity concerns, thereby safeguarding the inferential stability of the hypothesized relationships between AIEC, PU, PT, EV, and SI (see Table 1).

Table 1: Diagnostics for multicollinearity among predictors of SI ($N = 1,250$)

Predictor	<i>B</i>	S.E.	β	<i>t</i> -value	<i>p</i> -value	Tolerance	VIF
(Constant)	1.48	0.16	—	9.014	***	—	—
AIEC	0.14	0.03	0.14	5.227	***	0.891	1.123
PU	0.15	0.03	0.15	5.542	***	0.888	1.126
PT	0.23	0.03	0.23	8.294	***	0.848	1.179
EV	0.09	0.03	0.09	3.146	**	0.875	1.142

Note. S.E. = standard error; VIF = variance inflation factor. The dependent variable is support intention (SI). ** $p < .01$, *** $p < .001$. *B* = unstandardised coefficient; β = standardised coefficient.

AIEC = artificial intelligence energy cognition; PU = perceived usefulness; PT = policy trust; EV = environmental values.

4.1 Demographic Profile of Participants

The final dataset comprises $N = 1,250$ valid responses, exhibiting substantial heterogeneity across key demographic dimensions, including gender, age, educational attainment, and geographic distribution. This diversity provides a robust descriptive foundation for subsequent inferential statistics and CB-SEM.

Gender. The sample achieved near gender parity, with female respondents accounting for 51.1% ($n = 639$) and male respondents comprising 48.9% ($n = 611$). This balanced distribution minimizes gender-related response bias and facilitates nuanced group-based comparisons where analytically pertinent.

Age. The age distribution spans the adult demographic spectrum, with a plurality belonging to the 31 to 40 cohort (30.0%). While the sample is characterized by a strong representation of young-to-middle-aged adults—groups typically identified as early adopters of green technologies—the inclusion of older cohorts (18.0% for ages 51–60 and 8.0% for ages 61+) ensures a comprehensive capture of societal perspectives across different life stages.

Education. Regarding educational attainment, the sample reflects a high degree of academic qualification: 45.0% of respondents hold an associate or bachelor’s degree, while 40.0% have attained graduate-level education or higher. This profile aligns with the technical complexity of AI-enabled GH systems, ensuring that the participants possessed the requisite cognitive capacity to evaluate the sophisticated techno-policy scenarios presented in the survey.

Residential area. The geographic distribution of respondents closely mirrors Taiwan’s national population density, with primary concentrations in the Northern (39.0%) and Southern (33.0%) regions. This spatial alignment with urban development patterns underscores the geographic representativeness of the sample and enhances the external validity of the findings (see Table 2).

Table 2: Demographic characteristics of the sample ($N = 1,250$)

Variable	Category	<i>n</i>	%
Gender	Male	611	48.9
	Female	639	51.1
Age	20 to 30 years	300	24.0
	31 to 40 years	375	30.0
	41 to 50 years	250	20.0
	51 to 60 years	225	18.0
	61 years or above	100	8.0
Education	High school/vocational school or below	187	15.0
	Associate or Bachelor’s degree	563	45.0
	Master’s degree or above	500	40.0
Residential area	Northern Taiwan	487	39.0
	Central Taiwan	320	25.6
	Southern Taiwan	443	35.4

Note. Percentages may not total 100% due to rounding.

4.2 Reliability and Validity Analysis

During the measurement model evaluation stage, confirmatory factor analysis (CFA) was conducted to rigorously assess the psychometric properties of the constructs, including factor loadings, overall model fit, composite reliability (CR), average variance extracted (AVE), and discriminant validity.

The results indicate that all standardized factor loadings ranged from 0.675 to 0.783, consistently exceeding the recommended threshold of 0.50 suggested by Hair et al. (2010). These findings demonstrate robust measurement quality and satisfactory convergent validity, and no items were removed due to insufficient factor loadings. In addition, the overall proportion of missing data was below 1%, which falls well within acceptable limits for statistical modeling. Consequently, no data imputation or case deletion procedures were required (see Figure 2).

The measurement model demonstrated an exceptional fit to the empirical data. The χ^2/df ratio was 1.07, well below the conservative upper limit of 3.0. Furthermore, both the CFI and the TLI reached 0.998, substantially exceeding the threshold for superior model fit (> 0.95) as advocated by Byrne (1998), Hu and Bentler (1999), and Kline (2016).

While recent scholarship cautions that exceptionally high CFI values may warrant scrutiny to preclude potential model over-specification (Xiong et al., 2025), the concurrent Root Mean Square Error of Approximation (RMSEA = 0.007) and Standardized Root Mean Square Residual (SRMR = 0.023) indicate a well-behaved residual structure fully consistent with established CB-SEM standards (Hu & Bentler, 1999). Collectively, the convergence of these indices suggests that the proposed psycho-institutional framework exhibits high statistical stability and provides an accurate representation of the psychological constructs underlying public support for GH (see Table 3).

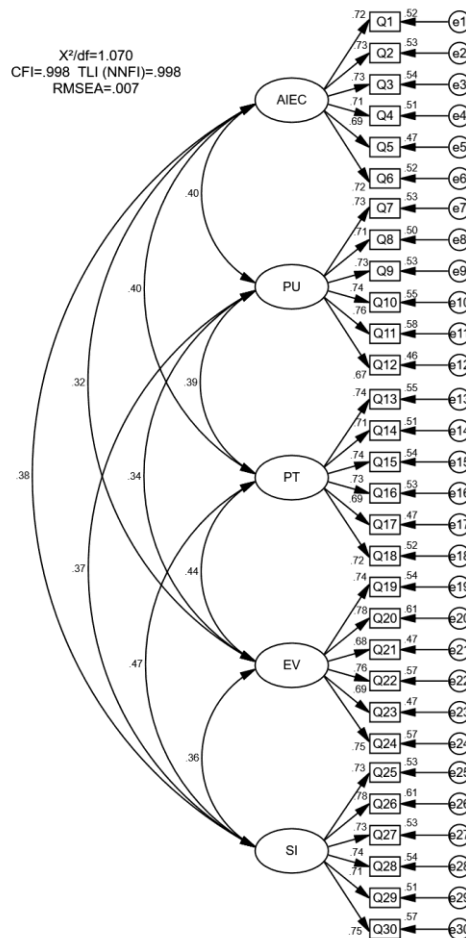


Figure 2. Confirmatory Factor Analysis (CFA) ($N = 1,250$). Source: Authors' own work

Note. AIEC = artificial intelligence energy cognition; PU = perceived usefulness; PT = policy trust; EV = environmental values; SI = support intention.

Table 3: Goodness-of-Fit indices for the confirmatory factor analysis (CFA) measurement model ($N = 1,250$)

Fit Index	Estimate	Recommended Criterion	Model Evaluation
χ^2/df	1.07	< 3	Excellent fit
CFI	0.998	> 0.90	Excellent fit
TLI (NNFI)	0.998	> 0.90	Excellent fit
RMSEA	0.007	< 0.08	Excellent fit
SRMR	0.023	< 0.08	Excellent fit

Note. χ^2 = chi-square; df = degrees of freedom; CFI = Comparative fit index; TLI = Tucker–Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

The psychometric properties of the latent constructs were rigorously evaluated via multiple established criteria. Internal consistency was confirmed, as Cronbach’s α coefficients (0.864 – 0.879) and Composite Reliability (CR) values (0.864 – 0.879) both comfortably surpassed the 0.70 benchmark (Hair et al., 2010; Nunnally & Bernstein, 1994).

Convergent validity was established through the Average Variance Extracted (AVE); all values (0.515 – 0.548) exceeded the 0.50 threshold, indicating that each construct accounted for more than half of the variance in its respective indicators.

Finally, discriminant validity was assessed using the Fornell and Larcker (1981) criterion. The square roots of the AVE for each construct (0.717 – 0.741) were consistently higher than the corresponding inter-construct correlations (0.318 – 0.473). These findings confirm that the latent variables are empirically distinct, thereby supporting the structural integrity of the hypothesized model (see Table 4).

Table 4: Reliability, average variance extracted (AVE), and Fornell–Larcker criterion ($N = 1,250$)

Construct	Cronbach’s α	CR	AVE	AIEC	PU	PT	EV	SI
AIEC	0.864	0.864	0.515	0.717				
PU	0.869	0.869	0.526	0.398	0.725			
PT	0.868	0.868	0.522	0.400	0.392	0.723		
EV	0.874	0.875	0.539	0.318	0.343	0.444	0.734	
SI	0.879	0.879	0.548	0.384	0.369	0.473	0.359	0.741

Note. Diagonal values in bold italics represent the square roots of the average variance extracted (AVE) for each construct; off-diagonal elements indicate the correlations between constructs.

AIEC = artificial intelligence energy cognition; PU = perceived usefulness; PT = policy trust; EV = environmental values; SI = support intention.

4.3 Descriptive Statistics of Research Variables

Descriptive analysis of the research variables reveals that mean (M) values across all measurement items ranged from 3.928 to 4.146, suggesting that respondents generally harbor moderately positive attitudes toward AI-driven GH applications. Notably, the relatively high standard deviations ($SD \approx 2.0$ for most items) underscore a significant degree of opinion heterogeneity. This variance reflects a lack of settled public consensus and divergent evaluative schemas regarding the integration of radical technologies into the energy grid.

Regarding AIEC, a scale-dependent cognitive pattern emerged: respondents expressed the highest endorsement for AI’s utility in macro-level system optimization, specifically in power load analysis and grid dispatch ($M = 4.098$). Conversely, AI applications at the localized, process-control level—such as enhancing electrolyzer operational efficiency ($M = 3.959$)—received lower scores. This discrepancy indicates a pervasive "technological caution" toward autonomous AI intervention in physical hardware and sensitive process-control operations compared to systemic data analysis.

Regarding PT, the data highlight a critical "capacity–fairness gap." While respondents expressed robust confidence in the government’s technical and administrative capacity to implement GH initiatives ($M = 4.146$), perceptions of procedural justice and impartial enforcement were markedly lower ($M = 3.953$). This discrepancy suggests that while the state is perceived as competent, its role as a fair arbiter remains under scrutiny.

EV exhibited the most stable distribution among the latent constructs, confirming a strong pro-environmental orientation. While the highest emphasis was placed on the immediate preservation of the natural ecosystem ($M = 4.091$), the item concerning protection for future generations ($M = 3.928$) received a slightly lower, yet still positive, mean score. This suggests that while environmental concern constitutes a resilient normative baseline, respondents prioritize immediate ecological protection over more abstract, long-term intergenerational obligations.

SI was characterized by a preference for socially-mediated participation ($M = 4.037$) over active individual advocacy ($M = 3.943$). This indicates that public support is currently reactive and contingent upon community discourse rather than proactive or self-driven.

Collectively, these descriptive patterns corroborate the "governance paradox" where technological promise is tempered by institutional skepticism and localized apprehension. These findings provide the necessary empirical grounding for the structural relationships examined in the subsequent path analysis (see Table 5).

Table 5: Descriptive statistics for research variables ($N = 1,250$)

Construct	Item	Mean	SD	Rank
AIEC	Q1. AI can analyze power loads and fluctuations in renewable energy to optimize decisions related to energy storage and grid dispatch.	4.098	1.956	1
	Q2. AI can enhance electrolyzer operational efficiency by reducing energy consumption and stabilizing green hydrogen production.	3.959	1.972	6
PU	Q7. I perceive that the use of green hydrogen reduces energy costs and enhances efficiency in practical applications.	4.030	1.955	1
	Q12. I perceive that well-designed operational interfaces of green hydrogen systems enhance task execution efficiency and overall operational performance.	3.942	1.983	6
PT	Q13. I believe that the government has the capacity to implement green hydrogen policies.	4.146	1.935	1
	Q14. I believe that the government enforces green hydrogen policies fairly, without favoring specific interest groups.	3.953	1.955	6
EV	Q19. I value protecting the natural environment.	4.091	1.991	1
	Q24. Protecting the environment for future generations is extremely important to me.	3.928	1.948	6
SI	Q27. Influenced by discussions in community or public settings, I would participate in green hydrogen-related activities.	4.037	1.957	1
	Q29. When others actively inquire, I am willing to provide or share information about green hydrogen in an accurate and reliable manner.	3.943	1.950	6

Note. AIEC = artificial intelligence energy cognition; PU = perceived usefulness; PT = policy trust; EV = environmental values; SI = support intention.

4.4 Pearson Correlation Analysis

Pearson correlation analysis revealed statistically significant positive correlations among all study variables ($p < .01$), indicating a consistent pattern of positive associations across the constructs included in the model. The strongest correlation was observed between PT and SI ($r = 0.333$), reflecting a moderate positive relationship and highlighting the salience of institutional trust in shaping public support for GH-related initiatives.

The remaining correlations ranged from $r = 0.202$ to $r = 0.294$, indicating small to moderate positive associations according to conventional benchmarks. While these correlations suggest meaningful linkages among AIEC, PU, PT, EV, and SI, they do not imply causal relationships. Accordingly, the magnitude and directionality of these associations were further examined through CB-SEM to test the hypothesized causal pathways (see Table 6).

Table 6: Pearson correlation analysis matrix table ($N = 1,250$)

Construct	AIEC	PU	PT	EV	SI
AIEC	1				
PU	0.230**	1			
PT	0.264**	0.247**	1		
EV	0.202**	0.234**	0.294**	1	
SI	0.256**	0.262**	0.333**	0.219**	1

Note. ** $p < .01$ (two-tailed); AIEC = artificial intelligence energy cognition; PU = perceived usefulness; PT = policy trust; EV = environmental values; SI = support intention.

4.5 Hypothesis Testing

Hypothesis testing was conducted using CB-SEM by simultaneously examining the significance of the hypothesized structural paths and the overall goodness of fit of the proposed model. The structural model demonstrated satisfactory fit to the empirical data, with all major fit indices meeting established evaluation criteria ($\chi^2/df = 1.635$; CFI = 0.985; TLI = 0.983; RMSEA = 0.023).

Although the standardized root mean square residual (SRMR = 0.091) slightly exceeded the more conservative threshold of 0.08, it remained within the acceptable range under less restrictive criteria suggested in the CB-SEM literature (Byrne, 1998). Collectively, these indices indicate an overall acceptable to good model fit, supporting the adequacy of the proposed psycho-institutional framework in capturing the structural relationships among the latent constructs.

Furthermore, the model satisfied the recommended cut-off criteria proposed by Byrne (1998), Hu and Bentler (1999), and Kline (2016) indicating that the hypothesized relationships among AIEC, PU, PT, EV, and SI were empirically plausible within a CB-SEM context (see Figure 3 and Table 7).

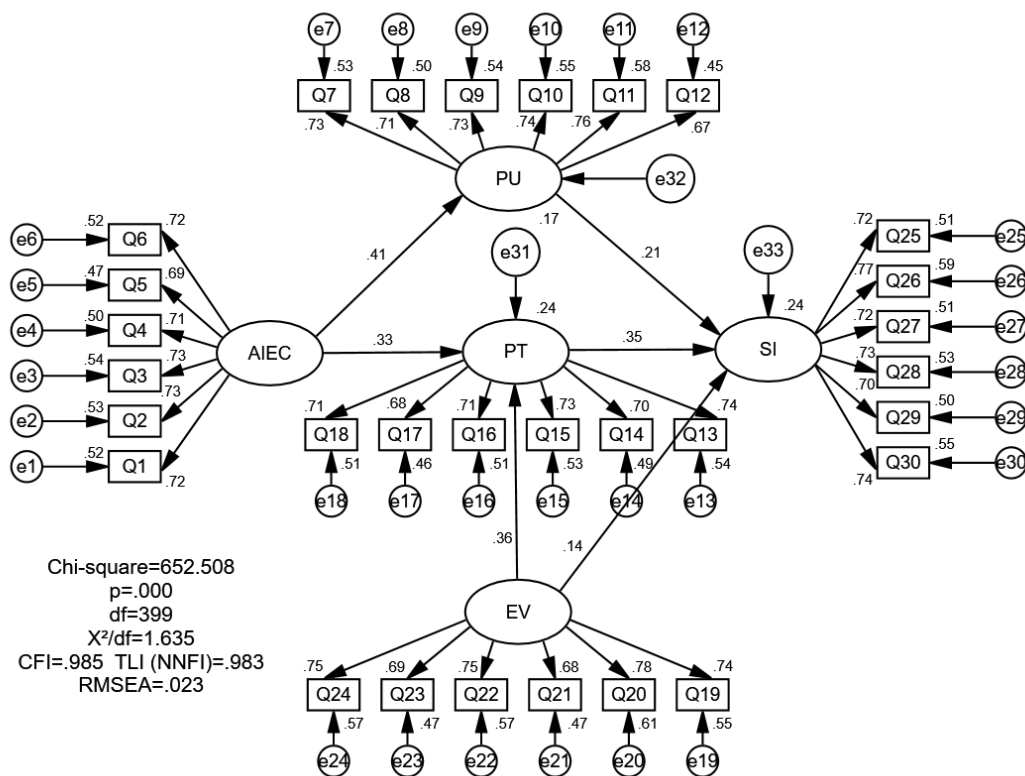


Figure 3. Structural equation model with standardized path coefficients ($N = 1,250$); Source: Authors' own work
Note. AIEC = artificial intelligence energy cognition; PU = perceived usefulness; PT = policy trust; EV = environmental values; SI = support intention.

Table 7: Structural model fit indices for the CB-SEM analysis ($N = 1,250$)

Fit Index	Estimate	Recommended Criterion	Model Evaluation
χ^2/df	1.635	< 3	Good fit
CFI	0.985	> 0.90	Excellent fit
TLI (NNFI)	0.983	> 0.90	Excellent fit
RMSEA	0.023	< 0.08	Excellent fit
SRMR	0.091	< 0.08	Acceptable fit

Note. χ^2 = chi-square; df = degrees of freedom; CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

4.5.1 Effects of AIEC and EV on PU, PT, and SI

Path analysis of the structural equation model indicated that AIEC functions as a pivotal antecedent shaping both technological appraisal and institutional trust. Specifically, AIEC exerted a significant positive effect on PU ($\beta = 0.41$, t -value = 11.973, $p < .001$), suggesting that public cognition of AI-enabled energy coordination forms a critical cognitive foundation for the instrumental evaluation of GH technologies. In parallel, AIEC significantly enhanced PT ($\beta = 0.33$, t -value = 10.191, $p < .001$), underscoring the role of technological transparency and knowledge diffusion in strengthening perceptions of governmental competence and credibility.

Regarding value-based orientations, EV exhibited a strong and significant positive effect on PT ($\beta = 0.36$, t -value = 11.190, $p < .001$). This finding implies that congruence between individuals' pro-environmental normative commitments and governmental sustainability objectives substantially reinforces institutional trust. Moreover, EV exerted a significant direct effect on SI ($\beta = 0.14$, t -value = 4.430, $p < .001$), thereby supporting Hypothesis H1 and indicating that personal EV operate as an endogenous motivational driver of public support for GH development.

4.5.2 Effects of PU and PT on SI

The results further confirmed the joint influence of rational evaluation and institutional trust in shaping SI. PU exerted a significant positive effect on SI ($\beta = 0.21$, t -value = 6.957, $p < .001$), lending support to Hypothesis H2 and indicating that stronger perceptions of the practical and economic benefits of GH applications are associated with higher levels of public support.

More importantly, PT demonstrated a substantially stronger effect on SI ($\beta = 0.35$, t -value = 9.833, $p < .001$) than PU, emerging as the most influential predictor in the structural model and thereby supporting Hypothesis H3. This result highlights that within the context of large-scale energy transitions characterized by uncertainty and long-term policy commitments, public confidence in governmental institutions exerts a more decisive influence on support intentions than purely technical assessments of utility.

4.5.3 Model Explanatory Power and Overall Structural Interpretation

In terms of explanatory power, AIEC exerted a significant influence on PU, accounting for 17% of its variance ($R^2 = 0.17$). This result indicates that AIEC represents a primary cognitive antecedent of instrumental technology appraisal. By contrast, PT exhibited greater explanatory power ($R^2 = 0.24$), with 24% of its variance jointly explained by AIEC and EV. This finding suggests that institutional trust in energy policy contexts is shaped by the combined effects of technological cognition and value-based orientations.

SI also demonstrated an R^2 of 0.24, indicating that PU, PT, and EV collectively explained a moderate proportion of variance in public support for GH. This pattern reveals that support intentions are jointly driven by rational evaluations of utility, confidence in governing institutions, and internalized EV. Overall, the structural model exhibits satisfactory predictive power and internal consistency in explaining public support behavior.

Collectively, these results confirm that an integrated psycho-institutional framework encompassing technological cognition, institutional trust, and EV effectively captures the core mechanisms underlying public support for AI-enabled GH applications. The convergence of strong model fit indices and statistically significant structural paths attests to the stability and robustness of the proposed theoretical model (see Table 8).

Table 8: Results of path analysis for the structural equation model ($N = 1,250$)

Independent Variable	→	Dependent Variable	β	S.E.	t -value	p -value	R^2
AIEC	→	PU	0.41	0.04	11.973	***	0.17
AIEC	→	PT	0.33	0.03	10.191	***	0.24
EV	→	PT	0.36	0.03	11.190	***	
EV	→	SI	0.14	0.03	4.430	***	0.24
PU	→	SI	0.21	0.03	6.957	***	
PT	→	SI	0.35	0.03	9.833	***	

Note. β = standardized estimate; *** $p < .001$; All coefficients are standardized estimates.

H1: EV → SI; H2: PU → SI; H3: PT → SI

AIEC = artificial intelligence energy cognition; PU = perceived usefulness; PT = policy trust; EV = environmental values; SI = support intention.

4.5.4 Mediation Effect Analysis

To examine the proposed mediation mechanisms, a nonparametric bootstrapping procedure with 5,000 resamples was employed to test the significance of indirect effects. Bias-corrected 95% confidence intervals (BC CIs) were used as the primary criterion for mediation assessment, in accordance with established methodological recommendations (Efron, 1979; Shrout & Bolger, 2002; Zhao et al., 2010). The results indicate that both PU and PT function as statistically significant mediators within the proposed psycho-institutional framework.

Hypothesis H4 (AIEC → PU → SI) was supported, exhibiting a pattern of full mediation. Specifically, the indirect effect of AIEC on SI via PU was statistically significant ($\beta = 0.202$, 95% BC CI [0.151, 0.236]), whereas the direct effect of AIEC on SI was non-significant. According to the mediation typology proposed by Zhao et al. (2010), this pattern indicates an indirect-only effect, suggesting that AIEC influences SI exclusively through its impact on PU.

Similarly, Hypothesis H5 (AIEC → PT → SI) demonstrated full mediation. The indirect effect of AIEC on SI through PT was statistically significant, while the direct effect remained non-significant. This finding underscores the pivotal bridging role of PT in translating technological cognition into behavioral support, highlighting institutional trust as a central psychological conduit between AI-related perceptions and public support intentions.

In contrast, Hypothesis H6 (EV → PT → SI) exhibited partial mediation. The total effect of EV on SI was significant ($\beta = 0.269$, 95% BC CI [0.187, 0.308]), as were both the indirect effect via PT ($\beta = 0.125$, 95% BC CI [0.087, 0.149]) and the direct effect ($\beta = 0.143$, 95% BC CI [0.069, 0.196]). This complementary mediation pattern indicates that EV influence SI through both direct normative motivation and indirect institutional pathways, thereby supporting Hypothesis H6.

Collectively, these mediation results demonstrate that cognitive evaluations and institutional trust mechanisms jointly shape public support for GH initiatives. The findings provide robust empirical evidence for the dual-mediation structure proposed in this study, reinforcing the theoretical integration of technology acceptance, value-based motivation, and institutional trust (see Table 9).

Table 9: Bootstrapping results for mediation effects ($N = 1,250$)

Mediation Path	Effect Type	β	95% BC CI Lower	95% BC CI Upper	Mediation Type
AIEC → PU → SI	Indirect effect	0.202	0.151	0.236	Full mediation
AIEC → PT → SI	Indirect effect	0.202	0.151	0.236	Full mediation
EV → PT → SI	Indirect effect	0.125	0.087	0.149	Partial mediation

Note. β = standardized estimate; Indirect effects were estimated using bootstrapping with 5,000 resamples and bias-corrected 95% confidence intervals (BC CIs).

H4: AIEC → PU → SI; H5: AIEC → PT → SI; H6: EV → PT → SI.

AIEC = artificial intelligence energy cognition; PU = perceived usefulness; PT = policy trust; EV = environmental values; SI = support intention.

5. DISCUSSION, IMPLICATIONS, AND CONCLUSIONS

5.1 Summary of the research

Integrating the TAM, VBN theory, and Institutional Theory, this study examined public SI toward AI-driven GH applications. Analyzing stratified survey data from 1,250 Taiwanese adults via CB-SEM, the research addresses the "governance paradox" where technological advancement outpaces public support. The structural model demonstrated superior fit ($\chi^2/df = 1.07$; CFI = 0.998; RMSEA = 0.007), accounting for 24% of the variance in SI ($R^2 = 0.24$).

Results indicate that AIEC and EV significantly drive SI, with PT emerging as the primary mediator ($\beta = 0.35, p < .001$). AIEC positively influenced PU ($\beta = 0.41$) and PT ($\beta = 0.33$), while EV impacted PT ($\beta = 0.36$) and SI ($\beta = 0.14$). Bootstrapping (5,000 resamples) confirmed full mediation for AIEC→PU→SI and AIEC→PT→SI pathways, and partial mediation for EV→PT→SI (Efron, 1979; Zhao et al., 2010). Descriptive data revealed a perceptual gradient: respondents favored macro-level optimization over micro-level autonomous control and trusted governmental capacity more than policy fairness. Overall, these findings indicate that under technological uncertainty, institutional trust remains more decisive than instrumental utility in shaping public acceptance of GH deployment (Davis, 1989; Stern et al., 1999).

5.2 Theoretical Implications

This study advances energy transition literature by synthesizing the TAM, VBN theory, and Institutional Theory into a unified psycho-institutional framework.

By examining AI-driven GH applications, the research addresses the theoretical gap where technological acceleration outpaces social legitimacy. Key Theoretical Contributions Refinement of TAM: The findings demonstrate that in macro-level energy governance, PEOU is less relevant than AIEC. AIEC serves as a pivotal antecedent, influencing SI solely through PU ($\beta_{\text{indirect}} = 0.202$). This suggests that for large-scale infrastructure, cognitive comprehension of system functionality supersedes operational usability (Davis, 1989; Venkatesh & Davis, 2000).

Centrality of Institutional Trust: PT emerged as the primary mediator linking AIEC and EV to SI ($\beta = 0.35$). This positions trust as a critical "bridging mechanism" for high-risk, NIMBY-associated infrastructures, extending VBN theory by showing that moral values alone cannot sustain support under high uncertainty (Gordon et al., 2025; Palomo-Vélez et al., 2025).

Dual-Path Value Activation: EV exerts both direct normative effects ($\beta = 0.14$) and indirect effects via PT ($\beta_{\text{indirect}} = 0.125$). This reflects concerns regarding algorithmic opacity, highlighting the necessity of explainability and accountability in governance (Afroogh et al., 2024).

Overall, the study validates AIEC as a critical construct, proving that a multi-layered model—integrating cognition, values, and trust—is essential for explaining public acceptance of emerging energy technologies.

5.3 Managerial Implications

This study provides evidence-informed managerial implications for stakeholders deploying AI-enabled GH systems. The primacy of PT ($\beta = 0.35$) suggests that institutional credibility outweighs technological performance in securing social acceptance. Consequently, governance must prioritize transparency, procedural fairness, and accountability over purely economic narratives.

Practitioners should disclose algorithmic decision rationales in grid balancing and risk management to mitigate concerns regarding opacity and legitimacy. Communication strategies should emphasize macro-level system benefits—such as grid stability and energy integration—rather than micro-level autonomous control. Framing AI as a decision-support tool rather than a human substitute aligns more effectively with public expectations.

Furthermore, linking GH to pro-environmental values through community dialogue can catalyze SI by framing the technology as a pathway to intergenerational sustainability. To address lower perceptions of policy fairness, managers should implement institutional safeguards, including independent third-party auditing and alignment with established renewable instruments like carbon pricing. Educational initiatives focusing on AIEC should present AI as an assistive governance mechanism.

Finally, while PU has a more moderate effect ($\beta = 0.21$), demonstrative pilot projects and community co-creation initiatives remain vital to translating abstract technological advantages into tangible social benefits. These integrated approaches are essential for bridging the gap between policy ambition and durable societal acceptance.

5.4 Limitations of the paper

This study acknowledges several limitations that provide pathways for future inquiry. First, the cross-sectional research design limits definitive causal inference. While CB-SEM effectively tests theoretical pathways, it cannot establish temporal sequencing. Future research should employ longitudinal or experimental designs to capture the dynamic evolution of AI cognition and trust over time (Kline, 2016).

Second, the empirical scope is restricted to Taiwan. Although the sample is nationally representative, findings may be influenced by specific institutional characteristics and energy transition stages. The reliance on online surveys and the high educational level of respondents may introduce self-selection bias, necessitating caution when generalizing to different socio-institutional contexts.

Third, the use of self-reported measures may be susceptible to social desirability and common method variance. Despite procedural remedies (e.g., Harman's single-factor test) indicating minimal bias, these effects cannot be entirely discounted (Podsakoff et al., 2003). Furthermore, with the model explaining 24% of the variance ($R^2 = 0.24$) in SI, incorporating variables such as perceived risk or media exposure could improve explanatory power.

Finally, PEOU was excluded to maintain parsimony in this macro-policy context. Future studies might reintroduce PEOU to compare micro-level interactions. Additionally, as a newly operationalized construct, AIEC requires further scale refinement to address potential attitude-behavior gaps.

5.5 Future Studies and Recommendations

Future research should extend the current psycho-institutional framework along several theoretically and methodologically significant trajectories. First, scholars should prioritize longitudinal or panel designs to establish the dynamic causal sequencing between AIEC, PT, and SI. Integrating behavioral indicators—such as participation in policy consultations—is essential to bridging the documented intention-behavior gap.

Second, cross-national comparative studies are necessary to validate findings across diverse political systems and energy transition stages. Comparing Taiwan with the European Union or Japan could clarify how institutional trust functions under varying governance structures (Gordon et al., 2025).

Third, subsequent models should incorporate algorithmic transparency, perceived risk, and political ideology as mediators or moderators. Refinement of the AIEC construct—differentiating between cognitive, affective, and functional dimensions (e.g., predictive vs. decision-making)—would further enhance theoretical precision (Afroogh et al., 2024).

Fourth, mixed-methods approaches—utilizing qualitative interviews to explore concerns regarding algorithmic opacity and experimental designs to manipulate AI explainability—are strongly encouraged.

Finally, policy-oriented research should evaluate the efficacy of trust-building interventions through field experiments. Future scholarship must also address the ethical dimensions of AI governance, including bias amplification and accountability, to foster more comprehensive frameworks for sustainable energy transitions.

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