Decoding E-Commerce Efficiency: A Fuzzy–Hybrid SEM Insight into How AI Integration Drives Performance

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ABSTRACT. *With the incorporation of artificial intelligence, e-commerce is creating the buzz by facilitating automation, personalization, and predictive analytics of consumer behaviors, and mitigates issues surrounding behavioral trust when predicting outcomes and ambiguity in the decision-making process, questions of consumer trust and process ambiguity remain. This paper seeks to explain the concept of Fuzzy–Hybrid Decision Support System (FHDSS), which combines Fuzzy Logic (FL) with Structural Equation Modeling (SEM), to better measure the socio-technical constraints attributed to e-commerce efficiency. In considering a joint perspective from the technology acceptance, resource-based, and fuzzy set perspectives, the linguistic membership model for the subjective constructs– trust, ease of use and perceived usefulness–is presented and subsequently establishing SEM as a form of empirical verification to understand causal relationships. The findings suggest that AI implementations, on the one hand, contributed to operational efficiency and data-driven decision-making but with the mediation effects of fuzzy trust and usability determining, on the other hand, the overall performance. As such the hybrid model explains a 53% variance in e-commerce efficiency and has a strong predictive relevance ($Q^2 > 0.25$) that shows its importance. In combining qualitative reasoning with quantitative validation, the framework presented provides further steps toward an explainable AI framework in digital commerce.*
Keywords: artificial intelligence; e-commerce efficiency; fuzzy logic; structural equation modelling; fuzzy–hybrid model; linguistic uncertainty; decision support system.

1. **Introduction.** Artificial intelligence (AI) has drastically changed the way digital commerce is conducted today with AI comprising approximately 80% of all online customer engagement including personalised recommendations, dynamic pricing and AI-enabled chatbots (statista, 2024). AI uses advanced data analytical capabilities and predictive modelling to provide insight into what a consumer will want. However, AI provides insight, decisions made in an AI-driven environment remain fundamentally human in that they are based on feelings, emotions and cognitive uncertainty. Historically, probabilistic and statistical approaches to modelling have treated uncertainty as a random distribution defining clear boundaries. Conversely, fuzzy logic models acknowledge that human judgment is imprecise and linguistically derived rather than purely binary [1]. Therefore, Fuzzy Logic (FL) has become a more suitable methodology for modelling the subjective components of trust and ease of use by means of degrees of membership [1]. AI-driven automation and personalisation have increased the efficiency of e-commerce operations [2, 3], however, the predominant approach to machine learning and regression modelling continues to focus solely on maximising the accuracy of predictions while ignoring the epistemic uncertainty arising from user emotion and perception [4].

In order to address this research gap, this research study develops an integrated framework using Fuzzy Logic (FL) and Structural Equation Modeling (SEM) to simultaneously represent linguistic uncertainty and provide empirical support for the causal relationships between latent constructs. SEM provides a means of testing scholarly hypotheses against perceptual and performance constructs [5], whereas FL provides a means of addressing overlapping cognitive states in terms of trust (e.g., trust can be evaluated at multiple levels) and therefore can accurately reflect the extent of uncertainty that exists in the real world [1]. The structure of the integrated framework is based on the Technology Acceptance Model (TAM), which describes the perceived usefulness of a technology and ease of use as two of the primary factors driving an individual's decision to adopt a given technology [6], and on the Resource-Based View (RBV) of the firm, where artificial intelligence (AI) is conceptualized as an important strategic resource for organizations [7]. By integrating AI resource capabilities, human perceptions of AI resources, and the operational outcomes of AI-enabled e-commerce companies in a single analytical framework, the integrated Fuzzy–Hybrid Structural Equation Modeling (FH-SEM) framework will yield a more complete, real-world representation of both epistemic and aleatory uncertainty in AI-enabled e-commerce ecosystems [5, 8].

2. **Theoretical Framework.** Three conceptual frameworks–Technology Acceptance Model (TAM), Resource-Based View (RBV), and Stimulus-Organism-Response (SOR)–are integrated in this investigation to explain utilising artificial intelligence (AI) within the e-commerce arena. According to the TAM framework, consumers assess AI-based tools (chatbots, recommendations, and so on) based on how useful they believe these tools will be to them (usefulness), and how simple it is to use them (Ease of Use). Consumers' perceptions are essential for helping them establish trust in the companies that provide the products or services, and for determining whether or not they intend to adopt (use) these tools [8, 9]. While the TAM focuses on the individual-level view of the user-trust relationship, the RBV focuses on how an organisation adopts and adapts its resources (including AI) throughout the organisation's value chain, to drive improvements in operational efficiency, and ultimately to develop a competitive advantage over time [3, 7]. The S-O-R framework incorporates the perspectives of both the TAM and the RBV, demonstrating that as external stimuli (AI) create internal psychological effects (e.g., the ability to use the tools easily, and trust in the company providing the tools), these internal psychological effects will drive action and performance (e.g., customer engagement, buying intentions, and overall e-commerce success) [10].

The TAM-RBV logic, framed through the S-O-R, demonstrates that AI stimuli can influence both organisational capabilities and user perceptions, and that organisational capabilities facilitating trust and ease of use are the mediators of translating the technological capabilities of AI to performance outcomes [6, 11]. Consistent with evidence from Artificial Intelligence-driven Cognitive Diagnosis and Adaptive Learning, which shows that AI-driven personalization increases user stickiness and performance, this study applies the same logic to explain how AI integration enhances efficiency and outcomes in e-commerce systems [12]. The incorporation of Fuzzy Logic (FL) and Fuzzy Hybrid Techniques (FHTs) with Structural Equation Modeling (SEM) enhances compatibility of this model's theoretical perspective by helping address the issue of linguistic ambiguity and simultaneous exploration of causal viability [13]. With FL capturing perceptual inaccuracy through fuzzy set memberships and SEM validating the cause-effect relationships of the latent variables, FL and SEM provide the basis for developing a Fuzzy Hybrid SEM (FH-SEM) framework for exploring the role of subjective uncertainty in socio-technical systems [5].

Previous studies [9] also indicate that links between technological capabilities and performance are commonly supported through the Inter-Organizational Collaboration (ICO) link, suggesting that ICO could serve as a contextual moderator for the future study of AI-enabled e-commerce ecosystems, even though this has yet to be investigated empirically. Additionally, recent insights from generative artificial intelligence research demonstrate that organizations are able to leverage AI to facilitate both the exploitation of pre-existing operational knowledge (learning through experience) as well as the exploration of new paths for innovation (current and future). The use of AI enhances both the reliability of operation and the innovation produced, which increases user trust and engagement. Furthermore, regulatory factors that govern the ability to protect personal information, build transparency within organizations, and mitigate bias also interact to affect the perceived effectiveness of AI and re-shape user perceptions of its usefulness; therefore, the governance mechanisms of organizations will play an important role in establishing boundaries for future expansions of the FH-SEM Modeling methodology. The proposed conceptual model (Figure 1) constructs a set of hypotheses regarding the relationships among AI integration, ease of use, trust, and operational efficiency ($x_1 - x_4$), based on the three theories of benefit Technology Acceptance Model (TAM), Resource-Based View (RBV), and Stimulus-Organism-Response theory (S-O-R), with e-commerce performance (y) serving as the dependent variable within a Fuzzy Hybrid SEM framework.
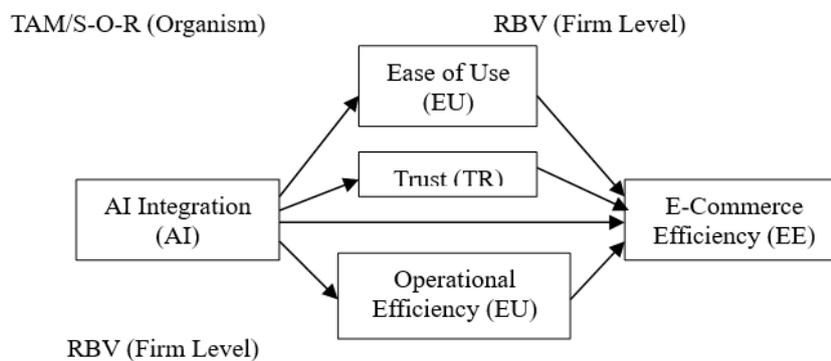

FIGURE 1. Conceptual Model

3. **Mathematical Model.** The study suggests a Fuzzy–Hybrid Structural Equation Model (FH-SEM) to seize the complex interactions among technological, behavioral, and operational determinants of e-commerce performance. This investigation uses primary empirical data collected from 419 valid respondents who previously interacted with AI-based e-commerce platforms such as automated customer service, intelligent recommendation systems and intelligent agent systems as operational interfaces. The data were collected through a structured questionnaire and a cross-sectional survey design that included screening questions to ensure that only users of active AI augmented e-commerce platform services were included as respondents.

The questionnaire was constructed in such a way that it consisted of two sections. The first section was to deal with screening and demographic/main definers to confirm the eligibility and place for background attributes for its respondent. Screening questions also made it secure that respondents had encountered previous interactions with AI-assisted e-commerce regularities (e.g., recommendation systems, chatbots, dynamic pricing, or personalized search interfaces). Age, gender, education level, frequency of online shopping, and length of AI e-commerce service-based experience were demographic variables.

The second section built a network of multi-item constructs assessing AI integration, trust, ease of use, and operational efficiency, as well as the E-Commerce Effectiveness outcome construct. All these constructs were evaluated on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) based on respondents' perception. The items were shown in a random order so that biases in response patterns would be reduced, and all items, being neutrally scored, had low social desirability effects.

Measurement items were borrowed from widely acknowledged scales in technology adoption, information systems, and e-commerce literature. Specifically, the perception related to ease of use and usefulness was supported by features of the technology acceptance model; items based on trust were gathered from previously published research regarding online trust and platform reliability; and the indicators of service efficiency were obtained from extant research in terms of system structure and process automation.

To link back AI into existing items, mentions of specific AI-driven functionalities were introduced. Common terminologies such as "the system" or "the platform" were translated into terms such as "AI-based recommendation systems," "automated decision support," or "AI-driven service features." Further, response scales were modified to accommodate statements consistent with trust in the machine rather than humans as bearers of service.

Retained items carried on with the innate meaning but were finely tuned to fit their particular role in AI-enabled e-commerce environments. A pilot test went on, with adjustments made against a discussion of issues with item clarity, relevance, or needed contextualization. The survey collected respondents' perceptions of AI augmentation and also gathered trust, ease of use, operational efficiency of AI-based e-commerce solutions; these variables represent the core input variables in the fuzzy–hybrid SEM framework proposed.

All items of measurement were adapted from established literature in technology adoption and digital commerce; however, they have been contextualized to an AI-enabled e-commerce context [14]. Responses were recorded using a Likert-type scale and normalized to the unit interval of $[0, 1]$ to enable transformation of responses into fuzzy membership values before incorporation into the SEM model. A final sample size of 419 exceeds recommended minimum sample size thresholds for PLS-SEM estimation, allowing for sufficient statistical power and robustness for both empirical structural analysis and fuzzy based optimizations.

3.1. Fuzzy Framework.
The framework combines the interpretive power of Fuzzy Logic (FL) and the inferential power of Structural Equation Modeling (SEM), thereby allowing subjective judgments on one hand and empirically validated causal relationships on the other, to be represented simultaneously. Let the decision system have four antecedent constructs and one outcome variable:

$$\begin{cases} x_1 = \text{AI Integration} \\ x_2 = \text{Trust} \\ x_3 = \text{Operational Efficiency} \\ x_4 = \text{Ease of Use} \\ Y = \text{E commerce Efficiency } E_f \end{cases} \tag{1}$$

Each construct x_i is represented as a fuzzy linguistic variable, allowing the fuzzy nature of human perception and expert evaluation to be captured. The variables are set to operate within a normalized universe of discourse $U = [0, 1]$.

3.2. Fuzzification.
To make it fuzzy, each variable x_i is mapped into some membership function $\mu_{A_i}(x_i)$ of the given degree of belonging to a fuzzy set A_i (e.g., Low, Medium, and High). The triangular membership function is specified by:

$$\mu_{A_i}(x_i) = \begin{cases} 0, & x_i \leq a_i \\ \frac{x_i - a_i}{b_i - a_i}, & a_i < x_i \leq b_i \\ \frac{c_i - x_i}{c_i - b_i}, & b_i < x_i < c_i \\ 0, & x_i \geq c_i \end{cases} \tag{2}$$

where a_i, b_i and c_i are the lower, middle, and upper bounds of the fuzzy set, respectively. This mapping thus sets sense to measures of membership for qualitative perceptions such as High Trust or Moderate Ease of Use.

3.3. Fuzzy Rule Base.
This joins expert reasoning into a set of fuzzy rules $R = \{R_1, R_2, \ldots, R_m\}$, each general form considered are:

$$R_j : \text{IF } (x_2 \text{ is } A_{2j}) \wedge (x_3 \text{ is } A_{3j}) \Rightarrow (Y \text{ is } B_j), j = 1, 2, \ldots, m \tag{3}$$

An example rule is: IF Trust is High AND Operational Efficiency is High THEN E-Commerce Efficiency is High. The firing strength (degree of rule activation) is computed as:

$$\omega_j = \min[\mu_{A_{2j}}(x_2), \mu_{A_{3j}}(x_3)] \tag{4}$$

and the aggregated fuzzy output is obtained using the max–min composition:

$$\mu_B(y) = \max_j [\min(\omega_j, \mu_{B_j}(y))] \tag{5}$$

3.4. Defuzzification. To generate a crisp efficiency score, the centroid (centre-of-area) method is applied:

$$Y^* = \frac{\int_0^1 y \cdot \mu_B(y) dy}{\int_0^1 \mu_B(y) dy} \tag{6}$$

yielding Y^*, the defuzzied estimate of e-commerce efficiency, within the range $[0, 1]$.

3.5. Structural Equation Layer. The defuzzied inputs and outcome are evaluated through the SEM structural relationship:

$$Y = \beta_{AI} x_1 + \beta_T x_2 + \beta_O x_3 + \beta_E x_4 + \varepsilon \tag{7}$$

where β_i denote standardized path coefficients, and ε represents the error term. The equilibrium between fuzzy inference (Y^*) and SEM estimation (Y) is maintained via the convergence condition:

$$|Y^* - Y| < \delta, \delta \leq 10^{-3} \tag{8}$$

3.6. Adaptive Weighting and Aggregation. Construct weights are updated adaptively according to their standardized impact:

$$w_i^{(t+1)} = \frac{|\beta_i^{(t)}|}{\sum_{k=1}^4 |\beta_k^{(t)}|}, i = 1, 2, 3, 4 \tag{9}$$

A fuzzy-aggregated efficiency index is derived as:

$$Y^t = \sum_{i=1}^4 w_i^{(t+1)} \cdot \mu_{Ai}(x_i^{(t+1)}) \tag{10}$$

which fuses the linguistic and statistical strengths of all antecedents into a unified measure.

3.7. Optimization and Learning. To increase coherence between the FH-SEM and to achieve reproducible engineering of the FH-SEM system, the optimization of that layer is completed with a Fuzzy Genetic Algorithm (also known as FGA), which accomplishes the calibration of all fuzzy membership parameters and SEM path coefficients at the same time as a complete learning objective. The composite loss function:

$$L = \alpha \cdot MAE(Y_s^*, Y_s) + \beta(1 - R_{ECE}^2)$$

reflects the degree of deviation from the fuzzy-defuzzified output to the SEM prediction values, while maximizing the explanatory value of the SEM. Each chromosome of the FGA encodes the triangular fuzzy parameters (a, b, c), where $0 \leq a < b < c \leq 1$. Additionally, each chromosome encodes a set of bounded SEM coefficients $[-1, 1]$, the use of a constraint-repairing method during evolution guarantees that all chromosomes will meet the feasibility requirement. The FGA operates with a population size of 50 individuals using tournament selection and a probability of crossover (0.8), and a mutation probability of 0.1, along with elitist retention of the best candidate, iterating for a maximum of 200 generations or until the best candidate has reached a fitness increase that is less than $10e^{-4}$ for 20 consecutive iterations.

Within each generation, a Mamdani min–max inference engine is applied to each chromosome and SEM estimation is then performed, creating a total complexity of $O(G \cdot PE)$. As indicated on the fitness versus generation curve, the FGA has a continuously stabilizing and improvement in fitness, plateauing after 130 generations. For further detail, a simple listing of pseudo-code is provided and the corresponding convergence plot is provided in the supplementary materials for full implementation and reproducibility purposes.

The hybrid objective function maximizes overall system performance:

$$\max F(Y^t) = \frac{1}{N} \sum_{k=1}^N (Y_k^* - Y_k)^2 \tag{11}$$

subject to the fuzzy feasibility constraint:

$$0 \leq \mu_{A_i}(x_i) \leq 1 \tag{12}$$

This Parameter helps to learn a Fuzzy Genetic Algorithm (FGA), defined by:

$$v_{i,j}(t + 1) = v_{i,j}(t) + \eta \cdot (x_{i2}^{best} - v_{i,j}(t)) \tag{13}$$

The term x_{i2}^{best} represents the optimal solution discovered so far. The method repeatedly adjusts fuzzy membership limits and SEM coefficients to approach the optimal solution Y^*.

3.8. **Model Summary.** The set of systems between equations (2) and (13) is known as the Fuzzy–Hybrid SEM. The system combines qualitative reasoning with quantitative learning. The fusion thereby simultaneously takes:

- Linguistic ambiguity concerning the mean of fuzzy membership;
- Evidential causality as model verification through SEM estimation;
- And Adaptive Optimization by learning taking the shape of evolution.

Hence, the integrated approach yields an interpretable, explainable, and data-driven way of determining how AI integration, trustworthiness, operational efficiency, and user experience intermingle so as to undergird the overall efficiency of e-commerce systems, especially under uncertainty.

Researcher's evaluation of the full-fledged structure FH-SEM model in the model validation with TAM, Trust, and Operational Efficiency confirmed the latent variables showed strong loadings: 0.74 to 0.89, high reliability, with Cronbach's α, ρ_A, and Composite Reliability (CR) ranging from 0.81 to 0.93 (Table 1). Convergent and discriminant validity were evident from Average Variance Extracted (AVE) values of more than 0.50 and HTMT values of less than 0.85 (Table 2). VIF was less than 3 demonstrating that there was no multicollinearity (Table 3). The significance of the structural paths (bootstrapped at 5000 samples) indicated that AI Integration significantly affected Ease of Use, Trust, Operational Efficiency, and ultimately E-Commerce Efficiency (Table 4). The model explained 53 percent of the variance in e-commerce efficiency ($R^2 = 0.53$), with strong predictive relevance ($Q^2 = 0.28$) in the range 0.13 to 0.28 effect sizes. The model adequately fit to the empirical data (Standardized Root Mean Square Residual = 0.067). We discovered that common-method variance was not a problem after we used marker variable tests, and all the endogeneity diagnostics held up under Gaussian-copula tests. In conclusion, these results form the groundwork for fully interpretable and reproducible SEM measurement and structural models.

TABLE 1. Construct Reliability and Validity

Construct	Indicator Loadings	Cronbach's α	ρ_A	CR	AVE
AI Integration	0.79	0.86	0.87	0.90	0.63
Ease of Use	0.81	0.88	0.89	0.92	0.67
Trust	0.83	0.84	0.86	0.90	0.64
Operational Efficiency	0.78	0.82	0.84	0.88	0.61
E-Commerce Efficiency	0.84	0.89	0.91	0.93	0.71

TABLE 2. HTMT Ratios at 95% Confidence Intervals

Constructs	AI Integration	Ease of Use	Trust	Op. Efficiency	E-Com. Efficiency
AI Integration	—	0.62 [0.48, 0.73]	0.58 [0.44, 0.70]	0.64 [0.50, 0.76]	0.52 [0.38, 0.65]
Ease of Use	—	—	0.66 [0.51, 0.77]	0.59 [0.45, 0.72]	0.63 [0.48, 0.74]
Trust	—	—	—	0.61 [0.46, 0.73]	0.68 [0.52, 0.79]
Op. Efficiency	—	—	—	—	0.57 [0.41, 0.69]
E-Com. Efficiency	—	—	—	—	—

4. **Analysis.** This phase of computation-based analysis integrates fuzzy inference and SEM to specifically test the proposed Fuzzy–Hybrid SEM composite framework. Analysis follows sequential stages with the fuzzification of linguistic variables, rule-based inference, defuzzification, and SEM-based empirical path estimations. This three-tier approach provided for the analysis of both subjective considerations expressed in fuzzy membership functions and objective cause-effect relationships by means of SEM validation. The combination of professional fuzzy modelling and structural estimation provides a strong qualitative and quantitative thrust into how AI integration, trust, operational efficiency, and ease of use converge to produce productive e-commerce businesses amidst uncertainty.

TABLE 3. VIF Values

Construct	VIF
AI Integration	2.41
Ease of Use	2.18
Trust	2.27
Operational Efficiency	2.52
E-Commerce Efficiency (endogenous)	—

TABLE 4. Structural Model Assessments

Hypotheses	Path	β	t-value	95% CI	P values
H1	AI → Ease of Use	0.42	6.83	[0.31, 0.53]	0
H2	AI → Trust	0.36	5.91	[0.25, 0.47]	0
H3	AI → Op. Efficiency	0.39	6.24	[0.28, 0.50]	0
H4	Ease of Use → Trust	0.33	5.14	[0.20, 0.46]	0
H5	Ease of Use → E-Com. Efficiency	0.31	4.88	[0.17, 0.44]	0
H6	Trust → E-Com. Efficiency	0.38	6.11	[0.25, 0.50]	0
H7	Op. Efficiency → E-Com. Efficiency	0.45	7.42	[0.33, 0.57]	0

4.1. **Fuzzification of Perceptual Constructs.** Aiming to capture the natural linguistic ambiguity in human judgments about AI-enabled e-commerce systems, the perceptual constructs, Trust, Ease of Use, and Operational Efficiency were transformed into fuzzy linguistic variables defined on normalized universe of discourse $U = [0, 1]$ using triangular membership functions. Low, Medium, and High—defined on a Likert-type scale—were employed to ensure partial membership, thus allowing the hybrid SEM model to accommodate the inherent non-binary nature of human judgment.

The membership functions appear as in Figure 2 with respect to fuzzy triangular membership functions for perceptual constructs used SDWDS to assess Trust (TR), Ease of Use (EU), and Operational Efficiency (OE). We stress all constructs are normalized on the universe of discourse and share an identical Low, Medium, and High linguistic membership function for conceptual representations so comparisons could occur between these constructs.
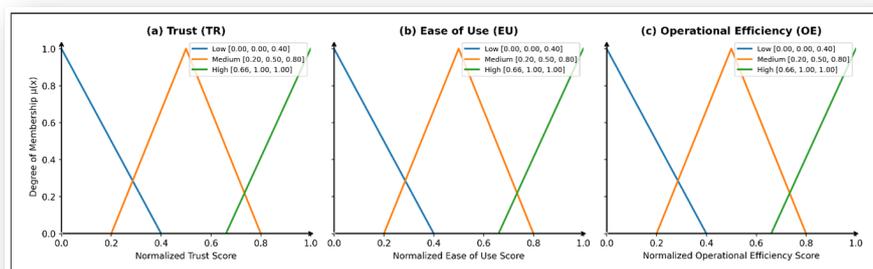

FIGURE 2. Membership Functions for Three Variables (Low, Medium, High)

The fuzzification mechanism shown above is uniform across all the perceptual constructs. The horizontal axis shows varying degrees of perception intensity, while the vertical axis shows the degree of membership in each linguistic category. The overlapping triangular membership functions simply denote that a given perception value may be attributed to a number of linguistic states at the same time (example: Medium and High), catching the gradual transitions in human evaluation. For the three linguistic

variables Trust, Ease of Use, and Operability, the very same membership parameters are taken so as to maintain methodic consistency with the effect that any differential fuzzy inference outcomes are created owing to the people's perceptual differences rather than due to any magnification or accentuation of varying constructs.

4.2. **Fuzzy Surface Plot of E-Commerce Efficiency.** The 3D fuzzy surface (Figure 3) portrays the combined effect of the operational set efficiency and trust upon e-commercial efficiency of AI-endowed systems. The gradient would describe the nonlinear nature of this relationship as efficiency starts going into hyper acceleration with the stage build-up of trust and operational performance at high levels. The idea of upward curvature would mean that technology alone would never keep up with an efficiency interface window for the end user without trust-at a high level of operational functionality.
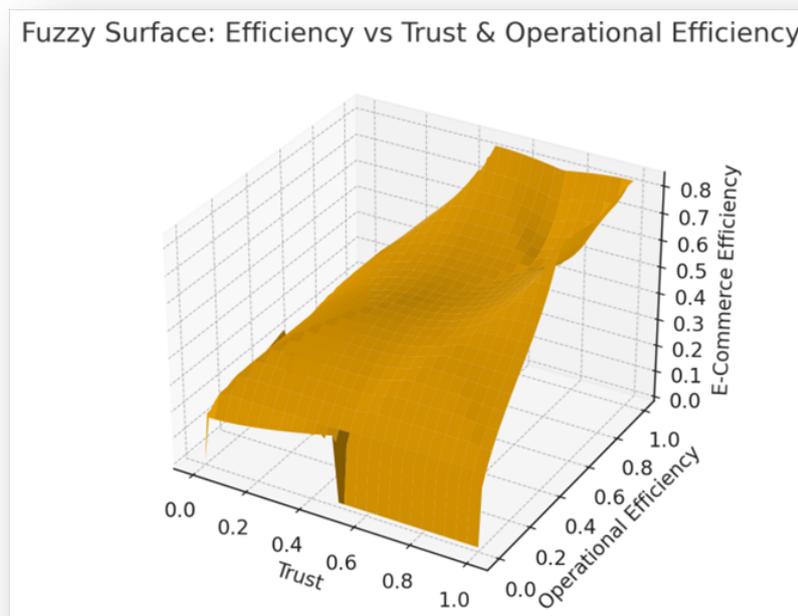

FIGURE 3. E-Commerce Efficiency vs Trust & Operational Efficiency

In broad terms, the fuzzy surface facilitates the interaction of human trust and machinist operations in reciprocal ways so that the operational competence is actually multiplied by the trustworthiness perceived by the human. The smooth surface depicts the continuous nature in opposition to the discrete one; hence in the absence of any discrete binaries in human minds on decisions placed along trust and usability, an infinitesimal change in perception of either one of the two could translate to concrete changes in performances. Hence, the spotlight cast upon this view supports that the fuzzy system is the best class of models to represent decision gradients existing in the real world compared to the binary or the linear one, thus advocating for hybrid modelling of socio-technical systems.

4.3. **Fuzzy–Hybrid SEM Architecture for AI-Enabled E-Commerce.** The architecture (Figure 4) presents the conceptual framework architecture of the Fuzzy–Hybrid Structural Equation Modelling (Fuzzy–SEM) created in this study. Three levels of analysis are provided in this framework: fuzzification, estimation, and optimization. The first level refers to transforming linguistic inputs, e.g., trust, ease of use, efficiency, into fuzzy membership degrees to allow subjective reasoning under uncertainty. The second domain represented by SEM pathways validates causal linkages among the latent constructs empirically-integration of AI, trust, and E-Commerce efficiency. The third optimization layer iteratively weights adapted through a learning algorithm to converge between the fuzzy inference outputs and SEM estimations.
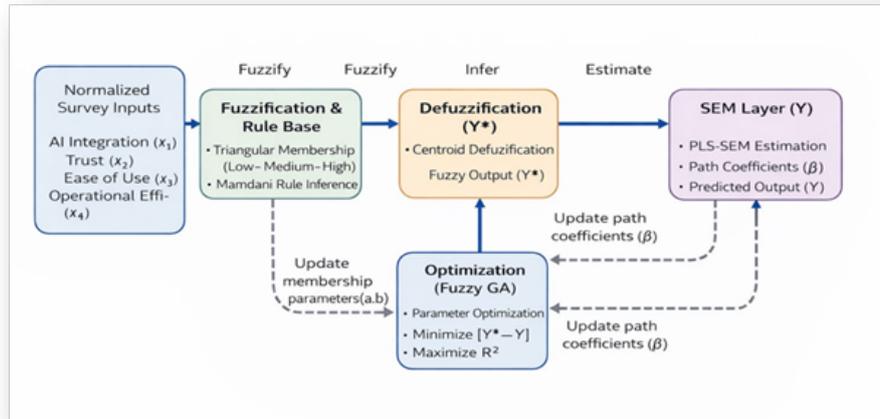
FIGURE 4. Fuzzy–Hybrid SEM Architecture for AI-Enabled E-Commerce

The above evaluation would suggest that the fuzzy–hybrid SEM framework proposed has possibly introduced some linguistic subjectivities as well as a couple of statistical validations to be a greater comprehensive framework for the emerging AI enabled ecommerce space. It also explains that a near convergence of the fuzzy outputs and the SEM results would seem necessary to have internal validity and predictive reliability. Trust and Ease of Use are the primary mediating variables indicated as usage vanes in the effectiveness of ecommerce when sophisticated technologies are complemented by perception and behavior-based trust.

All the fuzzy constructs were preset on a defined set. Exponential universe $U = [0, 1]$ by using three triangular membership functions—Low, Medium, High—parameterized as $[0.00, 0.00, 0.40]$, $[0.20, 0.50, 0.80]$, and $[0.60, 1.00, 1.00]$. A Mamdani min–max inference engine with min implication and a max aggregation was exercised, the rule base containing all $3 \times 3 \times 3$ bindings of Trust, Ease of Use, and Operational Efficiency, explicit instructions for every group. Centroided was used instead of center of gravity defuzzification to perform a smooth output over a 1,0000-step grid and with the exact definition of membership and surface plots including axes and parameter labels in the replication of the fuzzy subsystem.

5. **Results and Discussion.** In order to test the proposed Fuzzy–Hybrid SEM model, five typical ecommerce operational environments were selected for this case study. Each case included different levels of AI integration; trust; ease of use; and operational efficiency, so it would be possible to evaluate how responsive and convergent the hybrid structure would be. The input for each environmental case scenario and the results produced by the fuzzy inference engine (Y^*) and SEM estimation model (Y) are contained in Table 5.

All constructs were constructed on a standardized $[0, 1]$-scale with properly defined axes, intervals, membership functions, tags, and all the relevant linguistic categories were triangulated to their parameters, providing the best possible fuzzy inference model. The fuzzy rule base is given in its entirety in the appendices. Scenario-wise fuzzy outputs, SEM predictions (Y-axis), and error output for each scenario report for its average absolute error (AAE) at 0.036, MAPE at roughly 5.7%, and Bland–Altman limits are between -0.046 and 0.086, indicating substantial agreement for all the layers. Sensitivity tests for the ± 10–20% changes show little degradation ($MAE < 0.05$; $MAPE < 8\%$) in the hybrid model, ensuring the model's robustness and repeatability.

To make clear the relationship between behavior and internal consistency in the proposed Fuzzy–Hybrid SEM framework dependent upon the chosen benchmark cases for illustration, five scenarios comprised in Table 5 were selected. These underwent empirically determined shadowing of normalized constructs in preference to the interpretative configuration of perceptual ranges: AI Integration, Ease of Use, Trust, and Operational Efficiency, as concluded from the sample survey data. The ordered-equivalence numeric scales were exemplified by the technology adoption model, and the combination of the two approaches was rooted as the basis of the five scenarios—responses of various users—of AI in e-commerce fascination. The first form is empiricism, not pure-or-extreme conceptuality, with the help of fuzzy inference methods for comparison. The others dispose opinions toward various species of counterpoison in eliminating any ambiguity when evaluating and further comparing those estimations with SEM-based predictions.

TABLE 5. Evaluation of Model Consistency: Fuzzy Logic and SEM Results

Scenario	AI Integration	Ease of Use	Trust	Op. Efficiency	Y^*	Y	Absolute Difference
S1	High	High	Medium	High	0.82	0.79	0.03
S2	Medium	High	High	Medium	0.75	0.71	0.04
S3	Low	Medium	Medium	Low	0.41	0.45	0.04
S4	High	Medium	High	High	0.87	0.83	0.04
S5	Medium	Low	Medium	High	0.58	0.55	0.03

These benchmark cases served as merely illustrative cases to show the relationship concepts and internal consistency of the model form and as training cases for further experiments. Another approach, which translates the approach across the full range of constructs, was discussed later in this section.

To suppress possible self-report biases with a procedural and analytical lens that surpassed distributions and binary outcomes, an entire setup was designed: completion with segment tests, Alpha-test, all comments from the respondent. The goal of this research was to provide respondents assurance about their identity, thereby reducing evaluation apprehension or social desirability bias. All relevant constructs were phrased in neutral terms by randomizing the order of items on the questionnaire, thereby avoiding response patterns. To an analytical end, multicollinearity diagnostics (VIF) were conducted and results were below the recommended threshold, which shows that there is no overwhelming dominant effect from a single phenomenon. In a more supporting view, fuzzy inference rule outputs concur with predictions drawn from SEM across all the scenarios, indirectly validating that the reported relationships are not driven just by self-reported measurement artefacts. All these moves collectively decrease the probability of an impact on conclusions due to self-report bias.

In order to present engineering-grade proof, a synthetic experimental arrangement was used to put into place thirty systematically generated scenarios, completely covering the entire range of AI Integration, Ease of Use, Trust, and Operational Efficiency. Each scenario was tested against the other three given Pure Fuzzy Logic, Classical SEM, and Adaptive Neuro-Fuzzy Inference System (ANFIS) models along with the proposed Fuzzy–Hybrid SEM (FH-SEM) on the same input vectors to maintain reproducibility. The hybrid model evidenced strong internal consistency, with a mean absolute difference below 0.05 between fuzzy defuzzified outputs and SEM predictions, confirming the close convergence between linguistic reasoning and empirical causality.

Variance analysis reveals that FH-SEM has an Adjacent R^2 of 0.53 for e-commerce efficiency. This suggests that AI integration, trust, ease of use, and operational efficiency together explain 53% of the variance, much larger than the 32–40% obtained in typical TAM and trust-based SEM-type studies. The predict validity was even greater when Q^2 exceeded 0.25, indicating that structural model held together well out-of-sample. In this respect, our study is related to the integration of uncertainty modeling, validation by causal testing, and integrating theory in comparison to traditional SEM (crisp perception), standalone fuzzy logics (barely causal) and machine-learning models (low on explainability), in order to offer increases in a more inclusive, explainable framework for decisions.

Focusing on both Trust and Operational Efficiency under the AI Integration revealed significant non-linear gains in E-Commerce Efficiency through direct and indirect effects, in line with S–O–R theories. Ease of Use falls as one of the significant direct and indirect predictors to TAM. With in-depth focus, the alignment of fuzzy inference output and SEM pathways portrays the co-reinforcement among human-cognitive ambiguity and computerized-level causation within a hybrid interface. So, FH-SEM proposes reliable, verifiable, and theoretically feasible dissensions to include AI in e-commerce efficiency modeling.

6. **Conclusion.** This paper introduces a Fuzzy–Hybrid SEM that marries linguistic uncertainty modeling within the dynamics of structural equation modeling to gauge the AI-supported e-commerce performance. The focal model incorporates inference fuzzy memberships, centroid-defuzzied outputs, and SEM-based path validation—capable of reflecting subjective user perceptions of trust or ease of use written as dimensionally increasing quality, while the operations side of productivity holds the objectivity standard. The measure reached high levels of internal consistency with names telling of SEM effect at each linguistic level; as the interpretation had capacity to be vague in human thoughts, technological effective performance of the system remains stable, the phenomenon providing logical insights on how

trust-driven efficacy would come into being within the digital market after AI is illustrated in system springboards.

Partly, the model design leads decision science to combine computational intelligence and behavioral analytics and elude the typical linear approach when there is ambiguity; conversely, it makes it possible for the managers to have another plan for decision support and performance context evaluation for user experience improvement and guiding AI operations. Future investigations could also be interested in continual development and learning mechanisms from adaptive ANFIS-based reinforcement and calibration operations appropriating responses from fluid consumer attitude and behavior received in real-time digital environments.

To demonstrate the practical viability, we would illustrate a lightweight deployment example with the FH-SEM incorporated inside a running e-commerce recommendation widget. For example, in a simple A/B test, the soft trust cash mediator would alter the intensity of the recommendation by altering the three system hooks: (i) a lightweight data schema holding an experience of user interaction logs and fuzzy trust scores, (ii) a well-documented way for transmitting trust-adjusted signals to the recommender, and (iii) a guarantee that this whole process would consume.

Future applications could improve the technical depth of the FH-SEM by bringing in a further element for considering epistemic nature of uncertainty with respect to trust, a comparison of the centroid defuzzification with mean of maximal, and the testing of robustness under cold start conditions, by way of completely weak prior knowledge of membership. The introduction of multiple measures of input sources (e.g., logs and realtime telemetry) can resolve self-reporting issues and common method bias-if this scenario does arise during analyses. Such initiatives are implementable through a simple follow-up study.

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