The AHP–Empowerment–Entrepreneurship (AEE) Framework: Enhancing Transparency, Psychological Empowerment, and Trust Calibration in AI-Supported Decision Making

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Abstract

As artificial intelligence (AI) becomes increasingly embedded in decision support systems (DSS), a central challenge is not merely improving algorithmic accuracy but designing systems that effectively structure human judgment and regulate reliance. This study proposes the AHP–Empowerment–Entrepreneurship (AEE) framework, a human-centered decision system architecture that explains how analytic structuring enhances decision quality in AI-supported decision making. The framework conceptualizes AHP-based analytic structuring as a core decision structuring layer that externalizes criteria, priorities, and consistency, rather than as a standalone optimization tool. Psychological empowerment is positioned as the human judgment interface through which structured transparency translates into reflective evaluation, while trust calibration operates as a regulatory control mechanism governing appropriate reliance on AI recommendations. By integrating decision structuring, empowerment, and reliance regulation within a unified system logic, the AEE framework advances decision systems theory beyond explanation-centric approaches. The study contributes to decision system design by clarifying how structured interaction, preserved agency, and calibrated trust jointly support responsible and high-quality AI-supported decisions, particularly in complex and value-laden decision contexts.

Keywords: Decision support systems; Decision structuring; Analytic Hierarchy Process; Psychological empowerment; Trust calibration; Human–AI decision making.

1. Introduction

Artificial intelligence (AI) has become an integral component of contemporary decision support systems (DSS), offering unprecedented capabilities for data processing, prediction, and optimization (Power, 2007; Sharda et al., 2020). In entrepreneurial and strategic contexts, AI-enabled DSS increasingly assist decision-makers in evaluating alternatives, prioritizing criteria, and navigating uncertainty (Al-Mamary, 2025). Despite these advances, a fundamental challenge persists: many AI-supported systems enhance computational performance without adequately supporting the structure of human judgment. As a result, decision-makers may receive accurate recommendations yet lack a transparent, value-consistent, and controllable decision process.

Decision systems research has long emphasized that effective decision support is not defined solely by algorithmic accuracy, but by the system's ability to structure decision problems, externalize preferences, and guide reflective evaluation (Simon, 1960; Power, 2004). Classical DSS literature highlights decision structuring as a core function—one that transforms ill-defined, value-laden problems into analyzable forms that decision-makers can meaningfully engage with (Keen & Scott Morton, 1978; Turban et al., 2011). However, recent AI-driven DSS have increasingly shifted toward automation-oriented designs, where recommendations are generated by opaque models and presented as outputs to be accepted or rejected, rather than as components of an interactive decision logic (Shin, 2021).

This shift raises a critical concern for decision systems design: when AI systems provide answers without structuring the reasoning process, the decision system may fail to adequately structure judgment and regulate reliance. Empirical studies in human–AI decision-making have documented risks such as automation bias, over-reliance, and diminished reflective judgment in AI-assisted environments (Parasuraman & Riley, 1997; Schoeffer et al., 2024). These findings suggest that the central problem is not merely a lack of explanation, but the absence of a decision structuring mechanism that enables users to actively articulate, examine, and revise their priorities within the system.

Recent research in explainable artificial intelligence (XAI) has primarily focused on post-hoc transparency, often without addressing the underlying structure of the decision process (Kostopoulos et al., 2024; Tatasciore et al., 2024). While these approaches improve interpretability, they often remain system-centric: explanations describe how the algorithm reasoned, rather than supporting how users should reason. From a decision systems perspective, explanations alone are insufficient if they are not embedded within a coherent decision structure that aligns alternatives, criteria, and user values (Shin & Park, 2019). Consequently, there is a growing need for decision system architectures that integrate analytic structuring with human judgment, rather than treating explanation as an auxiliary feature.

One promising yet underexplored approach lies in integrating multi-criteria decision analysis (MCDA) methods into AI-supported DSS as core structuring mechanisms. Among these methods, the Analytic Hierarchy Process (AHP) is particularly relevant due to its intuitive hierarchy, explicit pairwise comparisons, and built-in consistency checks (Saaty, 1980). Within decision systems, AHP is best understood not merely as a decision method but as a decision structuring logic that externalizes preferences and priorities (Ishizaka & Labib, 2011). However, within AI-enabled DSS, AHP is often treated as a standalone optimization tool rather than as a system-level logic that governs human–AI interaction (Franco & Montibeller, 2010).

At the same time, research on human–AI decision-making has increasingly highlighted the role of psychological factors—such as perceived control, competence, and agency—in shaping decision quality (Spreitzer, 1995; Buschmeyer et al., 2023). Users who feel empowered are more likely to engage reflectively, question recommendations, and integrate system outputs with their own reasoning (Choung et al., 2024). Yet, empowerment alone does not ensure appropriate reliance on AI. Decision-makers must also be able to calibrate trust dynamically, increasing reliance when system reasoning is coherent and reducing it when inconsistencies arise (Lee & See, 2004; Li et al., 2024). Accordingly, the relevance of the AEE framework lies in its capacity to translate culturally embedded expectations into explicit decision structures and control mechanisms.

Despite parallel advances in decision structuring, psychological empowerment, and trust research, these streams remain largely fragmented. Existing decision system models rarely explain how analytic structuring mechanisms influence empowerment, nor how empowerment interacts with trust calibration to shape decision quality (Shin, 2021; Schoeffer et al., 2024). As a result, decision systems scholarship lacks an integrated framework that links decision structure, human judgment, and reliance regulation within AI-supported environments.

To address this gap, this study proposes the AHP–Empowerment–Entrepreneurship (AEE) Framework, a human-centered decision system architecture that explains how analytic structuring enhances decision quality through psychological empowerment and calibrated trust. Rather than viewing AHP as a technical method or empowerment as a purely psychological outcome, the AEE framework conceptualizes AHP-based structuring as a core decision system mechanism that shapes how users engage with AI-generated alternatives. Psychological empowerment is positioned as the human judgment interface through which structured transparency translates into reflective evaluation, while trust calibration functions as a regulatory mechanism that governs appropriate reliance on AI recommendations (Lee & See, 2004).

The AEE framework makes three primary contributions to decision systems research. First, it advances decision structuring theory by demonstrating how analytic hierarchy modeling can serve as an interactive logic within AI-enabled DSS, rather than as a post-hoc evaluation tool (Franco & Montibeller, 2010). Second, it integrates psychological empowerment into decision system architecture, clarifying how structured interaction enhances meaning, competence, autonomy, and perceived impact during AI-supported decisions (Spreitzer, 1995; Muneer et al., 2024). Third, it positions trust calibration as a moderating control mechanism that determines whether empowerment leads to improved decision quality or to over- or under-reliance on AI (Li et al., 2024).

By framing AI-supported entrepreneurship as a problem of decision system design rather than algorithmic performance, this study responds to recent calls for human-centered DSS that support judgment, accountability, and reflective reasoning (Power, 2007; Sharda et al., 2020). Although the framework is motivated by entrepreneurial decision contexts—where value trade-offs and uncertainty are especially salient—the proposed logic is applicable to a wide range of AI-supported decision systems. In doing so, the AEE framework contributes to the design and evaluation of decision systems that structure human reasoning, regulate reliance, and ultimately improve decision quality in AI-augmented environments.

2. Literature Review

This chapter reviews the theoretical foundations that support the AHP–Empowerment–Entrepreneurship (AEE) framework. It synthesizes research from four domains: (1) AI-enabled decision support, (2) psychological empowerment, (3) the Analytic Hierarchy Process (AHP), and (4) trust calibration in human–AI interaction. Integrating these streams establishes the conceptual logic through which analytic structuring enhances transparency, empowerment, and responsible reliance in AI-supported entrepreneurial decisions.

2.1. AI-Enabled Decision Support: From Automation to Cognitive Augmentation

Early decision-support systems aimed primarily at computational efficiency—processing data, generating forecasts, and recommending optimal choices. However, recent advances in explainable and generative AI have shifted attention toward cognitive augmentation, where AI acts not only as a problem solver but as a thinking partner. Such systems help users recognize opportunities, interpret complex trade-offs, and refine their reasoning (Al-Mamary, 2025; Cao et al., 2025).

A central insight from this evolving literature is that the value of AI does not lie solely in algorithmic performance but in how it shapes users' cognitive engagement. Transparent explanations, fairness cues, and interactive reasoning structures enable users to assess the relevance and validity of AI output. Consequently, leading DSS research argues for a transition toward human-centered decision-support systems that reinforce, rather than override, human judgment (Kostopoulos et al., 2024; Li et al., 2024).

Nevertheless, a persistent challenge remains: modern AI systems can provide information, but they often lack mechanisms for structuring users' cognitive priorities or aligning recommendations with users' values. This limitation creates a gap that AHP can fill by offering a systematic way to articulate, quantify, and integrate subjective criteria into AI-supported decisions.

2.2. Psychological Empowerment in Human–AI Decision Making

Psychological empowerment—meaning, competence, self-determination, and impact—is increasingly recognized as a core determinant of decision quality in human–AI collaboration. Initially conceptualized in organizational behavior (Spreitzer, 1995), these four dimensions are now relevant to AI-supported environments, where users must maintain both autonomy and clarity of thought.

2.2.1 Empowerment as a Mediating Mechanism

Recent studies have shown that empowered users interpret AI recommendations more critically, avoid blind reliance, and maintain reflective decision-making strategies (Choung et al., 2024; Muneer et al., 2024). Within the proposed decision system logic, empowerment functions as a judgment interface through which structured transparency influences decision outcomes. When users feel competent and autonomous, they can more effectively evaluate AI feedback and maintain ownership of their final decisions.

2.2.2 Empowerment as a Human-Centered Design Principle

Empowerment is also emerging as a design construct in the development of AI systems. Human-centered AI necessitates systems that foster agency, uphold values, and offer transparent and interpretable decision-making logic. These design expectations align directly with AHP's logic-based structuring. By enabling users to articulate and evaluate decision criteria, AHP can elevate meaning, strengthen competence, preserve autonomy, and enhance perceived impact—thus making empowerment an active component of decision support rather than a passive outcome.

2.3. Analytic Hierarchy Process (AHP): Structuring Cognition and Enabling Transparency

The Analytic Hierarchy Process (Saaty, 1980) is a widely adopted multi-criteria decision-making method valued for its intuitive structure, interpretability, and consistency evaluation. AHP’s strength lies in its ability to externalize complex, subjective reasoning into transparent, hierarchical models.

2.3.1. AHP as a Cognitive Structuring Tool

AHP decomposes complex problems into hierarchical layers (goal, criteria, subcriteria, alternatives) and quantifies subjective priorities through pairwise comparisons. This structured breakdown:

- Clarifies users’ reasoning
- Makes implicit values explicit
- Supports reflective judgment
- Provides consistency feedback ($CR \leq 0.10$)

These features transform intuitive reasoning into traceable analytic logic, making AHP an ideal cognitive scaffold for interacting with AI systems.

2.3.2. AHP and Human–AI Interaction

Recent work on explainable AI highlights a crucial limitation: explanations alone do not guarantee understanding or empowerment (Kostopoulos et al., 2024). AHP complements XAI by offering a user-driven logic that AI can reference when generating explanations. This alignment enables AI to deliver personalized, value-consistent reasoning, thereby enhancing interpretability, decision confidence, and engagement. In human–AI collaboration, AHP supports:

- Value-aligned AI recommendations
- Transparent comparison of alternatives
- Reduced automation bias
- Empowerment through cognitive participation

Thus, AHP is not merely an optimization tool but a mechanism for enhancing psychological empowerment.

2.4. Trust Calibration in Human–AI Interaction

Trust calibration refers to a user’s ability to adjust their trust in AI appropriately based on transparency cues, explanation depth, and perceived fairness (Choung et al., 2024; Li et al., 2024). Unlike static trust models, trust calibration emphasizes dynamic, context-sensitive trust adjustments that help prevent both over-reliance and under-reliance. Recent studies demonstrate that:

- Transparency improves error detection
- Clear reasoning reduces automation bias
- Value-aligned explanations increase confidence
- Adaptive feedback supports reflective learning (Lim et al., 2025)

In this context, trust calibration becomes a critical moderating mechanism. Users with high trust calibration can translate empowerment into higher decision quality, whereas users with poor calibration may misinterpret or misuse AI recommendations. Within the AEE model, trust calibration is both an outcome of transparency and an interactive moderator shaping how empowerment influences decision performance.

Within the AEE decision system architecture, trust calibration is not treated as a static user attitude but as a system-triggered control mechanism. Specifically, calibration is activated when predefined system signals are detected, such as inconsistencies in AHP pairwise judgments, divergence between AI-generated rankings and user-defined priorities, or insufficient explanatory coherence. These triggers prompt users to reassess reliance by revisiting criteria weights or decision logic, thereby preventing both over-reliance and premature dismissal of AI recommendations. Through such system-embedded controls, trust calibration dynamically regulates the integration of human judgment and algorithmic support.

2.5. Social and Ethical Concerns in AI-Supported Decision-Making in Asia

AI deployment in Asia reflects unique social and ethical dynamics shaped by cultural norms, governance models, and regional innovation ecosystems. Asian societies often place greater emphasis on collective welfare, hierarchical decision structures, and harmony-oriented value alignment, which influence how individuals perceive transparency, fairness, and accountability in AI-supported judgments. Research has shown that East Asian users tend to exhibit higher initial trust in structured or rule-based systems, leading to increased vulnerability to automation bias when transparency cues are insufficient. At the same time, strong regional commitments to digital transformation—especially in China, Singapore, South Korea, and Japan—have intensified ethical debates surrounding algorithmic governance, privacy expectations, and value alignment in entrepreneurial decision support. These contextual factors highlight the need for frameworks such as AEE, which emphasize structured reasoning, empowerment, and calibrated trust, offering a culturally relevant model for strengthening agency in AI-mediated decisions within Asia.

2.6. Integration: The Missing Link in Current Research

Although significant progress has been made across AI decision support, empowerment theory, AHP modeling, and trust calibration, the literature remains fragmented. Three gaps are evident:

(1) Lack of integrated frameworks explaining how analytic structuring (AHP) enhances psychological empowerment in AI-assisted decisions.

(2) Insufficient understanding of how transparency interacts with empowerment and trust calibration within human–AI co-decision systems.

(3) Absence of methodological models that link multi-criteria reasoning with human-centered AI governance.

The AEE framework proposed in this study addresses these gaps by conceptualizing empowerment as both a psychological mediator and a structured decision variable. Through AHP's analytic clarity and AI's adaptive feedback, the model establishes a comprehensive foundation for understanding how transparency, empowerment, and trust jointly enhance decision quality in the entrepreneurial domain.

3. Theoretical Framework

This chapter introduces the AHP–Empowerment–Entrepreneurship (AEE) framework developed in this study. It explains the theoretical relationships among its core constructs: AI Transparency & AHP Structuring, Psychological Empowerment, Trust Calibration, and Decision Quality. The chapter integrates insights from decision-support research, cognitive psychology, and human–AI interaction to justify the proposed structural model and derive the study's hypotheses.

3.1. Foundations of the AEE Framework

Entrepreneurial decisions are inherently complex, value-driven, and characterized by uncertainty. While AI systems provide computational power and rapid pattern recognition, their effectiveness depends on whether users can understand, evaluate, and appropriately rely on their outputs. Human–AI collaboration, therefore, requires not only accurate computation but also cognitive transparency and psychological empowerment.

The AEE framework addresses this challenge by combining: *AHP-based analytic structuring, which externalizes judgment and clarifies decision priorities*; *psychological empowerment, which strengthens agency and reflective evaluation*; *trust calibration, which ensures appropriate reliance on AI*; and *decision quality, the key outcome of human–AI collaboration*. This section describes how these components interact within a unified theoretical model. To integrate analytic structuring, psychological empowerment, and trust calibration within a unified decision system logic, the proposed AHP–Empowerment–Entrepreneurship (AEE) decision system architecture is illustrated in Figure 1.

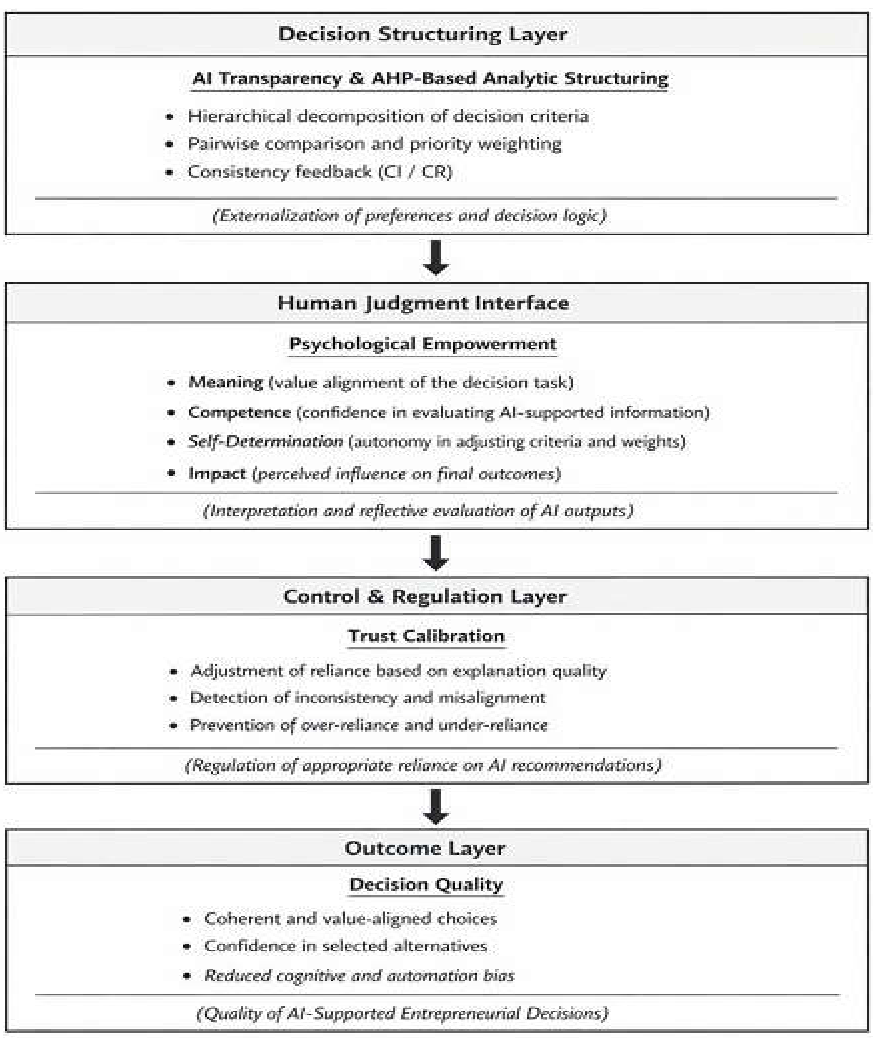

Figure 1. AHP–Empowerment–Entrepreneurship (AEE) Decision System Architecture

3.2. The Role of AI Transparency & AHP Structuring

AI transparency refers to the clarity, traceability, and interpretability of the reasoning underlying AI recommendations. However, transparency alone does not guarantee user understanding. Explanations must be grounded in a structure that users can actively engage with and influence. AHP provides this structure through hierarchical decomposition of decision criteria, explicit pairwise comparisons, user-defined priority weights, and consistency evaluation (CI and *CR)*.

These mechanisms enable users to articulate and reflect on their cognitive priorities, thereby increasing the interpretability of the decision-making process and fostering psychological involvement. Accordingly, AHP-based structuring functions as both a cognitive scaffold and a transparency mechanism, leading to:

H_1: AI transparency and AHP structuring positively influence psychological empowerment.

3.3. Psychological Empowerment as a Mediating Process

The four dimensions of empowerment—meaning, competence, self-determination, and impact—shape users' ability to interpret and reflect on AI-generated information. **Meaning** helps users understand why a decision matters. **Competence** provides the confidence to evaluate AI outputs. **Self-determination** ensures participants maintain autonomy in altering weights and priorities. **Impact** strengthens users' perception that they actively co-create decisions with AI.

When these dimensions are activated, users become more capable of evaluating alternatives, understanding trade-offs, and integrating AI recommendations into their decision logic. Accordingly, empowerment is the mechanism through which structured transparency leads to improved decision quality. Thus:

H_2: Psychological empowerment positively influences decision quality.

3.4. Trust Calibration as a Moderating Mechanism

While empowerment strengthens cognitive engagement, it does not guarantee that users will appropriately rely on AI. This is where trust calibration becomes essential. rust calibration operates as a regulatory control mechanism that adjusts reliance within the decision system.

Empowered individuals are more likely to interpret AI recommendations critically, yet this process only improves decisions when users simultaneously maintain calibrated trust. Without proper calibration:

- When trust calibration is high, empowered users integrate AI guidance reflectively, automation bias is reduced, and decision quality improves.
- When trust calibration is low, users may over-rely on AI or disregard high-quality AI advice.

Therefore, trust calibration moderates the link between empowerment and decision quality:

H_3: Trust calibration positively moderates the relationship between psychological empowerment and decision quality.

Moreover, transparency and structured reasoning enhance trust calibration:

H_4: AI transparency and AHP structuring have a positive influence on trust calibration.

3.5. Relevance of the AEE Framework to Asian Decision Contexts

The AEE framework is particularly relevant for Asian decision-making environments, where cultural norms, social hierarchies, and collective value orientations strongly influence how individuals interpret algorithmic authority. Many Asian contexts emphasize deference to expert systems, preference for structured and rule-based reasoning, and greater sensitivity to relational harmony and procedural fairness. These characteristics shape how users respond to AI transparency cues, how empowered they feel to question algorithmic recommendations, and how they calibrate trust when interacting with decision-support technologies. By integrating algorithmic transparency, human empowerment, and trust calibration, the AEE framework aligns closely with the social, ethical, and cultural expectations prevalent across East and Southeast Asia. As such, it provides a culturally grounded foundation for understanding responsible and autonomous AI-mediated decision-making in Asian societies.

3.6. Proposed Model

Figure 2 presents the proposed structural model, specifying the hypothesized relationships among AI transparency, psychological empowerment, trust calibration, and decision quality. The model positions empowerment as a central psychological pathway and trust calibration as a key moderator for responsible human–AI collaboration.

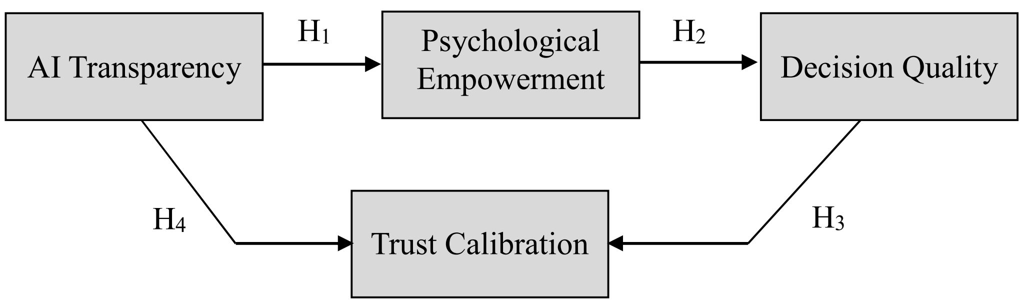

Figure 2. Structural Model with Hypotheses (H_1–H_4)

Based on the structural model illustrated in Figure 2, the following hypotheses are proposed.

3.7. Hypotheses Development

H_1: AI transparency and AHP structuring positively influence psychological empowerment.

Transparent structuring enables users to articulate and evaluate their own priorities, thereby enhancing meaning, competence, autonomy, and impact.

H_2: Psychological empowerment positively influences decision quality.

When individuals feel competent and autonomous, they approach AI recommendations more critically and integrate insights more effectively.

H_3: Trust calibration positively moderates the relationship between empowerment and decision quality.

Users with higher calibration capabilities benefit more from empowerment because they can adjust their trust in AI outputs appropriately.

H_4: AI transparency and AHP structuring have a positive influence on trust calibration.

Providing users with structured, value-aligned explanations facilitates accurate trust adjustments and reduces the risk of automation bias.

4. Methodology

This chapter outlines the methodological blueprint for empirically validating the AHP–Empowerment–Entrepreneurship (AEE) framework. Although the present study is conceptual, it establishes a rigorous operational foundation by integrating analytic hierarchy modeling with psychological constructs such as empowerment and trust calibration. The following sections describe the constructs, their operationalization, and the Analytic Hierarchy Process (AHP) procedures—including formal mathematical expressions—that are required for a transparent and replicable analysis.

4.1. Research Design Overview

From a decision system perspective, the proposed architecture operates through two complementary layers:

(1) **AHP-based cognitive structuring**, which externalizes subjective entrepreneurial judgments into transparent hierarchical models.

(2) **Psychological measurement**, assessing empowerment, trust calibration, and decision quality using validated scales.

This dual approach aligns with the theoretical logic articulated in Chapter 3, where transparency and analytic structure enhance empowerment, which interacts with trust calibration to shape the quality of decisions.

4.2. Constructs and Operationalization

Table 1 summarizes the core constructs and their operational definitions. As shown in Table 1, the constructs include:

- AI Transparency & AHP Structuring
- Psychological Empowerment (meaning, competence, self-determination, impact)
- Trust Calibration
- Decision Quality

Each variable is linked directly to the hypotheses presented in Section 3.

Table 1. Operational Definitions of AEE Constructs

Construct	Conceptual Definition	Operational Definition	Key References
AI Transparency & AHP Structuring	The degree to which AI-supported decisions are interpretable, traceable, and aligned with user-defined criteria through hierarchical decomposition and explicit pairwise comparisons.	Measured through the clarity of the criteria hierarchy, visibility of pairwise comparison matrices, consistency feedback (CI/CR), and perceived transparency of how user inputs shape AI recommendations.	Saaty (1980); Choung et al. (2024); Kostopoulos et al. (2024)
Psychological Empowerment	A motivational state characterized by meaning, competence, self-determination, and impact, shaping how individuals perceive control and agency in decision processes.	Assessed via a 7-point Likert scale across four subdimensions: (1) task meaningfulness, (2) perceived competence, (3) autonomy in adjusting decision parameters, and (4) impact on outcomes.	Spreitzer (1995); Muneer et al. (2024); Shi (2024)
Trust Calibration	The user's ability to appropriately adjust trust in AI recommendations based on the clarity of explanations, perceived consistency, and value alignment.	Measured using items capturing dynamic trust adjustment, increased trust under high-quality explanations, reduced trust under inconsistencies, and re-evaluation behavior when AI and user judgments diverge.	Li et al. (2024); Choung et al. (2024); Lim et al. (2025)
Decision Quality	The degree to which decisions are coherent, value-aligned, logically supported, and resistant to bias in AI-supported judgments.	Evaluated through clarity of rationale, confidence in chosen alternatives, alignment with user-defined priorities, and reduction of cognitive bias during decision-making.	Al-Mamary (2025); Cao et al. (2025)

As shown in Table 1, the constructs include AI Transparency & AHP Structuring, Psychological Empowerment, Trust Calibration, and Decision Quality, each grounded in validated conceptual definitions.

4.2.1 AI Transparency & AHP Structuring

This construct reflects the degree to which decision processes are decomposable, intelligible, and traceable through the hierarchical structure. AHP enables participants to articulate decision criteria, assign relative weights, and evaluate alternatives using pairwise comparisons. Transparency arises through:

- clearly documented criteria and subcriteria,
- accessible comparison matrices,
- verifiable consistency ratios ($CR \leq 0.10$), and
- full visibility into how judgments influence outcomes.

4.2.2 Psychological Empowerment

Empowerment is operationalized using the four dimensions proposed by Spreitzer (1995):

(1) Meaning: The perceived importance and value alignment of the task.
(2) Competence: Confidence in one's ability to evaluate and process information.
(3) Self-determination: Autonomy in adjusting weights, modifying criteria, and influencing outcomes.
(4) Impact: The extent to which users believe their judgments materially shape results.

Each item is measured using a 7-point Likert scale.

4.2.3 Trust Calibration

Trust calibration captures a user's ability to adjust trust upward or downward based on the clarity, consistency, and fairness of AI reasoning. This construct can be operationalized through the following items:

- *TC1*: I adjust my trust based on how clearly the AI explains its reasoning.
- *TC2*: I increase trust when the AI provides a reasonable justification.
- *TC3*: I reduce trust if explanations are unclear or inconsistent.
- *TC4*: I re-evaluate recommendations when they contradict my judgment.
- *TC5*: My trust changes based on transparency and information quality.

4.2.4 Decision Quality

Decision Quality reflects the user's ability to integrate structured reasoning and AI recommendations into coherent, value-aligned choices. It includes:

- clarity of evaluation,
- appropriateness of chosen alternatives,
- confidence in the final decision, and
- reduction of cognitive bias.

4.3. AHP Procedure: Formal Steps and Mathematical Foundations

The Analytic Hierarchy Process (AHP) transforms subjective judgments into structured priority weights through decomposing problems, conducting pairwise comparisons, and verifying consistency. The following subsections outline its formal procedure and mathematical foundations.

4.3.1 Step 1: Hierarchical Structuring

The AEE decision structure contains four levels:

- **Goal**: Entrepreneurial decision objective
- **Criteria**: Empowerment dimensions
- **Subcriteria**: Ethical alignment, capability fit, autonomy range, social contribution

- **Alternatives**: AI-supported options
  This hierarchical design externalizes cognitive priorities and increases transparency.

4.3.2 Step 2: Pairwise Comparison Matrices

Participants compare each criterion pair using Saaty's 1–9 scale. A general comparison matrix A is structured as:

$$A=\begin{bmatrix} 1 & \alpha_{12} & \cdots & \alpha_{1n} \\ \frac{1}{\alpha_{12}} & 1 & \cdots & \alpha_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{\alpha_{1n}} & \frac{1}{\alpha_{2n}} & \cdots & 1 \end{bmatrix}$$

A sample pairwise matrix is presented in Table 2, illustrating comparisons of empowerment criteria.

Table 2. Example Pairwise Comparison Matrix for Empowerment Criteria

Criteria	Meaning	Competence	Self-Determination	Impact
Meaning	1	3	2	4
Competence	1/3	1	1/2	3
Self-determination	1/2	2	1	2
Impact	1/4	1/3	1/2	1

Note. Values above are illustrative and follow Saaty's (1–9) scale.

As shown in Table 2, the pairwise comparison matrix provides a straightforward method for quantifying cognitive preferences and deriving normalized weights.

4.3.3 Step 3: Priority Weight Derivation

Priority weights are obtained by computing the principal eigenvector:

$$Aw=\lambda_{max}w$$

Where:

- A = comparison matrix
- w = normalized priority vector
- $\lambda_{\max}$ = maximum eigenvalue of A

Normalization procedure：

(1) Normalize each column of A
(2) Average each row to obtain w

4.3.4 Step 4: Consistency Evaluation

To ensure logical coherence in judgments, AHP computes:

Consistency Index (CI)

$$\mathrm{CI} = \frac{\lambda_{max} - n}{(n-1)}$$

Consistency Ratio (CR)

$$CR = \frac{CI}{RI}$$

If CR ≤ 0.10, the judgments are considered acceptably consistent.

If CR > 0.10, the user must revise their comparisons.

This built-in feedback enhances users' competence and reflective thinking, directly supporting the empowerment mechanism in the AEE model.

4.4. Integration of AHP with AI Decision-Support Systems

To operationalize the AEE framework in AI environments, AHP outputs are integrated into the AI decision-support module through three steps:

(1) **AHP-derived weights** are input into the AI model as personalized preference parameters.
(2) The AI system evaluates alternatives using user-defined criteria.
(3) **Adaptive explanations** highlight alignment or divergence between AI reasoning and user priorities.

This integration promotes transparency, supports trust calibration, and empowers users to maintain ownership of decision processes.

4.5. Methodological Implications

The methodological blueprint supports several empirical extensions:

- Structural equation modeling (SEM) for hypothesis testing
- Between-group experiments manipulating transparency
- Longitudinal studies on empowerment evolution
- Comparative evaluation of multiple MCDM methods

This flexible structure ensures the AEE framework can be validated across diverse entrepreneurial and AI-supported decision contexts.

5. Discussion

To illustrate how the proposed AEE architecture operates in practice, consider an AI-supported entrepreneurial decision scenario involving the selection of a strategic investment project. Decision-makers first structure the problem using AHP by decomposing strategic objectives into hierarchical criteria and conducting pairwise comparisons to externalize priorities. AI-generated alternatives are then evaluated within this structured logic rather than presented as autonomous recommendations. Decision quality in this context is defined not only by perceived confidence but also by coherence, value consistency, and the traceability of decision rationale within the system. By making trade-offs explicit and auditable, the AEE architecture supports reflective judgment while reducing automation bias and uncritical reliance on AI-supported outcomes.

The present study advances decision systems research by reframing AI-supported decision making as a problem of decision system design rather than algorithmic performance. By proposing the AHP–Empowerment–Entrepreneurship (AEE) framework, this study integrates analytic structuring, psychological empowerment, and trust calibration into a unified decision system architecture that explains how human judgment is supported, regulated, and preserved in AI-augmented environments. This discussion elaborates on the theoretical contributions, decision system design implications, and broader relevance of the proposed framework.

5.1. Reframing AI-Supported Decision Making as Decision Structuring

A central contribution of this study lies in its explicit return to decision structuring as the foundational function of decision support systems. While recent AI-enabled DSS emphasize predictive accuracy, optimization, and automation, the AEE framework highlights that decision quality ultimately depends on whether users can meaningfully structure and interrogate the decision problem itself. As illustrated in Figure 1, AHP-based analytic structuring serves as the decision structuring layer that externalizes criteria, priorities, and trade-offs, transforming implicit judgment into explicit, inspectable logic.

This perspective extends classical DSS theory by demonstrating that decision structuring is not a preliminary step that precedes algorithmic processing, but a continuous, interactive system function. Within the AEE architecture, analytic structuring actively shapes how AI-generated alternatives are evaluated, interpreted, and revised. In doing so, the framework responds to long-standing critiques that AI systems risk substituting human judgment rather than supporting it. The findings suggest that effective AI-supported decision systems must be designed to structure reasoning before generating recommendations, rather than relying solely on post-hoc explanations.

5.2. Psychological Empowerment as a Human Judgment Interface

A second contribution concerns the role of psychological empowerment within decision systems. Prior research has typically treated empowerment as an individual-level psychological outcome or an antecedent of technology acceptance. The AEE framework advances this literature by conceptualizing empowerment as a human judgment interface embedded within the decision system architecture. As shown in Figure 1, within the AEE decision system architecture, empowerment constitutes the judgment interface linking analytic structuring to decision quality by shaping how users interpret, evaluate, and act upon AI-supported information.

Each dimension of empowerment—meaning, competence, self-determination, and impact—corresponds to a specific design function within the system. Meaning emerges when decision criteria are explicitly aligned with user values; competence is reinforced through transparent weighting and consistency feedback; self-determination is preserved by allowing users to adjust criteria and priorities; and impact is enhanced when users can observe how their judgments influence outcomes. By embedding these functions into the system design, the AEE framework demonstrates how empowerment can be intentionally cultivated rather than assumed.

Importantly, this reconceptualization addresses a persistent gap in decision systems research: the lack of mechanisms explaining how system transparency translates into improved judgment. The results suggest that transparency alone is insufficient unless it is coupled with empowerment-oriented interaction that enables users to actively engage with structured decision logic.

5.3. Trust Calibration as a Regulatory Control Mechanism

Beyond empowerment, the AEE framework highlights trust calibration as a critical regulatory mechanism governing appropriate reliance on AI recommendations. Rather than treating trust as a static attitude toward technology, this study positions trust calibration as a dynamic control process that adjusts reliance based on explanation quality, consistency, and perceived alignment with user priorities.

Within the proposed architecture, trust calibration moderates the relationship between empowerment and decision quality. Empowered users are more capable of critical evaluation, but without calibrated trust they may either over-rely on AI outputs or dismiss valuable system guidance. By incorporating trust calibration as a distinct control layer (Figure 1), the AEE framework clarifies how decision systems can mitigate automation bias while avoiding underutilization of AI capabilities.

This insight contributes to decision systems theory by extending control concepts—traditionally associated with organizational or technical systems—into the cognitive domain of human–AI interaction. Trust calibration thus functions as a cognitive governance mechanism that regulates how human judgment and algorithmic support are integrated during decision making.

5.4. Implications for Decision System Design

The AEE framework offers several actionable implications for the design of AI-supported decision systems.

First, decision systems should prioritize structuring over explaining. Rather than focusing exclusively on generating explanations of algorithmic outputs, designers should embed analytic structuring mechanisms—such as hierarchical decomposition, pairwise comparison, and consistency feedback—directly into the user interface. This approach ensures that explanations are grounded in user-defined logic rather than system-centric reasoning.

Second, empowerment should be treated as a design objective, not merely a user perception to be measured after system deployment. Features that allow users to define criteria, adjust weights, and observe the consequences of their judgments are essential for sustaining agency and reflective engagement. The AEE framework demonstrates how such features can be systematically integrated into DSS architecture.

Third, decision systems must incorporate reliance regulation mechanisms. Trust calibration can be operationalized through adaptive feedback, inconsistency alerts, and explicit comparison between AI recommendations and user-defined priorities. These controls help users modulate reliance dynamically, reducing risks associated with automation bias and uncritical acceptance.

Collectively, these implications suggest that future DSS should be evaluated not only on predictive performance but also on their capacity to structure judgment, preserve agency, and regulate reliance.

5.5. Broader Theoretical and Contextual Implications

Although developed in the context of entrepreneurial decision making, the AEE framework has broader relevance for AI-supported decisions across domains such as finance, healthcare, public policy, and strategic management. In these contexts, decisions are similarly characterized by value trade-offs, uncertainty, and high stakes, making analytic structuring and calibrated reliance essential.

Moreover, the framework holds particular relevance for decision environments characterized by strong hierarchical norms and deference to expert systems, such as many Asian organizational contexts. In such settings, structured reasoning and explicit empowerment mechanisms may be especially important for counteracting excessive reliance on algorithmic authority and ensuring accountable decision making.

5.6. Summary of Discussion

In summary, this study advances decision systems research by specifying how decision structuring, judgment, and reliance are architecturally integrated within AI-supported systems.. By conceptualizing these elements as interacting components of a decision system architecture, the AEE framework provides both theoretical clarity and practical guidance for designing human-centered DSS. Rather than replacing human judgment, well-designed decision systems should structure, empower, and regulate judgment, enabling humans and AI to collaborate responsibly and effectively.

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Declaration of Interest Statement

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Ethical review and approval were not required for this study involving human participants in accordance with local legislation and institutional requirements. All research studies on humans have been performed in accordance with the principles stated in the Declaration of Helsinki.

Consent:

Written informed consent was obtained from all individual participants involved in the study. For participants with mild cognitive impairment, consent was additionally obtained from legally authorized representatives.