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AI Driven Behavioral Insights and Sustainable Decision Making among Information Technology Employees

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Abstract

Organizations are leveraging artificial intelligence (AI) systems to generate behavioral insights that enable data-driven and sustainability-focused decisions. Empirical studies exploring the role of AI-generated behavioral insights on sustainable decision-making through psychological and technological antecedents are scarce, particularly in the context of information technology (IT) industry. Therefore, this study aims to explore the association between AI-generated behavioral insights, algorithm transparency, perceived usefulness, trust in AI, behavioral intention, and sustainable decision-making among IT employees. Building on Socio-Technical Systems Theory, Theory of Planned Behavior, and UTAUT2, this study introduces a novel integrated framework that illustrates the impact of AI-enabled systems on individual sustainability-oriented decision-making. The study will employ quantitative research design and survey method to collect data from IT professionals who use AI systems at their workplace. The proposed hypotheses suggest that AI-driven behavioral insights, algorithm transparency, and perceived usefulness have a significant and positive effect on trust in AI. Trust in AI and behavioral intention positively predict sustainable decision-making. Additionally, trust in AI mediates the relationship between AI-driven behavioral insights and sustainable decision-making. The findings of this study will add value to the nascent literature on Sustainable AI by providing a behavioral-technological-sustainability lens together in a single framework. Practical implications will be drawn to assist organizations in implementing trustworthy and transparent AI systems that foster sustainable decision-making in digital workplaces.

1 Introduction

The accelerated development of various artificial intelligence (AI) technologies has transformed organizational decision-making processes within the information technology (IT) sector, in particular. AI-driven solutions provide insights that facilitate efficient and effective decisions, especially in IT-related data-intensive environments that require fast and reliable information processing and enhance operational efficiency [1, 2]. Even though AI adoption has been extensively studied in the past literature, the effect of AI-driven insights on sustainable decision-making has been relatively overlooked thus far.

In general terms, sustainable decision-making relates to people's ability to make sound and balanced decisions that take into account economic, environmental, and social aspects for the long-term organizational sustainability [3, 4]. In modern organizations, AI plays a central role in facilitating such decisions by providing relevant data-driven insights to reduce uncertainty. Yet, successful implementation of AI-driven recommendations depends not only on technological capabilities but also on human perceptions, attitudes, and actions.

The interface of humans and machines is inherently socio-technical, implying complex linkages between technological aspects and users' cognitive, affective, and behavioral characteristics. In this regard, the application of Socio-Technical Systems theory allows one to describe AI as a technological subsystem that affects decision-making processes by providing behavioral insights [5]. In turn, such insights act as

stimuli that shape users' actions and perceptions, especially in decision-making about sustainability issues.

Additionally, the Theory of Planned Behavior provides a useful theoretical background for understanding the link between intentions and behaviors. Accordingly, individuals' attitudes, subjective norms, and perceived behavioral control determine their willingness to perform certain activities [6]. Hence, AI-driven insights may also affect these constructs and influence behavioral intentions and outcomes accordingly.

Finally, trust emerges as another important aspect that affects sustainable decision-making in AI-powered environments. The level of AI-based trust depends on various factors, including perceived transparency, reliability, and fairness of AI algorithms [7,8.9]. Additionally, Corporate Digital Responsibility stresses the need for sustainable AI and highlights the importance of accountability and transparency [10]. Thus, even though various theoretical frameworks have already been applied to studying the effects of AI on human decisions, the current literature lacks an empirical approach that combines multiple perspectives to investigate this phenomenon. Namely, most studies tend to concentrate on either technology or sustainable practices in isolation, failing to incorporate both dimensions and explore behavioral mechanisms linking them. This study proposes an integrated framework based on UTAUT2, Theory of Planned Behavior (TPB), and Socio-Technical Systems Theory that allows us to study the impact of AI-driven insights on sustainable decision-making in the IT sector.

The study has empirically examined the role of trust in AI, algorithmic transparency, perceived usefulness, and behavioral intentions. Furthermore, this study adds to the knowledge of emerging scholarship on sustainable AI. It offers a nuanced understanding of how AI influence decision-making behavior at the individual level, providing both the theoretical comprehension and practical implications for organizations seeking to leverage AI for sustainability.

2 Review of literature and hypotheses development

2.1. AI-Driven behavioral insights and trust in AI

In general terms, AI-driven behavioral insights imply algorithmic recommendations aimed at guiding users' decisions based on analysis of vast datasets [1, 11,]. In the context of organizational decision-making, AI-driven insights increase accuracy and reduce uncertainties, thus shaping human perceptions regarding AI reliability and effectiveness.

Trust in AI refers to human trustworthiness toward machine capabilities, including the ability to generate reliable recommendations for decision-making [7, 12]. From the perspective of Socio-Technical Systems theory, technological subsystems affect behavioral outcomes based on their attributes. Specifically, reliable and effective systems increase the likelihood of user trust development. Thus, AI-based behavioral insights help to establish trust relationships between humans and machines.

H1: AI-driven behavioral insights positively influence trust in AI.

2.2. Algorithmic transparency and trust in AI

Algorithmic transparency refers to the ability of the AI system to explain the nature of algorithmic operations and decision-making process [8]. Algorithmically transparent systems allow users to comprehend machine recommendations better reducing uncertainty, which increases overall confidence in the system. From the viewpoint of Corporate Digital Responsibility, algorithmic transparency is an essential ethical requirement that allows for increased transparency and accountability [10]. Transparent and explainable AI-based algorithms increase users' perception of decision fairness. As previous studies have found, explainability and transparency play a significant role in establishing trust relations [9]. Thus, transparency emerges as an important antecedent of AI-based trust relationships.

H2: Algorithmic transparency positively influences trust in AI.

2.3. Perceived usefulness and trust in AI

Perceived usefulness refers to human perception of technology in terms of its usefulness for performing tasks efficiently [13]. In other words, the higher the user's belief in technology effectiveness, the higher the perceived usefulness. In the framework of Unified Theory of Acceptance and Use of Technology 2, perceived usefulness represents an essential driver of technology adoption and usage [13]. The same holds true for AI applications that enhance decision quality and performance. In this regard, users who perceive AI technologies as useful are likely to trust the output produced by such systems. Empirical studies demonstrate that perceived usefulness has a positive influence on technology adoption due to the fact that useful systems are believed to be more effective and reliable [7]. Thus, we hypothesize that the same relation will hold true in the case of trust in AI systems.

H3: Perceived usefulness positively influences trust in AI.

2.4. Trust in AI and Sustainable Decision-Making

Sustainable decision-making implies taking into account all aspects, such as environmental, economic, and social aspects, while making decisions [3]. In the context of AI-powered decision-making, trust plays an important role in determining the degree to which AI recommendations are followed. From the viewpoint of the Theory of Planned Behavior, trust represents an attitude that affects decision outcomes because trust is associated with specific behavioral outcomes [12]. Accordingly, individuals with high trust in AI-powered systems follow algorithmic recommendations and make corresponding decisions. Previous studies prove that increased trust levels result in a stronger willingness to use and rely on AI recommendations [7]. Thus, trust in AI systems plays a critical role in shaping sustainable decisions.

H4: Trust in AI positively influences sustainable decision-making

2.5. Behavioral Intention and Sustainable Decision-Making

Behavioral intention represents the degree to which people intend to use technology [6].. Behavioral intentions predict future decisions based on people's current attitude toward technology and related

recommendations. In the context of the IT sector, AI-powered behavioral intentions predict AI usage and decision-making in general terms. In this regard, TPB emphasizes the fact that people's intentions predict future behavior [6]. Thus, AI-powered behavioral intentions imply willingness to use the technology and adopt its recommendations when making decisions, including decisions related to sustainability. Previous research findings demonstrate that behavioral intentions predict usage and associated outcomes [13]. Thus, the same pattern is expected to be observed in the present study.

H5: Behavioral intention positively influences sustainable decision-making.

2.6. Mediating Role of Trust in AI

Trust represents an essential mediator that connects AI systems and user actions. Even though AI provides valuable insights, users might ignore these recommendations because they do not trust the output. From a socio-technical perspective, trust serves as a mediator in the relationship between technical input and behavioral outcomes. In the context of this study, AI-driven insights increase people's trust in the system because they are accurate and useful. Increased trust leads to willingness to use and follow algorithmic recommendations, which eventually affect behavioral outcomes. Empirical research proves that trust mediates the relationship between technology and behavioral outcomes [7, 9]. In the sustainability context, trust in AI is expected to act as a mediator.

H6: Trust in AI mediates the relationship between AI-driven behavioral insights and sustainable decision-making.

The hypothesized conceptual model for the study is provided in Fig. 1 and the participant characteristics are presented in Table 1

Table 1
Sample characteristics (N = 396)

Character	Category	Frequency	Per cent
Gender	Men	225	57
	Women	171	43
Age (years)	18–25	52	13.2
	26–30	69	17.4
	31–40	163	41.2
	41–50	89	22.4
	50 and above	23	5.8
Career	Technical Lead	42	10.6
	Programmer	68	17.2
	Testing Head	29	7.4
	Software Engineer	156	39.4
	Administrative support	59	14.8
	Other staff	42	10.6
AI Tool used	ChatGPT	181	45.7
	Quillbot	78	19.7
	Google Gemini (or other text generation AI tools	41	10.3
	Generative AI tools for image generation (Canva AI, Adobe Firefly, etc.)	89	22.4
	Any other AI tools	7	1.8
Frequency of AI too use	Extensive use every day	186	47
	Twice a day	83	21
	Once in a week	92	23.2
	When needed	29	7.32
	Few times in a week	6	1.5
Source: primary data processed			

3 Methodology

The research used a cross-sectional, quantitative survey design to investigate the association between AI driven behavioral insights in sustainable decision-making to assess six reflective constructs and their structural relationships among the constructs – AI-driven behavioral insights, Trust in AI, Algorithmic transparency, Perceived usefulness, Behavioral intention and Sustainable decision-making. The study further tested the mediating effect of Trust in AI on the relationship between AI-driven behavioral insights and sustainable decision-making.

3.1 Participants and procedure

Participants were recruited using non-probability purposive sampling intended to maximize heterogeneity across multiple information technology companies in and around Hyderabad encompassing varied cultural, educational and technical backgrounds. The population size of information technology in Hyderabad is not known, the minimum target sample size was estimated using Cochran[14] formula which resulted in 385. The final sample for data analysis comprised 396 participants, exceeding the threshold of assessed sample size of 385 which meets the commonly cited sample-size needed for structural equational modeling analysis [15].

The eligible participants are > 18 years old, can understand the questionnaire language, and complete survey voluntarily. Furthermore, the participants are working in the information technology industry and routinely use AI tools in their assignments and involve significant decision-making. Data were collected during January-March 2026, using a cross-sectional survey administered through Google Forms. The link for the survey was distributed to 450 information technology employees through email, WhatsApp. The survey resulted in 424 responses with response rate of 92.4%. The questionnaire which shared online has two parts in the part I the demographic information of the respondent were collected and in the Part II the study six reflective constructs were assessed.

Twenty-eight cases were excluded from data analysis due to incomplete responses (> 25% missing items) and straight lining (identical responses to all the items). This resulted that 396 valid responses were considered for data analysis.

3.2 Measures

AI driven behavioral insights capture the extent to which AI systems offer actionable and behaviorally relevant insights. Five items adopted from the scales of [1, 2]. Trust in AI which measures the confidence in AI systems and five items adopted from [12]. Algorithmic transparency captures the perceived explainability and clarity of AI systems and five items were adopted from [8, 9]. Perceived usefulness measure performance enhancement through artificial intelligence adopted from the UTAUT scale of [13]. The behavioral intention, which has 4 items were adopted from Theory of Planned Behavior scale of [6]. Finally, the five-item scale of sustainable decision making which measures the sustainability-oriented decision behavior was adopted from [3, 16].

4 Data analysis

Data were analyzed using IBM SPSS version 29 and IBM AMOS Version 28. Prior to the analysis data were screened for missing values, response-quality issues, outliers and distributional assumptions. First the exploratory factor analysis (EFA) was conducted using principal component extraction to investigate the dimensional structure of the initial item pool and to identify poorly performing indicators. Factors were retained based on the eigenvalue criterion (eigenvalue > 1). Using Kaiser-Meyer-Olkin index sampling adequacy was assessed. All the items with factor loadings > 50 on single factor with no problematic cross-loadings were retained [17].

Second, the confirmatory factor analysis (CFA) was carried out using maximum likelihood (ML) estimation, with all indicators treated as continuous variables to assess the measurement model for retained items of the constructs. Convergent validity was assessed using Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio analysis outside AMOS. The HTMT values are < 0.85 confirming the discriminant validity [18].

The structural equation modeling analysis was used to test the hypothesized relations among constructs AI-driven behavioral insights, Trust in AI, Algorithmic transparency, Perceived usefulness, Behavioral intention and Sustainable decision-making. The study further tested the mediating effect of Trust in AI on the relationship between AI-driven behavioral insights and sustainable decision-making. The structural paths were assessed in a single simultaneous model, with all exogenous constructs allowed to covary and ML estimation was used.

The model fit was assessed using χ^2/df, goodness-of-fit index (GFI), comparative fit index (CFI), Tucker–Lewis index (TLI), incremental fit index (IFI), normed fit index (NFI), standardized root mean square residual (SRMR), and root mean square error of approximation (RMSEA), to assess the model fit following commonly used SEM reporting conventions [19, 20, 21]. Squared multiple correlations (R^2) were examined to measure the proportion of variance explained in endogenous variables.

Mediating effect of Trust in AI on the relationship between AI-driven behavioral insights and sustainable decision-making was investigated by assessing the indirect effect of Trust in AI on sustainable decision-making through AI-driven behavioral insights and direct effect AI-driven behavioral insights and sustainable decision making. Following [22] indirect effects were quantified as a × b, while estimating the residual direct effect (c'). Indirect effects were estimated using bootstrap 95% confidence intervals based on 5,000 resamples, and evidence for mediation was inferred when the confidence interval did not include zero [22]. Full mediation was concluded as the indirect effect (a × b) and remained statistically significant [22].

Common method bias

As the study is cross-sectional, self-report design, common method bias was assessed using Harman's single-factor test as a preliminary diagnostic [23]. Specifically, all measured items were entered into an exploratory factor analysis with an unrotated factor solution; the proportion of variance explained by the first factor was examined, with values substantially below 50% interpreted as providing limited evidence

against a dominant single-factor account. When self-report questionnaires are employed to gather data from the same people, common method variance (CMV) may result [24]. A significant portion of the variation that may be accounted for by a single factor is represented by the CMV [25]. Harman's single-factor test was used to assess the CMV. After multiple iterations, we merged all 28 elements from the 6 constructs into a single factor to calculate the CMVand this component accounted for 21.06% of the total variance, suggesting that common technique bias had no effect on our dataset [26]. We have also emphasized he anonymity of participants, accuracy, careful wording of the statements, independent responses.

Furthermore, the study assessed the bias using marker variable technique following the [23]. To assess this the chi-square difference between the baseline model (950.303) and CMV controlled model (954.837) is 4.534, which is < 5, indicating that inclusion of a method factor did not significantly improve model fit. This implies that common method variance is not expected to provide a significant risk to the current investigation.

5 Results

5.1 Factor analyses and measurement model

The Sampling adequacy was acceptable (KMO = .906), and the six factors accounted for 77.8% of the total variance. The CFA evaluated the six-construct measurement model with 28 retained items. The model showed excellent fit to the data (CMIN/*df* = 1.289 GFI = .954, CFI = .989, TLI = .987, IFI = .989, NFI = .952, SRMR = .034; RMSEA = .027, *p*close = 1.00). Standardized factor loadings were generally strong, ranging from .73 to .93 (Table 2).

Table 2
Factor loadings, composite reliability and average variance extracted, and Cronbach's alpha values of the study variables

Item	Description	λ	CR	AVE	α
ADB1	AI systems provide actionable insights that support my decision-making.	0.89	0.946	0.778	0.945
ADB2	AI-generated recommendations help me make better decisions.	0.92			
ADB3	AI improves my understanding of complex work-related problems.	0.87			
ADB4	AI enables data-driven decision-making in my job.	0.87			
ADB5	AI systems help me identify sustainable or responsible alternatives in decision-making.	0.86			
TRUST1	I trust the AI system's recommendations.	0.84	0.915	0.683	0.913
TRUST2	AI systems are reliable in performing their functions.	0.87			
TRUST3	I feel confident when relying on AI for decision-making.	0.85			
TRUST4	AI systems behave as expected.	0.81			
TRUST5	I believe AI systems make accurate decisions.	0.78			
ATR1	AI systems clearly explain how decisions are made.	0.83	0.930	0.728	0.930
ATR2	I understand how AI systems generate their outputs.	0.83			
ATR3	AI decision-making processes are transparent.	0.88			
ATR4	AI systems provide sufficient explanations for their recommendations.	0.88			
ATR5	AI outputs are easy to interpret and understand.	0.85			
PU1	AI improves my job performance.	0.87	0.905	0.704	0.903
PU2	AI increases my productivity.	0.78			
PU3	AI enhances the effectiveness of my decision-making.	0.88			
PU4	AI is useful in my daily work tasks.	0.82			
BI1	I intend to use AI systems regularly in my work.	0.93	0.949	0.822	0.947

ADM: AI-driven behavioral insights; Trust: Trust in AI; ATR: Algorithmic transparency; PU: Perceived usefulness; BI: Behavioral Intention; SDM: Sustainable decision making

Item	Description	λ	CR	AVE	α
BI2	I plan to rely on AI for future decision-making.	0.87			
BI	I will continue using AI systems in my job.	0.93			
BI4	I am willing to increase my use of AI technologies.	0.90			
SDM1	I consider environmental impacts when making decisions.	0.77	0.877	0.587	0.877
SDM2:	I consider long-term sustainability outcomes in my decisions.	0.79			
SDM3:	I prioritize socially responsible choices in my work.	0.78			
SDM4	I balance economic, environmental, and social factors in decision-making.	0.75			
SDM5	I support sustainable practices through my decisions.	0.73			
ADM: AI-driven behavioral insights; Trust: Trust in AI; ATR: Algorithmic transparency; PU: Perceived usefulness; BI: Behavioral Intention; SDM: Sustainable decision making					

Convergent validity and internal consistency were supported within the measurement model (Table 2). CR values exceeded .70 and AVE values exceeded .50 across constructs. Cronbach's alpha values exceeded .70 for all constructs. Discriminant validity was supported by [27] and HTMT [18] (Henseler 2015), with all HTMT values below .85 (Tables 3–4).

Table 3
Fornell–Larcker Discriminant Validity (Square Roots of AVE and Interconstruct Correlations)

AIDBI	AIDBI	ALGTR	TRUST	BEHIN	SUSDM	PERUS
	0.882					
ALGTR	0.001	**0.853**				
TRUST	0.541***	-0.024	**0.827**			
BEHIN	0.435***	0.026	0.430***	**0.907**		
SUSDM	0.000	0.254***	0.012	-0.082	**0.766**	
PERUS	0.382***	0.015	0.432***	0.327***	0.044	**0.839**
AIDBI: AI-driven behavioral intentions; ALTGTR$: Algorithmic transparency; Trust: Trust in AI; BEHIN: Behavioral intentions; SUSDM: Sustainable decision-making; PERUS: perceived usefulness						

Table 4
Discriminant validity – Heterotrait-Monotrait analysis

AIDBI	AIDBI	ALGTR	TRUST	BEHIN	SUSDM	PERUS
ALGTR	0.005					
TRUST	0.513	0.023				
BEHIN	0.413	0.024	0.405			
SUSDM	0.001	0.225	0.008	0.080		
PERUS	0.358	0.015	0.398	0.300	0.037	

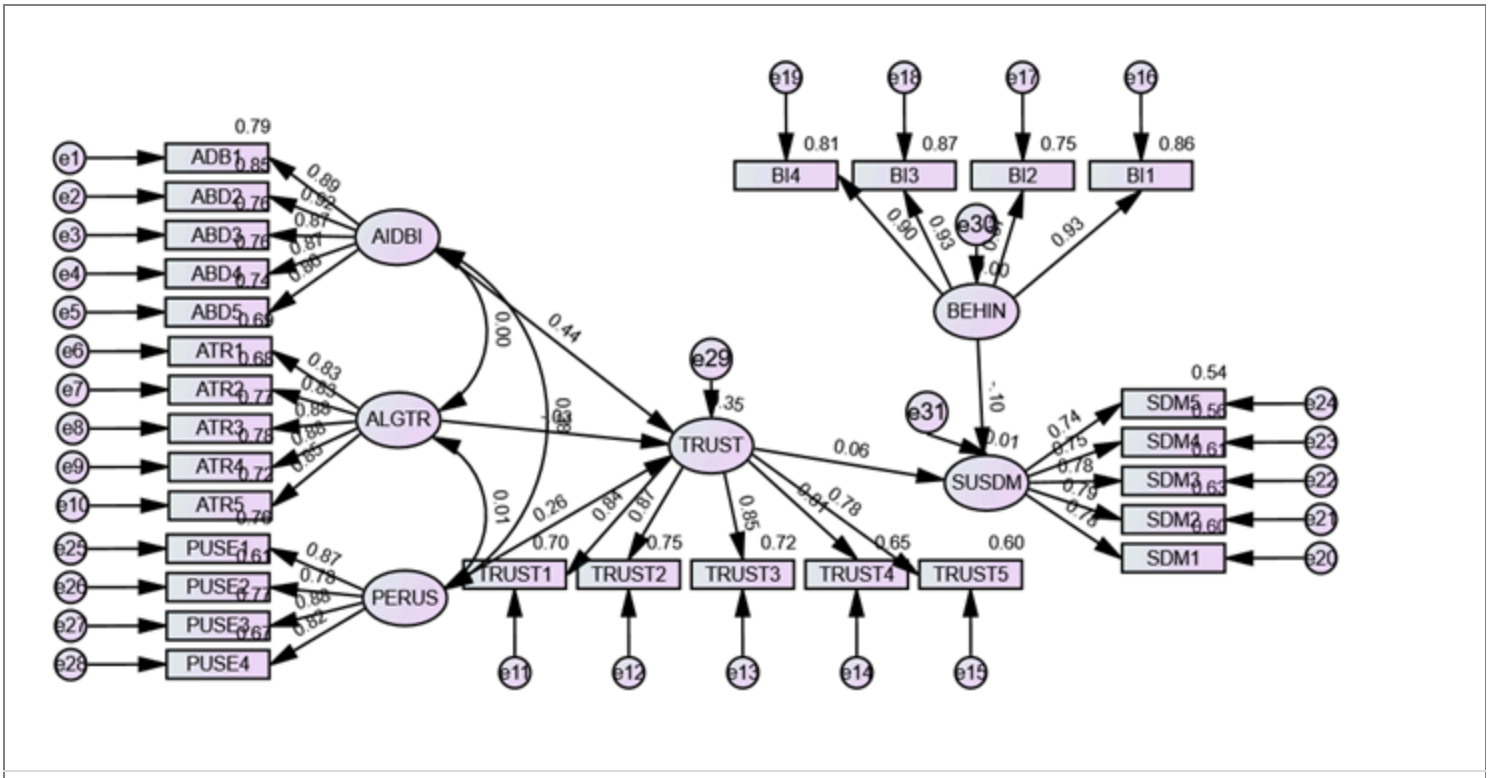
AIDBI: AI-driven behavioral intentions; ALTGTR$: Algorithmic transparency; Trust: Trust in AI; BEHIN: Behavioral intentions; SUSDM: Sustainable decision-making; PERUS: perceived usefulness

5.1 Structural model

After establishing adequate measurement-model fit and construct validity, a SEM was estimated to test the hypothesized associations between AI-driven behavioral insights, Trust in AI, Algorithmic transparency, Perceived usefulness, Behavioral intention and Sustainable decision-making. The structural model showed excellent fit to the data (CMIN/*df* = 1.38, GFI= .923, CFI = .987, TLI = .984, IFI = .981, NFI = .945, SRMR = .04, RMSEA = .033, *p*close = .998). Squared multiple correlations (R^2) indicated that the predictors AI-driven behavioral insights, Trust in AI, Algorithmic transparency, Perceived usefulness, accounted for 35% of the variance in Trust in AI, 25% in sustainable decision making by behavioral intentions, (standardized direct effects and *p* values are reported in Table 5 and Fig. 2).

Table 5
Testing of hypotheses

Structural path (Exogenous → Endogenous construct)	β	*t* value	R^2	F^2 (Effect size)	*p* value	Decision
H1: AI-driven behavioral insights → Trust in AI	.369	8.435	.35	0.28	< .001	Supported
H2: Algorithmic transparency→ Trust in AI	.119	3.718	.32	0.26	< .001	Supported
H3: Perceived usefulness → Trust in AI	.225	5.139	.28	0.22	< .001	Supported
H4: Trust in AI → Sustainable Decision-Making	.197	3.862	.25	0.21	< .001	Supported
H5: Behavioral Intention → Sustainable Decision-Making	.226	4.092	.33	0.28	< .001	Supported



Structural mode linking AI-driven behavioral insights, Trust in AI, Algorithmic transparency, Perceived usefulness, Behavioral intention and Sustainable decision-making.

5.2 Testing of Hypotheses

H1: AI-driven behavioral insights → Trust in AI

The findings corroborate H1 by showing a strong positive correlation between trust in AI and AI-driven behavioral insights (β = .369, p < .001). According to this research, users are more likely to see AI systems as dependable and trustworthy when they provide actionable, pertinent, and context-sensitive insights. This is in line with other studies showing that data-driven decision support systems improve perceived system competency and lower uncertainty [1, 2].

From the standpoint of socio-technical systems, technological subsystems that exhibit dependability and efficiency promote user trust [5]. By offering empirical proof that AI-driven insights operate as cognitive inputs that influence trust judgments, and the outcome from current findings strengthens this claim. Research on automation posits that perceived system competence and predictability are important precursors of trust [12, 28]. This results in AI-driven behavioral insights enhances user trust in AI systems while concurrently enhancing decision quality.

H2: Algorithmic transparency → Trust in AI

There is a positive relation between algorithmic transparency and trust in AI (β = .119, p < .001), supporting H2. This finding indicates that when people are aware of how decisions are made, they are more motivated to trust AI systems. Transparency enhances perceived fairness and reduces ambiguity, which are important determinants of trust [9]. The finding aligns with the principles of Corporate Digital

Responsibility, which highlight accountability and transparency in AI systems [10]. The past research posits explainable AI enhances user trust by allowing people to analyze and assess the veracity of system results [8]. Moreover, transparency improves perceived control and lowers perceived risk, two key concepts in the development of trust [29]. Therefore, the current findings supports the claim that transparency is a psychological facilitator of trust in AI-driven systems rather than just a technological attribute.

H3: Perceived usefulness → Trust in AI

Perceived usefulness is positive and significantly influences trust in AI ($\beta = .225$, $p < .001$) supporting H3. This exhibits that when consumers believe AI systems are helpful and efficient with enhanced decision-making and performance, their confidence in these systems increases. This outcome aligns with UTAUT2, showing that technology adoption is strongly influenced by performance expectations [13] (usefulness). When AI systems provide measurable advantages, users see them as more capable and trustworthy, which boosts confidence [7].

H4: Trust in AI → Sustainable decision-making

Trust in AI is positive and significantly influences sustainable decision-making ($\beta = .197$, $p < .001$). According to this research, people who have faith in AI systems are more inclined to follow their advice when making choices that take social, economic, and environmental factors into account. Theory of Planned Behavior posits that trust may be seen as an attitude that affects behavioral results [6]. Trust provides a psychological assurance that AI recommendations are reliable and consistent with long-term sustainability objectives in challenging and unpredictable decision-making scenarios [3, 9].

H5: Behavioral intention → Sustainable decision-making

Behavioral intention significantly influences sustainable decision-making ($\beta = .226$, $p < .001$) supporting H5. This finding shows that those who want to use AI technology are more likely to really make sustainable choices. in line with TPB, which maintains that intention is the most direct predictor of behavior [6]. A person's behavioral intention toward AI technology reflects their readiness to utilize and rely on it, which influences their decision-making [13].

Mediation Analysis

Using bootstrapping procedures (5,000 resamples) following Hayes (2018) the mediation analysis was carried out. The indirect effect of Trust in AI on the relationship between AI-driven behavioral insights and sustainable decision making was significant (ß=0.119, 95% CI [0.058, 0.269], $p < 0.001$) as the confidence interval did not include zero. Although the direct effect of AI-driven behavioral insights remained positive but statistically non-significant (ß=0.089, $p > 0.05$), the presence of significant indirect effect indicates full mediation.

The findings reveal that AI-driven insights alone do not directly influence sustainability decisions, however, they do so indirectly through trust formation. This aligns with the past research studies demonstrating that trust is a critical psychological mechanism linking technology inputs and behavioral outcomes [7, 9].

Model Explanatory Power

Trust in AI ($R^2 = 0.35$)

The three predictors AI-driven behavioral insights, algorithmic transparency, and perceived usefulness—account for 35% of the variation in trust in AI exhibiting a modest degree of explanatory power.

In behavioral research settings, this a modest explanatory power [30]. The R^2 values between 0.20 and 0.40 are common and appropriate in social science models where a variety of unobserved variables impact behavior [31].

Although the model acknowledges the significance of other psychological and environmental variables, the estimated R^2 value of 0.35 shows that it captures key drivers of trust.

This level of explanatory power is consistent with previous studies on AI trust, which acknowledge that trust is a complicated and multidimensional concept impacted by both technological and human variables [7, 32].

Sustainable Decision-Making ($R^2 = 0.25$)

The model largely uses behavioral intention and faith in AI to explain 25% of the variation in sustainable decision-making. In behavioral research, an R^2 value of 0.25 is regarded as moderate, especially when forecasting complex outcomes like sustainability-oriented behaviors that are impacted by several contextual, ethical, and cognitive aspects [30] (Hair et al., 2021).

Theory of Planned Behavior posits since behavioral outcomes rely on attitudes, norms, perceived control, and environmental factors, they are seldom described by a small number of predictors [3]. The model successfully captures important behavioral characteristics, according to the observed R^2 value, which also permits future improvements with other variables. Because sustainable decision-making is inherently complicated and multidimensional, even moderate R^2 values are deemed noteworthy in the context of sustainability research.

Table 6
Summary of mediation analysis

Relationship	Direct effect	Indirect effect	CR 95%		P value	Result
H6: AI-driven Behavioral Insights→ Trust in AI → Sustainable decision making	0.089 (> 0.05)	0.119	0.058	0.269	< 0.001	Full mediation

6 Discussion

The present study advances the literature on AI adoption through several avenues. Firstly, the study demonstrates that AI-driven behavioral insights significantly increase users' trust in AI systems, specifically, from a socio-technical systems theory, technology and planned behavior and UTAUT2 perspectives. This finding strengthens the argument that AI is not merely used for computational purposes, rather it serves as another cognitive agent that humans must regard as it can affect their intentions. From a social technical systems viewpoint, technology and human behavior are mutually dependent; thus, system effectiveness and performance shape the users attitudes toward systems [5]. The strong relationship discovered in this study denotes that AI systems which provide accurate, relevant, and actionable insights will be considered more effective and competent, in-turn increasing trust.

The finding is important in sustainable decision-making perspective as it often involves uncertain and complex situations. AI-driven insights help reduce cognitive strain and provide structured information that facilitating users to make confident decisions that benefit sustainability goals [1]. Thus, this study expands on prior research by providing evidence that AI-generated insights are influential in fostering trust, which is necessary for users to act on decisions.

Secondly, the study highlights the significance of explainable AI; specifically how algorithmic transparency increases user trust. Transparency allows users to understand the decision-making process, which reduces uncertainty and increases feelings of fairness [9]. This finding is consistent with the principles of Corporate Digital Responsibility which underscores organizations for ethical practices by being transparent and accountable [10].

This implies that businesses should invest in models that are simple to understand and can clearly justify their results rather of sticking with "black-box" technologies. Theoretically, by demonstrating how explainable AI directly affects organizational trust, this discovery adds to the current explosion of research on the subject. Additionally, algorithmic openness raised consumers' sense of control over the technology, which is proven to affect adoption and confidence [29].

Thirdly, perceived usefulness was found to be a strong predictor of trust, which validates the central hypothesis of UTAUT2. Specifically, users who believe that AI will help them perform better and make

high-quality decisions are more likely to trust AI systems. This finding suggests that usefulness can act as a facilitator for adoption and a foundation for trust.

Fourthly, trust in AI was shown to have a strong effect on sustainable decision-making, highlighting its importance as a mediator on the relationship between AI-driven behavioral insights and sustainable decision-making. This finding aligns with the Theory of Planned Behavior (TPB) which suggests that attitude toward behavior predicts behavioral outcomes [6]. Within AI-mediated decisions, trust represents a positive evaluation of the technology; thus, reducing resistance to behavior and promoting reliance on AI suggestions.

The mediation analysis further supports this claim by indicating that trust fully mediates the relationship between AI-driven insights and sustainable decision-making. This implies that the capabilities of AI will not incentivize behavioral change unless it is translated into trust by the user. This is supported by prior research that illustrates trust as a mediator between technology and behavioral outcomes [7, 9].

The implication of this finding is critical from a sustainability perspective. Decisions that benefit the environment, economy, and society will often force trade-offs between these three spheres. As a result, you need to have high levels of confidence in the systems that aid you with decision-making. Trust ensures that users will rely on AI suggestions, despite complex and ambiguous trade-offs, promoting sustainable outcomes [3].

Lastly, behavioral intention was found to have a strong effect on sustainable decision-making, demonstrating that TPB is applicable in AI-mediated decisions. This finding indicates that regardless of AI technology, intentions remain a strong predictor of behavior. Users who intend to use AI will likely use AI when prompted to make a decision.

This study bridges the gap on the sustainable AI scholarship by including both behavioral and technological aspects. Previous studies often viewed sustainability and AI adoption as distinct concepts. It underscores the importance of elements like psychological acceptability and technological efficacy in human-AI interactions, revealing how AI might affect sustainability through behavioral processes. Perceived usefulness, transparency, and trust are important factors that determine how well AI systems are used.

Adoption of AI is growing in developing economies, which calls for a thorough understanding of user behavior. The findings indicate that contextual factors like organizational procedures and cultural attitudes have a big impact on decision-making and trust. The study shows that using trust as a mediator, AI may improve sustainable decision-making. Using a variety of theoretical frameworks, the research also provides a thorough understanding of AI's contribution to environmental sustainability.

7 Theoretical contributions

To empirically capture behavioral processes through which AI influences sustainability outcomes, this study draws on numerous theoretical perspectives in AI and sustainable decision-making research. This study makes theoretical contributions in the following six ways. While prior work has examined AI adoption and sustainability in silos, this study integrates and tests an inclusive framework which integrates theories from Socio-Technical Systems Theory, Theory of Planned Behavior, and UTAUT2.

7.1 Bridging AI adoption literature and sustainable decision-making literature

By linking AI-driven behavioral insights to sustainable decision-making outcomes, this study bridges the gap between research on AI technologies and research on sustainable decision-making outcomes. Rather than looking at AI solely through the lenses of technological adoption and operational performance, this research conceptualizes AI as a behavioral intervention that facilitates sustainability-minded decisions through psychological factors such as trust and behavioral intention [1, 2]. The emphasis on individual decision-making processes at the micro-level also improves the sustainability literature by answering recent calls to link sustainability research to digital transformation efforts (e.g., “sustainable AI”). The findings reinforce the idea that AI is not solely a technological intervention; its effects on sustainability are filtered through human cognition and action [3].

7.2. Extending Socio-Technical Systems Theory to AI-enabled decision-making contexts

By applying socio-technical principles to AI-enabled contexts, this research contributes to Socio Technical Systems Theory by underscoring the interplay between technology and user behavior in sustainable contexts. Rather than viewing AI as a neutral tool exclusively governed by designers, this study repositions AI as a socio-technical intervention that directly influences user perceptions and behavior outcomes such as trust and sustainable decision-making. This study also underscores the value of psychology constructs in understanding the socio-technical relationships between AI and users, providing deeper insights into technology’s influence on human cognition and decision-making under high-risk situations.

7.3. Advancing trust in AI by demonstrating its mediating role

Extending prior work on trust in AI applications, this study deepens understanding of the role that trust plays in AI-enabled settings by demonstrating that trust fully mediates the relationship between AI-driven behavioral insights and sustainable decision-making. Contrary to prior work that positions trust as a determinant of behavioral metrics [7, 33]. This research theoretically positions trust as a psychological process that enables AI interventions to influence decision-making. This is especially critical in sustainable contexts where decisions are often associated with uncertainty and moral concerns. Furthermore, this study addresses a gap in literature and contributes to AI adoption models by unifying

AI trust antecedents (i.e., AI-driven insights, algorithmic transparency, and perceived usefulness) into a cohesive framework Shing2.

7.4. Extending UTAUT2 by including trust and sustainable decision-making outcomes

This study also contributes to UTAUT2 by incorporating two main factors. First, by demonstrating that perceived usefulness positively influences trust in AI, this study shows that performance expectancy can also influence users' trust in technology. Second, by linking behavioral intention to sustainable decision-making, this study expands the outcome scope of UTAUT2 beyond use behavior to include sustainability decisions and decision quality. Responding to recent calls to extend TAM studies to accommodate downstream organizational and social outcomes (e.g., [13]) this contribution extends the reach of UTAUT2 to include impacts on organizational and societal sustainability.

7.5. Integrating Theory of Planned Behavior with AI-driven behavioral processes

This research also contributes to the Theory of Planned Behavior by integrating it with AI-driven decision-making. By adopting trust as an influential attitudinal construct and establishing behavioral intention as a significant predictor of sustainable decision-making, this study reinforces the notion that TPB is applicable in AI-mediated contexts. This research enhances TPB's explanatory power by including AI-specific factors (AI insights, algorithmic transparency, and perceived usefulness) and demonstrating how AI-based interventions can shape TPB constructs through behavioral insights.

7.6. Contributing to sustainable AI literature

Finally, this study contributes to a nascent body of literature focusing on sustainable AI. By providing empirical evidence on how AI facilitates sustainability-minded decisions, this study begins to fill a literature gap on AI and behavioral outcomes. The study goes one step further to show that AI-driven behavioral insights can lead to sustainable outcomes when mediated by psychological constructs like trust and purpose. Additionally, this research implies that sustainable AI cannot be actualized by technology effectiveness alone; user trust and responsible behavior are essential. This has important implications for Corporate Digital Responsibility initiatives and highlights the need for transparency and ethics in AI.

In conclusion, this study contributes to theory by:

1. 1. Bridging AI adoption and sustainable decision-making literature through STST.
2. 2. Demonstrating how AI drives behavioral outcomes using TPB.
3. 3. Establishing trust as a mediator between AI and sustainable decision-making.
4. 4. Improving UTAUT2 by adding constructs and outcomes related to sustainability. and
5. 5. Empirically grounding sustainable AI scholarship.

7 Limitations

As several significant conclusions might be drawn from the current research, there are several limitations to be aware of that provide space for future research and frame our understanding of the discovered outcomes. The following aspects should be considered when interpreting the findings of this study:

7.1 Cross-sectional design

This study's cross-sectional research design prevents researchers from determining any causal relationships between the study's variables. Due to the lack of longitudinal or experimental research design, SEM analysis cannot establish a cause-effect link between the study variables while simplifying the calculation of complex relationships and offering estimates of data consistent with the recommended causal paths (Kline, 2016; Hair et al., 2021). Rather than definite causal impacts, the connections discovered in this study, especially the mediation impact of confidence in AI, should be considered theoretically based and empirically validated relationships. Future research should focus on longitudinal studies that track changes in reliance on AI over time and assess the impact of extended AI use on long-term sustainability outcomes.

7.2 Reliance on self-reported measurements

The study relies on self-reported data as is standard in behavioral and organizational sciences. Self-reported measurements can be influenced by potential biases like common method variance (CMV) and social desirability bias [23] (Podsakoff et al., 2003). The research attempted to reduce these issues by taking procedural measures like ensuring respondent anonymity and carefully writing items. Statistically, the Harman single-factor test indicated that only one factor explained 21.06% of the variance (vs. the normally expected 50%), and the marker variable approach showed a non-significant chi-square difference ($\Delta\chi^2 < 5$), indicating that CMV is unlikely to be a major problem that undermines this research's validity. Objective performance metrics should be included in future studies to triangulate self-reported data with multi-source inputs such as supervisor assessments, system log data, or behavioral observations to increase robustness.

7.3 Sample and generalizability

Because the sample was chosen from IT professionals working in Hyderabad who are likely to have prior exposure to AI, the study employs non-probability purposive sampling. Although the sample was chosen with people who had expertise about AI technology in mind, the results' generalizability to bigger populations or different cultural contexts may be constrained. Compared to people in other industries or geographical locations, people who work in the IT industry may have unique opinions regarding AI because the IT industry has a high degree of digital expertise and frequently uses AI. Therefore, extrapolating these results to those who work in industries outside of IT or who have a lesser degree of digital sophistication should be done with caution. Researchers may strengthen external validity and

cross-cultural generalizability by randomly selecting samples or replicating the model in other sectors and geographic locations.

7.4 Limited contextual scope of AI application

The study does not distinguish between various AI types and concentrates exclusively on how people accept AI-enabled decisions in a corporate environment. Although AI as a whole is expanding at a rapid rate, unique sorts of AI applications like generative AI, predictive analytics, and decision-support systems may vary in autonomy, transparency levels, and human interaction. These differences may influence decision-making and confidence in various ways. For example, some unique issues like unforeseen uncertainties, ethical dilemmas, and explainability concerns could arise with new generative AI technologies that are not adequately addressed by the current model. The current research might serve as a foundation for subsequent research that seeks to expand our knowledge by concentrating on particular AI deployments or contrasting other forms of AI to one another to learn about their distinct behavioral impacts.

7.5 Inclusion of a single mediator

The current study focuses on trust in AI as a key mediator variable between sustainable decision-making and behavioral intentions predicted by AI. Trust was found to have a substantial mediating effect in this connection; however, this does not rule out the possibility that user behavior in response to AI-generated insights could be mediated by other psychological and situational factors. Factors including but not limited to perceived risk, ethical concerns, AI literacy, organizational culture, and technical readiness could all have an impact. The single mediator concentration does produce a more parsimonious model but at the sacrifice of the complexity found in human-AI interactions. Researchers should look into including additional mediators and moderators in the model to better capture the behavioral intricacies of AI-influenced decision-making in future studies.

7.6 Measurement and construct dimensions

Operationalization of the study variables was done using a few questions per construct to allow for greater feasibility of the questionnaire even though all of the scales used were validated with good reliability and validity (CR, AVE, HTMT) scores. Despite following SEM best recommendations for scale construction, this study may have oversimplified some of the study's constructs, such as algorithmic transparency and sustainable decision-making. Sustainable decision-making involves considerations of the environment, society, and the economy, implying that future research could benefit from more granular or domain-specific measurements. Similarly, more variables could potentially be employed to assess the algorithmic transparency element, such as explainability, interpretability, and user control.

7.7 Contextual factors

The current study is unable to consider broader organizational or contextual factors that may influence the use of AI for sustainable decision-making. Factors like organizational sustainability policy, perceived organizational support, leadership buy-in, and the regulatory climate are just a few of the organizational

and institutional factors that we believe will have a significant impact on users. Especially in complex organizational environments, the absence of these factors may hinder explanatory power of the model. They should be accounted for in subsequent research to create a more comprehensive model that accounts for organizational and individual influences.

8. Theoretical implications

By combining many viewpoints—Socio-Technical Systems Theory, the Theory of Planned Behavior (TPB), and UTAUT2—this study advances theory and provides a more comprehensive framework for comprehending AI-driven sustainable decision-making, which has not received enough attention in previous studies. By presenting trust as a whole mediating process rather than just a direct predictor, it expands on the trust literature and improves on current models of AI adoption. Additionally, by showing how technology acceptance influences sustainable decision outcomes, the research links the hitherto divided fields of AI adoption and sustainability. Lastly, by demonstrating how AI indirectly affects sustainability via behavioral (intention) and cognitive (trust) routes, it offers deeper behavioral insights and advances our knowledge of the fundamental processes underpinning sustainable behavior in technologically enabled situations.

9. Practical implications

To increase user confidence and trust, organizations should concentrate on creating visible and understandable AI systems. Successful adoption requires the development of trust-centric AI techniques that guarantee accuracy, fairness, and dependability. Simultaneously, emphasizing the concrete performance advantages of AI might improve its perceived utility, especially in accomplishing sustainability goals. Organizations should fund training initiatives that improve users' behavioral intentions about AI in order to encourage real use. Lastly, in order to facilitate more responsible and knowledgeable decision-making, AI-enabled decision systems should specifically include sustainability indicators across environmental, social, and economic aspects.

10. Conclusion

Through the mediating function of confidence in AI, this research shows how AI-driven behavioral insights greatly help to sustainable decision-making. The study emphasizes that trust and purpose are essential factors that translate AI capabilities into sustainable results by fusing behavioral and technical ideas. The results highlight how crucial it is to create transparent, practical, and reliable AI systems in order to ensure long-term organizational sustainability.

11. Future Research directions

In order to establish stronger causal conclusions beyond the constraints of cross-sectional research, longitudinal designs should be used in future studies. The model's generalizability outside of the Indian

IT industry would be improved by extending it to other cultural and geographical situations. Deeper understanding of boundary conditions may be obtained by including pertinent modifiers, such as company culture, ethical environment, and AI literacy. Furthermore, using objective behavioral measurements would increase scientific rigour and lessen dependence on self-reported data. Lastly, in order to stay up with changing technical advancements, future research should investigate advanced AI settings, such as generative AI and autonomous decision-making systems.

Declarations

Ethical approval

The empirical research complied with the Declaration of Helsinki and was reviewed and approved the exemption by **the Institute Research and Ethics Committee, Symbiosis Institute of Business Management, Hyderabad; Symbiosis International (Deemed University), Pune, India**. The Committee issued a formal exemption statement on 19th January 2026 (No. 3/2026). The participants were informed about the data purpose, about the study, voluntary participation, the intended use of data, and the participants' right to withdraw anytime from the survey exercise. Oral/written informed consent was obtained from all the participants.

Consent for publication

Not applicable

Competing interests

The authors declare no competing interests

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Author Contribution

KDVP: Writing original drafdt, conceptualization, formal analysis, investigation, validation; KSY: writing original draft, formal analysis, review and visualization; DN: data collection, data curation, data validation, review; AP: methodology, investigation, conceptualization, review; VS: data collection, data curation, resources; RR: project administration, supervision, resources, reviewers concerns

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Data Availability

Data is available on public platform figshare @ https://figshare.com/s/7128565f269d694a0423

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Figures

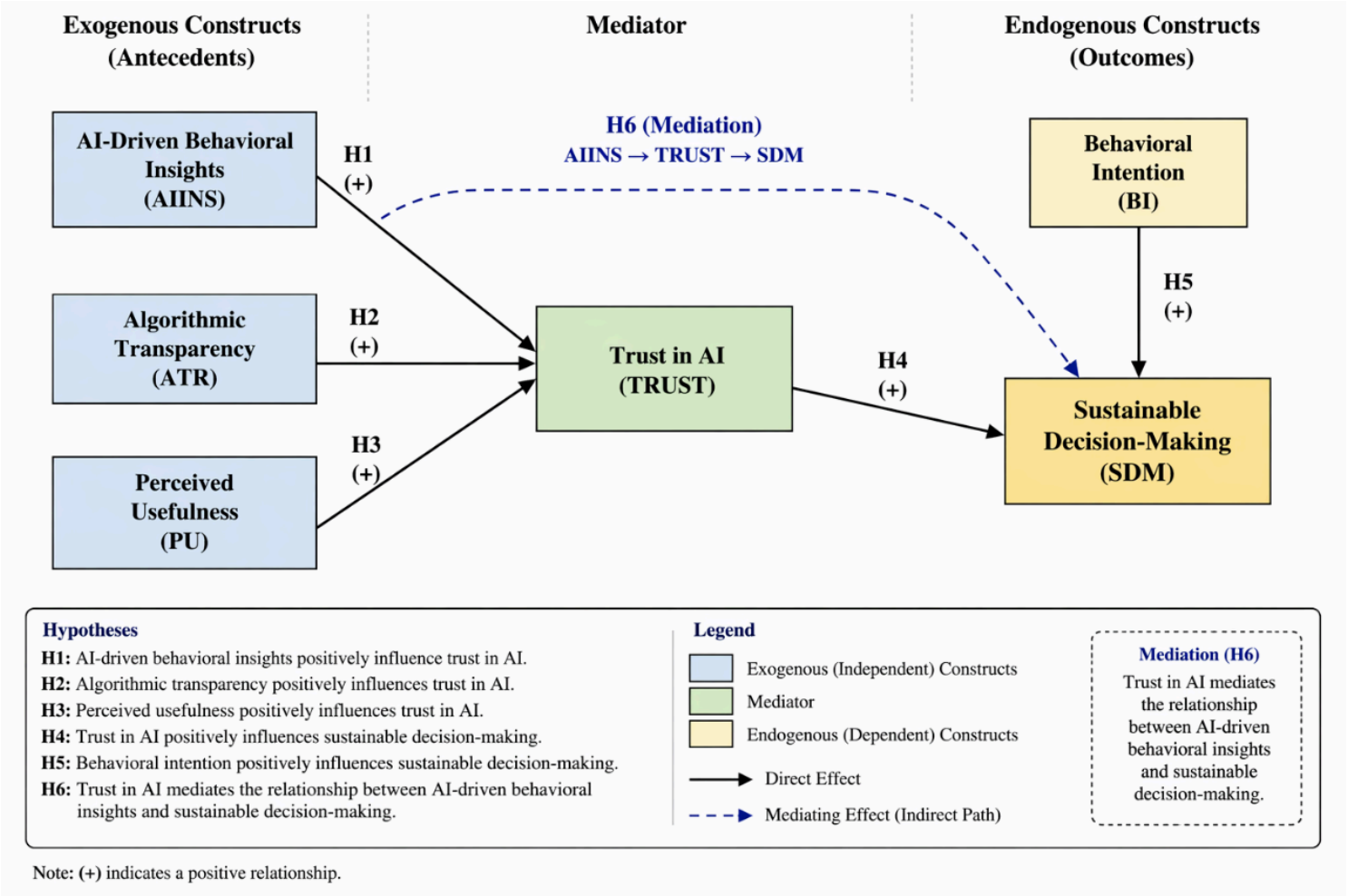


Figure 1

Hypothesized conceptual model linking AI-driven behavioral insights, Trust in AI, Algorithmic transparency, Perceived usefulness, Behavioral intention and Sustainable decision-making.