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Smart material adoption in mechanical engineering: additive manufacturing and green material perception under the moderating influence of cost-benefit evaluation

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Abstract

This research investigates the determinants that steer the incorporation of smart materials in mechanical engineering, with a keen eye on the effects of additive manufacturing (AM) abilities, attitudes toward sustainable materials, and cost-benefit evaluation (CBE). Utilizing the Technology Adoption Model (TAM) alongside the Triple Bottom Line (TBL) framework, this investigation formulates a comprehensive model that interconnects technological readiness, environmental awareness, and economic evaluation. Employing a quantitative, cross-sectional methodology, data were gathered from 385 professionals engaged in Vietnam's mechanical engineering industry and subjected to analyses including reliability testing, exploratory factor analysis, multiple regression, and moderation analysis utilizing SPSS 20. The findings indicate that both AM capabilities (β = 0.712) and perceptions of green materials (β = 0.816) exert a significant and positive impact on the adoption of smart materials. Furthermore, CBE serves as a moderating variable (β = 0.470), enhancing the effect of environmental perceptions on adoption decisions. These results underscore the notion that technological proficiency and a commitment to sustainability foster innovation, but only when organizations recognize economic justification. The research contributes to theoretical discourse by augmenting TAM with considerations of ecological and financial dimensions, while offering practical insights for managers and policymakers seeking to harmonize sustainability with profitability in material innovation.

Keywords: *Smart Materials Adoption, Additive Manufacturing, Green Perception, Cost–Benefit Evaluation*

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INTRODUCTION

The incorporation of intelligent materials in mechanical engineering signifies a revolutionary progression in enhancing performance, functionality, and sustainable design. These materials, such as shape-memory alloys, piezoelectric composites, and thermochromic polymers, possess the capability to respond dynamically to external stimuli, facilitating innovations across aerospace, automotive, and biomedical domains (Addington & Schodek, 2012). Concurrently, the emergence of additive manufacturing (AM), particularly three-dimensional printing, has transformed engineering practices by enabling intricate geometries, reducing material wastage, and expediting prototyping processes (Gibson et al., 2015). Recent investigations have underscored the increasing convergence of AM and intelligent materials, illustrating how AM can promote the development of responsive structures and multifunctional components (Gardan, 2019). Notwithstanding these advancements, the assimilation of intelligent materials remains inconsistent across various industries due to technological, economic, and organizational ambiguities.

Existing literature has scrutinized both the technological prospects of additive manufacturing and the ecological significance of material selections. For instance, AM has been associated with sustainability outcomes by facilitating efficient production and diminishing resource consumption (Ikram et al., 2022). Simultaneously, the rising societal consciousness regarding green materials—materials that are recyclable, biodegradable, or energy-efficient has exerted pressure on industries to conform to environmental sustainability objectives (Ardoin et al., 2012). However, these research trajectories frequently operate in isolation, addressing either technological capability or environmental perception, while disregarding their collective influence in shaping the adoption of intelligent materials. This fragmented perspective engenders a substantial research void in comprehending the multidimensional drivers of intelligent material adoption in mechanical engineering. While investigations have accentuated the potential of intelligent materials for advanced design and ecological innovation (Kantaros & Ganetsos, 2023), there exists a paucity of understanding regarding how adoption decisions are moderated by firms' assessments of costs and benefits. Indeed, the readiness to embrace novel technologies is contingent not solely on technical feasibility or environmental imperatives but also on the extent to which perceived financial returns surpass the associated investments (Avery et al, 2025). In the absence of an integrated approach encompassing technological, environmental, and economic perspectives, contemporary scholarship provides a partial depiction of the dynamics influencing adoption of smart materials.

To rectify this void, the inquiry explores the following research questions: (1) To what extent does additive manufacturing capability influence the adoption of smart materials in mechanical engineering? (2) How does green material perception shape the adoption of smart materials in mechanical engineering? (3) How might cost–benefit considerations alter the strength or direction of the relationship between technological and environmental factors and smart material adoption? Through addressing these inquiries, this study proffers three principal contributions. First, it formulates an integrative framework that amalgamates technological, environmental, and economic dimensions in elucidating intelligent material adoption. Second, it emphasizes the moderating function of cost–benefit evaluation, thereby augmenting the comprehension of technology adoption within engineering contexts. Third, it furnishes practical guidance for managers and engineers to reconcile innovation, sustainability, and financial viability in the adoption of novel materials.

LITERATURE REVIEW

Smart Material Adoption in Mechanical Engineering

The incorporation of smart materials within the realm of mechanical engineering pertains to the degree to which engineers and organizations assimilate materials that exhibit responsiveness to external stimuli, such as shape-memory alloys, piezoelectric composites, and thermochromic polymers, into various industrial applications. In contrast to traditional materials, smart materials are engineered for dynamic adaptability, thus facilitating innovative functionalities and responsive performance (Addington & Schodek, 2012). The notion of adoption transcends the mere technical feasibility of such materials; it encapsulates strategic choices that navigate the intricate balance between innovation, sustainability, and cost-effectiveness, rendering it an essential construct for comprehending the technological evolution within mechanical engineering.

Theoretical Framework

Triple Bottom Line (TBL) Theory

The Triple Bottom Line (TBL) framework represents a foundational theoretical lens through which sustainability may be assessed, positing that organizational performance ought to be evaluated across three interdependent dimensions: economic viability, environmental integrity, and social equity (Elkington & Rowlands, 1999). Instead of limiting scrutiny solely to financial profitability, the TBL emphasizes that enduring success necessitates the equilibrium of interests about "people, planet, and profit." Within the realm of mechanical engineering, this framework intimates that the implementation of smart materials should not merely be appraised in terms of efficiency enhancements and cost savings, but also in relation to their ecological advantages, such as waste reduction and energy conservation, and their congruence with societal expectations and regulatory standards. The application of TBL to the adoption of smart materials elucidates the multifaceted nature of the construct. The adoption of smart materials corresponds to the economic and technological dimension, as organizations harness innovation to bolster competitiveness. The independent variable concerning perceptions of green materials aligns with the environmental dimension, wherein organizational cognizance of recyclability, biodegradability, and energy efficiency informs strategic decisions regarding adoption. Moreover, the moderating effect of cost–benefit evaluation encapsulates the integrative rationale of TBL: even in instances where technical advantages are acknowledged, adoption determinations are contingent upon organizations' perceptions of a balanced outcome across profitability, ecological merit, and societal legitimacy.

Empirical investigations substantiate this integrative approach. Dwyer et al. (2015) underscored that organizations that incorporate TBL principles into their decision-making frameworks achieve greater alignment between innovation, environmental stewardship, and societal welfare. Hacking & Guthrie (2008) further delineated TBL as a comprehensive framework for sustainability assessment, emphasizing its capacity to evaluate trade-offs among competing objectives. From a pragmatic standpoint, Gardan (2019) accentuated that additive manufacturing facilitates the integration of smart materials while simultaneously enhancing resource

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efficiency and diminishing waste, thereby exemplifying synergies between economic and ecological performance. More recently, Avery et al. (2025) scrutinized how cost–benefit analyses in the context of sustainable technology adoption influence decision-making by balancing profitability with environmental implications. In addition, academics indicate that TBL operates as a crucial management approach that prompts organizations to weave sustainability into their operational practices. Slaper & Hall (2011) contend that when organizations systematically evaluate their performance against the three pillars, they are more likely to attain a sustainable competitive advantage. Collectively, these findings corroborate that the adoption of smart materials, when guided by the TBL framework, can produce a "triple win": fostering innovation and profitability, alleviating environmental impacts, and satisfying societal and regulatory requirements.

Technology Adoption Model (TAM)

The Technology Adoption Model (TAM), articulated by Davis in 1989, represents a widely acknowledged micro-level framework focused on clarifying the decision-making journeys of individuals and organizations as they consider the adoption of emerging technologies. This model posits that adoption behaviors are predominantly influenced by two cognitive assessments: perceived usefulness (PU), defined as the degree to which a technology is perceived to enhance performance, and perceived ease of use (PEOU), which refers to the perceived effortlessness associated with its implementation. Collectively, these factors shape individuals' attitudes towards the technology, subsequently impacting actual adoption outcomes. In the context of mechanical engineering, TAM serves as a significant foundational tool for examining the rationale behind firms' integration of smart materials, as their adoption is influenced not solely by technical availability but also by engineers' perceptions of utility and practicality.

The application of TAM to the adoption of smart materials within mechanical engineering elucidates how perceived usefulness manifests in the acknowledgment that responsive materials can enhance operational efficiency, diminish energy consumption, and facilitate design adaptability (Ikram et al., 2022). Concurrently, the perceived ease of use is affected by the additive manufacturing (AM) capabilities of firms, as sophisticated AM systems mitigate the technical challenges associated with the production and incorporation of intricate smart materials (Gardan, 2019). In this regard, AM capabilities function as a catalyst that amplifies both perceptions of usefulness and ease of use, consequently fostering adoption intentions. The TAM framework further facilitates the incorporation of environmental and economic considerations into the decision-making processes surrounding technology adoption. For instance, engineers who recognize smart materials as environmentally advantageous (e.g., recyclable, energy-efficient) are more inclined to assess them as useful, thereby aligning adoption with broader sustainability objectives (Kantaros & Ganetsos, 2023). Moreover, the moderating influence of cost–benefit analysis reflects the manner in which organizational decision-making recalibrates TAM's variables: even in instances where usefulness and ease of use are acknowledged, the pace of adoption may either be hindered or expedited based on whether financial benefits surpass the associated investment costs (Wang, 2022). Empirical investigations substantiate this theoretical integration. Venkatesh & Davis (2000) expanded TAM into TAM2 by incorporating social influences and cognitive instrumental processes, thereby illustrating that organizational adoption is influenced by factors beyond mere functional utility. Marangunić & Granić (2015) conducted a comprehensive review of TAM applications, emphasizing its versatility across various technological landscapes, including manufacturing. In the domain of mechanical engineering, research focusing on AM adoption corroborates that perceptions of technical advantages and ease of integration serve as strong predictors of the acceptance of advanced manufacturing technologies (Ben-Ner & Siemsen, 2017). These findings reinforce TAM's pertinence to the adoption of smart materials, while simultaneously highlighting the necessity of integrating economic considerations into the framework.

Determinants of Smart Material Adoption in Mechanical Engineering

Additive Manufacturing Capability

The capability in additive manufacturing (AM) involves an organization's skill in adeptly executing additive strategies such as 3D printing, fast prototyping, and direct digital production aimed at product design and manufacturing. This capability transcends the mere ownership of AM technologies; it incorporates technical acumen, infrastructural preparedness, material accessibility, and managerial proficiency that together influence how enterprises utilize AM to attain competitive superiority (Gibson et al., 2015). Within the domain of mechanical engineering, AM capability denotes the degree to which organizations can convert design ideations into functional prototypes and end-use components with accuracy, adaptability, and sustainability.

The significance of AM capability is multifaceted. From a technical standpoint, AM facilitates the fabrication of intricately complex geometries and lightweight structures that are challenging or unfeasible to manufacture using subtractive methods, thereby fostering innovation in sectors such as aerospace, automotive, and biomedical engineering (Mellor et al., 2014). Economically, AM capability diminishes tooling expenses, expedites time-to-market, and augments customization on a large scale (Ben-Ner & Siemsen, 2017). Furthermore, AM offers ecological benefits, as its layer-by-layer manufacturing approach curtails raw material waste and mitigates the carbon footprint in comparison to conventional manufacturing processes (Ford & Despeisse, 2016). In this context, AM capability is congruent with the overarching aims of Industry 4.0 and sustainable manufacturing, thereby synthesizing technological advancement with ecological efficiency.

Notwithstanding its potential, the evolution of AM capability encounters numerous obstacles and challenges. The substantial financial investment required for advanced AM equipment, specialized software, and compatible materials constitutes a considerable limitation for small and medium-sized enterprises (Kellens et al., 2017). Moreover, workforce deficiencies, particularly the scarcity of engineers proficient in AM design and production, further obstruct capability enhancement (Holmström et al., 2010). Additionally, apprehensions regarding process reliability, the absence of standardized certification, and scalability challenges hinder industrial assimilation (Baumers et al., 2017). These limitations underscore that AM capability is not merely a technological function but rather a dynamic organizational capability necessitating investment, training, and institutional endorsement. The theoretical foundation for AM capability can be extrapolated from both the Resource-Based View (RBV) and the Dynamic Capabilities Theory. From the RBV perspective, AM capability constitutes a valuable, rare, and difficult-to-replicate resource that has the potential to generate sustained competitive

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advantage (Barney, 1991). Concurrently, dynamic capabilities theory highlights that the capacity to recognize technological opportunities, capitalize on them, and reconfigure resources is crucial for organizations functioning in volatile environments (Teece, 2007). Consequently, AM capability embodies both a static resource and a dynamic competence that enables firms to swiftly adapt to evolving customer demands, regulatory requirements, and sustainability challenges.

Grounded in both theoretical insights and empirical evidence, this study formulates the following first hypothesis *H1: Additive manufacturing capability positively impacts smart material adoption in mechanical engineering.*

Green Material Perception

The concept of green material perception focuses on how engineers, corporations, and stakeholders acknowledge and evaluate the ecological traits of materials, entailing factors such as recyclability, biodegradability, energy efficiency, and lower emissions. In contrast to adoption, which signifies behavioral execution, perception encapsulates the cognitive and attitudinal predisposition towards environmental accountability in the utilization of materials. Emerging from the discourse surrounding consumer green perception, this construct has progressively been integrated into engineering domains, wherein it exerts influence over decision-making processes related to material selection and innovation strategies (Chen, 2010).

The pragmatic significance of green material perception resides in its capacity to engender market legitimacy and stakeholder confidence. Corporations that are regarded as embracing environmentally sustainable materials not only acquire reputational benefits but also fortify their standing within value chains dedicated to sustainability (Jiao et al., 2020). Perceptions regarding environmental quality further augment brand equity and cultivate long-term competitiveness, as stakeholders correlate such practices with corporate social responsibility (Han & Kim, 2010). Within the realm of mechanical engineering, green material perception serves as a cognitive conduit between technological innovation and sustainable development, harmonizing material choices with societal anticipations and regulatory obligations.

Notwithstanding its advantages, the impact of green material perception encounters numerous impediments and challenges. Perceptions may be compromised by information asymmetry and greenwashing, in which corporations amplify ecological assertions without substantial corroboration (Delmas & Burbano, 2011). Furthermore, even when environmental attributes are recognized, financial considerations frequently obstruct the translation of favorable perceptions into actual adoption (Kellens et al., 2017). Additionally, the lack of internationally standardized criteria for defining and certifying “green” materials generates ambiguity, diminishing the dependability of stakeholder perceptions and hindering the progression towards sustainable production. The construct of green material perception can be situated within both the Theory of Planned Behavior (TPB) and Stakeholder Theory. TPB (Ajzen, 1991) asserts that affirmative perceptions of environmental benefits cultivate favorable attitudes, which, when combined with subjective norms and perceived control, enhance the probability of pro-environmental adoption. Stakeholder Theory (Freeman, 2010) broadens this viewpoint by emphasizing how external pressures, spanning customer demand to regulatory frameworks, affect corporate perceptions and subsequent actions. Collectively, these theories highlight that perception transcends a mere individual cognitive process, representing a socially embedded evaluation shaped by both internal convictions and external expectations.

Drawing from both theoretical perspectives and prior empirical findings, the study advances the following second hypothesis *H2: Green material perception positively impacts smart material adoption in mechanical engineering.*

Cost–Benefit Evaluation in Smart Material Adoption

Cost–Benefit Evaluation (CBE) constitutes a rigorous analytical framework employed to systematically examine both economic and non-economic outcomes arising from the integration of smart materials within the discipline of mechanical engineering. Building upon the established principles of cost–benefit analysis (CBA) within the realm of economics, CBE encompasses a comparative analysis of measurable costs, including research and development investments, manufacturing expenditures, and lifecycle maintenance, against the projected benefits, which may encompass improvements in performance, material efficiency, and ecological sustainability. Within the engineering sector, this evaluative approach is increasingly being utilized to advance sustainable material innovation, as enterprises endeavor to quantify the trade-offs associated with substantial initial financial outlays against prospective long-term operational and environmental advantages (Mourato, 2006).

The pragmatic significance of CBE is underscored by its ability to promote evidence-based decision-making processes. Smart materials, exemplified by shape-memory alloys and piezoelectric composites, frequently necessitate considerable upfront investments; however, their potential to diminish weight, enhance energy efficiency, and prolong product longevity yields quantifiable economic benefits (Gibson et al., 2015). Furthermore, when integrating environmental and social metrics, CBE elucidates that sustainable innovations can offer not only economic returns but also bolster reputational credibility and ensure adherence to regulatory requirements (Jiao et al., 2020). Consequently, CBE serves as a systematic framework for engineers and managers to harmonize innovation strategies with the overarching goals of green engineering and sustainable development.

Nevertheless, the assessment of costs and benefits is confronted with numerous impediments and challenges. Firstly, the quantification of intangible or long-term advantages such as augmented brand reputation, diminished ecological footprint, or enhanced stakeholder confidence remains methodologically intricate (Delmas & Burbano, 2011). Secondly, the prohibitive initial capital demands associated with research and prototyping frequently hinder widespread adoption, particularly among firms operating under resource constraints (Kellens et al., 2017). Thirdly, the lack of standardized metrics for life cycle costing and sustainability benefits engenders uncertainty, complicating the process of comparing traditional materials with advanced smart materials on an equivalent basis. These constraints underscore the pivotal influence of perception and institutional frameworks in shaping adoption decisions that extend beyond mere economic evaluations. Considering it from a theoretical angle, CBE gains credibility through the Triple Bottom Line structure (Elkington, 1999), which points out the interdependence of economic, environmental, and social consequences. An evaluation of adoption predicated solely on financial returns risks neglecting the ecological and societal benefits that underpin long-term sustainability. Moreover, Diffusion of Innovation Theory (Rogers,

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2003) posits perceived relative advantage, defined as the perception that benefits surpass costs, serves as a crucial factor influencing adoption decisions. The synthesis of these theoretical perspectives suggests CBE in the adoption of smart materials should not be confined to a narrow economic framework; rather, it should be regarded as a multidimensional evaluation encompassing financial, ecological, and stakeholder considerations.

Integrating insights from established theories and existing empirical research, the study posits the third hypothesis *H3: Cost–benefit evaluation positively moderates the relationship between green material perception and smart material adoption in mechanical engineering.*

Anchored in robust theoretical underpinnings, this study enhances its academic value by presenting the following conceptual framework:

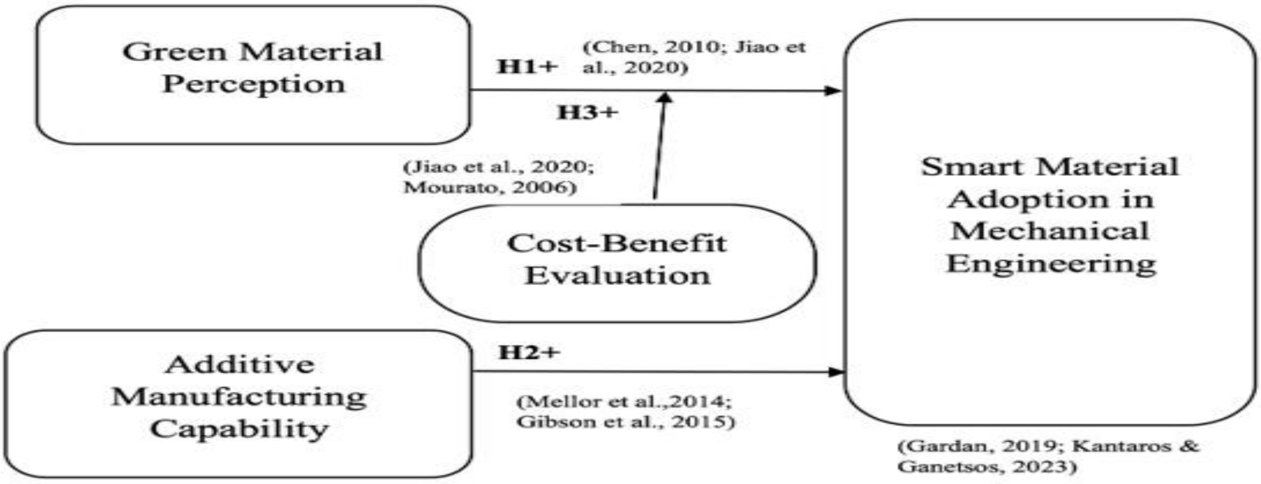

Figure 1. The paper's Conceptual Framework

Source: (The authors, 2025)

Methodology

This investigation employed a quantitative, cross-sectional research framework to systematically scrutinize the interconnections among additive manufacturing capability, green material perception, and the adoption of smart materials, alongside the moderating influence of cost–benefit evaluation within mechanical engineering enterprises. A stratified sampling strategy based on probability was utilized to guarantee representativeness across various industrial sectors, including aerospace, automotive, and biomedical engineering. This methodological selection is congruent with Bryman's (2016) proposition that stratified probability sampling enhances external validity by incorporating distinct yet pertinent subpopulations. The unit of analysis was delineated at the organizational level, specifically targeting engineers, R&D managers, and production supervisors who are directly involved in material selection and innovation in manufacturing.

A meticulously structured questionnaire was formulated with each variable was evaluated through multiple items adapted from previously validated scales and operationalized via a five-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"). To ensure methodological validity and contextual pertinence to the Vietnamese mechanical engineering domain, the research employed a stratified probability sampling technique. This methodology facilitated representativeness among four principal stakeholder cohorts actively involved in technology-oriented manufacturing and the adoption of sustainable materials. The initial cohort comprised mechanical engineers and production managers (25%), who were directly responsible for material selection, process optimization, and design efficiency. The second cohort consisted of research and development as well as additive manufacturing experts (25%), who provided specialized technical knowledge concerning innovation, infrastructure, and material integration. The third category (25%) encompassed executive-level decision-makers, including chief engineers, innovation directors, and department heads, who were tasked with reconciling sustainability considerations and cost-benefit analyses with strategic objectives. The final group (25%) included academicians, consultants, and policymakers, who contributed insights on sustainability policy and regulatory adaptation within the context of Vietnam's industrial landscape. The research utilized structured interviews alongside self-administered online surveys conducted through Google Forms. The survey was disseminated across professional networks, university-industry collaboration platforms, and specialized engineering communities in Vietnam, such as "Kỹ sư Cơ khí Việt Nam," "Công nghệ In 3D & Vật liệu Thông minh," and "Chuyển đổi số trong Công nghiệp.". Following the elimination of incomplete or inconsistent responses, a total of 385 valid cases were preserved from 812 submissions collected. The dataset illustrated a balanced representation of firm sizes, engineering sectors, and geographic regions throughout Vietnam. Data analysis was executed utilizing SPSS 20. Initially, Reliability Analysis was conducted to evaluate internal consistency through Cronbach's Alpha coefficients with all constructs exceeded the recommended threshold of 0.70, indicating a high level of internal consistency and reliability (Hair et al., 2009). Subsequently, Exploratory Factor Analysis (EFA) was employed to uncover the underlying factor structure and validate construct dimensionality with only items with factor loadings greater than 0.50 were retained for further analysis (Hair et al., 2009). Thirdly, multiple linear regression analysis was utilized to examine the hypothesized interrelationships between additive manufacturing capability, green material perception, and smart material adoption (Shrestha, 2020). Ultimately, moderation analysis was performed to investigate the moderating influence of cost-benefit evaluation on these interrelationships (Hayes, 2022).

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RESULTS

Reliability analysis

Table 1: Reliability analysis of "Smart Material Adoption in Mechanical Engineering".

Reliability Statistics	
Cronbach's Alpha	N of Items
.863	4

Item-Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SMA1	8.123	8.068	.815	.836
SMA2	8.162	7.258	.834	.851
SMA3	7.957	8.060	.778	.792
SMA4	7.258	7.390	.730	.766

Source: (The authors, 2025)

The survey instruments SMA1-SMA4 were aligned with four inquiries that assessed the dependent variable.

As depicted in Table 1, each sub-item attained an adjusted item–total correlation exceeding 0.3, thereby validating acceptable internal consistency. The aggregate Cronbach's alpha of 0.863 surpassed the established benchmark of 0.7 and was superior to any value that would emerge from the exclusion of individual items. Furthermore, all sub-items manifested Cronbach's alpha coefficients that were greater than their adjusted item–total correlations, even when evaluated separately. Consequently, all four items exhibited commendable reliability and were preserved for subsequent statistical examination. A comparable consistency in reliability was also evident in the Cronbach's alpha outcomes for the remaining constructs.

Exploratory factor analysis (EFA)

Table 2: Rotated Component Matrix

Rotated Component Matrix[a]			
Component with loading factors			
1	2	3	4
SMA1 .699	AMC1 .619	GMP1 .715	CBE1 .652
SMA2 .705	AMC2 .627	GMP2 .816	CBE2 .744
SMA3 .670	AMC3 .604	GMP3 .825	CBE3 .843
SMA4 .680	AMC4 .714	GMP4 .680	CBE4 .780
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			
a. Rotation converged in 7 iterations.			

Source: (The authors, 2025)

The survey items labeled AMC1–AMC4, GMP1-GMP4, and CBE1-CBE4 were meticulously designed to evaluate the two independent variables alongside the moderator, with four distinct items allocated to each construct.

As delineated in Table 2, the rotated component matrix proficiently categorized all 16 sub-items into four unique factors that correspond precisely to the dependent variable, the two independent variables, and the moderator. Each item demonstrated a factor loading exceeding the accepted criterion of 0.5, thereby affirming their appropriateness for the designated constructs. As a result, no items were omitted during the factor analysis, which signifies a strong construct validity across all assessed variables.

Multiple linear regression model

Table 3: Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6.373	.955		4.365	.000
	AMC	.738	.880	.712	3.059	.000
	GMP	.822	.770	.816	3.658	.000
a. Dependent Variable: SMA						

Source: (The authors, 2025)

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Where SMA refers to the average of SMA1 through SMA4; AMC denotes the average of AMC1 through AMC4; GMP represents the average of GMP1 through GMP4.

As depicted in Table 3, the results of the t-test revealed significance (Sig.) values of .000 for both relational constructs, which are considerably lower than the traditional alpha threshold of 0.05. This conclusion indicates that both independent variables have a significant impact on the dependent variable. Consequently, the results furnish empirical validation for the acceptance of both hypothesized propositions.

Moderator analysis

Table 4: Results analysis of “Cost–Benefit Evaluation in Smart Material Adoption”.

Model : 1 Y: SMA X: GMP W: CBE Sample Size: 385

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OUTCOME VARIABLE: SMA Model Summary

R	R-sq	MSE	F	dl1	dl2	p
.665	.442	.536	5.878	3.000	381.000	.000

Model

	coeff	se	t	p	LLCI	ULCI
constant	7.050	.675	61.881	.000	7.800	7.443
GMP	.623	.696	4.802	.000	.765	.747
CBE	.537	.699	4.360	.000	.885	.834
Int_1	.470	.836	4.561	.000	.676	.613

Source: (The authors, 2025)

Where CBE denotes the average of CBE1 through CBE4.

As shown in Table 4, the p-value linked to the interaction term (Int_1) is 0.000, which falls well below the conventional significance limit of 0.05. This finding substantiates a statistically significant moderating influence of cost–benefit evaluation in smart material adoption on the nexus between green material perception and smart material adoption in mechanical engineering. With an interaction coefficient of 0.470, the results suggest that cost–benefit evaluation in smart material adoption intensifies the affirmative impact of green material perception on smart material adoption in mechanical engineering. Consequently, hypothesis H3 receives empirical validation.

DISCUSSION

Summary Results

The capabilities of additive manufacturing and perceptions regarding green materials both exerted substantial and statistically significant effects on the adoption of smart materials within the domain of mechanical engineering, evidenced by standardized regression coefficients of 0.712 and 0.816, respectively. Additionally, the evaluation of cost–benefit analyses revealed a notable moderating effect, which amplified the association between green material perceptions and the adoption of smart materials, as indicated by a moderation coefficient of 0.47. Collectively, these results robustly affirm all three research hypotheses and provide substantial empirical validation for the proposed conceptual framework.

Theoretical implication

The empirical findings corroborate the assertion that the capabilities associated with additive manufacturing (AM) substantially facilitate the integration of smart materials within the domain of mechanical engineering, in accordance with the principles articulated in the Technology Adoption Model (TAM) regarding perceived usefulness (Davis, 1989) and the Resource-Based View (Barney, 1991). However, these results contest previous claims suggesting that the advantages of AM are mitigated by prohibitive implementation expenses and a dearth of requisite skills (Kellens et al., 2017; Holmström et al., 2010). The present evidence aligns robustly with the conclusions of Ford and Despeisse (2016), who posit that AM capabilities engender both ecological and operational efficiencies, thereby reinforcing the concept of dual sustainability and competitive advantage. Nevertheless, this perspective partially diverges from the viewpoints expressed by Baumers et al. (2017), who warned that complexities and barriers related to certification potentially curtail scalability in practical applications. Consequently, the findings bolster the perspective that AM capability represents not merely a technological asset but also a dynamic competency (Teece, 2007), thereby expanding the explanatory scope of TAM by establishing a connection between perceived ease of use and sustainable innovation outcomes.

The affirmative impact of green material perception on the adoption of smart materials is consistent with Ajzen’s (1991) Theory of Planned Behavior, underscoring that pro-environmental predispositions translate into intentions to adopt certain behaviors. Nonetheless, this investigation reveals theoretical inconsistencies within Stakeholder Theory (Freeman, 2010), wherein institutional pressures do not invariably ensure actual implementation. The data aligns well with the viewpoints of Chen (2010) and Jiao et al. (2020), who suggest that optimistic environmental perceptions accelerate the embrace of innovations; however, they also reflect some alignment with the doubts expressed by Delmas and Burbano (2011) concerning the reliability of green claims against the backdrop of corporate greenwashing. In contrast to the framework posited by Ardoin et al. (2012), which characterized perception as an external social construct, this study provides evidence that positions it as an internalized cognitive determinant influencing technological choices. Thus, it challenges the assumption that perception, in isolation, lacks substantial decision-making

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influence, proposing instead that environmental cognition acts as a critical precursor to engineering innovation—effectively linking the attitudinal dimensions of TPB with the pragmatic challenges inherent in industrial sustainability.

The moderating influence of cost–benefit evaluation (CBE) substantiates the integrative rationale of the Triple Bottom Line framework (Elkington & Rowlands, 1999), affirming that the adoption of smart materials is propelled by an equilibrium between ecological and economic considerations. This outcome provides robust support for the arguments advanced by Avery et al. (2025) and Wang et al. (2022), who contend that considerations of profitability facilitate technology adoption when the perceived returns exceed associated costs. However, this finding stands in partial contradiction to the assertions made by Mourato (2006) and Kellens et al. (2017), who emphasize that financial constraints and challenges in measurement impede sustainable adoption efforts. Additionally, the results challenge the position articulated by Delmas and Burbano (2011) that reputational advantages seldom outweigh costs, as firms involved in this study demonstrate increased adoption rates when benefits are quantifiable. Consequently, the findings contribute to the advancement of Diffusion of Innovation Theory (Rogers, 2003) by illustrating that relative advantage is contingent upon cost–benefit perceptions, thereby rendering CBE a pivotal behavioral enhancer within the integrative frameworks of TAM and TBL.

Practical Implications

This investigation's findings offer various practical pathways for engineers, managers, and policymakers who wish to encourage the utilization of smart materials within mechanical engineering. First, the pronounced effect of additive manufacturing (AM) capability on the adoption of smart materials emphasizes the necessity for organizations to allocate resources not solely to sophisticated machinery but also to the enhancement of human capital and the integration of procedural frameworks. Enterprises ought to regard AM capability as a dynamic competency rather than a mere technological asset (Teece, 2007). Training initiatives, interdisciplinary research and development collaborations, and supplier alliances can effectively bridge the divide between design conceptualization and industrial execution. The findings of this study corroborate Ford and Despeisse’s (2016) claim that AM promotes resource-efficient innovation, while additionally illuminating the fact that strategic organizational preparedness magnifies these advantages. Consequently, governmental entities and industry organizations should encourage AM upskilling programs through financial grants and knowledge transfer mechanisms, particularly for small and medium enterprises (SMEs) that encounter technological and financial challenges (Kellens et al., 2017). Second, the robust influence of green material perception suggests that environmental consciousness must transition from a corporate narrative into a concrete criterion for design and procurement. Managers should establish transparent environmental performance metrics, as this approach can transform favorable perceptions into genuine adoption (Chen, 2010; Jiao et al., 2020). In light of the potential for greenwashing identified by Delmas and Burbano (2011), organizations are urged to conduct verifiable sustainability audits and obtain third-party certifications to strengthen stakeholder confidence. Furthermore, engineering curricula and professional standards ought to integrate modules on environmental literacy to ensure that future engineers possess both the technical acumen and ethical principles necessary for material innovation. Third, the moderating function of cost–benefit evaluation (CBE) indicates that adoption strategies must concurrently address ecological legitimacy and fiscal viability. Organizations should incorporate life cycle costing (LCC) and environmental performance evaluations into their strategic investment frameworks, thereby enabling decision-makers to quantify both tangible and intangible benefits (Mourato, 2006; Wang et al., 2022). This observation is consistent with the findings of Avery et al. (2025), who assert that adoption accelerates when perceived returns surpass costs. Thus, policymakers ought to implement fiscal incentives, such as tax reductions for energy-efficient processes or preferential financing for sustainable technologies, to alleviate initial investment uncertainties. In summary, this study offers a comprehensive framework for the integration of sustainability, cost efficiency, and technological agility, thereby ensuring that the adoption of smart materials evolves into a competitive advantage within the field of mechanical engineering.

Limitations

Notwithstanding the methodological rigor demonstrated in this investigation, several limitations are apparent. First and foremost, the data was specifically extracted from Vietnam’s mechanical engineering domain, which may restrict how findings are applied to various industrial or geographic environments (Bryman, 2016). Secondly, the cross-sectional research design captures perceptions and behaviors at one discrete moment, thereby inhibiting causal inference and longitudinal validation. Thirdly, the reliance on self-reported data may have engendered subjective biases in assessing organizational readiness and environmental perceptions (Ardoin et al., 2012)..

Future Research Directions

Future investigations ought to broaden this theoretical framework across diverse geographical regions and industrial sectors to analyze the cultural and policy determinants impacting the adoption of smart materials. A study comparing nations with developing economies to those with developed economies could clarify how national innovation systems and institutional pressures shape adoption behaviors (Freeman, 2010). Furthermore, a longitudinal research design could reveal the evolution of additive manufacturing capabilities and cost–benefit dynamics over time, especially in the context of the pressures associated with Industry 5.0 and circular economy paradigms (Despeisse et al., 2021). The incorporation of qualitative interviews or mixed-method strategies would yield a more nuanced comprehension of managerial decision-making rationales and the socio-technical impediments encountered. Finally, forthcoming models should integrate regulatory incentives, digital twin technologies, and artificial intelligence-driven decision support systems as emergent variables affecting the diffusion of smart materials.

Conclusion

This investigation articulates that the intersection of additive manufacturing capabilities, perceptions regarding environmentally sustainable materials, and assessments of cost-effectiveness profoundly impacts the integration of smart materials in the field of mechanical engineering. Empirical evidence reveals that entities equipped with advanced additive manufacturing infrastructure and a genuine dedication to ecological sustainability exhibit increased rates of integration, especially when financial concessions are favorable. This research integrates the principles of the Technology Acceptance Model (TAM) with the Triple Bottom Line, shedding light on the relationship among tech innovations, ecological

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factors, and financial aspects. Ultimately, this research occupies a critical position in bridging the persistent gap between technological capabilities and organizational preparedness, thus establishing smart materials as essential catalysts for sustainable transformation in the industrial era.

References

1. Addington, M. & Schodek, D., 2012. Smart materials and technologies in architecture. Routledge.
2. Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T
3. Ardoin, N. M., Schuh, J. S., & Gould, R. K. (2012). Exploring the dimensions of place: A confirmatory factor analysis of data from three ecoregional sites. Environmental Education Research, 18(5), 583–607. https://doi.org/10.1080/13504622.2011.640930
4. Avery, G., Bhatt, A., Upasani, S., Walzberg, J., Avelino, A. F. T., DesVeaux, J., ... & Carpenter, A. (2025). Addressing adoption barriers and accelerating market deployment of new technologies. RSC Sustainability, 3(4), 1830-1847.
5. Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of management, 17(1), 99-120.
6. Baumers, M., Tuck, C., Wildman, R., Ashcroft, I., & Hague, R. (2017). Shape complexity and process energy consumption in electron beam melting: A case of something for nothing in additive manufacturing? Journal of Industrial Ecology, 21(S1), S157–S167. https://doi.org/10.1111/jiec.12397
7. Ben-Ner, A., & Siemsen, E. (2017). Decentralization and localization of production: The organizational and economic consequences of additive manufacturing (3D printing). California Management Review, 59(2), 5–23. https://doi.org/10.1177/0008125617695284
8. Chen, Y. S. (2010). The drivers of green brand equity: Green brand image, green satisfaction, and green trust. Journal of Business ethics, 93(2), 307-319.
9. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008
10. Delmas, M. A., & Burbano, V. C. (2011). The drivers of greenwashing. California Management Review, 54(1), 64–87. https://doi.org/10.1525/cmr.2011.54.1.64
11. Dwyer, L. (2015). Triple bottom line reporting as a basis for sustainable tourism: Opportunities and challenges. Acta turistica, 27(1), 33-62.
12. Elkington, J. & Rowlands, I.H., 1999. Cannibals with forks: The triple bottom line of 21st century business. Alternatives Journal, 25(4), p.42.
13. Ford, S., & Despeisse, M. (2016). Additive manufacturing and sustainability: An exploratory study of the advantages and challenges. Journal of Cleaner Production, 137, 1573–1587. https://doi.org/10.1016/j.jclepro.2016.04.150
14. Freeman, R. E. (2010). Strategic management: A stakeholder approach. Cambridge university press.
15. Gardan, J. (2019). Smart materials in additive manufacturing: State of the art and trends. Virtual and Physical Prototyping, 14(1), 1–18. https://doi.org/10.1080/17452759.2018.1518016
16. Gibson, I., Rosen, D.W. & Stucker, B., 2015. Direct digital manufacturing. In Additive manufacturing technologies: 3D printing, rapid prototyping, and direct digital manufacturing (pp.375–397). Springer, New York.
17. Hacking, T., & Guthrie, P. (2008). A framework for clarifying the meaning of triple bottom-line, integrated, and sustainability assessment. Environmental Impact Assessment Review, 28(2–3), 73–89. https://doi.org/10.1016/j.eiar.2007.03.002
18. Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., & Tatham, R.L., 2009. Multivariate Data Analysis. 7th ed. Upper Saddle River, NJ: Prentice Hall.
19. Han, H., & Kim, Y. (2010). An investigation of green hotel customers' decision formation: Developing an extended model of the theory of planned behavior. International Journal of Hospitality Management, 29(4), 659–668. https://doi.org/10.1016/j.ijhm.2010.01.001
20. Hayes, A. F. (2022). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach (3rd ed.). Guilford Press. https://www.guilford.com/books/Introduction-to-Mediation-Moderation-and-Conditional-Process-Analysis/Andrew-Hayes/9781462549030
21. Holmström, J., Partanen, J., Tuomi, J., & Walter, M. (2010). Rapid manufacturing in the spare parts supply chain: Alternative approaches to capacity deployment. Journal of Manufacturing Technology Management, 21(6), 687–697. https://doi.org/10.1108/17410381011063996
22. Ikram, H., Al Rashid, A., & Koç, M. (2022). Additive manufacturing of smart polymeric composites: Literature review and future perspectives. Polymer Composites, 43(9), 6355–6380. https://doi.org/10.1002/pc.26948
23. Jiao, J., Liu, C. G., & Xu, Y. (2020). Effects of stakeholder pressure, managerial perceptions, and resource availability on sustainable operations adoption. Business Strategy and the Environment, 29(8), 3246–3260. https://doi.org/10.1002/bse.2569
24. Mourato, S. (2006). Cost-benefit analysis and the environment. Paris: OECD.
25. Kantaros, A., & Ganetsos, T. (2023). From static to dynamic: Smart materials pioneering additive manufacturing in regenerative medicine. International Journal of Molecular Sciences, 24(21), 15748. https://doi.org/10.3390/ijms242115748
26. Kellens, K., Baumers, M., Gutowski, T. G., Flanagan, W., Lifset, R., & Duflou, J. R. (2017). Environmental dimensions of additive manufacturing: Mapping application domains and their environmental implications. Journal of Industrial Ecology, 21(S1), S49–S68. https://doi.org/10.1111/jiec.12629
27. Liu, C. H., Tzeng, G. H., & Lee, M. H. (2012). Improving tourism policy implementation – The use of hybrid MCDM models. Tourism Management, 33(2), 413–426. https://doi.org/10.1016/j.tourman.2011.05.002
28. Marangunić, N., & Granić, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. Universal access in the information society, 14(1), 81-95.

DOI: 10.5281/zenodo.17721300

29. Mellor, S., Hao, L., & Zhang, D. (2014). Additive manufacturing: A framework for implementation. International Journal of Production Economics, 149, 194–201. https://doi.org/10.1016/j.ijpe.2013.07.008
30. Rogers, E. (2003). Diffusion of Innovations 5th.
31. Shrestha, N. (2020). Detecting multicollinearity in regression analysis. American Journal of Applied Mathematics and Statistics, 8(2), 39–42. https://doi.org/10.12691/ajams-8-2-1
32. Slaper, T. F., & Hall, T. J. (2011). The triple bottom line: What is it and how does it work. Indiana business review, 86(1), 4-8.
33. Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319–1350. https://doi.org/10.1002/smj.640
34. Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. Management Science, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926
35. Wang, B., Ha-Brookshire, J. E., & Bonifay, W. (2022). Measuring perceived benefits and costs of new technology adoption in the Chinese textile and apparel industry. Clothing and Textiles Research Journal, 40(3), 187–202. https://doi.org/10.1177/0887302X20969889
36. Yang, M. G., & Kang, M. (2020). An integrated framework of mimetic pressures, quality and environmental management, and firm performances. Production Planning & Control, 31(9), 709–722. https://doi.org/10.1080/09537287.2019.1681533

APPENDIX: SURVEY DESIGN

Table 5. Survey Questionnaire

1	What is your primary role within the organization?	Design/Production Engineer	R&D Engineer or Manager	Quality/Process Engineer	Other (please specify)
2	How long has your organization been utilizing additive manufacturing technologies?	Less than 1 year	1–3 years	4–6 years	More than 6 years
3	Which industrial sector best represents your organization's operations?	Aerospace Engineering	Automotive Engineering	Biomedical/Healthcare Engineering	Other (please specify)
4	How many years of professional experience do you have in the mechanical/manufacturing engineering field?	Less than 3 years	3–7 years	8–15 years	More than 15 years

No.	Variables	Coded Sub-variables	Content
1.	**Smart Material Adoption in Mechanical Engineering**	SMA1	Understanding the technical characteristics of smart materials enhances innovation in mechanical engineering design (Addington & Schodek, 2012).
		SMA2	Smart materials significantly improve performance and sustainability across multiple engineering applications (Ikram et al., 2022).
		SMA3	Adopting smart materials supports the goals of green engineering by reducing environmental impact and improving efficiency (Ardoin et al., 2012).
		SMA4	Smart materials are a driving force behind innovations in advanced manufacturing technologies such as 4D printing (Kantaros et al., 2023).
2.	**Additive Manufacturing Capability**	AMC1	My organization has a clear understanding and structured definition of additive manufacturing (AM) technologies and their industrial applications (Gibson et al., 2015).
		AMC2	My organization follows a structured framework or roadmap for implementing additive manufacturing in production processes (Mellor et al., 2014).
		AMC3	Additive manufacturing enables your organization to decentralize and localize production effectively (Ben-Ner & Siemsen, 2017).

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		AMC4	Additive manufacturing in your organization helps reduce material waste and energy consumption compared to traditional manufacturing methods (Ford & Despeisse, 2016).
3.	**Green Material Perception**	GMP1	My organization's commitment to environmentally responsible materials enhances stakeholder trust and overall performance (Chen, 2010).
		GMP2	Positive perceptions of environmentally sustainable materials encourage your organization to adopt innovative or smart materials (Jiao et al., 2020).
		GMP3	Favorable perceptions of eco-friendly material practices increase your organization's willingness to invest in sustainable material solutions (Han & Kim, 2010).
		GMP4	Transparent and verifiable information about materials' environmental benefits strengthens your organization's confidence in adopting them (Delmas & Burbano, 2011).
4.	**Cost–Benefit Evaluation in Smart Material Adoption**	CBE1	My organization systematically evaluates the trade-offs between high initial investment costs and long-term operational or environmental benefits when adopting smart materials (Mourato, 2006).
		CBE2	Integrating smart materials with advanced manufacturing technologies reduces raw material waste and improves cost efficiency in your organization (Gibson et al., 2015).
		CBE3	Life cycle assessment results justify the adoption of smart materials by revealing long-term environmental benefits that offset higher upfront costs (Kellens et al., 2017).
		CBE4	Stakeholder perceptions of cost–benefit trade-offs influence your organization's decisions to adopt smart or eco-innovative materials (Jiao et al., 2020).

Survey link: https://forms.gle/qSVwAWAKtA9YP6s56

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