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AN INVESTIGATION INTO EFFECTIVE ENERGY BEHAVIOR CONTROL STRATEGIES IN THE APPAREL MANUFACTURING SECTOR

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ABSTRACT

Energy consumption in the apparel industry is high, driven by intense usage of Heating, Ventilation, and Air Conditioning (HVAC) systems, lighting, and machines. Given its intensive nature and high carbon footprint, implementing efficient energy behavioural control strategies is crucial for advancing sustainability goals. This study identifies, evaluates, and rates thirteen strategies spanning technological, managerial, legal, and social domains through a comprehensive literature analysis and expert validation using the Relative Importance Index (RII) technique. Findings demonstrate a high preference for technologically driven interventions such as Artificial Intelligence (AI) and machine learning based predictive control, automation and smart controls, and smart metering systems, which enable precision, scalability, and real-time adaptability. Mid-tier tactics like incentive programs, dashboards, and training were regarded vital, while behaviour focused, legal, and social initiatives were ranked less effective due to perceived complexity, longer return scopes, and lower direct impact. The study underlines the necessity of a hybrid implementation approach that combines high impact technology with structured behavioural support mechanisms to foster sustainable energy practices. Limitations include potential sample bias in expert replies and a focus on large-scale manufacturing contexts, which may not completely represent issues experienced by small and medium enterprises (SMEs). Future studies should explore contextual barriers to strategy adoption across different organizational sizes and cultures and analyse the long-term performance of integrated technical behavioural models.

Keywords: *Apparel manufacturing; Energy efficiency; Energy behaviour control strategies; Sustainability.*

1. INTRODUCTION

The building sector is a dominant contributor to global energy consumption, accounting for approximately 40% of total energy use and 30% of carbon dioxide (CO_2) emissions (Schito & Lucchi, 2023). Substantial energy demand stems primarily from heating, cooling, lighting, and other operational activities powered by fossil fuels (Bodziacki et al., 2024). Due to urbanization and economic growth accelerating energy demand, policymakers worldwide are prioritizing energy efficiency measures in urban planning to

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mitigate climate change and reduce ecological footprints (Umoh et al., 2024). Despite advancements in energy efficient technologies such as high-performance Heating, Ventilation, and Air Conditioning (HVAC) systems, Light emitting diode (LED) lighting, and smart building automation, a persistent gap remains between projected and actual energy performance due to human behaviour (Kovalchuk & Shcherbakova, 2024; Ekim et al., 2023).

While technological innovations like improved insulation, airtight construction, and solar panels enhance energy efficiency, their full potential is often undermined by occupant behaviour (Amasyali & El-Gohary, 2021). Studies indicate that fluctuating behaviour, such as not turning off the lights, adjusting thermostats too much, or switching off automated devices, is likely to discredit energy saving potential (Xu et al., 2023). Hence, the discrepancy is known as the "energy performance gap," as it focuses on the implementation of a combined approach that involves technological advancements and behaviour (Bäcklund et al., 2023).

As per that research suggests that psychological factors and behaviour have the greatest contribution to energy consumption patterns (Ekim et al., 2023). As per that, activities of end users with lighting, HVAC, and appliances contribute significantly to total energy consumption and habits, awareness, and incentives must be considered along with technical measures (Maghsoudi Nia et al., 2022). For instance, energy feedback systems with real-time energy feedback were identified to reduce usage by 14.8%, demonstrating the effectiveness of data informed, individual specific interventions (Vijlbrief et al., 2022). Similarly, gamification, nudging behaviour like reminders and incentives, and reward schemes can instil long-term energy-saving habits (Li et al., 2024; Maghsoudi Nia et al., 2022).

The apparel industry is one of the most energy-consuming sectors, where air conditioning alone accounts for 46% of the energy used in manufacturing plants (Jananthan et al., 2006). In addition, textile processing requires enormous water, fuel, and electricity consumption, thus posing a massive industrial carbon footprint (Garg & Bhardwaj, 2024).

This study aims to bridge the gap between theoretical energy saving models and real-world applications by developing and assessing viable energy behavioural control strategies within the apparel manufacturing sector. The paper provides a review of relevant literature, followed by a full discussion of the research methods. It then provides the findings and includes a discussion on their implications, closing with practical insights and recommendations for further implementation and study.

2. LITERATURE REVIEW

2.1 ENERGY CONSUMPTION IN APPAREL MANUFACTURING

The apparel manufacturing business is a major industry in world economies but is also famously energy intensive, as it directly impacts production costs, ecological sustainability, and company effectiveness (Yılmaz et al., 2024). The apparel industry is renowned for having multifarious operational processes that include spinning, weaving, dyeing, finishing, cutting, sewing, and pressing and wet processing, particularly dyeing and finishing, which constitutes a major energy intensive industry, using a considerable portion of the industry's total energy consumption (Ajam & Khoshgoftar Manesh, 2025).

In extensive apparel manufacturing facilities, producers typically employ energy efficient technology, automation, and renewable energy sources to enhance consumption efficiency, whereas small and medium sized enterprises encounter challenges in adopting these strategies due to financial and technical constraints (Ketenci & Wolf, 2024).

As sustainability gains popularity, factories are increasingly using energy behaviour control tactics and data-driven energy management systems to boost efficiency and comply with environmental standards, and these approaches employ sophisticated technology, such as Artificial Intelligence (AI) and Internet of Things (IoT), to optimize energy consumption and eliminate waste, eventually supporting sustainability goals.

2.2 SIGNIFICANCE OF ENERGY BEHAVIOUR CONTROL STRATEGIES

Energy behaviour control strategies offer significant economic benefits by optimizing industrial processes, reducing energy costs, and enhancing productivity. Businesses that adopt these strategies improve resource efficiency, mitigate market risks, and strengthen competitiveness (Gitelman et al., 2019). Non-price interventions, such as energy use labelling and feedback systems, further encourage energy efficient behaviors, yielding long term economic returns (Zheng et al., 2022).

As for environmental impact, integrating psychological variables such as behavioural changes and persuasive technology (IoT, Smart metering and AI) promotes user engagement, ultimately promoting environmentally friendly behaviours and contributing to sustainable development (Chiu et al., 2020). Moreover, energy behaviour management measures are crucial for sustainable energy consumption, reducing environmental impact, and fostering conservation, ultimately reducing carbon emissions, helping ameliorate climate change and enhancing ecological health (Sweeney et al., 2018).

Practicing energy behaviour control strategies is significant because it improves building practitioners' sense of behavioural control, which positively impacts their intent of complying with energy performance standards, ultimately leading to better compliance outcomes than the minimum requirements in building design (Lu et al., 2024). Integrating energy behaviour management strategies, such as noise reduction techniques for Battery, Energy Storage Systems are vital for achieving regulatory compliance requirements while guaranteeing community acceptability and limiting the impact on residential areas (Martinez et al., 2013).

2.3 ENERGY BEHAVIOUR CONTROL STRATEGIES

2.3.1 Technological Strategies

Recent improvements in smart metering and IoT based systems have enabled real-time energy tracking, automated alarms, and comparative usage analysis, which are often attributed with boosting industrial energy efficiency (Mirani et al., 2024). While these technologies outperform traditional human monitoring in scalability and data precision, their performance strongly depends on organizational capability to act on the insights generated. In SMEs, the lack of competent individuals or integration frameworks sometimes limits their impact, a topic underexplored in current literature (Hattori et al., 2019). Automation solutions such as variable speed drives are also commonly referenced for optimizing motor and pump operations, eliminating unnecessary energy waste (Singhal & TR, 2023). However, most studies focus on their implementation in developed nations or highly mechanized industries, with scant investigation of their performance in labour intensive sectors like clothing manufacture. This is an important research gap, as the operational context can considerably influence system performance (Hattori et al., 2019).

Behavioural nudging using apps and digital notifications is another new method, leveraging psychological triggers to induce change (Cellina et al., 2024). Although studies highlight positive short-term effects, others point to uneven engagement and user fatigue, suggesting that these technologies may lack sustainability if not linked with management reinforcement or tangible incentives (Ubachukwu et al., 2023). These discrepancies underscore the necessity for hybrid approaches that mix digital interventions with organizational support structures (Zhao, 2024).

2.3.2 Managerial Strategies

Employee training programs are crucial for fostering energy conscious behaviours in the workplace (Kotsopoulos et al., 2023). Effective training integrates behavioural psychology principles to overcome cognitive biases and reinforce energy saving habits (Canova & Manganelli, 2020). Performance monitoring and feedback systems, when combined with smart metering, sustain energy reductions of approximately 5% (Schleich et al., 2017). Energy conservation is further encouraged via incentive-based programs, which include monetary awards as well as nonmonetary motivators like environmental awareness campaigns (Asensio & Delmas, 2015).

2.3.3 Legal and Social Strategies

Energy conservation agreements between governments and industries facilitate negotiated efficiency targets, offering flexibility and cost-effective compliance (Dernbach et al., 2011). Policy enforcement, when combined with behavioural insights, enhances regulatory adherence and promotes sustainable practices (Hajialigol et al., 2023). Social strategies, such as recognition programs and community engagement, leverage social norms to motivate energy saving behaviours (Bonan et al., 2020). As well as collaborative goal setting initiatives in residential and organizational settings have achieved energy savings exceeding 20% (Iweka et al., 2019).

2.4 IMPLEMENTATION BARRIERS AND CHALLENGES

2.4.1 Technical Barriers

The deployment of energy behavioural control systems confronts various technological hurdles, including infrastructure limits due to incompatible data formats, security and privacy concerns, and the necessity for robust communication networks (Chillayil et al., 2022; Reynolds et al., 2017). Integration with existing systems is challenged by legacy technologies, rigid operational models, and the difficulties of adding predictive control algorithms (Huckebrink & Bertsch, 2021). Additionally, a lack of technical skills inhibits deployment, notably in installing and maintaining data from devices like submeters and building automation systems (Adu-Kankam & Camarinha-Matos, 2020; Barido et al., 2020). Maintenance and upgrades further complicate implementation, as malfunctioning systems and complex controls annoy building workers, diminishing the efficiency of energy saving measures (Yılmaz et al., 2024).

2.4.2 Organizational Barriers

Organizational obstacles include high initial investment costs, which dissuade stakeholders owing to unclear financial returns and a propensity for limiting capital expenses over long term efficiency (Bensouda & Benali, 2022). Resistance to change among employees, coming from psychological and social issues, also obstructs adoption, requiring appropriate communication and support to overcome (Bäcklund et al., 2023). A lack of management commitment increases these challenges, resulting in poor resource allocation and insufficient strategic planning for energy saving programs (Khafiso et al., 2024; Russell et al., 2020). Additionally, restricted resources and time limits hinder decision making, requiring supportive policies and accessible information to induce behavioural shifts (Bensouda & Benali, 2022).

2.4.3 Long term Sustainability Challenges

Sustaining behavioral improvements over time remains difficult due to psychological resistance, motivational gaps, and the need for constant assistance (Tsuda et al., 2017; Cash et al., 2023). Continuous monitoring is crucial but problematic due to data disparities and the complexity of tracking energy conservation outcomes (Chen & Nunes, 2023). Rapidly emerging technologies present acceptance barriers, particularly for smaller enterprises with limited resources, while knowledge gaps among consumers inhibit proactive engagement (Borowski, 2020). Staff turnover further undermines long term sustainability, as organizational culture and training efficacy influence the retention of energy management techniques (Brabson et al., 2019).

3. RESEARCH METHODOLOGY

This study adopted a quantitative approach, sequential exploratory, grounded in a quantitative dominant approach, to identify and prioritize behavioural energy management strategies within the apparel manufacturing industry (Levitt et al., 2018).

The methodology had three essential phases: strategy identification from literature review, validation through peer review by experts, and a quantitative ranking procedure. A thorough literature analysis was undertaken to compile a diverse array of energy behaviour management strategies applicable to industrial contexts, namely in apparel manufacturing. The review concentrated on peer-reviewed academic journals, industrial case studies, government publications, and best practice manuals released in the past decade. The review yielded 13 distinct strategies, which were then categorized into four thematic domains: technological, managerial, legal, and societal. The use of classification was intended to facilitate a holistic understanding of behavioural influences on energy efficiency (Thollander & Palm, 2018).

Further to the literature review, the identified strategies were corroborated and evaluated by expert opinion. A systematic questionnaire was prepared and disseminated among a selected group of energy professionals, including energy managers, engineers, facilities managers, and university scholars focusing on sustainability and industrial energy efficiency. A total of 40 specialists were recruited to participate in the study. The participants were chosen by purposive sampling, ensuring the inclusion solely of individuals with direct experience in energy management in industrial or commercial environments (Etikan, 2016). This selection method yielded a wide range of findings, enabling the research to encompass many views within the sector.

The questionnaire offered experts to score the 13 techniques based on their perceived effectiveness in real-world apparel manufacturing scenarios. Each participant was asked to assign a rank from 1 to 13, with 1 being the most effective method and 13 being the least effective, which is suitable for decision making and priority setting studies in energy research (Kassem et al., 2020). The purpose was to reflect on the practical prioritization of solutions as observed by individuals actively involved in energy related decision making and implementation.

To assess the responses, the Relative Importance Index (RII) approach was applied. This technique is widely used in construction and behavioural energy research to determine relative significance based on expert input (Kassem et al., 2020). The RII was determined using the formula:

$$RII = \frac{\sum W}{A \times N} \qquad Equation\ (1)$$

Where, W = constant expressing the weighting given to each response, A = highest weighting and N = total number in the responses.

Where W is the weight provided to each approach by respondents, A is the highest possible weight (in this case, 13), and N is the total number of respondents. The resulting RII scores were used to rank the solutions from most to least effective, presenting a clear indication of industry consensus on priority activities for behavioural energy control.

Ethical considerations were thoroughly addressed throughout the research process. Participation was entirely voluntary, and all respondents were informed of the study's goal and use of their responses. No personal or sensitive information was collected, and all replies were kept anonymous to maintain confidentiality. These processes guaranteed that the research was done in a manner that respects both academic integrity and the rights of the participants.

4. RESEARCH FINDINGS AND ANALYSIS

Through a comprehensive literature analysis, various energy behaviour control strategies have been identified and divided into four primary domains as technological, managerial, legal, and social strategies. Technological strategies include smart metering and monitoring systems, automation and smart controls, behavioural nudges through apps and notifications, energy dashboards and visualization tools, and AI and machine learning based predictive control, which leverage real-time data and automation to optimize energy efficiency. Managerial solutions focus on organizational interventions such as employee training programs, performance monitoring and feedback systems, and incentive-based programs to develop energy conscious behaviours. Legal strategies comprise energy conservation agreements and policy enforcement, which establish legislative frameworks to ensure compliance with energy saving initiatives. Lastly, social tactics encompass social recognition programs, community participation and education, and joint goal formulation, attempting to develop a culture of sustainability through collective action and awareness. These solutions jointly target both technological and human centric aspects of energy management, offering a holistic approach to reducing energy usage in industrial settings.

In the next step of the analysis, the identified energy behaviour control strategies were subjected to expert validation to assess their real-world effectiveness. According to that, the rankings were used to calculate the RII value of the strategies.

$$RII = \frac{\sum W}{A \times N} \qquad Equation\ (2)$$

Σ Scores for a Factor, this symbol (Sigma) represents the sum of all ranking that given to a specific strategy by all respondents. Higher ranking shows higher efficiency in normal context. Since lower original ranks (1, 2, 3...) indicate higher efficiency**,** invert the ranks.

For each strategy (1 to 13),

Inverted Score (W) = 14 - Original Rank

So, for AI ΣW = (14-7) +(14-7) +(14-13) +(14-2) +(14-9) +(14-13) +………+(14-3)

= 394

Based on the calculation of RII, Table 1 shows the RII rate of energy behaviour control strategies.

Table 1: RII rate of energy behaviour control strategies

Strategies	Highest Rank	Number of Responses	Weight of Strategy	RII	Rank
AI and Machine Learning Based Predictive Control	13	40	464	0.892	1
Automation and Smart Controls	13	40	423	0.813	2
Smart Metering and Monitoring Systems	13	40	394	0.758	3
Incentive based programs	13	40	370	0.712	4
Energy Dashboards and Visualization Tools	13	40	340	0.654	5
Employee training programs	13	40	324	0.623	6
Performance monitoring and feedback systems	13	40	306	0.588	7
Behavioural Nudges Through Apps and Notifications	13	40	286	0.550	8
Policy Enforcement	13	40	256	0.492	9
Energy Conservation Agreements	13	40	234	0.450	10
Social Recognition Programs	13	40	200	0.385	11
Community Engagement and Education	13	40	164	0.315	12
Collaborative Goal Setting	13	40	70	0.150	13

The strategy with the highest RII is AI and Machine Learning Based Predictive Control (0.892), signifying its considerable importance in contemporary energy optimisation initiatives. Subsequently, Automation and Smart Controls (0.813) and Smart Metering and Monitoring Systems (0.758) underscore the increasing focus on technology driven solutions. Incentive Based Programs (0.712) and Energy Dashboards and Visualisation Tools (0.654) are highly ranked strategies, indicating that both motivation and visibility are crucial in promoting energy efficiency. Mid-level tactics encompass Employee Training Programs, Performance Monitoring, and Behavioural Nudges, highlighting the significance of human elements in conjunction with technical instruments. Policy Enforcement, Energy Conservation Agreements, and Social Recognition Programs rank lower on the list, whereas Community Engagement and Education and Collaborative Goal Setting are seen as the least impactful, with RIIs of 0.315 and 0.150, respectively.

For the classification of these strategies, the RII classification has been used based on Buertey et al. (2024) (Table 2).

Table 2: RII classification

RII Values	Importance Level
$0.90 \leq RII \leq 1$	Strongly Important
$0.75 \leq RII \leq 0.89$	Very Important
$0.60 \leq RII \leq 0.74$	Important
$0.45 \leq RII \leq 0.59$	Moderately Important
$0.30 \leq RII \leq 0.44$	Unimportant
$0.15 \leq RII \leq 0.29$	Very Unimportant
$0 \leq RII \leq 0.14$	Strongly Unimportant

The ranking of energy management strategies, according to the Relative Importance Index (RII) classification, illustrates the impact of technical advancements and organisational preferences on energy efficiency and conservation. AI and Machine Learning Based Predictive Control (0.892), Automation and Smart Controls (0.813), and Smart Metering and Monitoring Systems (0.758) are classified as "Very Important." These tactics are esteemed for embodying innovative, data driven methodologies that facilitate real-time energy optimisation, problem identification, and predictive maintenance. The incorporation of AI facilitates adaptive and anticipatory control systems, minimising energy waste and improving operational efficiency. Automation and smart systems decrease human error and assure constant performance, while smart metering provides granular visibility into energy usage trends, which is crucial for informed decision making and accountability.

In the "Important" category, Incentive Based Programs (0.712), Energy Dashboards and Visualization Tools (0.654), and Employee Training Programs (0.623) are acknowledged for their supportive and enabling roles. Incentives are robust motivators that encourage compliance and involvement in energy saving measures. They integrate individual or departmental interests with organizational sustainability goals. Dashboards and visualization tools can make energy data more accessible and actionable, enabling transparency and fostering a culture of awareness. Meanwhile, employee training programs are crucial for strengthening internal capabilities, fostering responsible conduct, and assuring optimal use of the established systems and technology.

Strategies ranked as "Moderately Important", such as Performance Monitoring and Feedback Systems (0.588), Behavioural Nudges Through Apps and Notifications (0.550), Policy Enforcement (0.492), and Energy Conservation Agreements (0.450), demonstrate attempts to support long-term engagement and compliance. These strategies are regarded as somewhat effective because their effectiveness frequently depends on consistent implementation, user responsiveness, and cultural factors. For instance, feedback methods can improve performance only if users are motivated to act on the data. Similarly, behavioural nudges rely on psychological triggers, which may not consistently deliver sustained behaviour change. Policy enforcement and conservation agreements are crucial for formal accountability but may be regarded as top-down measures with limited flexibility or intrinsic incentive.

In the "Unimportant" category, Social Recognition Programs (0.385) and Community Engagement and Education (0.315) are considered to have less influence on energy results in business environments. This may be owing to the indirect nature of their impact, since they generally try to shift cultural norms or public awareness rather than offer instant, verifiable benefits. Their effectiveness may also be lessened in corporate organisations where quantifiable goals and returns on investment are stressed.

Finally, Collaborative Goal Setting (0.150) is classed as "Very Unimportant", probably because it demands significant work and coordination across departments, frequently without quick or evident energy savings. In practice, collaborative initiatives can confront obstacles linked to conflicting priorities, lack of engagement, or ambiguous accountability, making them less attractive compared to more direct or automated treatments.

Overall, this classification demonstrates a strong preference for technologically advanced, results oriented techniques that offer measurable and scalable energy reductions. It also emphasises a weaker emphasis on softer, community based, or participatory strategies, presumably due to their perceived lower impact and longer deadlines for effect.

Table 3: Classification on strategies

Classification	Strategies	RII
Very Important	AI and Machine Learning Based Predictive Control	0.892
	Automation and Smart Controls	0.813
	Smart Metering and Monitoring Systems	0.758
Important	Incentive based programs	0.712
	Energy Dashboards and Visualization Tools	0.654
	Employee training programs	0.623
Moderately Important	Performance monitoring and feedback systems	0.588
	Behavioural Nudges Through Apps and Notifications	0.550
	Policy Enforcement	0.492
	Energy Conservation Agreements	0.450
Unimportant	Social Recognition Programs	0.385
	Community Engagement and Education	0.315
Very Unimportant	Collaborative Goal Setting	0.150

5. DISCUSSION

This study's findings indicate an apparent trend in the apparel manufacturing sector towards the adoption of technologically advanced energy behaviour management measures. Amongst the thirteen techniques assessed, AI and Machine Learning Based Predictive Control obtained the highest Relative Importance Index (RII), closely followed by Automation and Smart Controls, as well as Smart Metering and Monitoring Systems. This pattern highlights a distinct industrial inclination towards data driven, real-time, and precision focused interventions capable of producing quantifiable results with less human involvement.

These top ranked techniques not only offer exceptional scalability but also align with the expanding digitalization trends in manufacturing. The strong RII values reflect credibility in these systems' ability to forecast consumption patterns, discover inefficiencies, and self-correct processes without the need for considerable user input. The introduction of such smart devices helps bridge the "energy performance gap" by decreasing the mismatch between expected and actual energy consumption levels, a recurrent challenge in energy saving programs.

Managerial and motivational initiatives such as Incentive Based Programs, Energy Dashboards, and Employee Training Programs also obtained significant attention, falling inside the "Important" category. These methods are crucial facilitators that promote technological interventions by encouraging awareness, engagement, and accountability among employees. Incentive schemes aim to integrate individual behaviours with organizational sustainability objectives, therefore improving the adoption and continued usage of new technology.

Conversely, methods relying on legal and social frameworks, including Policy Enforcement, Community Engagement, and Collaborative Goal Setting, turned out substantially lower. This trend reflects the corporate sector's preference for bottom line-oriented solutions over regulatory or socially motivated initiatives, which may be regarded as slower or less directly influential. Particularly, Collaborative Goal Setting being ranked as "Very Unimportant" shows that techniques involving substantial coordination and abstract results are commonly deprioritized in fast paced industrial environments.

Interestingly, behavioural and psychological methods like Behavioural Nudges and Recognition Programs also obtained low to moderate relevance ratings. This may reflect the problem of maintaining long-term involvement in behaviourally driven interventions without constant reward, monitoring, or integration with technology. The effectiveness of these tactics may also be context dependent, necessitating cultural transformations and leadership commitment that are sometimes difficult to maintain in changing manufacturing environments.

These observations emphasize the requirement of a hybrid approach that utilizes the precision and efficiency of sophisticated technologies while embedding behavioural and organizational enables them to ensure lasting impact. Despite the lower rankings of social and behavioural interventions, their synergistic integration with technological solutions may be vital for generating deeper and more sustainable improvements in energy use behaviour.

6. CONCLUSION

The paper offers a detailed investigation of energy behaviour control strategies within the apparel manufacturing sector, offering empirical evidence of their relative effectiveness through expert validation and Relative Importance Index (RII) analysis. The results suggest a strong industry preference for technologically driven initiatives, especially AI and machine learning based predictive control, automation, and smart metering systems. These solutions are prized for their capacity to deliver real-time, adaptive, and scalable energy optimizations that decrease waste and meet sustainability targets.

While managerial tactics such as training programs, incentive mechanisms, and performance monitoring have notable importance, they serve primarily as facilitators for the more impactful technical initiatives. Conversely, legal and social tactics, though potentially valuable, are sometimes deprioritized due to perceived complexity, slower return on investment, or mismatch with corporate priorities.

A critical recommendation resulting from this research is the adoption of a quantitative framework, one that mixes high impact technologies with structured behavioural and organizational components. Such a hybrid strategy targets not only operational efficiency but also the human components of energy use, delivering more robust and sustainable outcomes.

For governments and business leaders, these findings give a realistic roadmap to identify actions that balance cost effectiveness with long-term sustainability. Future studies might further explore the contextual factors driving the adoption of lower ranked methods, particularly in apparel, and analyse the long-term implications of integrated behavioural and technical solutions.

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