Available on: https://jefrr.ep-journals.org/ E-: 3051-3650 P-ISSN: 3051-3642

Journal of Economic Finance Research and Review

Volume: 02 Issue: 02 February 2026

Behavioural Science and AI-Driven Interventions in Energy Conservation: A Systematic Literature Review

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Published Date: February 27, 2026 **Article DOI: 10.65150/EP-jefrr/V2E2/2026-08**

ABSTRACT: This systematic literature review synthesises findings from 45 peer-reviewed studies (2016–January 2026) on behavioural interventions for energy conservation. Key results show that social comparison nudges lower electricity use by 1.5% to 2.9%; about 52% of savings persist post-intervention via technology. Intervention efficacy is 2–4 times higher among liberals versus conservatives and is context-dependent. AI-personalised interventions outperform static nudges, reducing decay effects by up to half. Boosts foster sustained performance, with 26.6% greater long-term effects than nudges. Notable challenges include moral licensing (5–8% rebound), boomerang effects among low users, and publication bias that inflates impact estimates. There are gaps in cross-cultural validation, long-term persistence, transparency, trust, and integration in energy planning. This review provides actionable policy recommendations for designing ethical and effective behavioural programs that support technology-driven climate action.

KEYWORDS: behavioral economics; energy conservation; nudges; boosts; AI personalization; social norms; rebound effects; choice architecture; sustainability

JEL Classification: Q41; Q55; D91; O33

I. INTRODUCTION

The need to address climate change has increased interest in ways to save energy that work alongside renewable energy and better infrastructure. Homes and buildings account for a large share of the world's energy use, and this share is growing, especially in developing regions. For instance, Indonesia's demand could rise sharply if patterns continue. Traditional policies such as carbon taxes, efficiency rules, and payment incentives have had some effect but face challenges, including political pushback, high costs, and limited impact on behaviour. The problem is called the energy efficiency gap: people do not always adopt cost-saving energy technology, even when it's in their interest. This suggests the main barrier is not technology, but how people make choices. Researchers use ideas from behavioural economics—such as bounded rationality (people use shortcuts) and how people respond to risk—to help people make better decisions about energy use.

Current research focuses on two main approaches. Nudges, based on Thaler and Sunstein's work (2008) involve changing how choices are presented to people, such as using easy defaults or comparison feedback, while still allowing choice. More recently, boosts aim to help people build skills to make better decisions. The newest work uses artificial intelligence to tailor feedback and support to each person's energy use patterns. But there are still problems. The effects of these programs often fade over time, and people can end up using more energy later (the rebound effect), especially if people feel justified after making an initial effort. How well the interventions work depends on personal beliefs, backgrounds, and settings, raising questions about their use across many settings. Unethical use or hidden influences are also concerns, especially when people are not aware of how public are being influenced.

This systematic review examines three principal inquiries: (1) What is the relative efficacy of various behavioural intervention types (nudges, boosts, AI-personalised approaches) in diminishing energy consumption in residential, institutional, and commercial environments?, (2) How do the effects of interventions differ based on demographic factors, political beliefs, starting levels of consumption, and the context in which interventions are carried out?, (3) What factors determine the long-term persistence or decline of intervention effects, and what strategies can effectively reduce rebound effects and moral licensing?. Author provides actionable information for policymakers, utility providers, urban planners, and researchers. These insights support the integration of behavioural strategies into climate action plans. Our findings are based on data from field experiments, quasi-experimental studies, and meta-analyses published between 2016 and 2026.

II. THEORETICAL FOUNDATIONS

2.1 Behavioral Economics and Decision Architecture

Behavioural energy programs are based on the idea that people do not always act as purely rational decision makers. Theory of bounded rationality showed that the study use shortcuts because of limits in what author knows and how much author can process (Kahneman 2003). Kahneman and Tversky (2007) explained that people tend to avoid losses, respond to how choices are framed, and focus more on immediate outcomes. These patterns allow policies to try shaping how people make choices. The idea behind nudge programs is that people are always influenced by how choices are presented, so policymakers should help them make good choices while preserving freedom. For example, making renewable energy the default choice, providing feedback on how energy use compares to others', or using simpler bills can help people save energy without forcing them to do so. But there are criticisms. Some argue that nudges push people to act without thinking deeply, which could reduce control and prevent people from learning better decision-making skills. This has led to increased interest in boosts, which focus on teaching skills rather than relying on automatic responses.

2.2 Social Norms and Conformity Mechanisms

There are two kinds of social rules: what most people do (descriptive norms) and what public approve of (injunctive norms). Studies show that telling households how their energy use compares with their neighbours can reduce high energy use, both by showing what behaviour is normal and by making people want to fit in. However, this feedback can actually cause low users to use more, since individuals adjust to the norm. Research shows that giving both types of feedback—what's normal and what's approved—can prevent low users from increasing energy while still helping high users cut back. Other studies confirm that comparing energy use to others is a reliable method, but effectiveness varies by belief and culture. This makes designing these programs more complex, especially when people resist influence.

2.3 AI Personalization and Adaptive Interventions

Using artificial intelligence moves programs from set messages to tailored advice. AI can review energy habits, spot patterns, predict choices, and offer help at the right time. This approach solves a major problem with earlier methods: one-size-fits-all programs do not work for everyone. Studies show that using AI to personalise advice makes efforts to save energy more successful. For example, when the way recommendations work is clear to users, younger energy consumers in new markets are more likely to trust and follow green advice. This shows that building trust and explaining AI improves results. But AI personalisation also raises new concerns, including privacy concerns, the risk of algorithmic bias, and the possibility of manipulation on an unprecedented scale. The technology also has the potential to make people dependent on it, as people rely on automated guidance rather than learning to save energy and develop good habits on their own. These tensions lead to calls for hybrid approaches that mix AI optimisation with competence-building that is more akin to a boost.

2.4 Rebound Effects and Behavioral Persistence

Energy efficiency measures are always up against the problem of rebound effects, which can partially or completely cancel out the savings intended. When lower per-unit energy costs lead to higher consumption, this is called a direct rebound. For example, a household that installs energy-efficient lighting may leave the lights on longer. Empirical estimates indicate that direct rebound effects account for about 32% of the potential efficiency gains (Gillingham, Newell, and Palmer 2009). Behavioural rebound occurs through moral licensing, in which individuals who conserve energy in one area perceive themselves as justified in excessive consumption in another (Dorner, 2018). This mechanism operates through self-concept maintenance, in which individuals strive to preserve a consistent environmental identity rather than optimising each decision in isolation. When conservation is automated through nudges or defaults, people may not see it as a personal accomplishment, which makes them more vulnerable to licensing effects. Long-term persistence is another important aspect. Brandon et al., (2017) conducted 38 field experiments, revealing that roughly 52% of initial energy reductions persist beyond intervention periods, chiefly through single capital investments in efficient technologies. Nonetheless, the residual behavioural element demonstrates significant deterioration as novelty diminishes and focus transitions. It is still important to know how to sustain conservation behaviour and how to stop it to make long-lasting changes.

III. METHODOLOGY

3.1 Search Strategy and Data Sources

This systematic review adheres to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to guarantee transparency and reproducibility. The study conducted extensive searches across several academic databases, including Scopus, Web of Science, ScienceDirect, MDPI, and Google Scholar, for literature published from January 2016 to January 2026. The search strategy utilised Boolean operators to integrate intervention descriptors with outcome measures: ("behavioural nudges" OR "choice architecture" OR "boosts" OR "social norms") AND ("energy efficiency" OR "energy conservation" OR "electricity consumption") AND ("artificial intelligence" OR "AI personalisation" OR "smart grid") AND ("rebound effect" OR "moral licensing" OR "persistence"). The study enhanced database searches by employing backward citation tracking of seminal works (Allcott 2011; Heukelom 2015; Richard H. Thaler and Cass R. Sunstein 2003) and forward citation analysis to pinpoint recent studies. The study also looked at working papers from behavioural economics research centres like the NBER, behavioural insights teams, and universities to find the most up-to-date findings that have not yet been published in peer-reviewed journals.

3.2 Inclusion and Exclusion Criteria

Studies were included if the papers met the following criteria: (1) empirical measurement of energy consumption outcomes using experimental, quasi-experimental, or rigorous observational designs; (2) implementation of behavioral interventions as primary treatment rather than purely financial incentives or regulatory mandates; (3) publication in peer-reviewed journals, working papers from reputable research institutions, or official reports from international organizations (IPCC, World Bank, IEA); (4) availability of full text in English; and (5) sufficient methodological detail to assess validity and extract effect sizes. The study did not include studies that were only correlational without strategies for identifying causes, theoretical papers without empirical validation, simulations that were not validated through field implementation, studies that focused only on transportation or industrial energy (not residential or commercial buildings), or duplicate publications of the same research. The final set of studies included 45 studies from 15 countries that examined residential programs, institutional settings, and commercial applications.

3.3 Data Extraction and Quality Assessment

Author coded each study systematically for the type of intervention (informational feedback, social comparison, defaults, boosts, AI-driven personalization), the setting (residential, dormitory, office, commercial), the sample size and duration, the primary outcomes (percentage reduction in electricity, gas, or total energy consumption), the persistence measures (follow-up periods beyond intervention), the moderating factors (political ideology, income, baseline consumption, climate), and the reported unintended effects (boomerang, rebound, moral licensing). The Cochrane risk-of-bias framework was used to assess the quality of behavioural interventions. It looked at randomisation procedures, sample attrition, measurement validity, selective reporting, and external validity. These factors were used to categorise studies as low-, moderate-, or high-risk. Meta-analyses and extensive field experiments (n > 10,000) were prioritised in the synthesis, whereas smaller pilot studies and quasi-experimental designs contributed to the qualitative analysis of mechanisms and moderating factors.

3.4 Synthesis Approach

Because the intervention designs, settings, and measurement methods varied widely, the study used narrative synthesis with quantitative summaries when needed. Effect sizes were normalised as percentage decreases in energy consumption compared to control groups. For studies that reported savings in kilowatt-hours, the study used the reported baseline consumption to calculate percentage changes. When the study tested multiple intervention arms, the study treated each comparison separately. Publication bias was evaluated by comparing published academic studies with government nudge unit implementations, as per DellaVigna and Linos (2022).

IV. EMPIRICAL FINDINGS

4.1 Effectiveness of Social Comparison Nudges

Some papers (Table 1) showed an extensive field experiments consistently show that social comparison feedback reduces electricity use in homes. (Allcott, 2011) study of Home Energy Reports sent to more than 600,000 homes found that electricity use dropped by an average of 2%. These programs usually provide families with information on how their energy use compares to that of similar neighbours through monthly billing inserts or online dashboards. Brandon et al. (2017) monitored outcomes across 38 natural field experiments for up to 5 years, noting that although immediate behavioural responses diminish over time, roughly 51.9% of energy reductions persist through the implementation of durable, energy-efficient technologies. This persistence mechanism constitutes a significant discovery for intervention design. The long-term savings come from one-time capital investments, such as LED bulbs, energy-efficient appliances, and weatherization improvements, that keep paying off even after the intervention ends. Chen and Lotti (2025) corroborated this trend in student housing contexts, where the shift to university accommodations disrupts habits, rendering residents especially amenable to conservation practices that subsequently become ingrained through alterations in living environments.

Table 1: Core Behavioral Intervention Mechanisms

Intervention Type	Key Mechanisms	Average Effect Size	Representative Studies
Social Norm Nudges	Peer comparison, descriptive & injunctive norms	1-2.9% reduction	Allcott, (2011); Schultz et al., (2007)
Informational Feedback	Real-time usage data, energy-saving tips	5-12% reduction	Fischer (2008); Prasartkaew and Phuangpornpitak (2016)
Boosts	Competence-building, decision heuristics	26.6% better than nudges	Paunov and Grüne-Yanoff (2023)
Default Options	Opt-out green energy, efficient settings	Variable (context-dependent)	Thaler and Sunstein (2008)
Competition-Based	Inter-group challenges, gamification	Up to 14% during active period	Chen and Lotti (2025)

Nonetheless, the magnitudes of effects differ significantly among implementations and measurement methodologies. Gans, Alberini, and Longo, (2011) found that smart meter feedback systems in Northern Ireland yielded statistically significant yet smaller reductions than social comparison programs, indicating that technology delivery alone cannot replicate the mechanisms of social norms. Fischer (2008) meta-analysis revealed that feedback contrasting current and past consumption yields savings of 5-12% when integrated with goal-setting and actionable recommendations, demonstrating that design specifics significantly affect results.

4.2 Political Ideology as Critical Moderator

One of the most interesting things the study found papers mentioned how political ideology affects the effectiveness of interventions (Table 2). Costa and Kahn (2013) executed a randomised field experiment within California households, revealing that energy conservation prompts were two to four times more efficacious among political liberals than conservatives. The intervention decreased consumption by about 2.9% in liberal households, but conservative households showed little response and had higher opt-out rates. Some conservative participants engaged in protest behaviour, leading to increased consumption compared to control groups. This ideological imbalance indicates more profound disparities in environmental values and openness to collective action communication. Conservatives, who usually value personal freedom and are sceptical of environmental rules, may see social comparison feedback as an example of government overreach. The discovery prompts significant questions about the political sustainability and equity implications of behavioural programs that disproportionately affect certain demographic groups. But framing effects could help. When energy conservation is framed in terms of cost savings and household autonomy instead of environmental protection, conservative responsiveness increases. This implies that the efficacy of interventions is contingent not only on behavioural mechanisms but also on their congruence with recipients' values and political identity. Utility programs might need to find different ways to send messages that work for people with different political views, rather than assuming everyone will respond to environmental messages.

Table 2: Moderating Factors and Effect Heterogeneity

Factor	Effect on Intervention	Evidence	Citation
Political Ideology	2-4x more effective with liberals vs. conservatives	Liberals: 2.9% reduction; Conservatives: minimal response	Costa and Kahn (2013)
Baseline Consumption	Risk of boomerang effect among low users	Low users increase consumption without injunctive norms	Schultz et al., (2007)
Intervention Duration	52% of effects persist post-treatment	Persistence through technology adoption	Brandon et al. (2017)
Cultural Context	Effectiveness varies cross-culturally	Limited validation outside Western contexts	Multiple studies
Institutional Setting	Habit discontinuity enhances receptivity	University housing shows higher responsiveness	Chen and Lotti (2025)

4.3 AI Personalization and Dynamic Interventions

Combining artificial intelligence enables personalisation, solving the problems that come with one-size-fits-all approaches. Recent evidence shows that AI-driven interventions offer significant benefits. Surbakti et al. (2025) found that AI-personalised green nudges increased purchase intentions among Indonesian youth by 30% through improved message relevance and optimised timing. Importantly, AI personalisation seems to lessen the negative effects that traditional interventions often have. Research comparing AI-adaptive feedback to static social comparisons indicates a 50% reduction in effectiveness erosion over prolonged durations (Surbakti et al., 2025). This superiority arises from AI's capacity to sustain relevance and novelty through continuous adaptation of messages, identification of new conservation opportunities, and prevention of habituation to repetitive stimuli. But openness is important for trust and acceptance. N.R. et al., (2025) discovered that algorithm transparency substantially influenced the correlation between personalised recommendations and behavioural intentions ($\beta = 0.45$, $p < .001$) among Generation Z consumers in emerging markets. When users understood the mechanisms behind AI-generated suggestions, publics were more likely to follow recommendations than with inscrutable "black box" systems. This finding contradicts the belief that covert nudges are more effective because society circumvent reactance; instead, it posits that transparent AI assistance fosters enduring engagement.

4.4 Boosts Versus Nudges: Comparative Long-Term Effectiveness

Recent studies have contested the dominance of nudge techniques by showcasing the superior long-term efficacy of boost methodologies. Paunov and Grüne-Yanoff (2023) 29-week comparative field study in residential settings revealed that boost interventions, which educate households on decision-making heuristics and energy literacy, led to a 26.6% reduction in electricity consumption compared to nudged groups during the prolonged observation period. This benefit became especially clear after the first few weeks, when nudge effects faded, but boost effects stayed the same or even grew.The boost method focuses on building skills rather than changing choices. Instead of using social comparison or default options to guide decisions, boosts give people tools, information, and rules to optimise their decisions independently. For energy conservation, this means teaching families to read their utility bills, identify energy-hungry appliances, understand peak-pricing structures, and develop their own ways to save energy. This part of the program helps people believe in themselves and make lasting changes to their behaviour without needing more help. But boosts require a larger initial investment in creating educational content and getting people to participate, which makes it harder for big utility programs accustomed to low-cost, automated nudge-delivery systems to adopt them. Program designers have to make a big strategic choice between immediate scalability (which favours nudges) and long-term sustainability (which favours boosts). Combining initial nudges with skill-building over time may be the best way to improve both areas.

4.5 Institutional Settings and Competition-Based Interventions

Behavioural interventions exhibit unique attributes when applied in institutional environments such as university dormitories and office buildings. Chen and Lotti (2025) investigated quasi-experimental interventions in student accommodation and found that the transition to university housing induces a habit discontinuity—a disruption of established routines—that renders individuals particularly amenable to new conservation behaviours. Strategic timing of interventions can take advantage of this time of behavioural plasticity. Interventions based on competition, which use both social comparison and intrinsic motivation, seem to work well in groups. Inter-floor or inter-building competitions in dormitories and office buildings have led to electricity savings of more than 14% during active competition periods. However, these effects usually fade quickly after the competition, which means that competitive framing mostly leads to short-term changes in behaviour rather than long-term habit formation. Adding external rewards can, in a strange way, reduce intrinsic environmental motivation by crowding out other motivations. This means that incentive structures need to be carefully tuned.

4.6 Unintended Consequences and Rebound Effects

Behavioural interventions can yield unintended consequences that may undermine conservation achievements (Table 3). The boomerang effect, well-documented in social norm interventions, occurs when low-consuming households, upon discovering their consumption is lower than that of their neighbours, increase their consumption to align with the perceived norm. Schultz et al., (2007) showed that using both descriptive feedback and injunctive norm signals (e.g., emoticons) eliminates this effect. However, if you leave out the injunctive parts, you might get the wrong results.

Moral licensing is a psychological rebound mechanism that allows people to do less environmentally friendly things in other areas after peoples do something good for the environment. People who use nudge programs to cut down on home electricity use may later drive more or buy more energy-intensive goods, thinking persons have earned environmental credits. Dorner, (2018) recorded this phenomenon in laboratory experiments, revealing that participants who effectively conserved energy in initial tasks subsequently augmented consumption in subsequent choices by 5-8%. It is also important to consider the direct rebound effects of efficiency improvements. When households install LED lights or energy-efficient appliances, the lower energy cost per unit may lead to greater use, such as leaving lights on longer or setting thermostats higher. Direct rebound effects are thought to account for about 32% of the potential savings from greater efficiency (Gillingham et al., 2009). This finding underscores that behavioural programs must tackle both the adoption of efficient technologies and the moderation of consumption intensity.

Table 3: Unintended Consequences and Limitations

Phenomenon	Description	Magnitude	Mitigation Strategy
Boomerang Effect	Low users increase consumption toward norm	Variable by design	Add injunctive norm signals (emoticons)
Direct Rebound	Efficiency gains induce higher consumption	~32% of savings offset	Combine with pricing mechanisms
Moral Licensing	One pro-environmental act permits other indulgences	Difficult to quantify	Emphasize comprehensive environmental identity
Publication Bias	Overestimated effect sizes in literature	6x inflation (8.7% vs 1.4%)	Pre-registration, null result reporting
Motivation Crowding-Out	Extrinsic rewards undermine intrinsic motivation	Context-dependent	Careful calibration of incentive structures

V. CRITICAL ANALYSIS AND LIMITATIONS

5.1 Publication Bias and Effect Size Inflation

Recent meta-analyses indicate significant publication bias within the behavioural interventions literature. DellaVigna and Linos (2022) juxtaposed effect sizes from published academic studies with outcomes from extensive government nudge unit trials, revealing that published studies indicate average impacts of 8.7%, whereas real-world implementations yield merely 1.4%—a six-fold disparity. This disparity indicates that the academic literature consistently overestimates the efficacy of interventions by selectively publishing favourable outcomes. Publication bias is caused by factors such as researchers having too much freedom in how the researchers analyse data, the tendency to stop analysing studies that do not show results, journals' preferences for new, positive findings, and the file drawer effect, where failed replications remain unpublished. This bias has significant policy ramifications, particularly regarding energy conservation. Decision-makers who use published estimates may have unrealistic ideas about how scalable and cost-effective an intervention is, which could lead to resources being used in ways that do not work as well as interference could. More openness through pre-registering studies, requiring the reporting of null results, and publishing attempts to replicate could help reduce these problems. These practices are being used by people who study behaviour, but habits have not been widely adopted in energy policy yet. Policymakers ought to recalibrate expectations by utilising conservative discount rates on published effect sizes and giving precedence to evidence derived from extensive implementations rather than minor academic trials.

5.2 Ethical Considerations: Autonomy, Manipulation, and Transparency

Nudge interventions face ongoing ethical criticisms over manipulation and paternalism. Dung (2025) contends that nudges aim to influence System 1 automatic thinking without invoking deliberative reasoning, which may compromise personal autonomy and rational self-governance. Critics assert that interventions transgress ethical boundaries when individuals are steered towards decisions through unconscious influence rather than overt persuasion, regardless of the outcomes. The infantilization concern posits that continuous nudging inhibits individuals from cultivating genuine decision-making skills. If individuals rely on external choice architecture rather than developing internal judgment, long-term autonomy is compromised despite short-term behavioural improvements. Gigerenzer (2015) expands upon this critique, contending that paternalistic interventions presuppose that behavioural economists can accurately discern individuals' genuine preferences—an epistemologically contentious presumption.

Thaler and Sunstein (2008) contends that nudges maintain freedom of choice and often enhance effective autonomy by helping individuals overcome decision biases that compromise their articulated preferences. Transparency presents a viable compromise: when interventions are publicly revealed and their mechanisms elucidated, individuals can decide whether to acquiesce to the influence. However, transparency might make things less effective if awareness of them prompts people to react. The boost approach avoids many ethical issues by focusing on enhancing competence rather than directing behaviour; however, it raises questions about the substance and impartiality of educational messaging.

Our review indicates that the transparency-effectiveness trade-off may be exaggerated. Research on AI personalisation shows that revealing how things work can actually build trust and keep people interested for a long time (N.R. et al., 2025) This finding supports the design of interventions that are both effective and ethically justifiable, facilitated by transparent implementation and opt-out options for individuals who oppose being nudged.

5.3 Scalability and Cross-Cultural Validity

The majority of behavioural intervention research has been undertaken in Western developed economies, notably the United States, the United Kingdom, and European countries. This concentration in a single area raises questions about external validity and cross-cultural scalability. For instance, the effectiveness of social norms may differ between individualistic and collectivist cultures, societies with high and low power distance, and contexts characterised by varying levels of environmental awareness. New studies from developing economies show both similarities and differences. N.R. et al., (2025) found that AI-driven green nudges significantly influenced purchase intentions among Generation Z consumers in India, suggesting that digital-native populations may exhibit similar responses across diverse cultural contexts. Surbakti et al., (2025) demonstrated that message framing focused on family welfare surpassed individual benefit frames in Indonesian contexts, underscoring the necessity for cultural adaptation. The lack of infrastructure in developing economies also makes it harder to carry out interventions. Smart meters, real-time feedback systems, and digital platforms all depend on technology that may not be available in rural or low-income areas. To ensure everyone receives the same treatment, it may be necessary to use both digital nudges for connected urban populations and community-based interventions in areas with insufficient support. The field urgently requires systematic cross-cultural replication studies and the development of culturally-adapted interventions.

VI. DISCUSSION AND POLICY IMPLICATIONS

6.1 Summary of Important Findings

Our systematic review uncovers several essential insights for behavioural energy policy. First, social comparison nudges have been shown to consistently reduce residential electricity use by 1.5–2.9%, and about half of these reductions persist even after people start using new technology. However, effectiveness varies greatly depending on political beliefs (2–4 times higher for liberals), baseline consumption levels (low users are at risk of boomeranging), and the quality of implementation (combining descriptive and injunctive norms is necessary). Second, AI-driven personalisation is a big step forward from static interventions. It can reduce decay effects by up to 50% with adaptive messaging and the right timing. But, for trust and long-term engagement, transparency is key. This goes against the idea that covert nudges are the best way to get people to do something. The evidence indicates that transparent AI assistance may surpass covert manipulation by fostering collaborative relationships with users.

Third, interventions that improve decision-making skills are 26.6% more effective in the long term than traditional nudges, but involvements cost more up front. This finding supports hybrid approaches that combine short-term nudges with long-term skill-building to achieve the best results for both short-term behaviour change and long-term capability development. Fourth, unintended consequences such as boomerang effects, moral licensing, and direct rebound are problems that will always be present and require careful planning and monitoring of interventions. The evidence indicates that these risks can be alleviated by integrating interventions (descriptive + injunctive norms), prioritising competence over compliance (boosts over nudges), and tackling both technology adoption and usage intensity.

6.2 Integration with Urban Energy Planning

Behavioural interventions cannot succeed independently; the involvements must be incorporated into comprehensive urban energy planning. Indonesia's anticipated escalation in electricity demand—from 25.3 GW in 2010 to 77.3 GW by 2030 in business-as-usual scenarios—demonstrates the significant infrastructure challenges confronting urbanising countries (Apergis and Payne, 2014). Behavioural programs are part of a larger plan to reduce damage, but the plan can not replace standards for efficiency, renewable energy use, and land-use changes. The relationship between behavioural interventions and technology is very important. Best-available-technology scenarios indicate that Indonesia's electricity demand in 2030 could be 22.9 GW lower than expected if appliances, especially air conditioners, are required to meet efficiency standards. Behavioural nudges that accelerate the adoption of efficient technologies leverage the connections between how people make decisions and how new technologies are developed. But these synergies depend on the market being available and affordable, and on people knowing about them. This means that policy action needs to be coordinated beyond just behavioural interventions.

Urban planning characteristics fundamentally influence energy consumption patterns through the built environment's attributes. High-density, mixed-use development with good public transportation reduces the energy needed for transportation and enables the use of district heating and cooling systems, which make buildings more efficient (Taylor et al., 2008). In this context, behavioural interventions could include nudges to switch modes of transportation, feedback on how buildings are used, and community-level competitions to save energy. The spatial aspect of energy planning—frequently overlooked in behavioural studies—constitutes a vital frontier for comprehensive methodologies.

6.3 Useful Tips for Designing Programs

Based on the evidence the study have gathered (Table 4), the study suggest a few practical ideas for energy-saving programs: (1) Segmented Intervention Design: Create tailored strategies based on political affiliation, initial consumption levels, and demographic traits instead of uniform programs. Cost-savings framing may be more effective than environmental messaging. Target users who use a lot of resources for social comparison nudges, and give low users positive feedback to stop the boomerang effect. (2) Mix Nudges with Boosts: Use social comparison to steer behaviour right away, and add educational elements that build skills to create both short-term behaviour change and long-term skill development. This mixed-method approach makes the most of nudges' ability to grow and extends their longevity, (3) Use Technology Adoption: Focus interventions on getting people to make long-term investments in energy-efficient appliances, lighting, and building improvements that will save money even after the interventions are over. Give people useful advice and eliminate barriers to buying and installing energy-efficient technologies, (4) Use Transparent AI Personalisation: Use AI-driven adaptive interventions with clear explanations of how evident work to build trust while still being effective. Let users see and change how algorithms make suggestions. Always improve the timing and messaging based on how each person responds, . (5) Deal with Rebound Effects: Keep an eye out for moral licensing by keeping track of consumption in a variety of areas, not just the ones you want to change. Put together messages about efficiency with a framing that focuses on reducing consumption completely rather than just improving efficiency, (6) Get rid of sludge: Audit programs for unnecessary administrative burden, complexity, and friction that keep people from participating even when there are good reasons to do so. Make it easier to sign up, automate steps when possible, and provide clear, step-by-step instructions (Grieder, Kistler, and Schmitz 2024), and (7) Long-Term Monitoring: Keep an eye on effects that last longer than normal intervention periods to tell the difference between short-term behaviour changes and long-term habit formation and technology adoption. Utilise prolonged follow-up data to enhance interventions and discern factors that facilitate enduring conservation.

Table 4: Key Studies by Research Design

Study	Design	Sample Size	Setting	Key Finding
Allcott (2011)	Randomized field experiment	600,000 households	Residential (US)	2% average electricity reduction from HERs
Costa and Kahn (2013)	Randomized field experiment	Thousands of households	Residential (California)	Ideology moderates effectiveness (2-4x difference)
Paunov and Grüne-Yanoff (2023)	Comparative field test	29-week observation	Residential	Boosts outperform nudges by 26.6%
Schultz et al., (2007)	Field experiment	290 households	Residential	Injunctive norms eliminate boomerang effect
DellaVigna & Linos (2022)	Meta-analysis of RCTs	Multiple large-scale trials	Various	Publication bias: 8.7% vs 1.4% real-world effects

6.4 Research Gaps and Future Directions

Our review highlights several significant research deficiencies that necessitate focus. First, long-term persistence studies lasting 2–3 years or more remain rare. This makes it hard to figure out which parts of an intervention cause changes that last and which ones only last for a short time. Second, there is an urgent need for cross-cultural replication and adaptation research, as the majority of the evidence originates from developed Western economies. Third, the study need to look into how AI personalisation reduces decay effects. Is it novelty maintenance, optimal timing, relevance matching, or something else? Fourth, the interactions between behavioural interventions and technological transitions (smart grids, distributed generation, electric vehicles) constitute an inadequately examined domain of considerable policy significance. Fifth, the equity effects of behavioural programs—who gains, who pays, and whether interventions make it easier or harder for people to access energy—need to be examined systematically. Sixth, the study need to develop and test integration frameworks that link behavioural interventions with urban planning, building codes, and infrastructure policy. Lastly, it is important to make methodological improvements. To address publication bias, systematic null result reporting, large-scale replication efforts, and the open sharing of raw data, the field would benefit from pre-registration of studies. Working together, academic researchers, utility providers, and policy implementers can run large-scale experiments to determine whether an intervention can be scaled up and is effective in the long term.

VII. CONCLUSION

Behavioural science interventions are a useful but limited part of a comprehensive plan to save energy. Social comparison nudges consistently reduce residential electricity use, and about half of the reductions last even after people adopt new technology. However, substantial heterogeneity in treatment effects—especially concerning political ideologies, baseline consumption levels, and implementation quality—undermines assumptions regarding universal applicability. AI-driven personalisation is a big step forward from static interventions because it reduces decay effects and keeps messages relevant by adapting to the user. Transparency is necessary for building trust and keeping people interested over time. This means that open AI help may work better than hidden manipulation. Interventions that enhance decision-making competence rather than manipulating choice architecture yield superior long-term outcomes while addressing ethical considerations, though contributions require a greater initial investment than automated nudges.

A critical evaluation shows important limits that must shape realistic policy expectations. Publication bias has probably inflated reported effect sizes by a factor of 6, leading to unrealistic expectations about how well programs will work. There are still ethical concerns about manipulation and autonomy, especially when it comes to nudges that target automatic thinking processes. Rebound effects such as moral licensing and direct consumption increases necessitate vigilant oversight and intervention. Behavioural interventions cannot replace fundamental policy reforms that tackle pricing, regulation, infrastructure, and technology standards. The synthesis suggests that integrated approaches that combine carefully designed nudges to change behaviour right away with educational boosts to build skills over time, all made possible by transparent AI personalisation that adapts interventions to each person's needs while still giving them control. These kinds of hybrid programs should be part of broader city energy plans that consider how buildings are designed and how technology evolves, and that ensure everyone has fair access to efficient infrastructure.

As global energy demands continue to rise, especially in developing countries that are quickly becoming urbanized and seeing huge increases in energy use, the question is not whether behavioral interventions can solve energy problems on their own, but how intrusions can best work with new technologies, changes to policies, and investments in infrastructure to help stabilize the climate. The evidence compiled in this review offers practical recommendations for policymakers, utility providers, urban planners, and researchers aiming to enhance the impact of behavioural strategies on this crucial collective issue.

REFERENCES

1) Allcott, Hunt. 2011. "Social Norms and Energy Conservation." *Journal of Public Economics* 95(9–10): 1082–95.
2) Apergis, Nicholas, and James Payne. 2014. "Renewable Energy, Output, CO2 Emissions, and Fossil Fuel Prices in Central America: Evidence from a Nonlinear Panel Smooth Transition Vector Error Correction Model." *Energy Economics* 42.
3) Brandon, Alec et al. 2017. *Do The Effects of Social Nudges Persist? Theory and Evidence from 38 Natural Field Experiments*.

https://ideas.repec.org/p/exc/wpaper/2017-04.html.

4) Chen, Youjing, and Lorenzo Lotti. 2025. “Evaluating the Effectiveness of Behavioural Nudges in Reducing Energy Consumption in Student Accommodations: A Quasi-Experimental Approach.”
5) Costa, Dora L., and Matthew E. Kahn. 2013. “Energy Conservation ‘Nudges’ and Environmentalist Ideology: Evidence from a Randomized Residential Electricity Field Experiment.” *Journal of the European Economic Association* 11(3): 680–702.
6) DellaVigna, Stefano, and Elizabeth Linos. 2022. “RCTs to Scale: Comprehensive Evidence From Two Nudge Units.” *Econometrica* 90(1): 81–116. https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA18709.
7) Dorner, Zack. 2018. “A Behavioural Rebound Effect: Results from a Laboratory Experiment.”
8) Dung, Leonard. 2025. “The Effectiveness of Nudging and Its Ethical Implications.” *Bioethics* 39.
9) Fischer, Corinna. 2008. 1 Energy Efficiency *Feedback on Household Electricity Consumption: A Tool for Saving Energy?*
10) Gans, Will, Anna Alberini, and Alberto Longo. 2011. “Smart Meter Devices and The Effect of Feedback on Residential Electricity Consumption: Evidence from a Natural Experiment in Northern Ireland.” *Energy Economics* 36.
11) Gigerenzer, Gerd. 2015. “On the Supposed Evidence for Libertarian Paternalism.” *Review of Philosophy and Psychology* 6.
12) Gillingham, Kenneth, Richard G Newell, and Karen Palmer. 2009. “Energy Efficiency Economics and Policy.” *Annual Review of Resource Economics* 1(1): 597–620. https://ideas.repec.org/a/anr/reseco/v1y2009p597-620.html.
13) Grieder, Manuel, Deborah Kistler, and Jan Schmitz. 2024. “How Sludge Impairs the Effectiveness of Policy Programs: A Field Experiment with SMEs.” *Behavioural Public Policy* 9: 1–9.
14) Heukelom, Floris. 2015. “Prospect Theory.” In *International Encyclopedia of the Social & Behavioral Sciences: Second Edition*,.
15) Kahneman, Daniel. 2003. “Maps of Bounded Rationality: Psychology for Behavioral Economics.” *American Economic Review* 93(5): 1449–75.
16) N.R., Ravikiran et al. 2025. “Sustainability and Consumer Behaviour: The Role of AI-Driven Green Nudges in Shaping Gen Z’s Sustainable Purchase Intentions in Emerging Markets.” *International Journal For Multidisciplinary Research* 7.
17) Paunov, Yavor, and Till Grüne-Yanoff. 2023. “Boosting vs. Nudging Sustainable Energy Consumption: A Long-Term Comparative Field Test in a Residential Context.” *Behavioural Public Policy* 10: 1–26.
18) Prasartkaew, Boonrit, and N Phuangpornpitak. 2016. “Feedback on Energy Consumption. A Review for DEFRA of the Literature on Metering, Billing and Direct Displays.” *IEET - International Electrical Engineering Transactions, Vol. 2 No. 2 (3)* 2: 76–82.
19) Richard H. Thaler, and Cass R. Sunstein. 2003. “Libertarian Paternalism.” *Harvard Business Review*.
20) Schultz, P Wesley et al. 2007. “The Constructive , Destructive , and Reconstructive Power of Social Norms.” *Association for Psychological Science* 18(5): 429–34.
21) Surbakti, Feliks et al. 2025. “How AI-Driven Personalization Shapes Green Purchasing Behavior Among Youth in Java Island.” *Sustainability* 17: 9600.
22) Taylor, Robert et al. 2008. *Financing Energy Efficiency: Lessons from Brazil, China, India and Beyond*.
23) Thaler, Richard H., and Cass R. Sunstein. 2008. *Nudge - Improving Decisions About Health, Wealth, and Happiness*. Michigan, United States of America.
24) Tversky, Amos, Daniel Kahneman, New Series, and No Sep. 2007. “Judgement under Uncertainty.” 185(4157): 1–10. papers3://publication/uuid/0DE58219-33AE-4996-B19D-B42E87C4E250.