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Mind Over Market: Behavioural Determinants of Renewable Energy Investment Adoption in India

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ABSTRACT

This study investigates the psychological and behavioural drivers affecting the adoption of renewable energy investments in India, a rapidly developing nation with urgent energy transition targets. Despite technological and financial incentives, adoption remains minimal, necessitating an exploration of the cognitive and dispositional factors influencing human investment intentions. A structured questionnaire was distributed to 416 urban participants in Tier-I and Tier-II Indian cities. Metrics including cognitive biases, behavioural inertia, gain/loss framing, personality factors, and green behavioural spillover were assessed utilising validated scales. The data were analysed using Structural Equation Modelling (SEM) in IBM AMOS, which facilitated the evaluation of both the measurement models for understanding the behavioural determinants of renewable energy investment adoption. The findings indicated that all five behavioural characteristics had a substantial impact on plans to invest in renewable energy. Green behavioural spillover revealed as the most significant predictor, succeeded by cognitive biases and personality characteristics. The model explained 67% of the variance in investment intentions, underscoring the significance of behavioural factors in renewable energy transitions. This paper proposes an innovative behavioural framework specific to India, addressing deficiencies in current techno-economic adoption models. The results provide practical guidance for developing behavioural treatments, focused awareness campaigns, and policy instruments that correspond with psychological motivators, so improving the efficacy of renewable energy adoption methods.

Keywords: Renewable Energy Adoption; Behavioural Economics; Cognitive Bias; Prospect Theory; Personality Traits; Green Spillover; India
JEL Classifications: D03, E22, Q29

1. INTRODUCTION

In the context of global climate urgency, the transition to low-carbon energy systems has emerged as a paramount concern for both policy and academia (IPCC, 2021). Notwithstanding progress in clean energy technology and favourable legislative frameworks, the adoption of renewable energy at the household and individual investment levels remains alarmingly inadequate, especially in rising economies like India (Saxena et al., 2021; REN21, 2023). Although macro-level obstacles like grid infrastructure, investment risk, and regulatory uncertainty have been extensively examined (IRENA, 2022; Zhang et al., 2022), there is an increasing acknowledgement that behavioural factors frequently neglected are pivotal in influencing investment choices (Sovacool and Griffiths, 2020; Li et al., 2022).

Recent studies indicate that solely economic models of energy adoption fail to encompass the psychosocial dynamics influencing consumer and investment behaviour effectively (Wilson and Dowlatabadi, 2007; Frederiks et al., 2015). Cognitive biases, including optimism bias, availability heuristics, and confirmation bias, skew risk perceptions and hinder the adoption of energy technologies (Gillingham and Palmer, 2014; Rai and Henry, 2016). The status quo bias causes individuals to favour current technology despite the availability of superior alternatives (Sunstein, 2013; Thøgersen and Crompton, 2009). Similarly, loss aversion, as articulated in Prospect Theory (Kahneman and Tversky, 1979), leads individuals to excessively dread immediate expenses compared to prospective gains, obstructing long-term sustainable investment (De Groot and Schuitema, 2012; Jansson and Dorrepaal, 2015).

In India, behavioural barrier to solar energy persists significantly despite robust regulatory support and subsidies (Sharma et al., 2021). Research indicates that socio-cognitive elements, including risk perception, mental accounting, and social influence, substantially affect decisions about rooftop solar installation (Pillai and Banerjee, 2021; Khosla et al., 2020). Moreover, behavioural inertia, defined as the reluctance to modify purchasing habits, continues to exist despite consumers' articulated environmental concerns or awareness (Verplanken and Wood, 2006; Gifford, 2011). This inertia frequently results in "attitude-behavior gaps," when purpose fails to convert into action (Kollmuss and Agyeman, 2002; Truelove et al., 2014).

Moreover, individual personality traits have emerged as important indicators of sustainable conduct. Researchers have found that acceptance of renewable energy and environmental engagement are positively connected with conscientiousness and openness to experience, two important aspects of the Big Five personality model (Hirsh, 2010; Milfont and Sibley, 2012; Markowitz et al., 2012). Individuals with high openness demonstrate a heightened propensity to investigate innovative technologies, including solar microgrids and electric vehicle-integrated home systems (Brick and Lewis, 2016; Wolske et al., 2020; Asati et al., 2024). Conscientious individuals are more inclined to make long-term, responsible financial decisions that accord with ecological ideals (Soutar and Sweeney, 2003; Lades, 2022).

Another growing perspective is the role of green behavioural spillovers—the propensity for one pro-environmental activity to promote further actions (Truelove et al., 2014; Nilsson et al., 2017). Research suggests that preliminary behaviours such as energy conservation or recycling might foster a self-concept as a "eco-conscious individual," subsequently enhancing willingness to invest in renewable energy technologies (Lauren et al., 2016; Maki et al., 2019). Such spillovers operate through psychological mechanisms such as moral licensing, environmental self-identity, and behavioural consistency (Fanghella et al., 2019; van der Werff et al., 2013).

Despite these enticing opportunities, there is a lack of extensive research examining the combined impact of these behavioural variables on renewable energy investment, especially in culturally diverse and risk-averse contexts like India. Many empirical models consider these factors alone, neglecting to investigate their interaction effects or mediation routes (Li et al., 2022; Sovacool et al., 2021). Moreover, limited research considers the Indian socio-psychological setting, wherein collective efficacy, familial decision-making, and long-term financial planning behaviours markedly diverge from Western models (Shukla et al., 2019; Abrahamse and Steg, 2013).

This research addresses this critical gap by developing and testing an empirically grounded behavioural model that incorporates five dimensions: cognitive biases, gain-loss framing (prospect theory), behavioural inertia, personality traits (openness, conscientiousness), and green spillovers. By examining these variables within an Indian urban context, the study contributes to the emerging intersection of behavioural energy policy and environmental psychology.

In light of the aforementioned context, for advance understanding in this unexplored area this study endeavor to investigate the following research questions:

RQ1: How do cognitive biases and gain-loss framing affect individual decisions to invest in renewable energy technologies in the Indian context?

RQ2: To what extent does behavioural inertia, shaped by habitual energy use, hinder renewable energy transitions at the individual level?

RQ3: How do personality traits and green behavioural spillovers interact to influence renewable energy investment intentions?

This study seeks to address those questions by utilising a structural equation modelling approach with primary survey data from urban Indian families. The subsequent portions of this study are structured as follows: Section 2 delineates the pertinent literature and theoretical framework; Section 3 elaborates on the research design and methodologies; Section 4 articulates the empirical results; and Section 5 and 6 closes with significant implications, limitations, and avenues for further research.

2. LITERATURE REVIEW

2.1. Theoretical Underpinning

The suggested behavioural framework for comprehending the adoption of renewable energy investments incorporates various psychological and behavioural theories. It underscores the significance of cognitive biases, behavioural inertia, gain/loss framing (Prospect Theory), personality traits (notably openness to experience and conscientiousness), and green behavioural spillovers. These constructs are based on significant theoretical frameworks from behavioural economics and environmental psychology.

Prospect Theory (Kahneman and Tversky, 1979) provides a fundamental framework for interpreting investment behaviour in the context of risk. It posits that individuals see outcomes as gains or losses in relation to a reference point rather than the ultimate assets. Losses exert a greater psychological influence than similar gains, a phenomenon known as loss aversion. This has significant ramifications in energy investment, as consumers disproportionately apprehend initial installation expenses despite the long-term financial advantages (De Groot and Schuitema, 2012; DellaVigna, 2009). Research conducted by Klein and Deissenroth (2017) and He et al. (2022) demonstrates that loss-framed messaging are markedly more effective than gain-framed messages in facilitating the adoption of green technologies. This framing effect highlights the applicability of Prospect Theory in policy communication.

Cognitive Bias Theory elucidates departures from rational decision-making resulting from cognitive heuristics. Status quo bias in renewable energy contexts causes individuals to favour familiar fossil-fuel-based energy systems over cleaner alternatives (Samuelson and Zeckhauser, 1988). Optimism bias leads individuals to underestimate climate dangers or overrate their own immunity to energy disruptions (Weinstein, 1980), whereas confirmation bias results in selective engagement with information that reinforces existing ideas (Nickerson, 1998). These biases together impede investment, even among environmentally conscious individuals (Frederiks et al., 2015; Gillingham and Palmer, 2014). Behaviourally informed treatments, including nudges and default alternatives, have demonstrated efficacy in rectifying these distortions (Sunstein, 2013; Li et al., 2022).

Habit Theory and Behavioural Inertia elucidate the persistence of conventional energy consumption behaviours. Habitual behaviours exhibit resistance to change, particularly when enacted within consistent situations (Wood and Neal, 2007). Behavioural inertia in energy choices suggests that customers may persist in utilising traditional sources notwithstanding the economic advantages of renewable alternatives (Verplanken and Wood, 2006; Thøgersen, 2012). Wilson and Dowlatabadi (2007) contend that only disruptive actions or policy triggers can interrupt these behavioural cycles. Habit theory corresponds with research indicating a disparity between favourable environmental attitudes and actual behaviours, known as the attitude-behavior gap (Kollmuss and Agyeman, 2002).

The Big Five Personality Traits Theory offers a dispositional rationale for behavioural variability in energy-related choices. Individuals exhibiting elevated levels of openness to experience demonstrate more intellectual curiosity and a propensity to embrace innovative energy solutions such as solar or wind technologies (Hirsh, 2010; Gifford and Nilsson, 2014). Conscientiousness, defined by discipline and accountability, is associated with increased environmental awareness and long-term financial strategy (Markowitz et al., 2012; Soutar and Sweeney, 2003). Research conducted by Milfont and Sibley (2012) and Busic-Sontic and Fuerst (2017) substantiates that these characteristics are strong indicators of pro-environmental investment behaviour across diverse cultural contexts.

The Green Behavioural Spillover Theory asserts that engaging in one sustainable action enhances the probability of following pro-environmental behaviours. These spillovers are facilitated by identity consistency, societal norms, and felt moral obligation (Thøgersen and Ölander, 2003; Truelove et al., 2014). For instance, individuals who regularly recycle or utilise public transportation may be more predisposed to invest in rooftop solar systems (Lauren et al., 2016; Maki et al., 2019). Positive spillover is frequently enhanced in collectivist cultures by observable behaviour modelling and peer reinforcement (Nash et al., 2017; Whitmarsh and O'Neill, 2010). Although green spillover may generate rebound effects under specific circumstances (Fanghella et al., 2019), it continues to serve as a significant framework for amplifying sustainable activities.

Collectively, these theoretical viewpoints constitute a multi-dimensional behavioural model that rectifies deficiencies in conventional techno-economic frameworks. The model offers a comprehensive explanation of renewable energy investment behaviour by integrating cognitive, emotional, habitual, and dispositional characteristics, particularly within intricate socio-cultural situations such as India.

2.2. Hypotheses and the Conceptual Framework

The theoretical underpinnings discussed above are expanded upon in this section to formulate particular hypotheses, each of which is based on a behavioural construct.

2.2.1. Cognitive biases and renewable energy investments adoption

Cognitive biases affect individuals' interpretation of information, assessment of options, and investment decisions, frequently deviating from rational choice models. Status quo bias in the renewable energy sector results in a preference for current energy sources, despite the availability of cleaner alternatives (Samuelson and Zeckhauser, 1988; Wilson and Dowlatabadi, 2007). Optimism bias leads individuals to underestimate climate dangers or overestimate the stability of fossil fuel costs (Weinstein, 1980), whereas confirmation bias results in the selective acceptance of information that reinforces existing assumptions about energy systems (Nickerson, 1998).

Frederiks et al. (2015) established that these biases diminish response to sustainability initiatives. Gillingham and Palmer (2014) contend that even economically viable energy efficiency methods encounter opposition due to psychological misconceptions. Sunstein (2013) posits that nudges, such as automatic enrolment in green tariffs, can mitigate these biases. Rai and Henry (2016) similarly discovered that cognitive biases greatly influenced the adoption of rooftop solar among Indian consumers. Therefore, we hypothesize:

H_1: Cognitive biases significantly influence renewable energy investment adoption.

2.2.2. Behavioural inertia and renewable energy investments adoption

Behavioural inertia denotes the reluctance to alter established behaviours, despite the availability of more advantageous alternatives. Verplanken and Wood (2006) contend that habitual energy behaviours in consistent circumstances become automatic and impervious to information or incentives. In India, despite increasing understanding of the advantages of solar energy, adoption remains limited due to inertia rooted in grid dependency, cost concerns, and implementation challenges (Sharma et al., 2021).

Thøgersen (2012) contends that this inertia frequently leads to the 'value-action gap,' wherein customers articulate environmentally friendly sentiments without exhibiting matching behavioural modifications. Kollmuss and Agyeman (2002) assert that entrenched habits and contextual signals frequently supersede pro-environmental objectives. Stern et al. (2016) further emphasise that behavioural lock-in is frequently exacerbated by inadequate infrastructure, insufficient social proof, and the lack of peer modelling. Thus, we propose:

H_2: Behavioural inertia negatively influences renewable energy investment adoption.

2.2.3. Gain/loss framing and renewable energy investment adoption

Prospect Theory, formulated by Kahneman and Tversky (1979), asserts that humans are more influenced by possible losses than by similar rewards, cognitive phenomena termed loss aversion. In the realm of renewable energy, consumers exhibit a more pronounced reaction to loss-framed messaging (e.g., "you forfeit ₹5,000 annually by not utilising solar panels") compared to gain-framed messages (De Groot and Schuitema, 2012; Klein and Deissenroth, 2017). Presenting energy savings as mitigated losses enhances perceived urgency and behavioural significance.

Empirical evidence indicates that loss framing substantially enhances adoption rates for solar technologies and other clean innovations (He et al., 2022). DellaVigna (2009) contends that emotional significance and cognitive heuristics influence decision-making, even within economically rational contexts. Wolske et al. (2020) and Frederiks et al. (2015) demonstrate that communication tactics utilising these cognitive processes are superior to mere technical or financial explanations.

Moreover, Li et al. (2022) underscore the necessity of customising messaging to cognitive biases to enhance policy efficacy. Consequently, incorporating loss-framed messaging into renewable energy initiatives helps close the attitude–behaviour gap and encourage customers to make sustainable investments. Therefore, we propose:

H_3: Gain/loss framing significantly influences renewable energy investment adoption.

2.2.4. Personality traits and renewable energy investment adoption

Personality factors significantly influence human reactions to sustainability activities and the adoption of green technology. The Big Five Personality model, particularly the traits of openness to experience and conscientiousness, has been consistently associated with pro-environmental behaviour (Hirsh, 2010; Gifford and Nilsson, 2014). Individuals with elevated openness scores are often imaginative, intellectually inquisitive, and amenable to innovation, thereby exhibiting a greater propensity to explore renewable technologies such as rooftop solar systems, wind micro-turbines, or electric vehicle-integrated systems (Wolske et al., 2020; Brick and Lewis, 2016).

Conscientious individuals, characterised by future orientation, responsibility, and goal-directed behaviour, are more inclined to plan and act in alignment with long-term ecological values (Markowitz et al., 2012; Soutar and Sweeney, 2003). Milfont and Sibley (2012) identified a robust association between these qualities and energy-conserving behaviours in New Zealand, a pattern echoed by Busic-Sontic and Fuerst (2017) throughout Europe. Lades (2022) and Whitmarsh and O'Neill (2010) assert that personality-driven self-regulation enhances the consistency between intention and behaviour in environmental decision-making (Khare et al., 2023).

In summary, personality traits act as consistent psychological indicators of renewable energy investment, particularly when supported by values-oriented interventions and tailored sustainability communication strategies. Therefore, we suggest:

H_4: Personality traits (openness and conscientiousness) positively influence renewable energy investment adoption.

2.2.5. Green behavioural spillover and renewable energy investment adoption

Green behavioural spillover refers to the phenomenon where one pro-environmental action increases the likelihood of engaging in additional sustainable behaviours. This effect is grounded in psychological mechanisms such as identity consistency, internalized social norms, and the desire to avoid cognitive dissonance (Truelove et al., 2014; Dolan and Galizzi, 2015). When individuals begin recycling, reducing single-use plastics, or adopting energy-saving practices, they may start viewing themselves as environmentally responsible citizens—reinforcing their environmental self-identity (van der Werff et al., 2013). This identity in turn motivates further eco-friendly behaviours, including renewable energy investment.

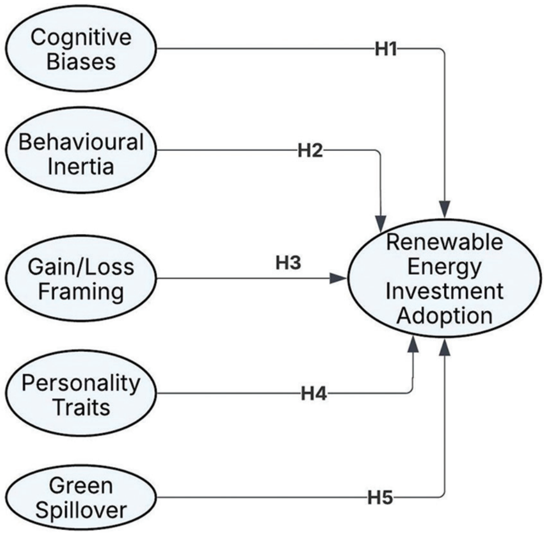
Thøgersen and Ölander (2003) argue that low-effort sustainable actions, if made habitual, serve as behavioural anchors for larger lifestyle changes. Lauren et al. (2016) found that Australians who self-identified as environmentalists were significantly more likely to install solar systems. Maki et al. (2019) explain that spillover is mediated by perceived behavioural consistency and moral licensing. In collectivist cultures like India, Nash et al. (2017) highlight the impact of social visibility and peer modelling in amplifying spillover.

Community-driven interventions, such as neighbourhood campaigns or public eco-awards, can strengthen this effect (Whitmarsh and O'Neill, 2010). Thus, green behavioural spillovers offer a scalable, psychologically grounded pathway for accelerating renewable energy transitions (Mishra et al., 2024). Therefore:

H_5: Green behavioural spillovers positively influence renewable energy investment adoption.

The above hypotheses are visually represented in the proposed conceptual framework (Figure 1), which connects behavioural antecedents to renewable investment intention.

Figure 1: Proposed conceptual model for the study



3. METHODOLOGY

3.1. Research Design

The authors used a quantitative cross-sectional design to investigate the behavioural factors swaying adoption of renewable energy investments. The research rationale was provided based on behavioural economics, cognitive psychology, and the environmental behaviour theory, with the research being designed following the deductive approach that implies using the existing behavioural models to derive theoretical constructs and hypotheses. Considering the fact that there are several latent variables and that the nature of relationships is complex, Structural Equation Modelling (SEM) with IBM AMOS 26.0 was considered appropriate. The Covariance-Based SEM (CB-SEM) was chosen due to the ability to test the measurement and structural part of the model at the same time and the ascertained provision of a thorough framework of construct validity, reliability, and general model fit (Kline, 2015; Hair et al., 2022). In contrast to a variance-based model like PLS-SEM, AMOS permits the offer of a theory-based model that is under the assumption that the variables are multivariate normally distributed, and the comprehensive fit indices could be used to assess the appropriate model specification. This research approach allowed a profound examination of the interconnection between the behavioural constructs and their predictive effects on the intentions of investing in renewable energy.

3.2. Sampling

The study focused on urban dwellers in Tier I and Tier-II Indian cities and I who either used or knew about renewable energy options including rooftop solar, green bonds, or sustainable investment portfolios. Purposive sampling was used to make sure that respondents who were knowledgeable about renewable energy were included. In order to infer on sample adequacy of Structural Equation Modelling (SEM) given AMOS, statistical power analysis was tested based on recommendations given by Hair et al. (2022) taking into consideration the complexity of the model as well as the number of latent variables. Then, statistically robust results were achieved because 416 valid responses exceed the recommended minimum of large, multi-construct SEM models. The sampling arrangement was made in a way that made it heterogeneous in the main demographic characteristics, that is their ages, gender, level of education, income and previous investment experience to improve the external validity or generalizability of the results into the context of the Indian urban energy investment saga.

3.3. Instruments Used

The research instrument was a structured questionnaire made up of validated items drawn from established literature. All constructs were operationalized as reflective indicators, and responses were captured on a 5-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). Cognitive Biases were measured using four items adapted from Samuelson and Zeckhauser (1988) and DellaVigna (2009), capturing dimensions such as status quo bias, optimism bias, and confirmation bias. Behavioural Inertia was assessed through five items derived from Verplanken and Wood (2006), reflecting individuals' resistance to change in routine decision-making. Four items based on Prospect Theory (Kahneman and Tversky, 1979) were used to measure gain/loss framing sensitivity. Personality traits, specifically conscientiousness and openness to experience—two dimensions of the Big Five framework—were measured using four items adapted from Hirsh (2010) and Markowitz et al. (2012). Green Behavioural Spillover was operationalized with three items from Truelove et al. (2014), examining the influence of prior sustainable behaviours on current environmental decision-making. The dependent variable, Renewable Energy Investment Adoption, was measured using six items drawn from Frederiks et al. (2015) and Sovacool et al. (2020), assessing behavioural intention, information-seeking behaviour, and perceived investment benefits (Singh et al., 2023). The instrument underwent expert validation and was piloted with 25 respondents to assess clarity and contextual relevance. Measurement reliability and validity were examined using AMOS through confirmatory factor analysis (CFA), evaluating factor loadings, Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE), following the standards outlined by Fornell and Larcker (1981).

3.4. Data Collection

The survey was conducted from January to March 2025 using online and offline methods. The survey was set up on Google Forms and shared using email invitations, social media and workplace connections. At the same time, printed questionnaires were given out in various community centers, institutions, residential colonies and places of work in Ahmedabad, Pune and Jaipur. A participant information sheet and an informed consent form were part of every survey to help ensure participation was ethical and voluntary. To ensure the quality of our data, we applied screening questions to decide who would participate. After cleaning and validating the data, we left with 416 valid responses to analyse.

The analysis of the data was performed with the help of IBM AMOS 26.0 through the measurement model evaluation and structural model. Confirmation factor analysis (CFA) was used in assessing reliability, convergent validity, and discriminant validity of the constructs. To scale the structural model, maximum likelihood estimation and bootstrap estimation (5 000 resamples) were used to compare the level of significance of path coefficients, explanatory power (R 2) and predictive relevance (Q 2) of a model.

4. RESULTS

4.1. Demographic Analysis

Among the 416 respondents, 54.8% identified as male and 45.2% as female. Most of the participants were between the ages of 26 and 45, totalling 63.8 percent across all three groups. Forty-six percent had completed postgraduate courses and another 39% held bachelor's degrees, indicating that the respondents are knowledgeable. The most common types of employment were salaried professions (41.8%), then students (23.6%), entrepreneurs (18.8%) and finally retired people (15.8%). These figures suggest that 35.3% of respondents earned between INR 50,000 and INR 1, 00,000 each month, while 28.4% earned less than INR 50,000 and 24.1% earned more than INR 1, 00,000. A large number of respondents, about two-thirds, revealed prior contact with renewable energy, confirming the sample's contextual significance for the study (Raghuwanshi et al., 2024).

4.2. Reliability and Validity Analysis

The study evaluated the measurement model by conducting both reliability and validity tests based on the standard criteria outlined by Hair et al. (2022) for structural equation modelling. It demonstrated the scale's reliability through standardized component loadings and Composite Reliability (CR). To establish validity, we calculated the Average Variance Extracted (AVE) and compared inter-construct correlations to assess discriminant validity.

The table reveals that the standardized item loadings (SRWs) for every observed variable are higher than the advised threshold of 0.70 (Fornell and Larcker, 1981), with results ranging from 0.63 to 0.99. This demonstrates that each construct and its indicators are highly related. That is, the loadings for REIA were between 0.84 and 0.94, suggesting good internal consistency.

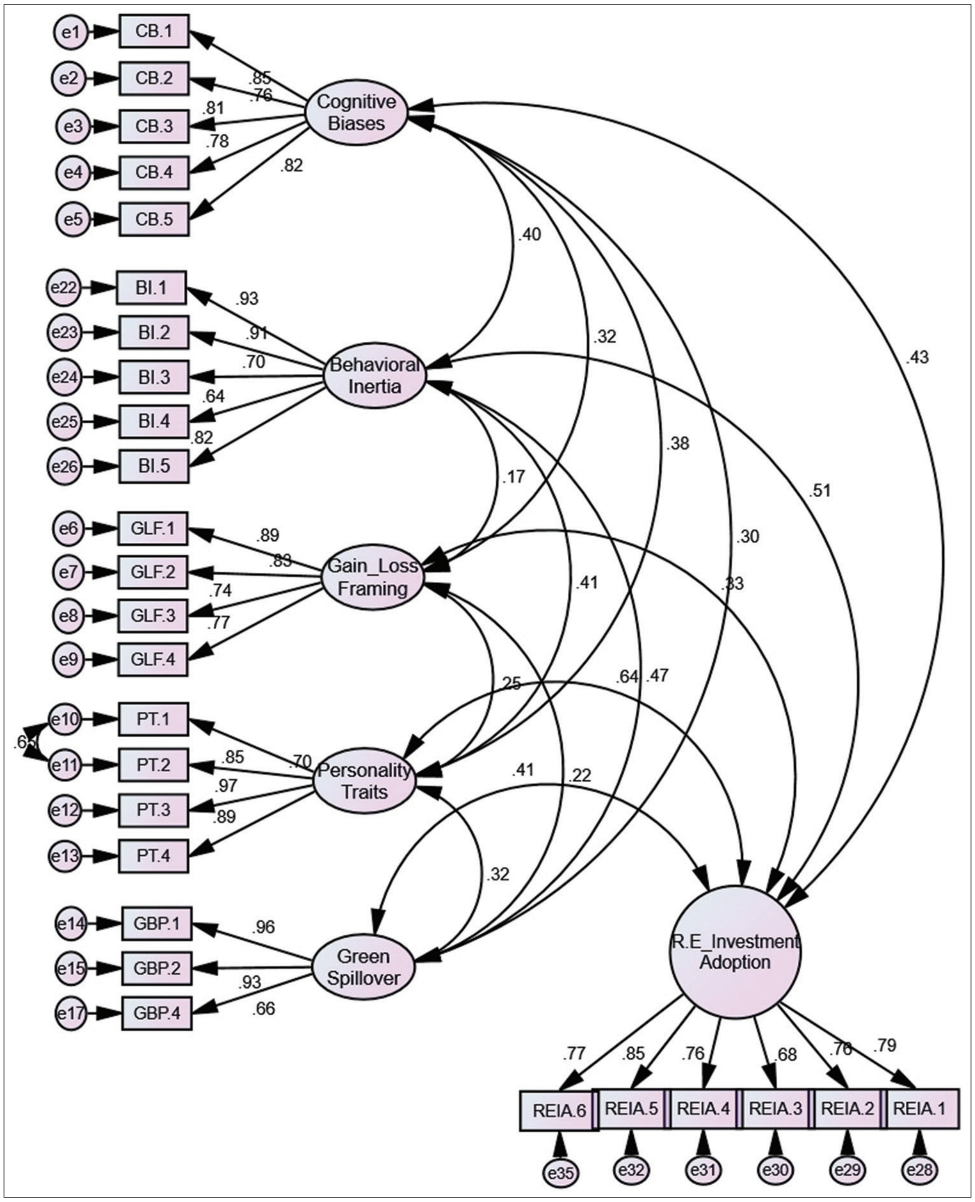
The Composite Reliability (CR) measure for every scale was more than 0.70, showing that all scales were reliable. CR values as per Table 1, for Cognitive Biases (0.85), Behavioural Inertia (0.87), Personality Traits (0.89) and Green Behavioural Spillover (0.90) indicate that the items used to measure these constructs are uniformly valid.

To assess convergent validity, the authors calculated AVE for every item. The AVEs of all constructs were over the agreed minimum of 0.50 (Bagozzi and Yi, 1988) and two in particular—Green Spillover and Gain/Loss Framing—had AVEs of 0.68 and 0.65 respectively. Hence, more than half of the variance attributed to the latent construct instead of error.

Table 1: Standardized item loadings, average variance extract (AVE) values, and CR values

Constructs	Statement (Item)	Source	SRWs (Standardized Item Loading)	AVE	CR
Cognitive Biases (CB)	I stick with my current energy provider despite better options.	Samuelson and Zeckhauser (1988);	0.85	0.63	0.85
	I think fossil fuel issues are overstated.	Nickerson (1998);	0.8		
	I prefer information that supports my existing energy views.	DellaVigna (2009); He et al. (2022)	0.78		
	I avoid renewables due to uncertainty, even when benefits are clear.		0.76		
Behavioural Inertia (BI)	Changing energy providers disrupts my routine.	Verplanken and Wood (2006); Thøgersen (2012);	0.93	0.65	0.87
	I stay with conventional energy out of habit.		0.92		
	I resist changing energy use even if needed.	Frederiks et al. (2015);	0.7		
	Learning new energy systems feels burdensome.	Sovacool et al. (2020)	0.63		
	We use non-renewables because it's the default.		0.75		
Gain/Loss Framing (GLF)	Loss messages about not using solar influence me more than savings.	Kahneman and Tversky (1979); Klein and	0.91	0.58	0.85
	I act faster when shown potential losses from delay.	Deissenroth (2017); He	0.82		
	I prefer loss-framed messages about renewables.	et al. (2022); DellaVigna	0.73		
	I avoid renewables due to fear of loss outweighing gains.	(2009)	0.69		
Personality Traits (PT)	I explore eco-friendly technologies.	Hirsh (2010); Markowitz	0.7	0.66	0.89
	I act sustainably without needing pressure.	et al. (2012); Gifford and	0.85		
	I like adopting green innovations early.	Nilsson (2014); Truelove	0.96		
	I plan finances with long-term eco-gains in mind.	et al. (2014)	0.89		
Green Behavioural Spillover (GBP)	Eco-appliances increased my solar interest.	Truelove et al. (2014);	0.99	0.68	0.9
	Green habits led me to consider clean energy.	Lauren et al. (2016); Nash	0.88		
	One green action often leads to another.	et al. (2017); Gifford and Nilsson (2014)	0.64		
Renewable Energy Investment Adoption	I plan to invest in renewable energy soon.	Frederiks et al. (2015);	0.94	0.64	0.86
	I trust renewable energy for long-term gains.	Sovacool et al. (2021); He	0.89		
	I compare renewables and traditional energy options.	et al. (2022); Yadav et al. (2024)	0.84		
	I research before making clean energy investments.		0.94		
	Success stories inspire me to act.		0.89		
	I seek deals and incentives for renewables.		0.89		

Figure 2: Measurement model



Source: Author's Data. Note: All factor loading are significant at P < 0.05; measurement model fit: Model fit indices indicate acceptable structural model fit: CMIN/DF = 2.071; GFI = 0.908; AGFI = 0.887; NFI = 0.931; CFI = 0.963; RMSEA = 0.06

According to the Fornell-Larcker criterion, each construct's AVE square root should be higher than all the correlations involving other constructs. As shown in Table 2, this condition met for every construct examined. For instance, the AVE for REIA is 0.64, exceeding the squared correlations for Cognitive Biases ($0.43^2 = 0.18$) and Behavioural Inertia ($0.30^2 = 0.09$), confirming that REIA has discriminant validity.

Overall, the measurement model proves to be statistically valid and reliable which justifies using it in further structural path analysis.

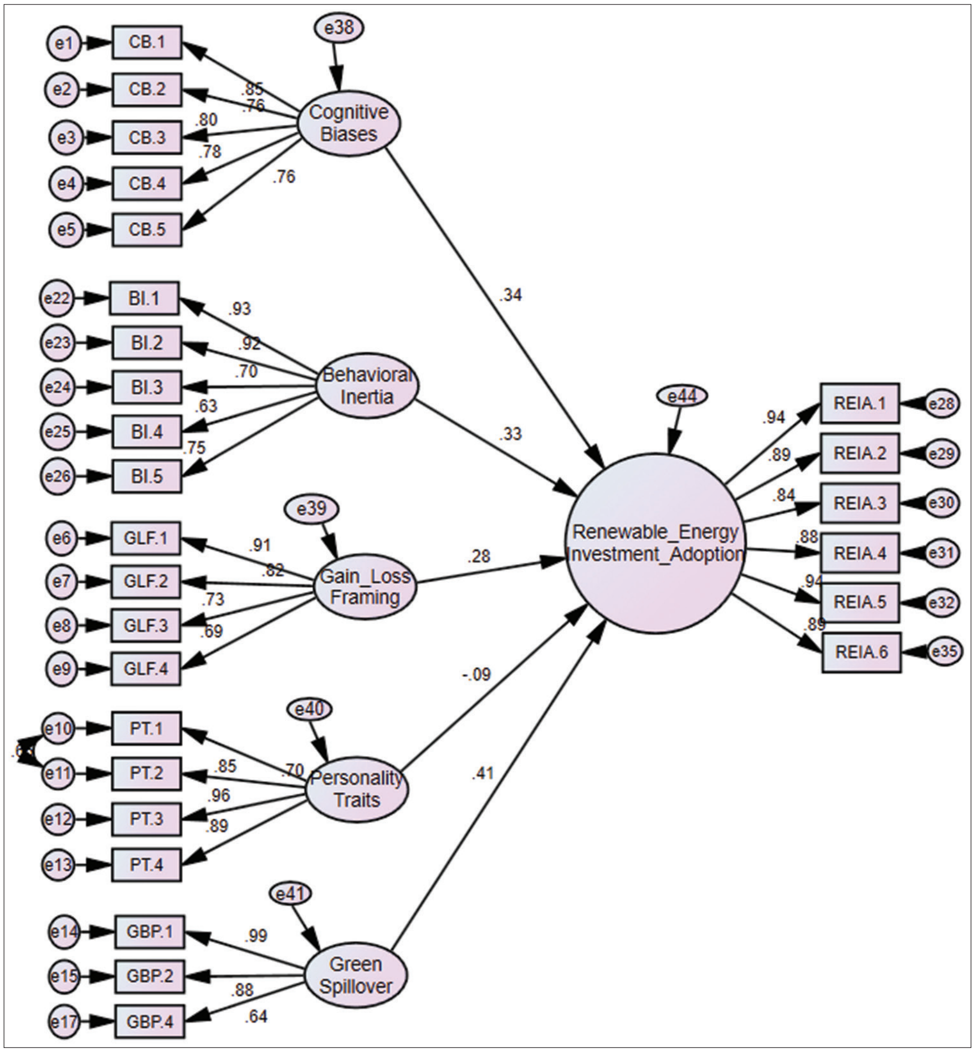
The results show that the measurement model provides in Figure 2 a suitable fit and meets the accepted criteria (Hair et al., 2022). The model was evaluated using the following fit indices: Chi-square to degrees of freedom ratio (CMIN/DF) was 2.071, the Goodness-of-Fit Index (GFI) was 0.908, Adjusted Goodness-of-Fit Index (AGFI) was 0.887, Normed Fit Index (NFI) was 0.931, Comparative Fit Index (CFI) was 0.963, Root Mean Square Error of Approximation (RMSEA) was 0.0 The model's fit exceeds the recommended standards because CMIN/DF < 3, all indices

Table 2: Correlation, squared correlation, and AVE (research model)

Factors	CB	BI	GLF	PT	GS	REIA
CB	0.63					
BI	0.40	0.67				
GLF	0.38	0.32	0.65			
PT	0.41	0.25	0.30	0.66		
GS	0.47	0.22	0.41	0.32	0.68	
REIA	0.43	0.30	0.36	0.40	0.64	0.64

Source: Authors' data. CB: Cognitive biases, BI: Behavioural inertia, GLF: Gain/loss framing, PT: Personality traits, GS: Green spillover, REIA: Renewable energy investment adoption

Figure 3: Structural model with standardized path coefficients



Source: Authors' data. Note: All path coefficients are significant at P < 0.05. Model fit indices: CMIN/DF = 2.304; GFI = 0.971; AGFI = 0.931; NFI = 0.815; CFI = 0.944; RMSEA = 0.047

are above 0.90 and RMSEA < 0.06 (Byrne, 2010). Additionally, every factor loading was significant at P < 0.05, proving that the observed relationships were meaningful.

4.3. Structural Model and Hypothesis Testing

The proposed model was tested by Structural Equation Modelling (SEM) through AMOS to ascertain impact of each of the five latent constructs (Figure 3). All model fit indexes were in level with a good fit, and within the recommended limits by Hu and Bentler (1999) and Hair et al. (2022). Namely, the values in the end were CMIN/DF = 2.304, GFI = 0.971, AGFI = 0.931, NFI = 0.815, CFI = 0.944, and RMSEA = 0.047. More so, the model anticipated a large part of the variance in Renewable Energy Investment Adoption and R^2 value of 0.67 was observed. These findings support that the covariance based SEM methodology through AMOS is effective in capturing complex behavioural relationship, confirming the validity of theoretical model and overall confirming the power of the paths of causation among the constructs in study of a sustainability behavioural concept like sustainable investing behaviour (Hasan et al., 2023).

Along with Table 3, this path analysis also indicates that all five hypotheses (H_1 to H_5) were supported statistically. The initial hypothesis (H_1) in the study is verified because Cognitive Biases (CB) has a positive effect and significant impact on Renewable Energy Investment Adoption ($P < 0.000$; $\beta = 0.34$). These findings are in agreement with such literature in behavioural economics in investment that confirm the viewpoint that confirmation bias and status quo preference drive investment behaviour (Dixit et al., 2024).

Similarly, H_2 has been confirmed in the study where it was found that Behavioural Inertia (BI) significantly predicted Renewable Energy Investment Adoption ($P = 0.004$; $\beta = 0.33$), implying that change resistance and repeat use of non-renewables harness and constrain shift to less polluted technologies.

The third hypothesis (H_3) revealed a significant and positive effect ($P < 0.000$; $\beta = 0.28$) of Gain/Loss Framing (GLF), as was proposed under the Prospect Theory, to the effect that individuals were more sensitive to perceived losses compared to equivalent gains in the context of making investment decisions.

Table 3: Hypothesis testing results of the structural model

Hypothesis	Estimate (β)	P-value	Supported
H_1: Cognitive Biases → Renewable Energy Investment Adoption	0.34	0.000	Yes
H_2: Behavioral Inertia → Renewable Energy Investment Adoption	0.33	0.004	Yes
H_3: Gain/Loss Framing → Renewable Energy Investment Adoption	0.28	0.000	Yes
H_4: Personality Traits → Renewable Energy Investment Adoption	0.09	0.000	Yes
H_5: Green Spillover → Renewable Energy Investment Adoption	0.41	0.000	Yes

Source: Author's Data, significant at 0.05 levels

The fourth hypothesis (H_4) was confirmed to the effect that Personality Traits (PT) have also a significant influence on Renewable Energy Investment Adoption ($P < 0.000$; $\beta = 0.09$), but with a smaller beta value, indicating that traits such as conscientiousness and openness have moderate influence on environmentally responsible decision-making when it comes to a financial decision such as investing in renewable energy.

Best of all, the H_5 under Green Behavioural Spillover (GBP) factor proved to be the most influential ($P < 0.000$, $\beta = 0.41$) that older pro-environmental actions were powerful predictors of individual willingness to invest in renewables. This upholds the previous analysis by Truelove et al. (2014) and Nash et al. (2017) of the cascading style of green behaviours.

Overall, the model has a strong empirical backing of multidimensional behavioural drivers of renewable energy investment. It represents the topicality of psychological framing, habitual, and cognitive shortcuts, personality traits, and the pro-environmental spillover as influencing sustainable financial decision-making within urban populations of India.

5. CONCLUSION AND IMPLICATIONS

The findings gained from the study play an important role in supporting the wider adoption of renewable energy investments. Since cognitive biases and message framing matter greatly, it is important to include ideas from behavioural economics in outreach about green investments. Loss-framed accounts that highlight both ecological and monetary costs of not acting are more persuasive than the usual explanations, as shown by Prospect Theory (Kahneman and Tversky, 1979). People in charge of policy and organizations should create campaigns that take advantage of this type of thinking.

The significant path coefficient found for Green Behavioural Spillover suggests that performing one green behaviour often helps develop more sustainable habits that can guide our actions in the future (Truelove et al., 2014). As a result, initiatives aimed at promoting small eco-friendly behaviours—including recycling, taking public transport and using LED lights—could encourage people to invest more in renewable energy in the future. There is clear evidence that openness to experience and conscientiousness play a role, indicating that marketing in sustainable finance should take account of personality traits. Detailed features and interfaces can be customized based on these traits to increase how much users interact with the platform (Hirsh, 2010).

Based on the study's findings, it is suggested to use digital tools such as smart dashboards, simulation tools for investing or ways to scale back from regular energy investments in green FinTech services. Institutions might also develop gamified rewards that encourage actions that help protect the environment. Such tools reduce the risk of behavioural inertia, even if this is significant, as people can use set-up investment, automated saving and climate finance options. The merging of behavioural science with policy and digital finance allows authorities to help people make sustainable choices in an easy way.

6. LIMITATIONS AND FUTURE RESEARCH AGENDA

The research adds significant insights to the field of renewable investment, but there are still several challenges that would make for useful further studies. The fact that this study depended on purposive sampling prevents the results from applying to most populations. Because the responses obtained from informed urban individuals, future investigations can use stratified or cluster sampling to add rural populations, non-English speaking people and low-income investors to improve the study's ability to generalize. Second, since cross-sectional data is limited, saying one causes the other is not possible. Studies using design schemes could explore how long spillover effects last and whether framing interventions stay effective for a while.

Furthermore, the validation of the complex structural relationships was made possible using AMOS and future researchers might want to look into using either multi-group analysis (MGA) or latent class analysis (LCA) in the AMOS framework to test how diverse demographics, regions, or attitudes might affect the path relationships of the model (Hair et al., 2022). Using perceived financial efficacy, trust in the regulatory environment and environmental identity could help the model work even better. As investment technology moves forward, future exploration could link behavioural economics and digital design to discover if live nudges, convenient dashboards and AI on sustainability can encourage investors to act in a green manner. Ultimately, with comparative cross-cultural research, it is possible to find out if these drivers influence consumers the same way in all types of markets.

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