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RETRACTED: Energy Efficiency in the Post-COVID-19 Era: Exploring the Determinants of Energy-Saving Intentions and Behaviors

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The COVID-19 pandemic has a long-lasting influence on global economies. Households are expected to consume more electricity for their usual routine activities due to mandatory stay-at-home restrictions, resulting in greater energy utilization. The proposed study seeks to investigate the most relevant energy consumption factors amid the COVID-19 pandemic. The study employs a structural equation modeling approach to evaluate the responses from 511 Pakistani residents. Empirical results report a positive and significant association among perceived behavioral control (PBC), perceived environmental concern (PEC), perceived monitory benefits (PMB), and intention to save energy (ISE). Positive anticipated emotions (PAE) is found to be a significant predictor of ISE and energy-saving behavior (ESB). As a step further, we extend the analysis to find the moderating effect of perceived COVID-19 disruptiveness (PCD) between the relationship of ISE and ESB. Results reveal that PCD positively moderates this relationship. Based on research findings, policy implications and future research directions are provided for practitioners, researchers, and academicians to fulfill the country's energy needs on its way to a future of sustainable development.

Keywords: perceived behavioral control, perceived environmental concern, perceived monetary benefit, intention to save energy, energy saving behavior, perceived COVID-19 disruptiveness

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INTRODUCTION

The worldwide COVID-19 pandemic has afflicted the majority of countries and has influenced the activities of every household. Many industries, including energy, transportation, manufacturing, and residential construction, have been severely damaged by the pandemic (Qarnain et al., 2021). Severe lockdowns by local governments have compelled household inhabitants to utilize more energy for their routine tasks, resulting in higher energy consumption. For this research, energy usage has been investigated in Pakistan during the COVID-19 pandemic. More than 200 M Pakistanis were limited to their homes during the country-wide lockdown, resulting in dramatically higher residential energy consumption (Baloch et al., 2021). The largest Pakistani cities, such as Lahore and Karachi, reported a substantial increase in residential energy usage during this period. This growth in household energy

consumption may revoke the comparable decrease in industrial and commercial energy consumption (Irfan et al., 2021a; Zhang et al., 2021).

Presently, research activities focusing on household energy consumption behavior may be classified into three broad categories, including (i) economic, (ii) technological, and (iii) psychological behavior-oriented perspectives (Arawomo, 2017; da Silva and Cerqueira, 2017; Zhou and Yang, 2016). However, several investigations have indicated that the impacts of these procedures are relatively scarce in reality (Wang et al., 2018a). This is due to the fact that, in comparison to other household expenses, energy expenditure is very small and typically displays low price volatility (Yu and Guo, 2016). Most households are unconcerned about changes in energy prices and are reluctant to forgo their luxurious lifestyle and prosperity in their everyday lives to preserve energy (Yu and Guo, 2016). Profit-making programs seek to compensate individuals for their sacrifices by providing subsidies. Previous research has found that profit-making strategies can only be successful for a limited amount of time unless they are long-term (Handgraaf et al., 2013; Frederiks et al., 2015; Akbar et al., 2020). As a result, profit-making solutions may not successfully drive energy-saving behavior (ESB) in the long run.

Given the constraints of the industrial and technological perspectives, experts have increasingly acknowledged that the psychological behavior-oriented approach is essential in attaining energy savings objectives (Martinsson et al., 2011; Hori et al., 2013). Researchers have previously given consideration to cognitive attributes. In this regard, numerous cognitive behavior models have been produced to comprehend residential energy adoption behavior and discover the relevant influencing factors (Judith and Linda, 2009). The theory of planned behavior (TPB) is the most extensively utilized theory among other models and theories to understand consumers' energy adoption behavior (Rivis et al., 2009). In this vein, we attempt to use TPB to explain ESB from a cognitive standpoint. In contrast to the theory of reasoned action and norm activation model, TPB considers unforced factors, i.e., perceived behavioral control (PBC). As a result, it is relevant to adopt TPB as the dominant conjectural foundation for this study in order to better recognize domestic ESB.

Furthermore, numerous researchers have noticed that other cognitive attributes and variables may contribute to TPB to strengthen the model's effectiveness (Kaiser and Scheuthle, 2003; Shi et al., 2017). This study introduced an emotional factor named Positive anticipated emotions (PAE) into the TPB model to better explain ESB. The study answers the following questions: (i) to determine if these proposed factors and variables have a substantial impact on household ESB, (ii) what actions could be implemented to enhance household ESB?

The next section discusses the "Theoretical background and research hypotheses," which describes TPB as a theoretical foundation, as well as a detailed literature review and conceptual model. The section "Research methods" discusses the research design. The section "Data analysis and results" describes the testing of hypotheses. The section "Discussion" explains the findings, implications, and conclusion of the study.

THEORETICAL BACKGROUND AND RESEARCH HYPOTHESES

Theory of Planned Behavior

TPB has been extensively used in recent studies to explain how people develop behavioral intentions (Han et al., 2016; Ye et al., 2017). According to Google Scholar, this theory has been discussed about 90,000 times as of 2019. An underlying feature of a specific behavior is the intention to perform or act (Ajzen, 1985; Ajzen, 1991). It is also widely used in the realm of environmental behaviour, such as saving energy, low-carbon commuting, environmental innovation, and green buying. Three main components affect persons' behavioral intentions (Ahmad et al., 2020), namely behavioral beliefs, normative beliefs, and PBC. Scholars have widely employed TPB to measure individuals' pro-environmental behaviors, and many studies agree that TPB predicts various behavior effectively. For example, this theory has been used in past research to analyze customers' green behavioral intentions (Mancha and Yoder, 2015; Wang et al., 2018b). Furthermore, another research employed the TPB model to demonstrate that subjective norms, environmental attitudes, information publicity, lifestyles, and PBC could substantially influence residents' energy-saving behavior (Wang et al., 2014). Also, Wang et al. (2018a) investigated the influence of non-cognitive and emotional variables on residents' ESB by employing a proper framework that included the TPB and social behavior. Furthermore, a recent study used the theory of planned behavior to examine how favorable and unfavorable thoughts influence people's ISE (Fu et al., 2021). It also confirmed the moderating influence of pricing and incentive-making strategic concept on people's ISE and ESB.

Perceived Behavioral Control

The perceived ease or difficulty of performing a certain activity is referred to as PBC (Fornara et al., 2016; Sembada and Koay, 2021). Individuals are inclined to achieve a behavior when it is not difficult to do so as a choice. The worldwide outbreak of COVID-19 has influenced the majority of countries and has influenced every family's lifestyle. Legally required stay-at-home policies have compelled housing residents to consume more energy for their regular everyday operations, resulting in greater energy consumption (Qarnain et al., 2020). The growing energy consumption by housing inhabitants results in overpriced energy bills and a shortage of energy supply. However, perceived behavior may be utilized to control energy consumption, and this behavior serves as an energy conservation factor in homes, reducing the excessive energy cost.

Wang et al. (2018a) demonstrated that PBC positively affects residents' understanding of energy conservation. The more strongly individuals can control their behavior, the more intention they have to save electricity and the more inclined individuals are to acquire energy-saving habits. Moreover, several researchers have found that PBC has a favorable consequence on both behavioral intentions and actual behavior, such as ESB at home and at the workplace (Wang et al., 2014; Fornara et al., 2016). Consistent with TPB, it can be argued that residents' desire

to preserve energy would expand when they believe they have a sufficient amount of control, such as the competence, timing, abilities, and resources to execute the ESB. Some factors, such as opportunity, resource, time, knowledge, and abilities, may be beyond an individual's control and thus affect their intention to engage in a specific behavior (Gao et al., 2017). During the COVID-19 pandemic, individuals who have greater control over themselves and have the necessary knowledge and skills to conserve energy in the workplace are more likely to build the intention to save energy. Thus, we suggest the following hypothesis.

H_1: PBC is positively related to individuals' ISE

Perceived environmental Concern

The concept of PEC refers to people's views of the eco-friendly environment by adopting energy-saving behavior, emphasizing the achievements made by energy conservation behavior to the environment (He et al., 2018; Li et al., 2019). It is generally presumed that ESB is beneficial for both decreasing exhaustion of energy and preventing environmental breakdown, especially during the period of COVID-19 outbreak. Individuals acquire satisfaction from their actions as an intrinsic benefit (Kankanhalli et al., 2005; Wasko and Faraj, 2005). An individual who enjoys a specific behavior might acquire satisfaction from that behavior, which significantly encourages their positive attitude toward that behavior. Similarly, Individuals who believe they have a high degree of satisfaction from energy conservation are more inclined to acquire a favorable attitude toward the behavior

Many investigations on ESB have demonstrated the importance of environmental factors in influencing inhabitants' behavior. Steinhorst et al. (2015) investigated whether conserving energy is driven by financial or environmental benefits; the findings demonstrated that environmental discourse had a strong favorable influence on ISE. Energy consumption may be reduced through conserving energy, which eliminates carbon emissions and, as a result, helps to avoid global warming and environmental damage. This approach can be considered as an environmental benefit of energy savings (Banfi et al., 2008). Whereas the influence of ESB on the factors of environmental regulation, and based on home residents' environmental awareness and understanding, the PEC assistances variable was developed to investigate this influence on inhabitants' motivation to save energy. As a result, the following hypotheses have been proposed as:

H_2: PEC is positively related to individuals' ISE

Perceived Monitory Benefits

According to Orbell et al. (1996), the concept of perceived benefit is the anticipated opportunity that a favorable outcome would occur as a result of the suggested action. In this study, PMB is defined as inhabitants' impression of saving money during the COVID-19 crisis via electricity-saving habits, emphasizing the environmental benefits of these habits (He et al., 2018). This is an example of an intellectual sentiment that impacts a person's morality (Tsujikawa et al., 2016). He et al. (2018) investigated the process of perceived financial incentives on customers' purchasing behavior for electric vehicles in China. Wang et al. (2019) analyzed attitudes on and adoption of fossil fuels based on perceived advantage; the findings revealed that perceived advantage had a beneficial influence on the public's perspective and acceptability of green energy. Dianshu et al. (2010) investigated the relationship between electricity price and consumption level in China to explore if economic benefits have a major impact on energy-saving behavior. Several studies have been conducted to support this assumption by exploring how financial cost affects residential electricity consumption (Banfi et al., 2008; Steinhorst et al., 2015; Fu et al., 2021). Based on the description above, the study employed PMB as one of the absolute perspectives affecting home residents' intention to conserve energy and to explore how it influences household residents' energy-saving habits. Therefore, we suggest the following hypothesis.

H_3: PMB is positively related to individuals' ISE

Intention to Save Energy

Ajzen (1985) defines behavioral intention as a collection of motivating elements that impact each individual's behavior, indicating the individual's desire or effort to invest in performing the activity. Energy in overall, and electricity in particular, is a product that is required in daily life. Whether you like it or not, every household must buy and use it. ESB is the act of turning off when not needed, using high-efficiency energy, and investing in energy-saving technology to reduce energy consumption (Zaidan et al., 2021). Residential building energy consumption is not addressed during situations such as this COVID-19 pandemic (Qarnain et al., 2021). During the COVID-19 pandemic, energy consumption levels reach the maximum due to unexpected demands, resulting in high energy costs and energy waste. If the factors leading to increased consumption are identified before the pandemic demand levels, solutions may be more easily provided. According to the TPB, as a direct intervening variable of ESB, residents' ISE can substantially anticipate household ESB. In other terms, the more motivated you are to conserve energy, the more tend you are to execute it. Inhabitants' ISE is strengthened when they have a constructive orientation toward conserving energy. Residents believe they have an acceptable degree of control, such as the capability, time, skills, and opportunity to engage in the energy-saving practice. Therefore, based on the aforementioned arguments, we suggest the following hypothesis:

H_4: Individuals' ISE is positively related to ESB

Positive anticipated Emotions

Anticipated emotions are the state of mind (e.g., pleasant and unpleasant) or responses to a particular situation (Russell et al., 2017). Individuals are more inclined to participate in a situation if they have a strong expected emotion about the event or subject; unless they are hesitant to participate. In this study, PAE consists of positive psychological sensations experienced when

completing a certain behavior (e.g., home ESB). According to Han and Hyun (2018), PAE initially communicates the relevance and importance of an event or problem and then offers stimulation for executing the activity. According to interpersonal behavior theory, PAE is considered a crucial indicator in executing environmentally friendly behavior, especially during the COVID-19 crisis (Russell et al., 2017; Qarnain et al., 2021). According to Webb et al. (2013), PAE has a favorable impact on the intention to participate in ESB.

According to the above research findings, PAE is a predictor of intention to engage in eco-friendly behavior. Applying the same rationale, it can be projected that within the perspective of energy reduction, citizens are more inclined to conserve energy if they believe that conserving energy in their everyday lives is environmentally beneficial and display a PAE about conserving energy. Furthermore, we know from effective event theory that PAE is a strong determinant of genuine engagement as it stimulates a psychological desire for performance (Weiss and Beal, 2007; Han and Hyun, 2018). Following affective events theory, this study posits that PAE has a significant impact on residents' ESB. We predict that the more PAE inhabitants display, the more inclined they are to perform ESB. Given such viewpoints, we hypothesize that:

H_{5a}: PAE is positively related to individuals' ISE
H_{5b}: PAE is positively related to individuals' ESB

The Moderating Role of Perceived COVID-19 Disruptiveness

The world pandemic of COVID-19 disruption has infected most countries and has influenced the functions of every family. Compulsory stay-at-home quarantines have compelled housing residents to consume more energy for their regular everyday activities, resulting in greater energy consumption. The high energy uses by housing residents results in overpriced energy bills and a shortage of energy supply. During the COVID-19 pandemic, transportation-related air pollutants were lowered by 44.3–55.4% in Pakistan, while overall energy consumption was reduced by around 7%, increasing home energy consumption (Jiang et al., 2021). The consumption is interlinked during the COVID-19 outbreak, where a decline in energy consumption at workplaces leads to increased energy consumption at home.

Due to the changing energy use dynamics after the COVID-19 outbreak, energy consumption has extensively risen due to unanticipated demands, resulting in high energy expenditures and energy losses. According to the TPB, as a direct instrumental variable of ESB, residents' ISE can be utilized to significantly and positively predict household ESB. However, due to COVID-19 shutdowns, several research studies indicate that a spike in home-based working, freelancing, and non-work travel may alter residents' ESB due to excessive energy consumption for their regular daily operations (Webb et al., 2013; Jiang et al., 2021). As a result of the disruptive nature of the COVID-19 outbreak, the more motivated you are to conserve energy at home, the less likely you are to perform it. Residents' ISE is boosted when they have a favorable attitude toward saving energy. For example, if residents believe they do not have an appropriate level of ISE, they would be unable to perform effectively (Banfi et al., 2008). Therefore, based on the above argument, we suggest the following hypothesis. **Figure 1** represents the conceptual framework of the study.

H6: COVID-19 disruptiveness negatively moderates the influence of ISE on ESB when it is high (*vs.* low).

TABLE 1 | Sample characteristics.

Respondents profile	Frequency	Percentage %
Gender		
Male	278	73
Female	102	27
Age		
20–25	94	24.7
26–35	135	35.4
36–45	85	22.3
46–55	67	17.6
Education level		
High school or below	20	5.2
Associate degree	135	35.4
Bachelor's degree	155	40.7
Master's degree	56	14.7
PhD	15	3.9
Monthly income (PKR)		
Less than 40,000	20	5.2
41000–60000	155	40.7
61000–80000	105	27.6
81000–100000	20	5.2
100000 above	81	21.3
Family size		
1–2	115	30.2
3–4	210	55.1
More than 4	56	14.7

RESEARCH METHODS

Sample and Data Collection

The study hypotheses are investigated through survey questions collected from the citizens of Lahore between mid-March and mid-August of 2021 because Lahore has been the most seriously afflicted location since the COVID-19 outbreak in Pakistan. The Lahore city is highly populated; thereby, the impact of COVID-19 has been immense.

As a result, Qualtrics Panel Services was employed to collect internet-based survey data for this research. We distributed 700 questionnaires to resistant's (professionals and students) working from their homes owing to COVID-19 lockdown. Moreover, participants were assured that their answers would be completely anonymous. After completing the survey, 532 filled responses were returned in total. The research team verified the questionnaires, and those with missing or incomplete data

were eliminated. Overall, 511 usable questionnaires were obtained, with a 73% response rate. **Table 1** shows the demographic features of the respondents. As seen in **Table 1**, the vast majority of respondents (73.44%) are male, and 30.1% are between the ages of 26 and 35. The respondents were generally well-educated, with 70% holding a bachelor's degree. Approximately 40.7% earns a monthly income ranging from Pakistani Rupees (PKR) 41000 to 60000, and 27.6% earns a monthly income ranging from PKR 61000 to PKR 80000. The majority of the sample (55.1%) had a medium-sized family of 3–4 persons.

Measures

In this study, the constructs are all key predictors that are assessed using multiple-item scales, and they were measured using a 5-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). To measure *perceived behavior control*, we used four items scales from previous literature by Wang et al. (2018a). A sample item is "energy-saving could reduce the carbon emission". Perceived environmental concern and perceived monitory benefits were adapted from previous literature by Fu et al. (2021), and it has been measured on a seven items scale. A sample item is "I think the energy cost of my family is very high". Energy-saving intentions and behavior scale were utilized from the study of Fu et al. (2021), and the responses were assessed on a eight items scale. A sample item is "I intend to save energy in my home' and "I always set the air conditioner at the right temperature, not the lowest or highest". *Positive anticipated emotion* was also derived from Wang et al. (2018a) and assessed on a 3-item scale. A sample item is "If I take measures to save energy in my home, I will feel excited". In last, COVID-19 disruptiveness scale was adapted from Epler and Leach (2021) and consist of 4-items scales. A sample item is "My energy costs have increased as a result of COVID-19 disruption".

DATA ANALYSIS AND RESULTS

We employed the SEM approach with SmartPLS 3 and SPSS version 26 for analyzing the data. Further, to test our proposed model—a two-step approach of measurement model (MM) and structural model (SM) estimation was taken into consideration for data analysis using SmartPLS (Hair et al., 2006; Ahmad et al., 2021). Constructs' reliabilities were gauged through the MM, whereas the SM was applied to observe the relationships among the five constructs. It is known as a component-focused method and adopted to analyze the relational dimensions in the study (Urbach and Ahlemann, 2010). PLS-SEM was chosen over all other covariance-based approaches because it enables researchers to consistently analyze calculations and factor structures. Another explanation for using PLS-SEM is that it facilitates this study with a small sample size and can process the various measurement scales together (Wold, 2006; Urbach and Ahlemann, 2010). Additionally, it allows scholars to analyze the model in both reflective and formative actions. At the earlier stages of model development, the PLS method is considered vastly acceptable, which is the case in this study. Prior research indicates that a sample size of 68 is a reasonable starting point for use in PLS-SEM (Hoelz and Bataglia, 2021).

Common Method Bias

The CMB was performed using two different ways in this study to ensure whether the collected data were free from biases. First, we used one of the traditional and frequently cited methods, "Harman's one-factor test" (Harman, 1976), using SPSS. Second, we used another most commonly used PLS-SEM technique to avoid the CMB threat (Kock, 2015). According to the first approach, if a single factor accounts for >50% of the variance, it can influence the study's findings (Harman, 1976; Podsakoff et al., 2012). The second method submits that variance inflation factor (VIF) values <3.3 for the indicators can be considered the model is free of CMB (Kock, 2015). Our model results for the first approach indicate that a single factor extracts <50% of the total variance (Harman, 1976; Podsakoff et al., 2012), and according to **Table 4**, the VIF values of all items were <3.3 (Kock, 2015). In line with these results, CMB is not a serious concern in the study (Harman, 1976; Podsakoff et al., 2012; Kock, 2015).

Measurement Model Assessment

The measurement model was analyzed to confirm the reliabilities of the constructs, where the four most commonly measures were used. First, the factor loadings of all items were confirmed, where Hair et al. (2019) suggested that the loadings of items should >0.708. Thus, the items with loadings <0.708 were removed from the model. Second, Cronbach's alpha was calculated. Third, composite reliability was weighed. Fourth, an average variance extracted was estimated (Hair et al., 2019). Such measures surpass the cut-off values of 0.70 and 0.50, correspondingly (**Table 2**). Additionally, discriminant validity was also ensured via Fornell and Larcker (1981) approach (see **Table 2**). Therefore, both reliability and validity are confirmed. Furthermore, the construct's discriminant validity was also assessed using the Heterotrait-Monotrait Ratio (HTMT) method. To obtain discriminant validity using the HTMT method, HTMT values must be lower than HTMT 0.90 (Gold et al., 2015). The HTMT analysis revealed that all correlation values were smaller than HTMT 0.90, indicating that the construct is discriminant. The Heterotrait-Monotrait Ratio findings are shown in **Table 3**.

Multicollinearity

Multicollinearity was tested using VIF pre-hypothesis testing, where VIF above five is deemed problematic, suggesting a multicollinearity issue (Irfan et al., 2020a; Irfan et al., 2021b). The highest value for VIF in this model is 2.478, which is far less than 5 (see **Table 4**), suggesting that our model is free from multicollinearity problems (Irfan et al., 2020b; Irfan et al., 2020c; Ahmad et al., 2021).

Model Fit

Model fit was examined using the three most widely used statistical techniques for SEM—the "standardized root mean

TABLE 2 | Mean, standard deviation, and discriminant validity using Fornell and Larcker's criterion.

S. No	Variables	Mean	SD	1	2	3	4	5	6	7
1	PCD	3.325	0.696	**0.820**						
2	ESB	2.402	1.201	0.749**	**0.757**					
3	ISE	3.021	0.542	0.745**	0.689**	**0.786**				
4	PBC	3.122	0.962	0.668**	0.740**	0.722**	**0.759**			
5	PEC	3.656	1.034	0.796**	0.673**	0.782**	0.712**	**0.830**		
6	PMB	2.111	0.113	0.631**	0.615**	0.612**	0.653**	0.669**	**0.853**	
7	PAE	3.405	0.265	0.740**	0.732**	0.785**	0.707**	0.711**	0.529**	**0.813**

Note: N, *511* ***Correlation is significant at the 0.01 level,* $p < 0.01$; **Correlation is significant at the 0.05 level,* $p < 0.05$; *SD, Standard deviation; PCD, Perceived COVID-19 disruptiveness; ESB, Energy-saving behavior; ISE, Intention to saving behavior; PBC, Perceived behavioral control; PE, Perceived environment; PMB, Perceived monitory benefit; PAE, Positive anticipated emotion.*
These are the square root values of AVEs.

TABLE 3 | Heterotrait-monotrait ratio (HTMT).

S. No	Variables	PCD	ESB	ISE	PBC	PE	PMB	PAE
1	PCD	–						
2	ESB	0.822	–					
3	ISE	0.784	0.879	–				
4	PBC	0.846	0.665	0.785	–			
5	PEC	0.654	0.848	0.811	0.778	–		
6	PMB	0.762	0.780	0.755	0.856	0.803	–	
7	PAE	0.454	0.771	0.658	0.745	0.890	0.673	–

squared residual" (SRMR), "normed-fit index" (NFI), and goodness of fit (GoF) formula (GOF = $\sqrt{}$ (AVE × R^2)), where SRMR value should be ≤0.08 (Hu and Bentler, 1998) and NFI value should be between 0 and 1 (Bentler, 1990). However, a higher NFI value represents a better fit (Bentler, 1990). This study finds the value of SRMR is 0.077 and NFI is 0.617, suggesting our model is relatively satisfactory. Next, the GoF formula was used to calculate the model fit (Henseler and Sarstedt, 2013), where GOF = 0.1 advocates small, GOF = 0.25 represents medium, and GOF = 0.36 signifies large (Wetzels et al., 2009). We find the value of 0.528 for GOF in our model, demonstrating that the model surpasses the cut-off value for the large section.

Structural Model Assessment

Consequently, necessary measurement model assessment and model fit, the structural model analysis was performed. Bootstrapping evaluation of 5,000 resamples was used to analyze the importance of straight paths and test normal

TABLE 4 | Factor loadings of measurements model.

Constructs	Item	SFL	VIF	Cronbach α	CR	AVE
Perceived behavioral control	PBC1	0.719	1.228	0.729	0.802	0.575
	PBC2	0.727	1.211			
	PBC3	0.825	1.381			
Perceived environmental concerns	PEC1	0.862	2.329	0.848	0.898	0.689
	PEC2	0.806	1.767			
	PEC3	0.875	2.478			
	PEC4	0.773	1.602			
Perceived monitory benefit	PMB1	0.864	1.899	0.813	0.889	0.728
	PMB2	0.896	2.104			
	PMB3	0.797	1.595			
Intention to save energy	ISE1	0.773	1.659	0.793	0.866	0.618
	ISE2	0.852	2.048			
	ISE3	0.763	1.485			
	ISE4	0.753	1.444			
Energy-saving behavior	ESB1	0.774	1.531	0.760	0.842	0.573
	ESB2	0.623	1.350			
	ESB3	0.826	1.432			
	ESB4	0.789	1.599			
Positive anticipated emotion	PAE1	0.839	1.743	0.739	0.823	0.661
	PAE2	0.882	1.919			
	PAE3	0.707	1.268			
Perceived COVID-19 disruptiveness	PCD1	0.733	1.486	0.837	0.897	0.673
	PCD2	0.847	2.041			
	PCD3	0.845	2.009			
	PCD4	0.850	2.045			

Note: N, *511; CR = composite reliability; AVE, average variance extracted; SFL, standard factor loading.*

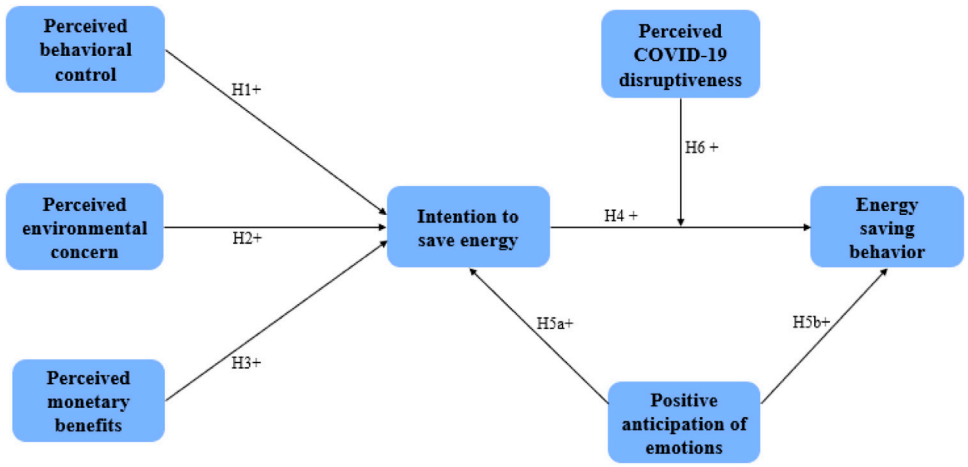

FIGURE 1 | Conceptual framework.

TABLE 5 | Hypotheses testing and specific indirect effects.

Hypotheses	B-values	p-values	t-values	Decision
H1: PBC →ISE	0.145	0.032	2.148	Accepted
H2: PEC →ISE	0.347	0.000	4.597	Accepted
H3: PMB →ISE	0.214	0.001	1.499	Accepted
H4: ISE →ESB	0.114	0.012	1.233	Accepted
H5a: PAE →ISE	0.395	0.000	6.526	Accepted
H5b: PAE →ESB	0.335	0.000	4.002	Accepted
H6: (PCD × ISE) →ESB	0.058	0.021	0.865	Accepted

faults. The results divulged a significant and positive influence of perceived behavior control (β = 0.145; $p < 0.001$), perceived environment (β = 0.347; $p < 0.001$), and perceived monitory benefit (β = 0.214; $p < 0.001$) on the intention to save energy, leading to the support of hypotheses H1, H2, and H3. Furthermore, the influence of intention to save energy on energy saving behavior (β = 0.114; $p < 0.001$) was found statistically significant and positive, confirming hypothesis H4. In addition, hypotheses H5a and H5b revealed a significant and positive influence of positive anticipated emotion on intention to save energy (β = 0.395; $p < 0.001$) and energy saving behavior (β = 0.335; $p < 0.001$). Thus, both are accepted. Finally, the perceived COVID-19 disruptiveness moderates the effect of intention to save energy on energy-saving behavior (β = 0.058; $p < 0.01$), confirming H6 only. Furthermore, perceived behavior control, perceived environment, and perceived monitoring benefit explains 73.3% of the variance in intention to save energy, while the overall model explains 63.6% variance in electric saving behavior, indicating a good model. **Table 5**; **Figure 2** provide the results.

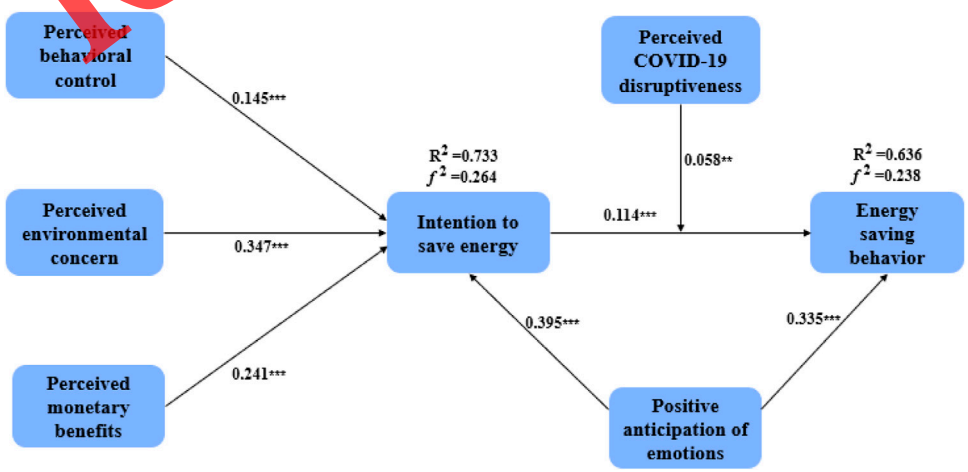

FIGURE 2 | Results of hypotheses.

DISCUSSION

Major Findings

According to the theory of planned behavior, this research investigates the influencing factors of residential ESB. We looked specifically at how cognitive factors influence residents' ISE and the moderating influence of COVID-19 disruptiveness on energy-saving intentions and behavior. SEM was employed to validate the hypotheses using survey data from 511 households in Pakistan.

The outcomes of this paper offer a meaningful theoretical contribution to the body of literature because limited research has been conducted on the relationship between intellectual factors and residents' ISE and ESB. The results indicate that perceived behavior control is positively and significantly associated with residents' ISE. These findings are consistent with past research on pro-environmental behavior, such as energy preservation and green buying (Klöckner, 2013; Webb et al., 2013; Cheung et al., 2016). In accordance with the prior research, Wang et al. (2018a) have also demonstrated that PBC has a positive effect on residents' understanding of energy conservation. Similarly, findings further suggest that PE and PMB are positively and significantly related to residents' intentions to save energy. These findings are consistent with the observations of Fu et al. (2021), as the authors discovered a significant relationship between perceived environmental concern, monitory benefits, and energy consumption behavior.

The study findings are also parallel to the theoretical foundations of TPB that propose a significant impact on perceived behavior and environmental control. From the TPB perspective, the results indicate that descriptive norms, environmental perception, information publicity, lifestyles, and perceived behavior control all significantly influence residents' energy-saving behavior. According to the TPB, residents' intention to preserve energy may be employed to significantly and positively predict household energy-saving behavior as a direct instrumental variable of energy-saving behavior. Furthermore, our study found a positive and significant impact of positive anticipate emotion on both ISE and ESB. According to the effective event theory, PAE is a powerful predictor of actual behavior because it creates a psychological desire for action (Weiss and Real, 2007; Han and Hyun, 2018). In accordance with affective events theory, this study posits that PAE has a significant impact on residents' energy-saving intentions and behavior. These findings are also consistent with the research of Wang et al. (2018a), who suggested that PAEs have a strong association with residents' energy-saving behaviors.

The findings showed that there is a positive relationship between ISE and ESB. These findings fully consent to the research of Wang et al. (2018a), who suggested that power saving behavior is the act of shutting off when not needed, adopting high-efficiency energy, and investing in energy-saving technologies to reduce energy consumption. If the factors causing higher consumption were discovered before hitting the COVID-19 pandemic, adjustments might be more easily provided. Our research findings refer to the moderating role of perceived COVID-19 disruptiveness, which strengthens the relationships between residents' ISE and ESB. Because of the changing power consumption dynamics after the COVID-19 outbreak, energy consumption has significantly increased, caused by unexpected demands, resulting in high energy costs and energy losses.

Policy Implications

More importantly, this study makes policy recommendations to the Pakistani government for implementing ways to encourage inhabitants to save energy. According to the findings of this study, awareness about energy challenges, level of attention, perceived energy-saving control, and sense of responsibility are all characteristics that may be used in policy programs aiming towards reducing household energy consumption. Pakistani policymakers should focus on promoting public awareness of energy challenges such as excessive energy consumption and limited energy resources. Conventional energy infrastructure is increasingly being changed into computerized power generation due to the revolutionary advancement of Internet-based new technologies, the Smart home, artificial intelligence technology, and Big Data storage (Zhou and Yang, 2016; Renström, 2019). This will have a significant impact on home energy consumption behaviors. Well-designed education programs addressing the relevance of energy and environmental challenges and the advantages of energy conservation might be helpful. Policies and initiatives should also concentrate on establishing in residents a feeling of responsibility to conserve energy when it is unnecessary. It may be advantageous to implement energy-saving awareness campaigns and capacity-building initiatives. The government should also pay close attention to public relations and the media to educate communities that these energy and climate challenges can be handled if everyone works together. The focus could be given to hosting activities where everyone can share their expertise and experience with energy conservation. As a result, individuals' energy-saving knowledge will be increased, and energy-saving behavior will be promoted.

CONCLUSIONS

This study investigated the impact of cognitive and emotional factors on residents' ISE and their impact on ESB. We also investigated the role of perceived COVID-19 disruptiveness as a moderator between the relationship of ISE and ESB. The following key conclusions may be drawn based on the outcomes of this study: Firstly, the three perceptual elements have a strong influence. Both PMB and PE are positively and significantly associated with residents' intentions to save energy. Similarly, perceived behavior control has a significant and positive influence on residents' intention to save energy. Secondly, PAE has a positive and considerable effect on the ISE and the behavior to save energy. Similarly, the direct impact of ISE has a favorable relationship with the ESB. Finally, perceived COVID-19 disruptiveness has a significant moderating influence on the relationship between ISE and ESB.

The energy consumption differentiates between populations of southern and northern Pakistan due to variations in climate and resource distribution. This investigation primarily looked

into participants' intentions to save energy in their homes. Actual data on energy-saving behaviour would be beneficial. As a result, the upcoming research could delve further into the participants' actual energy-saving behaviour and assess the difference between energy-saving intention and actual energy-saving behaviour. Future studies should concentrate on northern cities and a broader group of residential users to capture more general findings. Furthermore, because all of the variables in this research were gathered by a questionnaire survey, the results might be biased by cultural pressures. As a result, researchers would be able to get more actual and precise energy consumption data for residents via energy meter bills in future studies.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/**Supplementary Material**, further inquiries can be directed to the corresponding authors.

AUTHOR CONTRIBUTIONS

BA: Paper writing, MI: Data analysis, Writing-Review and Editing, MA: Proofediting and language, SS: Data analysis. All authors contributed to the paper and approved the submitted version.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2021.824318/full#supplementary-material

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