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Exploring Jordanian households' intentions to adopt solar energy systems using the theory of planned behavior

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Abstract
Sustainable development advocates for an energy transition as it is central to economic growth. Jordan is actively pursuing an energy transition agenda in line with its obligations under the Paris Agreement. This paper investigates households' intentions to adopt solar energy systems, a vital element of the sustainability transition process, using an extended model of the theory of planned behavior. In addition to the three predictors of the theory—attitude, subjective norms, and perceived behavioral control—the model incorporates perceived mandatory benefits. Energy poverty and socio-demographic factors such as income and governorate are also examined to assess their impact on the relationships between the four predictors and intention. Using convenience and snowball sampling, data was collected from 405 Jordanian households. After data cleaning, which involved removing flat liners and outliers, the final sample size was 381. Structural equation modeling was employed for the analysis, revealing that all predictors positively influence intention, with attitude having the highest path coefficient (0.363). Additionally, the findings indicate that socio-demographic factors and energy poverty levels do not significantly affect these relationships. This implies that Jordanian households' intention to adopt solar systems is primarily shaped by consumer knowledge, awareness, and behavior. Based on these results, the study proposes several policy recommendations to increase the adoption of household solar energy systems in Jordan, focusing on enhancing energy literacy and raising public awareness to promote climate resilience and support sustainable energy practices.

Keywords Theory of planned behavior · Consumers' adoption · Energy poverty · PLS-SEM · Energy transition · Environmental concern

1 Introduction

The sustainable development concept centers on economic growth, social advancement, and rational use of resources discourse [1]. This approach affects how we harness our resources to maintain the possibility of future generations' access to them. Energy, for example, is an essential resource for our daily lives. It is vital for our daily activities but also a primary source of CO_2 emissions. Reducing emissions from this sector is essential to limiting global warming [2] and support sustainability. Consequently, there is a global shift toward a just energy transition, moving from a

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fossil-fuel-based economy to one centered on clean energy while supporting low-income communities and carbon-dependent industries [3].

The energy transition can involve various approaches, such as phasing out coal, implementing energy efficiency standards for buildings, and adopting renewable energy systems. Such systems can substantially impact our way of life in the long term [4, 5]. In this context, governments need to promote the transition to cleaner renewable energy technologies, as scientific evidence shows that fossil fuels are depleting rapidly [6]. Consequently, using renewable energy sources and conserving energy are critical global concerns that impact both developed and developing countries [7].

Solar photovoltaics (PV) are among the most affordable renewable energy sources worldwide and are highly efficient in addressing the climate crisis [8]. Further, solar PV deployment will need to maintain an annual generating growth rate of 24% between 2020 and 2030, adding 630 gigawatts of new capacity additions and 6970 terawatt-hours of solar energy annually until 2030 to realize net-zero emissions globally by 2050 [8]. Solar energy is a readily available energy-producing technology used in residential settings [9]. Especially in the case of Jordan, solar energy is available almost all year round. However, in their research, [10] identified several barriers that determine the uptake and adoption of such systems, which can be summarized as households' decisions to adopt solar PV technology. These barriers are financial, socio-economic, cultural, environmental, technical, and policy-related factors.

Jordan largely depends on fossil fuels for its energy needs [11–13]. However, in recent years, the progress of different national and international environmental agendas has created the need to shift towards cleaner energy resources. The Government of Jordan has issued several other policies and strategies to combat climate change, assess fossil fuel dependency, and increase the ratio of renewable energy in the total energy mix [12, 14]. Jordan is working on the energy transition agenda as part of the Paris Agreement obligations and the updated Intended Nationally Determined Contribution (INDC) [15], and it has various renewable energy projects, such as wind, solar, hydroelectric, and biogas initiatives, located nationwide [16].

The Ministry of Energy and Mineral Resources (MEMR), through establishing the Jordan Renewable Energy and Energy Efficiency Fund (JREEEF), has created several programs that encourage improving energy efficiency and adopting solar energy systems for the residential and industrial sectors [17]. The funding programs are offered to Jordanian households with the help of community-based organizations and in collaboration with solar energy systems companies that sell those systems even without the funds. JREEEF aims to offer funding to support renewable energy sources and optimize energy usage. Since its establishment, over 2 million Jordanian citizens (17.5% of the total population) have benefited from the JREEEF's applications of energy efficiency and renewable energy programs, which have contributed to the reduction of Jordan's CO_2 emissions by 97,225 tons (1.1%) of Jordan's targeted NDCs [17]. Despite these efforts, Jordan still faces moderate levels of energy poverty, and progress toward emissions reduction remains modest. Residential electricity consumption is highest among other sectors, at 9863 and 10,525 Gigawatts/hour in 2022 and 2023, respectively, accounting for around 48% of total electricity consumption in both years [18]. Thus, a sustainable energy transition is needed in the residential sector, and solar power can play a vital role in Jordan's energy transition.

In this study, we aim to examine the Jordanian household's intentions to adopt solar energy systems. In our case, we are targeting two solar energy systems: photovoltaic solar panels used to generate electricity and solar water heaters used to heat water. These technologies can play a vital role in eradicating energy poverty while enhancing the resilience of the building sectors as a climate change mitigation action example [2, 19]. Our work contributes to the literature by bringing fresh insight into Jordanian households' perceptions of solar energy systems, their intentions to adopt those systems, and how energy poverty contributes to these intentions. It has been found that 46% of Jordan's electricity consumption is attributed to the residential sector, making it the highest consumer compared to other sectors, such as the industrial sector [20]. Understanding the relationship between renewable energy and households can help create new policies and programs that accelerate the energy transition in the household sector while alleviating energy poverty. Our model is unique in its approach, extending the theory of planned behavior (TPB) model by including new factors such as perceived mandatory benefits (PMB). Additionally, we consider socio-demographic characteristics, including income and the governorate of residence, in addition to energy poverty, to identify possible group differences. This study provides a better understanding of solar energy systems adoption practices in a developing country, enlightening the field with unique insights that were previously unexplored.

2 Literature review

Initially intended mainly for the study of individual behavior, the Theory of Planned Behavior suggests that the consideration of three components—the attitude toward the behavior in question, the subjective norms, and the perceived control over the performance of the behavior- will best predict the intention of performing the behavior by an individual [21]. It expands on the Theory of Reasoned Action (TRA) by incorporating Perceived Behavioral Control (PBC)—an individual's perception of their ability to perform a behavior. This addition makes TPB particularly useful in contexts where external constraints, such as financial limitations, play a role [22]. The description of these three predictors, along with other factors considered in this study, will be provided in the following section.

The TPB model has been applied across various fields and has demonstrated effectiveness, particularly in the context of pro-environmental behaviors, such as energy-saving actions. In this field, the attitude, subjective norms, and perceived behavioral control factors have been proven over time to influence behavioral intention [23–27]. To boost the predictive ability of TPB even further, some researchers have added more constructs to the model, such as consideration of future consequences or climate change beliefs [25, 28]. Some findings demonstrate that variables such as past behavior and habit also enhance the explained variance of intention and behavior, hence making TPB more flexible and practical across different domains [29, 30].

In Jordan, using an extended Theory of Planned Behavior, a study by ref. [31] identifies knowledge, attitudes, and price perceptions as the strongest predictors of Jordanians' intention to adopt solar panels. Demographic factors like age, income, and education significantly shape intentions, whereas gender does not. The findings suggest that increasing energy literacy and offering financial incentives are key to promoting renewable energy adoption.

Moreover, energy poverty (EP) is a potential factor driving the adoption of solar and other renewable energy technologies. Individuals facing energy poverty do not have enough energy to lead a healthy and satisfactory life and require additional energy to enhance their circumstances. Nevertheless, higher energy usage leads to increased carbon emissions unless derived from renewable sources (such as solar or biomass) or is balanced by reductions from those not experiencing energy poverty [32]. In Jordan, energy poverty is considered moderate, and it revolves around issues related to energy efficiency, economic and social capabilities of achieving suitable energy services [33, 34].

Solar panels can help reduce energy poverty; a study by [35] showed that solar energy can reduce energy burdens from 67 to 52% for all low-income households and from 21 to 13% for moderate-income families. Another study conducted in Australia demonstrated that adopting solar energy PV significantly reduces energy poverty, as measured by both objective and subjective indicators. These findings provide valuable insights for shaping future policies aimed at promoting residential solar PV by enhancing understanding of its potential impacts [36]. Another study from Jordan showed that adopting solar water heaters increased the share of electricity consumption and the human development index [37].

Nevertheless, according to ref. [3], adopting renewable energy technologies may inadvertently exacerbate inequality. Wealthier individuals are more likely to invest in carbon-reducing technologies, shifting demand away from fossil fuels. This shift could increase fossil fuel prices, disproportionately impacting low-income households that rely on them, thereby deepening energy poverty and widening inequality within countries.

Also, it is important to recognize that while intention is often the strongest predictor of behavior, it does not always align with actual actions. Factors such as income and energy poverty are expected to significantly influence the intention to adopt solar energy in Jordan. However, intentions may be more strongly shaped by other variables beyond financial constraints. While TPB focuses on attitudes, subjective norms, and PBC, the inclusion of moral norms is particularly relevant in ethical decision-making, such as sustainability and social responsibility [22]. Moral norms reflect an individual's personal ethical obligation to engage in or avoid certain behaviors [38]. In this context, while income and energy poverty may significantly impact the actual adoption of solar energy systems, they do not necessarily have the same effect on the intention to adopt them**.** Despite growing public interest in sustainability and positive consumer attitudes, actions do not consistently align with these attitudes, a disconnect often exists between their intentions and actions [39].

Renewable energy technologies, such as solar PV, have the potential to greatly reduce energy poverty and enhance living conditions, as demonstrated by studies in various regions. However, their implementation must be managed carefully to prevent worsening inequality. Additionally, while measuring Jordanians' intention to adopt solar energy systems is useful, it does not always align with their actual actions, as financial constraints and national regulations can influence behavior. Therefore, policymakers must develop inclusive strategies that ensure equitable access to renewable energy solutions while minimizing negative economic impacts on vulnerable populations.

3 Study variables, hypotheses, and model

The model used in the current analysis is an extended version of the TPB model applied to solar energy systems adoption aspirations in Jordan and includes the following variables:

- Attitude (ATT): This variable identifies households' perceptions of other energy-efficient practices. It is hypothesized that more positive attitudes would elicit stronger intentions to save energy [23, 24].
- Subjective Norms (SN): This variable represents the tendency of social pressure for energy conservation. Energy-saving intentions are found to be significantly impacted by both descriptive and injunctive norms [21, 23].
- Perceived Behavioral Control (PBC): This variable measures how capable households think they are of undertaking solar energy systems adoption actions. A higher PBC is predicted to enhance solar energy system adoption intentions [21, 29].
- Perceived Mandatory Benefits (PMB): This variable entails households' subjective monetary or rule-based advantages toward energy saving. It has been shown that such intentions can be easily based on their perceived advantage [23].
- Energy Poverty (EP): This variable investigates how reported energy hardships influence the adoption of behavioral intentions in solar energy systems. We use subjective indicators of energy poverty in this construct.
- Intention (INT): This is the main dependent variable, measuring households' intentions to carry out solar energy systems adoption activities. In support of TPB, where ATT, SN, and PBC are all high, stronger intentions are predicted [21].
- Socio-demographic variables, including household income and governorate.

The model also considered the influence of energy policies in Jordan and the Jordanian households' awareness of solar energy systems adoption programs implemented in the country. However, the initial analysis revealed that these factors had no significant effect on the intention of Jordanian households to adopt solar energy systems. Including them in the analysis weakened the model. Consequently, they were excluded from the model to enhance its robustness.

The conceptual model shown in Fig. 1 is used to test the following hypotheses.

H1 Attitude has a significant impact on the intention to adopt energy systems.

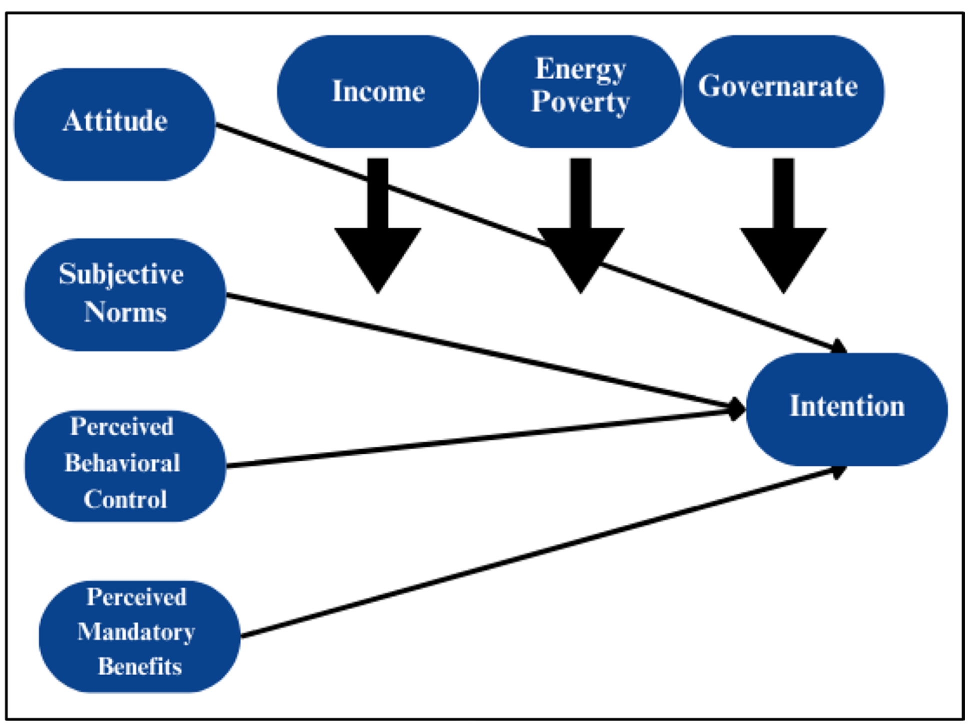

Fig. 1 Conceptual model. Source: Own compilation

H2 Subjective Norms have a significant impact on the intention to adopt energy systems.

H3 Perceived Behavioral Control has a significant impact on the intention to adopt energy systems.

H4 Perceived Mandatory Benefits have a significant impact on the intention to adopt energy systems.

H5 Income influences the relationships between the four main independent variables and intention, showing statistically significant differences across income groups.

H6 Energy poverty influences the relationships between the four main independent variables and intention, showing statistically significant differences across energy poverty groups.

H7 Governorate influences the relationships between the four main independent variables and intention, showing statistically significant differences across governorate groups.

4 Data and methods

4.1 Study design and data collection

To achieve the study goals, our survey design contained two main parts:

- Measurement of key constructs: This section measured key constructs outlined by the TPB, including attitude, subjective norms, perceived behavioral control, and intention. We also incorporated factors such as energy poverty, energy policies, and perceived mandatory benefits. Each respondent answered either yes or no (binary answers) on energy poverty and rated the other constructs on a scale of one to five using a Likert scale where one represents strongly disagree while five represents strongly agree.
- Demographic information: The demographic information section collected data on the respondents, including their household income, which governorate they live in, and other sociodemographic factors.

Survey items were adopted from existing and tested instruments in the literature. Questions based on the TPB were taken from ref. [21]. To ensure the appropriateness of language and culture, a forward and back translation from English to Arabic was employed with the assistance of a bilingual certified translator. A pilot test was conducted among 23 subjects to estimate the reliability and internal consistency of the instrument and correct any unclear items. As shown in Table 1, the Cronbach's Alpha values for the pilot test for all constructs exceeded 0.7, indicating that the data were reliable.

The survey design aims to achieve empirical novelty, as is customary in the social sciences. It is a thorough process, ensuring that every aspect is carefully considered and designed to meet the study's objectives [40]. The survey of our study was created using Google Forms and was open for responses from August 3 to September 4, 2024. Due to the nature of the study, we utilized convenience and snowballing sampling through online platforms. Given the constraints of the study, these methods were chosen for their practicality and efficiency. The data was collected through modern and efficient means, primarily using online tools and social media platforms, specifically Facebook, LinkedIn, WhatsApp, and X. The authors also sought help from two local community-based organizations to share the questionnaire through their

Table 1 Data reliability test. Source: Own results

Construct (Ordinal)	Cronbach's Alpha
ATT	0.739
SN	0.853
PBC)	0.705
PMB	0.759
INT	0.94

official channels to reach the highest number of respondents. This contemporary approach to data collection ensures that the research is conducted in line with current practices and technologies.

It is important to note that the use of non-probabilistic sampling methods, such as snowballing and convenience sampling, may inadvertently exclude certain social groups, particularly individuals with lower educational levels and those who do not engage with social media. This exclusion can introduce selection bias, as the sample may not accurately represent the broader population. Consequently, the findings may be skewed, overrepresenting digitally connected and more educated individuals. Although these sampling methods were deemed appropriate for this preliminary investigation, and social media has become a valuable tool for data collection—especially during the COVID-19 era [41, 42]—it's important to consider their limitations. In 2024, over 62% of Jordan's population (7.2 million people) had a Facebook account [43]. Nevertheless, to ensure a more accurate and inclusive representation of all social groups, future research should incorporate a variety of sampling techniques.

In Jordan, only 4% of the population is elderly (over 65 years old), and most live with their families. 66% of Jordanian households believe families should care for their elderly members at home. This means that it's likely that older people were included in our survey [41]. Initial data collection involved 405 responses; however, after data cleaning, which involved removing flat liners and outliers, the sample size was reduced to 381. Table 2 presents the socio-demographic characteristics of the respondents.

4.2 Sample representativeness

Regarding the representativeness of the sample, the socio-demographic characteristics of the respondents presented in Table 2 are compared with Jordan's national statistics for 2023 and 2024. In terms of gender distribution, the proportion of females in Jordan was 48.93% in 2023 [44], slightly lower than the 54.9% reported in Table 2. For age distribution, Jordan recorded 31.23% of the population below 15 years and 4.32% above 65 years in 2023 [44]. While a direct comparison with Table 2 is not feasible, the data presented appears reasonable and broadly aligns with national trends.

Regarding urban versus rural residency, 84.1% of Jordan's population was urban in 2024 [45], which is comparable to the 79.8% reported in Table 2. However, a notable discrepancy exists in educational attainment: only 2.43% of Jordanians aged 25 and older held postgraduate degrees in 2023 [44], whereas 26% of respondents in Table 2 reported such qualifications.

This divergence highlights a key limitation of the study—the representativeness of the sample. The sample appears to disproportionately represent a specific socio-economic group, particularly in terms of educational attainment. This

Table 2 Socio-demographic characteristics. Source: Own compilation

Variable	Values	Frequency	Percent (%)
Gender	Male	172	45.1
	Female	209	54.9
Age (Years)	24 or younger	132	34.6
	25–34	96	25.2
	35–44	81	21.3
	45–54	42	11.0
	55 or older	30	7.9
Urban/Rural	Urban	304	79.8
	Rural	77	20.2
Education	Diploma	25	6.6
	High School	22	5.8
	Bachelor	133	61.2
	Postgraduate	101	26.5
Household Income (JOD)	Less than 260	49	12.9
	261–460	89	23.4
	461–660	66	17.3
	661–860	60	15.7
	5861–1160	59	15.5
	More than 1160	85	15.2

likely reflects challenges in gathering data from individuals with lower levels of education or those lacking a high school diploma, which affects the overall results. Consequently, the results mainly reflect the views of more educated individuals. They do not provide an equal representation of all social groups within the Jordanian population. This limitation emphasizes the need for future research.

4.3 Structural equation modeling (SEM)

The analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) through the SmartPLS software. Unlike traditional SEM based on maximum likelihood estimation, PLS-SEM operates with a different algorithm. It is particularly advantageous when sample sizes are small or data distributions need to meet the requirements of traditional SEM. PLS-SEM is also preferred in studies where the theoretical foundation is underdeveloped or where there is limited prior knowledge of causal relationships. The focus of PLS-SEM is more on exploration rather than confirmation [46]. Furthermore, PLS-SEM does not require a large sample size, specific distribution assumptions, or complete data, making it suitable for testing causal relationships in studies with limited theoretical support or small sample sizes [47].

Structural Equation Models (SEM) can be reflective or formative. Three theoretical considerations distinguish these two types: the nature of the construct, the direction of causality between the indicators and the latent construct, and the characteristics of the indicators used for measurement [48]. In reflective models, the latent construct exists independently of the indicators used to measure it [49]. Conversely, the latent construct in formative models depends on the researcher's constructivist, operationalist, or instrumentalist interpretation [50].

In reflective models, causality flows from the latent construct to the indicators, meaning that changes in the construct lead to changes in the indicators. The opposite is true in formative models: causality flows from the indicators to the construct, so a change in the indicators results in the construct itself. Reflective models assume that changes in the latent variable must precede changes in the indicators, and the indicators are interchangeable, representing a common underlying theme. This interchangeability allows researchers to measure the construct using relevant indicators without significantly affecting its content validity [51]. In formative models, however, the indicators define the construct, making it more sensitive to the number and types of indicators used. Thus, the inclusion or exclusion of indicators can significantly affect the construct's validity. In this study, the hypothesized model and all constructs used are reflective. Figure 2 shows the basic SEM model.

4.4 Multi-group analysis (MGA)

Multi-group analysis (MGA) is a technique used in PLS-SEM to determine whether the results of group-specific analyses exhibit statistically significant differences across various groups. In this study, MGA is employed to assess the impact of energy poverty, income, and governorate of residence on the key constructs of the model. Based on these variables, the data is segmented into smaller groups, and the standardized path coefficient differences between the groups are evaluated for both value and significance.

Before conducting MGA, measurement invariance must be established. Measurement invariance ensures that the measurement models accurately capture the same attributes across different conditions [52]. Without this, observed differences in the relationships between latent variables might reflect variations in how respondents from other groups perceive the phenomena under study rather than actual differences in the structural relationships between the variables.

The measurement invariance of composite models (MICOM) procedure, as established by ref. [52] is employed to ensure the validity of the results and conclusions. The MICOM process involves three steps: (1) assessing configural invariance, (2) evaluating compositional invariance, and (3) testing for equality in the composite's mean value and variance across groups.

To establish configural invariance, it is necessary to confirm that identical indicators, data treatments, and algorithm criteria are used across groups. Compositional invariance is confirmed when the original correlation is either equal to or greater than the 5% quantile or when the p-value is insignificant. If both configural and compositional invariance are achieved, partial measurement invariance is confirmed, allowing researchers to compare path coefficients using MGA. Full measurement invariance is established when, in addition to meeting the criteria for partial invariance, the composites also show equal means and variances across the groups.

In this study, group comparisons are made using the permutation test [53]. This algorithm tests whether pre-defined data groups exhibit statistically significant differences in their group-specific path coefficients and provides crucial support to the MICOM procedure. It facilitates the measurement invariance analysis, enhancing confidence in the research

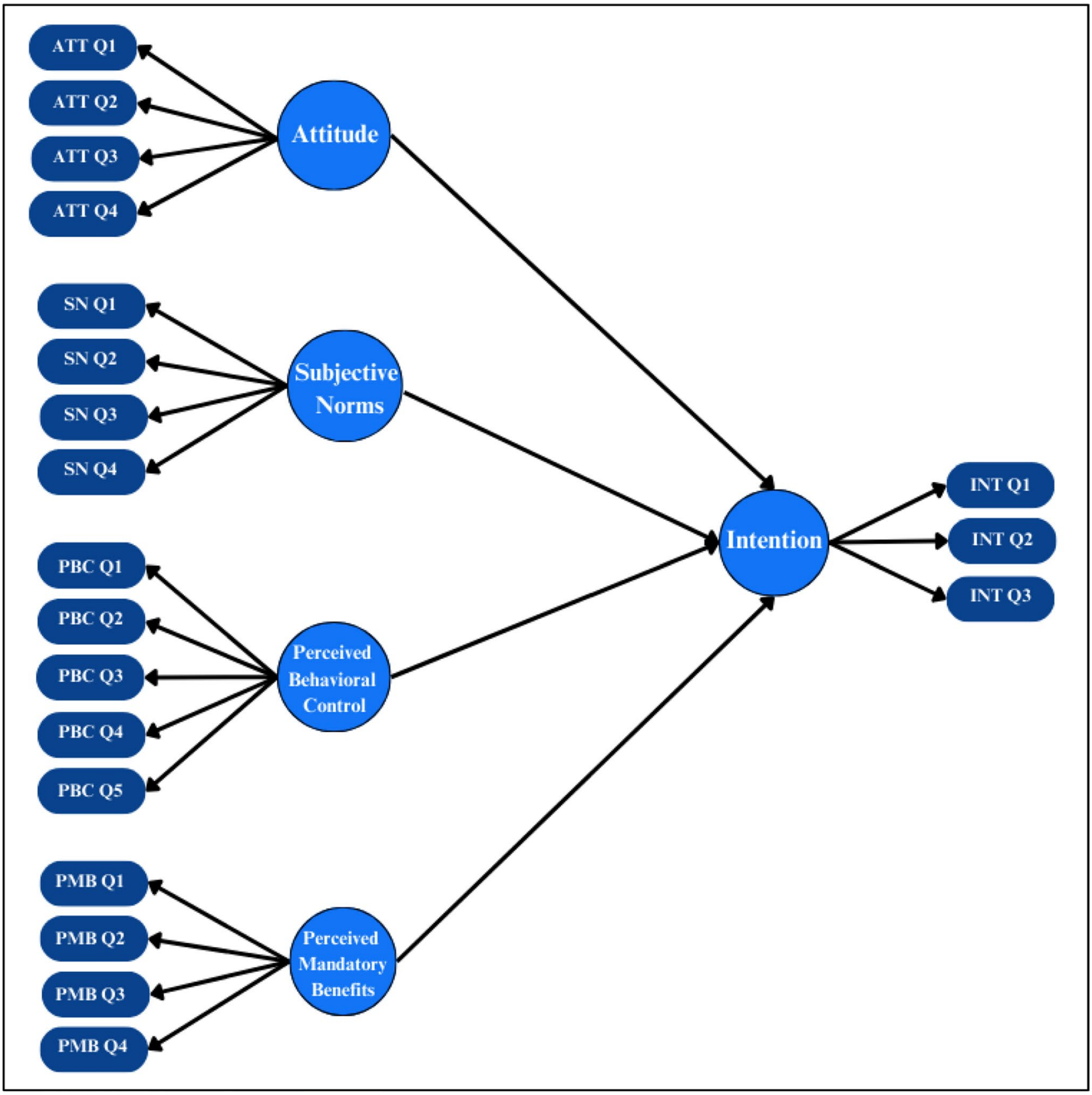

Fig. 2 Basic SEM model

methodology. For the permutation method to be effective, the number of cases in each group should be relatively similar; if one group's size is doubled, this method is not recommended [54]. A significance level of 0.05 is used to determine whether the differences between path coefficients are statistically significant.

5 Results and discussion

Energy poverty and socio-demographic variables (income and governorate of residence) were incorporated into the model to assess differences in path coefficients and examine how these factors influence the strength of relationships between the key constructs of the model. The data was split into two groups for each of these variables. The groups were classified as high and low for energy poverty and income. Energy poverty was measured through nominal yes/

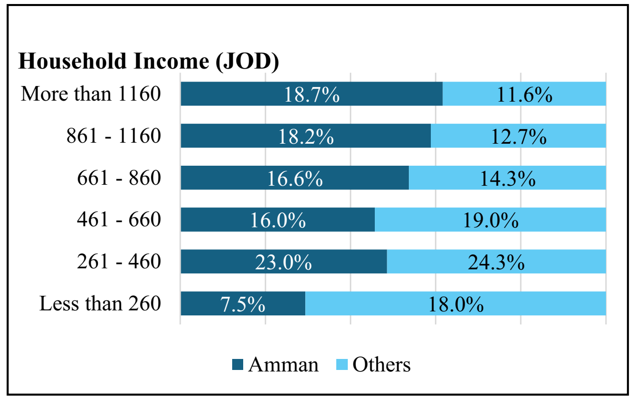

Fig. 3 Household income levels in Amman and other governorates of Jordan in 2024 (JOD). Source: Own results

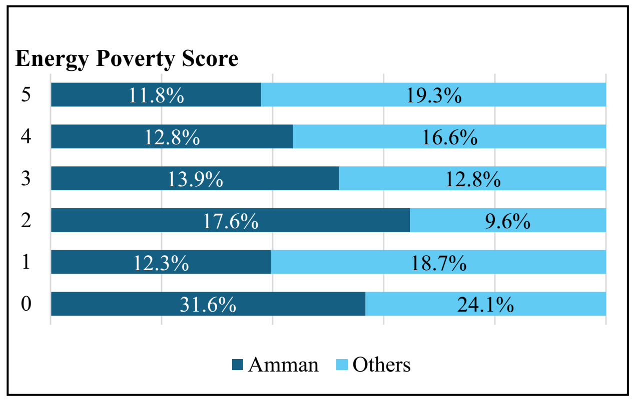

Fig. 4 Household energy poverty levels in Amman and other governorates of Jordan in 2024 (JOD). Source: Own results

no questions, with respondents who answered "yes" to three or more questions categorized in the high energy poverty group, while those who answered "yes" to two or fewer were placed in the low energy poverty group.

The data was divided into respondents from Amman (49.7%) and those from other governorates in Jordan (50.3%). This division was crucial as Amman, the capital, is more developed and expected to have higher income levels and lower energy poverty rates, providing a clear contrast for the analysis.

Figures 3 and 4 illustrate the income and energy poverty variations between respondents from Amman and other governorates. In Amman, 18.7% of respondents reported a high household income (over 1160 JOD), while 7.5% had a low household income (below 260 JOD). In contrast, among respondents from other governorates, only 11.6% had a high income, and 18% had a low income. These variations in income levels between Amman and other governorates have significant implications for the prevalence of energy poverty.

In terms of energy poverty, 31.6% of Amman respondents reported no energy poverty (answering "no" to all questions), while 11.8% reported high energy poverty (answering "yes" to all questions). For respondents from other governorates, 24.1% reported no energy poverty, and 19.3% reported high levels. These results confirm that households in Amman tend to have higher incomes and lower energy poverty rates than those in other areas of Jordan.

5.1 Model validity and reliability

Construct validity and reliability were assessed using factor loadings, Cronbach's Alpha, composite reliability, and average variance extracted (AVE) for all constructs, as shown in Table 3. Although some studies recommend that factor loadings should ideally exceed 0.60 for a valid and reliable measurement model [55], other research suggests that even weaker factor loadings can still produce consistent and asymptotically normal estimates, though at slower rates [56]. However, in this model, the factor loadings for the first questions of PMB and ATT were 0.386 and 0.568, respectively. As a result, these questions were eliminated, and the model was recalculated.

Cronbach's Alpha values for all constructs were above 0.7, while composite reliability ranged from 0.855 to 0.923, exceeding the recommended threshold of 0.60 [57]. Similarly, AVE values surpassed the recommended minimum of 0.5

Table 3 Model construct validity and reliability. Source: Own results

All data	Factor loadings	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
ATT				
ATTQ1	–	0.745	0.855	0.664
ATTQ2	0.867			
ATTQ3	0.837			
ATTQ4	0.735			
INT				
INTQ1	0.859	0.874	0.923	0.799
INTQ2	0.923			
INTQ3	0.898			
PBC				
PBCQ1	0.773	0.815	0.867	0.566
PBCQ2	0.808			
PBCQ3	0.708			
PBCQ4	0.753			
PBCQ5	0.713			
PMB				
PMBQ1	–	0.852	0.904	0.759
PMBQ2	0.853			
PMBQ3	0.859			
PMBQ4	0.902			
SN				
SNQ1	0.666	0.775	0.855	0.599
SNQ2	0.726			
SNQ3	0.859			
SNQ4	0.828			

[58]. This confirms that the items appropriately measure their respective constructs, ensuring the model's convergent validity.

The heterotrait-monotrait ratio of correlations (HTMT) was employed to assess the discriminant validity of the model. This assessment aims to ensure that a reflective construct demonstrates stronger relationships with its own indicators than with any other construct within the PLS path model [47]. The exact threshold for HTMT is debatable; some researchers recommend a threshold of 0.85, while others suggest 0.90 [59]. In this model, the HTMT values presented in Table 4 are below 0.85 for each pair of constructs, confirming the establishment of discriminant validity among these constructs.

5.2 Model fit

The fit statistics utilized in this study to evaluate model-data fit were the Standardized Root Mean Square Residual (SRMR) and the Normed-Fit Index (NFI). The SRMR represents the standard square root of the difference between the residuals of the sample covariance matrix and the hypothesized covariance model. SRMR values range from zero to 1.0, with well-fitting models typically scoring below 0.05; however, values up to 0.08 are considered acceptable [60].

Table 4 Discriminant validity—Heterotrait-monotrait ratio (HTMT) matrix. Source: Own results

All data	ATT	INT	PBC	PMB	SN
ATT					
INT	0.735				
PBC	0.411	0.471			
PMB	0.417	0.566	0.220		
SN	0.667	0.621	0.619	0.400	

The NFI evaluates the model by comparing its Chi-Square value to the null model, representing the worst-case scenario where all measured variables are assumed to be uncorrelated. NFI values range from 0 to 1, with a cutoff of 0.80 often recommended [61]. In this model, the SRMR was found to be 0.078, and the NFI was 0.813, indicating an acceptable fit and reinforcing our confidence in the study's findings.

5.3 Model results

Table 5 presents the model results for all respondents. The model exhibits an R-square value of 0.509, indicating that it accounts for more than half of the dependent variable's variance, a value considered high in the social sciences. The table also includes the standardized path coefficients, T-statistics, and P-values. All P-values are below 0.05, signifying significant relationships between the dependent variables and intention.

Among the constructs, attitude has the most substantial positive effect on the intention to adopt solar energy systems, with the highest standardized coefficient of 0.363. This is followed by perceived mandatory benefits (0.288), perceived behavioral control (0.165), and subjective norms (0.154). Precisely, a one standard deviation increase in intention corresponds to increases of 0.36, 0.29, 0.17, and 0.15 standard deviations in ATT, PMB, PBC, and SN, respectively. As a result, the first four hypotheses are accepted.

The intention of Jordanian households to adopt solar systems is primarily shaped by their perceptions and positive attitudes toward these systems. This intention is further strengthened by the perceived financial benefits and the households' confidence in their ability to adopt the technology. Households believe they can implement these systems and gain advantages from their use. Social pressure, however, has the most minor influence on adoption intentions.

5.4 Results of multi-group analysis (MGA)

Configural and compositional invariances were confirmed for all groups of categorical variables (energy poverty, income, and governorate of residence), establishing partial invariance. Complete invariance was not achieved due to variations in the composite variances across groups. Nevertheless, the establishment of partial measurement invariance allows for the execution of multi-group analysis (MGA) to compare standardized path coefficients across all groups. The number of cases in each pair of groups was adequate and reasonable. A permutation test was conducted with 5000 permutations.

Table 6 presents the path coefficients for each group, the differences between these coefficients, the permutation p-values, and the bootstrapping p-values for each hypothesis. While differences in path coefficients were observed across groups for all variables, these differences were not statistically significant, as the permutation p-values were not below 0.05. This indicates that these variables do not significantly impact the relationships between the main constructs of the model.

All independent variables positively influence the intention to adopt solar energy systems, which is consistent with the main model for all respondents. However, when examining the bootstrapping p-values (which reflect significance for each group separately), subjective norms do not significantly affect intention for respondents from other governorates, those experiencing high energy poverty, or those with high incomes. The p-values for these groups were above 0.05: 0.195 for "Others," 0.128 for "High Energy Poverty," and 0.116 for "High Income." This suggests that the influence of subjective norms on solar energy systems adoption intention weakens for respondents living in other governorates, those experiencing energy poverty, or those with higher incomes.

Besides subjective norms, socio-demographic factors and energy poverty levels do not affect the relationship between the predictors and adoption intention. This suggests that Jordanian households' intention to adopt solar systems is primarily influenced by consumer knowledge, awareness, and positive attitude rather than socio-demographic or energy poverty factors. This is clearly reflected in the low path coefficient of PBC, which represents Jordanians' beliefs about

Table 5 Model results—all respondents. Source: Own results

All respondents	R-square = 0.509			
Hypothesis	Path coefficients	T statistics	P values	Result
ATT→INT	0.363	7.420	0.000	Accepted
PBC→INT	0.165	3.255	0.001	Accepted
PMB→INT	0.288	5.522	0.000	Accepted
SN→INT	0.154	2.858	0.004	Accepted

Table 6 Multi-group analysis (MGA)—permutation test. Source: Own results

Hypothesis	ATT→INT	PBC→INT	PMB→INT	SN→INT
Governorate of residence				
Path coefficients				
Amman	0.391	0.193	0.226	0.176
Others	0.316	0.193	0.376	0.094
Difference	0.075	0.000	− 0.151	0.083
Permutation p-value	0.239	0.517	0.078	0.204
Bootstrapping p-value				
Amman	0.000	0.001	0.000	0.012
Others	0.000	0.007	0.000	**0.195**
Energy poverty				
Path coefficients				
High	0.280	0.159	0.369	0.134
Low	0.398	0.188	0.250	0.169
Difference	− 0.118	− 0.029	0.119	− 0.035
Permutation p-value	0.125	0.382	0.145	0.364
Bootstrapping p-value				
High	0.000	0.037	0.000	**0.128**
Low	0.000	0.003	0.000	0.007
Household income				
Path coefficients				
Low	0.288	0.150	0.318	0.197
High	0.437	0.189	0.256	0.107
Difference	− 0.149	− 0.039	0.062	0.089
Permutation p-value	0.064	0.347	0.282	0.194
Bootstrapping p-value				
Low	0.000	0.030	0.000	0.008
High	0.000	0.001	0.000	**0.116**

The results in the table and numbers are discussed below the table

their financial capacity to adopt solar systems. Jordanians' intentions are more strongly influenced by positive attitudes and the financial benefits of solar energy, supporting that financial conditions such as income and energy poverty do not have a significant impact on their intentions. The fifth, sixth, and seventh hypotheses are partially accepted.

Moreover, although not reflected in the results and omitted from the model to improve robustness, Jordan's energy policies and household awareness of solar adoption programs in the country showed no impact on intention, indicating these policies and programs are not sufficiently effective. This can be attributed to both policy adaptation and financial challenges. Previous research has shown that households in Jordan tend to respond slowly to new energy policies, taking considerable time to adjust to these changes [33]. This delay could be due to a lack of confidence in the long-term return on investment in solar technology. Additionally, household decisions regarding solar adoption are often influenced by broader economic and social factors. For instance, while energy expenditure in Jordan has the potential to improve well-being, this effect is more pronounced when accompanied by improvements in income, education, health, and urbanization levels [62]. Without these complementary factors in place, the effectiveness of solar adoption policies is likely to be constrained.

6 Conclusions

Our study examined Jordanian households' intentions to adopt solar energy systems, particularly solar PV and water heaters. Our motivation was to expand the Theory of Planned Behavior by incorporating energy poverty as a key factor and analyzing its impact on households' sustainable transition. Using an online survey with 381 valid responses, we applied structural equation modeling to test the relationships between attitudes, subjective norms, perceived behavioral control, perceived mandatory benefits, and adoption intentions.

The results confirm that all predictors positively influence adoption intentions, with attitude emerging as the most significant driver (standardized path coefficient = 0.363), followed by perceived mandatory benefits (0.288), perceived behavioral control (0.165), and subjective norms (0.154). However, our multi-roup analysis reveals that income, governorate, and energy poverty do not significantly alter these relationships, except for a weaker influence of subjective norms in certain subgroups, such as high-income households and those outside Amman. These findings highlight the importance of distinguishing between intention and behavior. While intention is a strong predictor of behavior, its relationship with actual adoption can vary. In the case of solar energy in Jordan, energy poverty was expected to have a significant impact on intention, yet our results show a limited impact. This suggests that intention is more influenced by positive attitudes and perceived financial benefits than by financial barriers or social pressure. However, in practice, financial constraints and other factors, such as energy regulations and policies, may restrict actual behavior. Therefore, future research should focus more on examining behavior to gain deeper insights.

However, the findings challenge previous assumptions that socioeconomic factors strongly influence energy transition intentions, demonstrating that consumer-perceived financial benefits and positive attitudes play a more significant role than income or energy poverty levels. This insight contributes to ongoing debates about the effectiveness of behavioral interventions versus financial incentives in promoting renewable energy adoption.

From a policy perspective, our findings suggest that public awareness and positive attitudes are more impactful than financial status in driving solar systems adoption. However, it is important to consider that the sample may not have been fully representative in terms of educational attainment, with the results largely reflecting the views of more educated individuals. Despite this, financial limitations may hinder the actual adoption of solar systems, which explains their lack of widespread popularity in Jordan. Therefore, policymakers should focus on the following:

- Energy Literacy Programs by increasing public knowledge about solar benefits and financing mechanisms.
- Transparent Regulations to ensure clear communication regarding solar system pricing, government incentives, and electricity pricing for solar users to build trust in the market.
- Decentralized Energy Models by introducing renewable energy communities, similar to those in Europe, to encourage collective solar adoption and enhance social acceptance. Such a step requires new regulations and standards but will result in enhancing accessibility to renewable energy.
- Strengthening JREEEF Oversight by addressing the misleading marketing of solar subsidies by ensuring companies accurately disclose financing options to consumers.
- Introducing new financial incentives to enhance the attractiveness of solar energy adoption and improve affordability, particularly for lower-income households and energy-poor communities. These incentives could include revised metering policies that offer higher compensation for surplus electricity fed into the grid.
- Introducing government subsidies that could be structured as low-interest loans for low-income households, enabling them to afford solar technologies. The repayment of these loans could be offset by the savings generated from reduced energy costs, making the transition to solar energy more financially viable.

While energy poverty does not significantly impact solar adoption intention, policies targeting low-income households should prioritize accessibility to financing mechanisms and community-based solar projects. By integrating these measures, Jordan can accelerate the adoption of household solar energy systems, reduce reliance on fossil fuels, and enhance climate resilience.

7 Limitations

In our study, we define three limitations. First, the sampling method used is non-probabilistic, meaning that we can't generalize our results in a broader context but need further assessments and research regarding renewable energy adoption and energy poverty. Second, using an online survey limits our respondents to those who own a mobile phone or a computer to access the questionnaire and fill it out. Third, and as suggested by ref. [63], it is advised to use a compilation of theories to investigate the factors affecting the study question. Lastly, our study is cross-sectional, and future research may focus on changes in intentions and such system adoptions through time by using longitudinal data to investigate the change in actual behavior of adopting such systems.

8 Future research

Future research should employ longitudinal studies or experimental interventions that help track whether households have followed through on their intentions and identify reasons for not adopting. Longitudinal studies or intervening experiments will therefore be required to see whether households are following their intentions and the barriers to adoption. It needs to include qualitative studies for deeper understanding.

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Data availability Data will be available upon a reasonable request.

Declarations

Ethics approval and consent to participate This study was observational, involving no interventions or experimental procedures. It was conducted in accordance with the ethical principles of the Declaration of Helsinki. Participation in the survey was voluntary, and all respondents provided informed consent before completing the questionnaire. Anonymity and confidentiality were strictly maintained throughout data collection and analysis.

Competing interests The authors declare no competing interests.

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