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Sustainable technologies adoption research: A weight and meta-analysis

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ABSTRACT

Along with escalating environmental problems, the role of technologies in mitigating those problems has also increased. Researchers have been studying the adoption of sustainable technologies, and the number of articles on the topic has grown in recent years. The current study presents a weight and meta-analysis that synthesizes and combines previous literature on sustainable technologies adoption, evaluating the state of the art and providing a comprehensive picture of the phenomena. Using 44 articles and 48 datasets, the results demonstrate that attitude, benefits, personal norms, incentives, and perceived behavioral control are the best predictors of the behavioral intention of sustainable technologies adoption. Moreover, journal ranking, innovation, individualism, and long-term orientation, as cultural moderators, as well as electricity access and renewable energy, as energy efficiency indicators, were found to moderate subjective norms and behavioral intention. The findings of this study are relevant for future research support.

1. Introduction

Nowadays, sustainability has been the main topic of research due to the current need to address environmental problems and climate change. Mitigation efforts, from the adoption of renewable energy and energy-efficient appliances to the adoption of new habits and regulations to better control wasteful behaviors, should be implemented and are being studied by both researchers and policymakers [1]. Regarding this, the concept of sustainable technologies has emerged. Sustainable technologies are those that resort to sustainable resources or reduce natural resource use [2], which by themselves are more sustainable and efficient [3], or can help consumers change their behavior toward sustainability through more active intervention based on metering technologies [4]. Sustainable technologies can be considered as a different type of technology, which are characterized by their technology element but distinguishes them from others by being innovative and requiring some knowledge on the part of the user, many of which are also able to invade user privacy and collect data.

The number of studies regarding sustainable technologies has grown recently, covering topics such as smart home technologies [5,6], efficient appliances [7,8], renewable energies [9,10], and electric vehicles [11,12], among others. These results reflect the maturity of these types of technologies. Sustainable technology literature is somewhat scattered, and the research process has become complex. There is therefore an urgent demand to provide a comprehensive and synthesized picture of the progress in the field of sustainable technologies by evaluating and integrating the findings reported in the literature.

The main goal of this study is to perform a weight and meta-analysis, which can be seen as a stronger method to synthesize the published quantitative findings, compared to the usual literature reviews [13]. A meta-analysis is considered to be a robust method that helps obtain a concise understanding of a topic (even when the literature presents contradictory results), exposing relationships, differences, and possible gaps [14]. A weight analysis is also performed in order to identify the most frequently used constructs such as the "best" and "promising" indicators [15]. These methods allow us to generalize results from different studies with different techniques and samples, evaluate the most used and most important variables, and quantify moderating effects.

This article makes two important contributions. First, to the best of our knowledge this is the first time that a weight and meta-analysis has been performed for this set of technologies, and given the variety of results in the area, it will contribute to a clearer and more harmonized view of sustainable technology adoption. Finally, it will contribute to the understanding of patterns in terms of the most-used variables and theories, facilitating theory development.

The paper is structured as follows. Section 2 presents the research methodology with a description of the selected studies and the merging

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process. Then some descriptive analytics are presented, together with the meta and weight analysis results, including the moderator's analysis. Section 4 introduces the discussion of results and their implications, followed by the limitations and future research directions in Section 5. Finally, the conclusion is advocated in Section 6.

2. Research methodology

2.1. Selection of studies

A systematic literature review was conducted during February and March 2021, resorting to the most well-known electronic scientific databases available, namely Emerald, IEEE, JSTOR, Scopus, Science Direct, Web of Science, Taylor & Francis, and Google Scholar [16]. Advanced queries were built using the logical operators (AND/OR) and the most related keywords, such as: sustainability, sustainable technology adoption, acceptance, smart home technologies, renewable energy, electric vehicles, smart meters, and smart homes. Initially, 2336 articles were found. Of those, the articles related to agriculture and firm level were excluded, and duplicates were removed. Of the remainder, the search was limited by a set of inclusion criteria: (1) studies published under a peer-review process; (2) studies analyzed at an individual level; (3) quantitative studies that show correlation values and sample sizes; (4) independent datasets; (5) studies using datasets already included were removed to avoid study bias by using the same sample [17]. In the end 44 articles were found to meet the criteria, representing the 48 datasets. Fig. 1 describes the selection process. Each article selected was fully examined, collecting the publication year, source, independent variable, dependent variable, the correlation coefficient of each relationship, significance, method, type of technology, sample size, country, and journal.

2.2. Variables merger and relationships

The independent and dependent variables were extracted from the selected articles. However, many of those variables had similar meanings even if written in different ways. So, based on the definitions of the variables and their names, the variables were merged. This will increase the meta-analysis precision. For example, "Attitude" and "Attitude on … (some technologies)", were merged as "Attitude". This was done for both

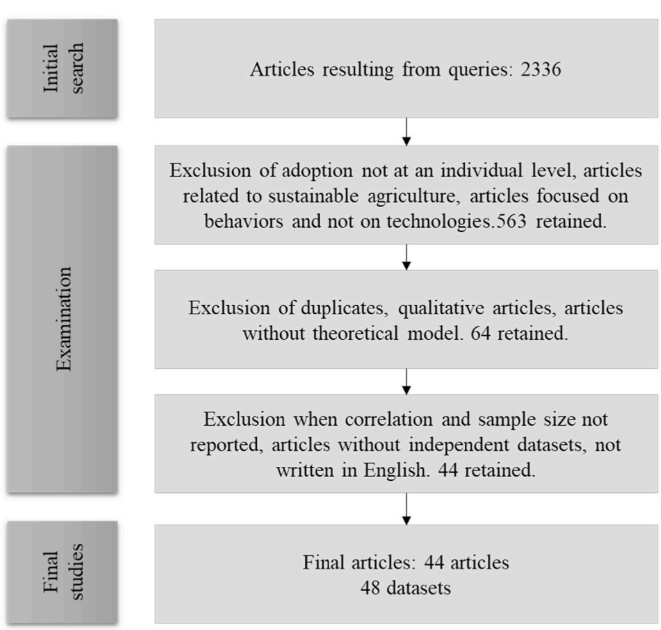

Fig. 1. Selection process.

dependent and independent variables. After that, 305 relationships were identified. Of those, 33 were used, as only the relationships that occurred three or more times across the studies should be selected for the meta-analysis [18]. Of these, the main dependent variable that appears in the literature is behavioral intention. Behavioral intention refers to the motivational factors that may lead to the performance of a certain behavior, in this case, the individual acceptance of sustainable technologies. Appendix A presents the codifications of the variables used.

2.3. Moderation analysis

Regarding the moderators, 12 possible variables were analyzed as possible moderators of some relationships. The journal impact factor was selected as a methodological moderator. The human development index (HDI) was also selected as a socio-economic factor. This variable is a summary of the three key development dimensions: life expectancy, standard of living, and education. The global innovation index (GII) was also considered as a possible moderator. GII comprises 81 different indicators and summarizes the level of economic innovation. Economic development can impact behavioral intention, so it is expected that developed and innovative economies have higher behavioral intentions compared to developing economies, as the first tend to invest more in sustainable solutions and have greater skills and familiarity with technologies [19,20].

Three energy related variables were selected, namely electricity access, renewable energy, and energy efficiency. These are energy efficiency indicators collected by the International Energy Agency (IEA) that are used to track and improve energy efficiency policies [21]. As many of the sustainable technologies are related to energy issues, it is expected that countries with better energy conditions and higher investment in energy efficiency are those that present higher levels of behavioral intentions to adopt sustainable technologies, due to their experience and investment power.

Finally, cultural factors were selected based on Hofstede et al. [23], namely power distance, individualism, masculinity, uncertainty, long-term orientation, and indulgence. These are conceptualized as indicators of individual values, and may therefore impact their behavior. Thus, cultural factors can be possible moderators influencing behavioral intentions [22].

3. Results

3.1. Descriptive analytics

As described above, 44 articles meet the defined criteria, resulting in 48 independent datasets (some studies use more than one dataset). Of these, 305 relationships were identified for their meta and weight analyses. The datasets cover 19 countries. Fig. 2 presents the distribution of samples by country. Note that one dataset is not included in the figure as the samples were jointly collected in more than one country. Fig. 2 portrays four countries with more than 2000 respondents, which are Germany (34% of total respondents), China (16% of total respondents), Pakistan (10% of total respondents), and Malaysia (7% of total respondents).

Regarding the research period, the studies selected range from 2014 to 2021. Of these, 61% are from 2019 to 2021, confirming an increased interest in the topic. Table 1 summarizes the number of articles per journal and year. Concerning the source of our data, articles mainly belong to the energy field, followed by information systems. The most important journals account for 50% of the articles, namely the *Energy Policy Journal* (14%), *Sustainability* (14%), *Journal of Cleaner Production* (11%), *Energy Research & Social Science* (7%), *Energy Journal* (5%).

The articles were also categorized according to the type of technology studied. Renewable generation technologies were the most frequent sustainable technology studied (25%), suggesting that broad research

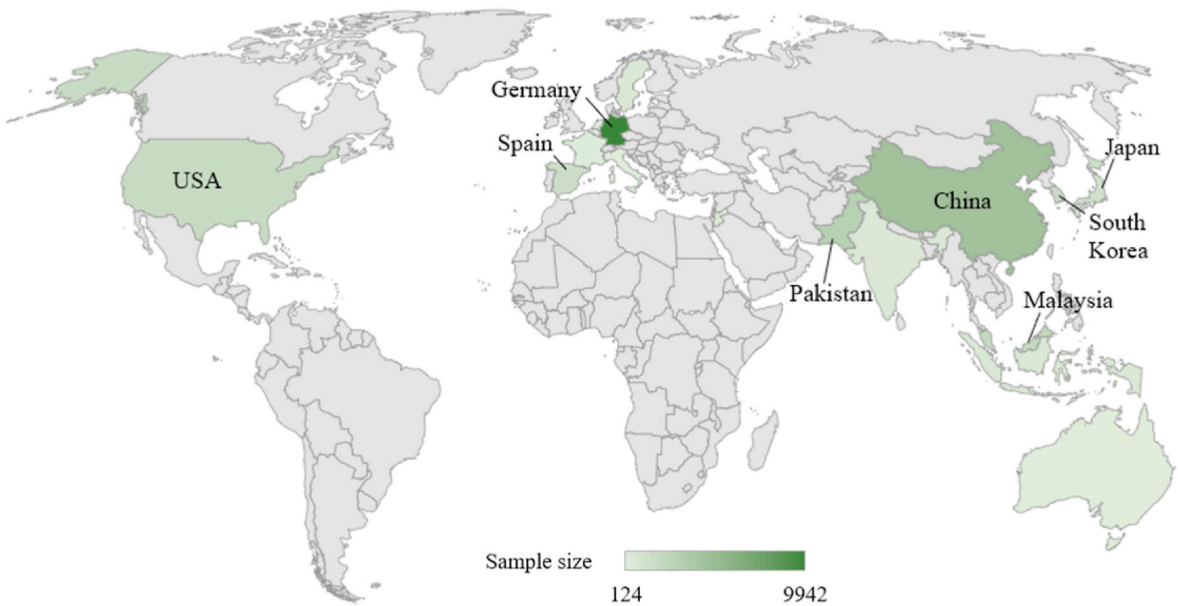

Fig. 2. Sample distribution per country.

Table 1
Research studies used in the meta-analysis by journal and year.

Journal	2014	2015	2016	2017	2018	2019	2020	2021	Articles
Applied Energy	**1**								[24]
Business Strategy and the Environment					**1**				[25]
Computers in Human Behavior					**1**				[26]
Ecological Economics				**1**					[27]
Economies							**1**		[28]
Energies						**1**			[29]
Energy								**2**	[30,31]
Energy Policy				**2**		**1**	**2**	**1**	[32–37]
Energy Research & Social Science			**1**			**1**	**1**		[38–40]
Environment, Development, and Sustainability								**1**	[41]
Environmental Science and Pollution Research								**1**	[42]
Global Environmental Change	**1**								[43]
International Journal of Energy Sector Management					**1**				[44]
International Journal of Environmental Research and Public Health							**1**		[45]
Journal of Cleaner Production		**1**				**3**		**1**	[46–50]
Journal of Environmental Planning and Management								**1**	[51]
Journal of Environmental Psychology		**1**							[52]
Journal of the Association for Information Systems				**1**					[53]
MIS Quarterly							**1**		[54]
Renewable and Sustainable Energy Reviews		**1**							[55]
Resources, Conservation and Recycling							**1**		[56]
Sustainability		**1**		**1**		**3**	**1**		[8,57–60]
Sustainability Accounting, Management and Policy Journal					**1**				[61]
Sustainable Production and Consumption								**1**	[62]
Technological Forecasting and Social Change							**2**		[63,64]
Transportation Research Part A				**1**					[65]
Total	**2**	**4**	**1**	**6**	**4**	**9**	**10**	**8**	

exists for renewables, followed by electric vehicles (20%). Finally, the third most frequent sustainable technology studied was energy-efficient appliances (14%), also showing the prominence of energy-related technologies. These results suggest the elevated awareness of sustainable technologies, especially in the energy and mobility areas.

3.2. Weight and meta-analysis results

A meta-analysis is a rigorous method that allows summarizing the quantitative results from a large number of previous studies on similar topics of research, and is a strong alternative to narrative and descriptive literature reviews [13]. This method allows presenting a consolidated review of prior research, analyzing the topic (in the present case of sustainable technologies) from a broader perspective [66]. For that, quantitative metrics of all relationships between variables relevant to the topic were collected, including both the statistically significant and non-significant, contributing then to a united conclusion and reinforcing the validity of the meta-analysis results [67]. This method combines effect sizes across relationships between variables, from different studies, allowing researchers to derive their pooled estimate of the independent variables used to explain the behavior intention to adopt sustainable technologies.

To perform this analysis, the main requirements are the effect size and the sample size for each relationship. For the meta-analysis the random-effects model was used instead of the fixed-effects model, since the effect size varies from study to study and the studies are heterogeneous [68]. This is a more realistic method, as the studies may be heterogeneous and effect sizes may vary according to each population. This effect has been applied in several meta-analyses [18,20,69] since it considers the variation between and within the studies. The meta for the R studio package was used. The meta-analysis results are presented in Table 2. The first columns present the number of times the relationship was examined (O), the cumulative sample size (N), the correlation found in the studies were corrected by sample size (Mna), the standardized effect size score (Z), the significance level (Sig). The confidence interval presents the lower (ICI) and upper (ICS) bound of 95% confidence level. Only if the interval includes zero are the relationships then not statistically significant. Otherwise, they are considered statistically significant.

Regarding heterogeneity, two measures were used. The Q Cochran measure indicates whether or not data from primary studies refute the homogeneity hypothesis. As such, of the 33 total relationships, 26 were rejected in this hypothesis ($p < 0.01$). The I^2 statistic is obtained from the Q Cochran and varies from 0 to 100% [70]. It indicates the percentage of variance in the dataset resulting from heterogeneity. Most relationships from Table 2 present a higher heterogeneity, above 90%.

Table 2 shows that of the 33 relationships, 26 are statistically significant and 7 are not statistically significant. Therefore, green self-identity (−0.115), costs (−0.063), householder age (−0.009), income (−0.034), gender (−0.023), trust in data protection (−0.068), and pro-environmental behavior (−0.011) were found to be not significant. The strongest effects on the behavioral intention to adopt sustainable technologies are from the capability to power blackouts (−0.714), perceived value (−0.604), subsidies (−0.584), convenience (−0.578), attitude (−0.565), benefits (−0.534), personal norms (−0.512), incentives (−0.479), status gain (−0.447), adoption norms (−0.428), and perceived behavioral controls (−0.402).

Regarding the weight analysis, this method allows researchers to estimate the importance of an independent variable, indicating its predictive power in the relationship with the dependent variable [15]. The combination of a meta and weight analysis provides different but interrelated views of the significance and strength (i.e., weight) of the predictors on the dependent variable. It therefore provides a summary of the cumulative impact of independent variables on the dependent variable under study [18]. The strength of an independent construct is calculated by dividing the number of times the independent variable is significant by the total number of relationships the independent variable analyzed. Therefore, a weight of 1 indicates that the relationship was statistically significant in all articles, and a weight of 0 indicates no relationship was statistically significant. According to Jeyaraj et al. [15], if the variable is tested five or more times it is considered to be “well-utilized”. If tested fewer than five times, but has a weight equal to 1, then the variable is considered to be a “promising predictor”. Finally, if a variable has a weight higher or equal to 0.8 and was examined five or more times then it is considered a “best predictor”. Of the 33 relationships, 15 were considered “best predictors” (BP) and 9 were considered “promising predictors” (PP) for the behavioral intention to adopt sustainable technologies. Therefore, the “best predictors” with a weight of 1 are attitude, perceived behavioral control, personal norms, benefits, effort expectancy, incentives, environmental benefits, awareness,

Table 2
Meta-analysis results on the Behavioral intention.

Meta-analysis										Weight analysis			
Relations	O	N	Mna	Z	Sig	ICI (95%)	ICS (95%)	Q	I^2	NonSig	Sig	Weight	Type
Subjective norm	23	13,212	.343	5.98	.001	.236	.443	1003.26	97.8%	1	22	0.957	BP
Attitude	20	10,152	.565	5.77	.001	.399	.695	2306.92	99.2%	0	20	1.000	BP
Performance expectancy	15	8054	.375	4.69	.001	.225	.507	917.08	98.5%	1	14	0.933	BP
Perceived behavioral control	14	8195	.402	5.62	.001	.270	.519	570.68	97.7%	0	14	1.000	BP
Knowledge	12	7039	.398	6.30	.001	.282	.502	307.27	96.4%	1	11	0.917	BP
Environmental concerns	12	6269	.327	5.37	.001	.212	.433	244.80	95.5%	1	11	0.917	BP
Personal norms	11	7366	.512	6.03	.001	.364	.634	577.91	98.3%	0	11	1.000	BP
Benefits	9	3439	.534	9.97	.001	.445	.613	94.95	91.6%	0	9	1.000	BP
Green self-identity	*10*	*3414*	*.115*	*1.39*	*.165*	*-.047*	*.273*	*523.38*	*98.3%*	*4*	*6*	*0.600*	
Costs	*8*	*4451*	*-.063*	*-.32*	*.747*	*-.422*	*.312*	*118.09*	*99.4%*	*4*	*4*	*0.500*	
Effort expectancy	8	9553	.298	3.14	.001	.115	.462	509.03	98.6%	0	8	1.000	BP
Adoption norms	8	1821	.428	3.70	.001	.212	.605	245.83	97.2%	2	6	0.750	
Incentives	7	3869	.479	5.67	.001	.329	.606	189.22	96.8%	0	7	1.000	BP
Economic benefits	6	9930	.301	.307	.002	.119	.469	424.60	98.8%	1	5	0.833	BP
Environmental benefits	6	4179	.310	3.44	.001	.137	.465	105.30	95.3%	0	6	1.000	BP
Privacy concerns	6	4036	-.134	−2.30	.020	-.245	-.020	91.52	94.5%	5	1	0.167	
Awareness	5	1638	.313	4.72	.001	.187	.429	29.84	86.6%	0	5	1.000	BP
Symbolic attributes	5	3293	.320	11.52	.001	.269	.370	5.28^{ns}	24.2%	0	5	1.000	BP
Instrumental benefits	5	3293	.200	1.89	.059	-.007	.392	62.67	93.6%	0	5	1.000	BP
Householder age	*5*	*9192*	*-.009*	*-.88*	*.377*	*-.029*	*.011*	*2.75^{ns}*	*0.0%*	*4*	*1*	*0.200*	
Innovativeness	4	2634	.308	2.33	.019	.050	.527	131.31	97.7%	0	4	1.000	PP
Status gain	4	1359	.447	3.55	.001	.212	.633	70.78	95.8%	0	4	1.000	PP
Perceived value	4	2282	.604	7.71	.001	.479	.705	47.64	93.7%	0	4	1.000	PP
Income	*4*	*4450*	*.034*	*1.61*	*.106*	*-.007*	*.075*	*5.89^{ns}*	*49.1%*	*2*	*2*	*0.500*	
Gender	*3*	*3520*	*.023*	*.99*	*.324*	*-.023*	*.071*	*4.09^{ns}*	*51.1%*	*1*	*2*	*0.667*	
Trust in data protection	*3*	*3106*	*.068*	*1.08*	*.280*	*-.055*	*.190*	*24.16*	*91.7%*	*2*	*1*	*0.333*	
Hedonic motivations	3	1990	.266	3.35	.001	.112	.407	22.84	91.2%	0	3	1.000	PP
Convenience	3	474	.578	9.66	.001	.482	.660	6.30	68.3%	0	3	1.000	PP
Subsidies	3	474	.584	17.41	.001	.532	.631	$.04^{ns}$	0.0%	0	3	1.000	PP
Capability to power a blackout	3	1098	.714	12.97	.001	.641	.774	9.68	79.3%	0	3	1.000	PP
Psychological benefits	3	1098	.309	8.93	.001	.245	.372	2.69^{ns}	25.6%	0	3	1.000	PP
Investment risk	3	1098	-.453	−7.57	.001	-.548	-.347	8.46	76.4%	3	0	0.000	
Pro-environmental behavior	*3*	*2692*	*.011*	*.55*	*.584*	*-.038*	*.054*	*2.40^{ns}*	*16.5%*	*0*	*3*	*1.000*	*PP*

Note: O = number of observations taken from the analysis of the studies; N = number of accumulated samples of the assessed studies; Mna = correlation found in the studies corrected by sample size; Sig = *significant ($p < 0.001$);* not significant ($p > 0.05$). ICI (95%) = lower bound of confidence interval; ICS (95%) = upper bound of confidence interval; Q = test of heterogeneity at the individual; I^2 = scale-free index of heterogeneity; Sig represents significant relationships; NonSig shows nonsignificant relationships; BP = Best Predictor; PP = Promising Predictor; Italic line represents not supported relationship given low correlation or confidence interval difference.

symbolic attributes, and instrumental benefits. The "best predictors" with a weight lower than 1, but higher than 0.8, are subjective norm (weight = 0.957), performance expectancy (weight = 0.933), knowledge (weight = 0.917), environmental concerns (weight = 0.917), and economic benefits (weight = 0.833). The "promising predictors" are innovativeness, status gains, perceived value, hedonic motivations, convenience, subsidies, capability to power a blackout, psychological benefits, and pro-environmental behaviors.

3.3. Moderation analysis

Moderation analysis was conducted to seek an explanation for any changes in effect size. The results are shown in Table 3. For this analysis, the relationships with a high number of observations (≥20) and high heterogeneity [71] were selected. Thus, only two relationships were analyzed: subjective norm and behavioral intention (23 relationships, I = 97.8%), attitude and behavior intention (20 relationships, I = 99.2%). Significant moderation of the journal impact factor (β =0.0027; p < 0.01), and GII (β =0.2434; p < 0.05) were found for subjective norm. Of the cultural factors, individualism (β =-0.0884; p < 0.05) and long-term orientation (β =-0.1506; p < 0.05) were found to be significant. Finally, of the energy related factors, electricity access (β =-0.1135; p < 0.05) and renewable energy (β =0.0918; p < 0.05) were found to be significant moderators. Last, a possible moderation was investigated between attitude and behavior intention, but no statistically significant effect was found. The Moderation results are discussed in the next section.

4. Discussion

Sustainable technologies have been studied using various theories and constructs. The current study indicates that in general the constructs and relationships used are several and scattered. From the systematic literature review, 305 relationships of the 44 articles were examined, providing a comprehensive review of the sustainable technology adoptions and the most important constructs used to explain them. By analyzing the relationships, the meta-analysis allows finding the statistically significant predictors, as well as some heterogeneity measures and publication biases. Some heterogeneity levels can be due to different sample sizes, methods, demographic variables, or even cultural differences. The meta-analysis results show that 26 of the 33 results are statistically significant.

Research on sustainable technologies has mainly used the theory of planned behavior (TPB) and the technology acceptance model (TAM), extending them with several variables such as pro-environmental behaviors and/or motivational theories. Some of the most used and significant predictors are attitude (0 β = .565), perceived behavioral control (0 β = .402), subjective norms (0 β = .343), and performance expectancy (0 β = .375). This set of variables has been so widely used for technology or behavioral acceptance that it is not surprising to find them significant. However, other studies have developed their own research models that are not grounded on any well-known theory, but instead on the variables related to the specific technology characteristics, as specifically confirmed by the importance of capability to power a blackout construct (0 β = .714), perceived value (0 β = .604), subsidies (0 β = .584), and benefits (0 β = .534). The impact of subsidies and benefits is noteworthy since they refer to concrete strategies that can be used to promote sustainable technology adoption. Subsidies refer to any financial exemptions or grants that can be applied over the adoption of some solutions. Subsidies have been widely used as a strategy to promote sustainable technology adoption. Especially in this set of technologies, some governments and public organizations provide financial and regulatory subsidies for the adoption of these solutions, mainly when the costs are considered high [34,37]. The benefits also refer to the advantages that the solutions offer, and are closely related to perceived value, which is also a strong predictor. The choice of individuals is mainly based on a comparison of perceived benefits and costs, and when the benefits exceed the costs, the decision may be to adopt or behave affirmatively [42,44,62].

Together with the weight analysis, our results confirm the same insights as the "best" and "promising predictors". The strongest top correlations (>0.34) and best predictors are attitude, benefits, personal norms, incentives, perceived behavioral control, knowledge, performance expectancy, and subjective norms, again confirming the relevance of TPB in previous studies about sustainable technology adoption. As motivational factors, personal and subjective norms are found to be significant and best predictors, suggesting that moral obligations to the environment and the opinion and decisions of relatives have a great influence on these types of adoptions. This conclusion is in line with the social component of these technologies, as sustainable technologies have enormous social and environmental contributions, providing not only individual but also shared benefits [53], which is also one of the strongest predictors of behavioral intention. Moreover, some controls arise, with attitude being one of the strongest predictors, together with knowledge and perceived behavioral control. The overall results demonstrate that non-technological factors have stronger effects on behavioral intention than technological ones when studying sustainable technologies.

Fig. 3 combines the meta and weight analysis results, presenting a research model based on the "best predictors" and "promising predictors" with statistically significant effects on the behavioral intention to adopt sustainable technologies.

Additionally, results were found for the moderators, as journals with higher impact factors tend to publish articles with stronger effects between the subjective norms and behavioral intention. Regarding the GII, the results show that countries with higher levels of innovation present a stronger relationship between subjective norms and behavioral intention, as expected. Cultures, in which the extension of knowledge and intellectual capabilities are forested, create individuals with the strongest willingness to try new and/or more complex technologies. Sustainable technologies fit in this description, as they are often seen to be more innovative or disruptive [2]. More innovative or disruptive cultures strengthen the relationship between subjective norms and behavioral intentions.

Regarding cultural factors, low individualism strengthens the relationship between subjective norms and behavioral intentions. More collectivist cultures emphasize societal needs over individual ones, which is exactly linked to the purpose of many shared benefits provided by sustainable technologies [53]. This suggests that in more collectivist cultures, perceived expectations from others regarding sustainable technology adoption will influence the behavioral intention more than in more individualistic cultures. Furthermore, cultures with a lower level of long-term orientation also present stronger relationships. Long-term orientation therefore refers to the common belief that the future can be more prosperous than the present. Short-term-oriented

Table 3
Moderation analysis.

Independent variables	Subjective norm		Attitude	
	Estimate	*P*-value	Estimate	*P*-value
Constant	10.0436	0.0820	1.3457	0.4865
Journal impact factor	0.0027	0.0079	0.0006	0.2546
IDH	21.1543	0.0822	3.8833	0.4792
GII	0.2434	0.0165	0.0072	0.7401
Power Distance	0.0432	0.0743	0.0023	0.6846
Individualism	−0.0884	0.0123	0.0102	0.4916
Masculinity	0.0370	0.0507	0.0182	0.1840
Uncertainty	0.0017	0.7602	0.0122	0.1301
Long-term orientation	−0.1506	0.0313	0.0138	0.5531
Indulgence	0.1153	0.0736	0.0037	0.8707
Electricity access	−0.1135	0.0289	0.0207	0.3000
Renewable energy	0.0918	0.0231	0.0112	0.2620
Energy efficiency	0.0277	0.0591	0.0278	0.1301

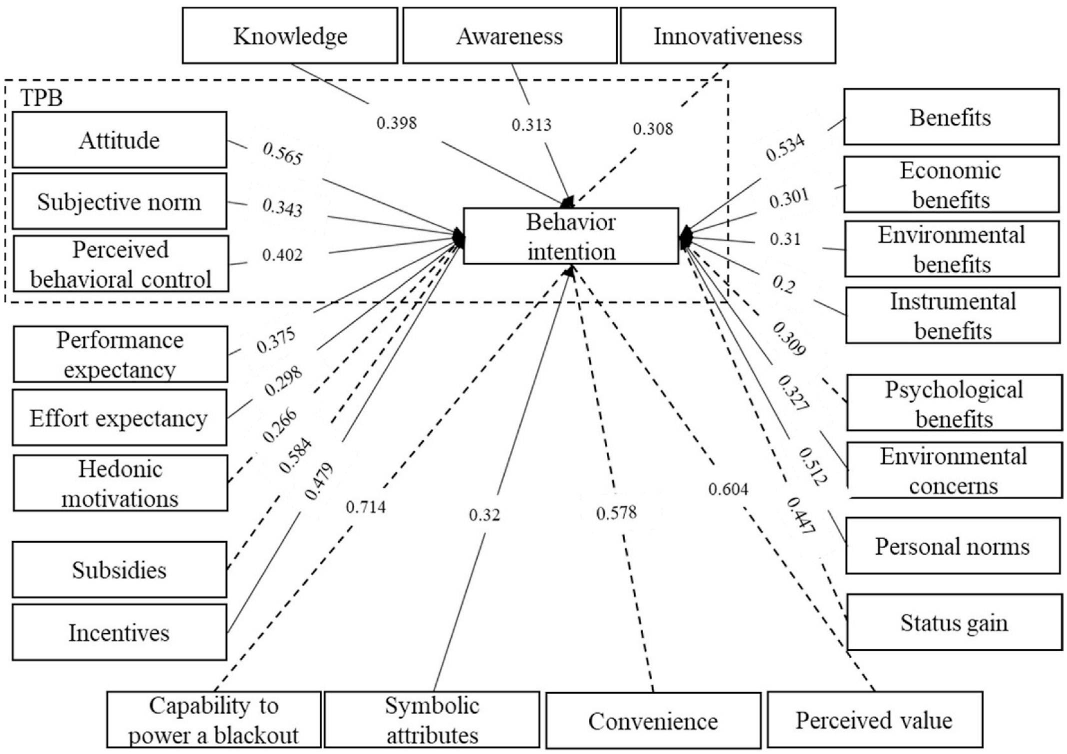

Fig. 3. Model resulting from meta-analysis. Note: Numerical values represent the average β. Continuous arrows represent "best predictors".

cultures concentrate more on the present than the future, focusing on immediate fulfillment [22]. This result may seem contradictory since sustainability, by definition, requires long-term perspectives. Nevertheless, it reveals the fact that individuals have urges to feel immediate gratification, and therefore, when others expect them to adopt these types of technologies, people feel the urge to do it. These results also alert us to the fact that individuals still do not have in mind the long-term benefits that sustainable technologies may offer, or still prefer investments that give them immediate benefits.

In terms of the energy efficiency indicators, the results show that the impact of the subjective norm in behavioral intention is stronger in countries with lower access to electricity. Especially in these types of country, people may resort to the self-production of energy based on natural resources to improve their energy conditions. Individuals may feel a greater social pressure to embrace this practice. On the other hand, more developed countries, especially those with the strongest investments in renewable energy, present a stronger positive impact of subjective norms in behavioral intentions. As expected, countries that have higher investments in these solutions, present stronger economies, and higher levels of innovation, promoting an environment of growing interest and social pressure to adopt these new sustainable lifestyles. Therefore, the impact of subjective norms is stronger in cultures with higher investments in renewable solutions. Our results suggest that social pressure has the greatest impacts on behavioral intentions mainly in extreme countries, i.e., those with higher or lower energy conditions/investments.

Concerning the implications for theory, the first main aspect is the resulting model that synthesizes the cumulative effect of independent variables on dependent variables. This model provides a comprehensive picture of the behavioral intentions of sustainable technology adoption. From that, it was concluded that many non-technological constructs are relevant predictors. Apart from the usual TPB and TAM theories, benefits, knowledge, awareness, and incentives should continually be used in future research as they have proven to be strongly significant and best predictors. Therefore, the resulting models can be seen as a support for future research, which encompasses the most used and significant predictors from the literature.

Regarding the practical implications, this study provides valuable suggestions for policymakers and organizations seeking to boost the adoption of sustainable technology. Performance expectancy, effort expectancy, perceived behavioral control, and attitude are best predictors, confirming their significance with the meta-analysis. This finding suggests that governments and policymakers should create strategies that generate a strong positive attitude around sustainable technologies, clearly showing their usefulness. It is also especially important to demystify the general idea that this type of technology may be somewhat complex [24], through general advertisement and strategies that contact the consumers in a more direct way. For example, workshops that allow demonstrations or trialability of some solutions might have a much greater impact, as consumers experience the required needs and effort for themselves. But strategies should not only focus on the technological aspects. In fact, strategies that focus on educating individuals and raising awareness for all positive benefits is essential, since knowledge, awareness, and benefits are also best predictors with statistical significance. As shown in the meta and weight analysis, motivations vary from environmental concerns to economic benefits. So, it is of extreme importance to promote these technologies close to the citizens, clearly showing them all environmental benefits, but also economical ones. Indeed, incentives are proven to still be a strong motivation for consumers, reinforcing the need of governments and policymakers to create or continue to implement this policy. Organizations and agencies should focus on providing all necessary information, in an accurate and especially in a way that is easy to understand. Moreover, results show that subjective norm is a best significant predictor, therefore, strategies (e.g., forums) that involve sharing experiences with both economic and environmental numbers such as money saved or household emissions reduction, might create an overall positive environment favorable to the adoption of these solutions. Overall, accelerating the understanding of all benefits of these solutions and the general awareness for the relevance of these technologies is extremely important, especially because energy literacy in Europe is still somewhat limited [72]. Knowledge about energy use, energy and water saving options, among others, is positively related to the adoption of sustainable technologies [73]. Therefore, all these strategies will not only increase the engagement in sustainable technologies but will also create more informed and educated consumers about sustainable options and its benefits.

5. Limitations and future research

The first limitation has to do with the number of articles used to perform the analysis. The main reason for the exclusion of articles was the need to have correlation coefficients and sample sizes in a way that only quantitative articles were selected. As such, only quantitative insights were used when interpreting the results. Also, when merging variables, some articles did not show the items used to measure their constructs, thereby being a limitation to the merging process. Nevertheless, the merging process was done by not only checking the names and items, when possible, but also by interpreting the paper's context, for which we believe that the limitations were addressed satisfactorily. Also, most articles were based on only one country, whose values may have influenced the results, especially when investigating pro-environmental behaviors. Therefore, for future research on the topic, country comparisons are a good direction, as well as the inclusion of cultural dimensions [74].

6. Conclusions

Sustainable technologies have been increasingly studied due to their relevance to efforts to help mitigate environmental problems through technology adoption. We applied a weight and meta-analysis of variables that were found in 44 articles, resulting in 305 relationships. Of these, 33 were analyzed since they appeared three or more times. Of those selected for examination, 26 relationships were found to be statistically significant. As a result, this study presents a comprehensive view of the best and promising predictors of the behavioral intentions for sustainable technology adoption. Moreover, six variables were found to be significant moderators, showing the impact of the journal impact factor, GII, individualism, long-term orientation, electricity access, and renewable energy on the relationships between subjective norms and behavioral intentions. This study therefore not only depicts the state of the art of sustainable technologies but also serves as a foundation and support for future research on the topic. The study also provides strong guidance to the practitioner, as organizations and policymakers may find herein the basis for strategies toward sustainable technologies adoption.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Variable Codification

Table A.1
Variable's codification

Original variable name	Merged/Modified variable name
Attitude, Attitudes in using smart meters, Attitudes, Attitudes toward BEVs, Attitudes toward environmental protection, Attitudinal constructs, Consumer attitudes, Green purchase attitudes	**Attitude**
Awareness, Awareness of renewable energy, Environmental awareness, Problem awareness	**Awareness**
Beliefs about renewable energy benefits, Beliefs about the benefits, Co-benefits, Perceived benefit components, Perceived benefits of a new technology, Perceived functional components	**Benefits**
Perceived green solutions to power blackouts	**Capability to power a blackout**
Perceived convenience policies, Perceptions of convenience policies, Product property cognition	**Convenience**
Beliefs about the cost of RE utilization, Cost concerns, Cost of renewable energy generation, Cost of renewable power generation technology, Perceived cost component	**Costs**
Economic benefit, Economic performance attitude, Financial benefits, Savings, Technical saving potential	**Economic benefits**
Ease of use, Easy implementation, Effort expectancy, Perceived ease of use	**Effort expectancy**
Environmental attributes, Evaluation of environmental attributes, Product environmental cognition, Utilitarian environmental benefits	**Environmental benefits**
Biosphere values, Ecological care, Environmental concern, Environmental norms, Environmental concerns, Evaluation of environmental attributes	**Environmental concerns**
Facilitating conditions, Infrastructure readiness	**Facilitating conditions**
Gender	**Gender**
Green consumer identity, Green identity, Green self-identity	**Green self-identity**
Hedonic motivations	**Hedonic motivations**
Age	**Householder age**
External PLOC, Government intervention, Perceived conditional component, Policy and propaganda, Support for policy	**Incentives**
Income	**Income**
Inherent innovativeness, Innovativeness, Personal innovativeness	**Innovativeness**
Evaluation of instrumental attributes, Instrumental attributes	**Instrumental benefits**
Perceived investment risk component	**Investment risk**
Eco-literacy, Environmental knowledge, Knowledge, Perceived knowledge	**Knowledge**
Consumers perceived behavioral control, Perceived behavior control, Perceived behavioral control, Perceived behavioral control on energy conservation	**Perceived behavioral control**
Perceived green value, Perceived value	**Perceived value**
Perceived performance risk, Perceived quality, Perceived usefulness, Perceived utility of new technology, Perceived utility of RE, Performance attributes, Performance expectancy, Relative advantage, Technical performance attitude, Usefulness	**Performance expectancy**
Consumer's personal moral norm, Internal PLOC, Moral norm, Moral norms, Moral obligation, Personal norm	**Personal norms**
Meter invasiveness, Perceived privacy risk, Privacy and cybersecurity, Risk beliefs, Third party access	**Privacy concerns**
Energy-efficiency behaviors, Past behavior	**Pro-environmental behavior**
Perceived emotional component	**Psychological benefits**
Face consciousness, Perceived social component	**Status gain**

(*continued on next page*)

Table A.1 (*continued*)

Original variable name	Merged/Modified variable name
Consumer's subjective norm, Injunctive norm, Introjected PLOC, Social influence, Social norm, Social norms, Subjective norm, Subjective norms, Subjective norms of sustainable behaviors	**Subjective norm**
Perceived information policy, Perceived subsidy policy, Perceptions of financial incentive policies	**Subsidies**
Evaluation of symbolic attributes, Symbolic attributes	**Symbolic attributes**
Trust in utilities, Trusting beliefs	**Trust in data protection**
Adoption intention, Behavior intention, Behavioral intention, Behavioral intention to adopt, Behavioral intention to use, Buying intention, Consumer adoption intention, Intention, Intention in using, Intention to adopt, Intention to buy, Intention to purchase, Intention to use, Intention to utilize RE, Purchase intention, Usage intention, User intention to use	**Behavior intention**

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