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Review

A Targeted Review on Revisiting and Augmenting the Framework for Technology Acceptance in the Renewable Energy Context

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Abstract: Given that the implementation of renewable technologies has some key bottlenecks in adoption, this topic has been explored. Particularly, we are reviewing existing theories and models to understand their fit for changing social structures and evolving world contexts. This review begins with an introduction followed by a background study on renewable energy technology (RET). We have employed a mixed-approach methodology to synthesize the relevant literature. The review comprises a summary and comparison of some existing theories and models such as TAM, TRA, and UTAUT, elucidating factors influencing technology adoption processes. Additionally, the review discusses the scope for future research, emphasizing the need for more nuanced frameworks that account for contextual intricacies and emerging trends in renewable energy adoption. Ultimately, the review concludes with insights into the ongoing discourse surrounding energy technology acceptance and recommendations on the inclusion of current world views in the scope for future study.

Keywords: technology acceptance model; energy; UTAUT; TRA; VUCA; social acceptance; renewable energy

Citation: Bhatia, T.; Bharathy, G.; Prasad, M. A Targeted Review on Revisiting and Augmenting the Framework for Technology Acceptance in the Renewable Energy Context. *Energies* **2024**, *17*, 1982. https://doi.org/10.3390/en17081982

Academic Editor: Gabrial Anandarajah

Received: 21 February 2024
Revised: 17 April 2024
Accepted: 19 April 2024
Published: 22 April 2024

1. Introduction

A greater emphasis is being placed on embracing and implementing cutting-edge energy technologies due to the quick development of technology and the urgent demand for sustainable energy solutions. However, most of these cases require a decentralized approach, where consumer acceptance and adoption play a critical role [1,2]. Numerous technology adoption models are utilized to understand and envisage acceptance and use in various contexts. For example, the technology acceptance model (TAM) [3] analyses how users perceive and behave when utilizing various technological breakthroughs. The TAM has proven helpful in identifying essential elements impacting the acceptability and incorporation of energy-efficient and green technologies in the broader picture of energy systems [4]. However, the world has become more complex and nuanced. In the past few decades, since the adoption models were first developed, the world has experienced a significant transformation, referred to as volatility, uncertainty, complexity, and ambiguity (VUCA) [5]. Therefore, examining the current frameworks to reflect the nuances and complexity inherent in the energy context as the energy landscape changes because of the growth of novel RET and grid infrastructure is crucial. A thorough understanding of these elements' impact on users' decisions to embrace and utilize energy-related technologies is intended to be achieved by revisiting and enhancing the model for adopting energy technologies [6].

With novel cutting-edge technologies such as microgrids, demand response systems, advanced energy storage systems, and Internet of Things (IoT)-enabled energy gadgets, the energy sector is undergoing a profound transformation. Thus, a revised framework is necessary to understand users' views and behavioral intents, given the specific problems and opportunities these technologies provide [7]. The implementation of sustainable energy solutions is gaining significance with global warming, and the environmental effects of conventional energy sources have become increasingly concerning. To encourage their widespread adoption and build a healthier energy future, it will be essential to understand the factors that determine whether these eco-friendly solutions are accepted. Energy technology adoption is determined by sociocultural elements and its technical characteristics, such as user attitudes, opinions, principles, and societal conventions. A framework must, therefore, consider these contextual factors to offer an in-depth comprehension of technology adoption in various energy environments [8]. These models and frameworks can be revisited in the context of energy, which can provide legislators and industry stakeholders with insightful information. Policy makers can create specific measures and promotions to hasten the switch to a less polluted and more efficient power system by studying the factors that influence and obstruct technological adoption [9].

The development of environmentally friendly energy technology has been prompted by grave social and environmental issues associated with energy consumption, such as rising air and water pollution, the depletion of ozone, global warming, and the reliance on fossil fuels. While some technologies are adopted in society quite easily (such as compact fluorescent lights, energy-efficient boilers, ozone-free refrigerator cooling systems, solar panels, and soot filtration systems), others have run into varying degrees of public opposition (such as wind turbines, carbon sequestration facilities, nuclear power plants, and hydrogen–gasoline stations). Perceived obstacles and safety threats may cause resistance. However, it may also develop because people believe that assets could have been used more wisely or because the ratio of costs to benefits is too poor. The adoption of RET may be hampered by social opposition to the technology [10], which hinders the achievement of crucial environmental and societal objectives. Understanding how people think about sustainable energy methods and why they decide against, or in favor of, them is crucial because it provides valuable insights into how the technology's design or implementation should be changed, as well as how it should be communicated so that support for the technology rises and its introduction is more successful. Even though numerous research studies have highlighted the psychological aspects affecting technology acceptance, the mainstream of these studies concentrated on a limited number of psychological components. The design of the technological advances, how they are communicated to users, and how they are put into practice can provide a more profound understanding of the key psychological aspects that encourage technology approval and how these elements are related [1].

For new technologies, particularly those in the energy sector like solar technology, to be implemented successfully and sustainably, there is an increased requirement for the social acceptability of those technologies. For instance, developments for wind power plants frequently meet strong local opposition because of NIMBY impacts [11]. This slows down the adoption of the technology. Thus, public perception of energy technology is an essential and studied subject. As it lies at the crossroads of innovation and/or the spread of new technology, in the study of decision making and the scientific research of energy, acceptance by society is of utmost importance [12]. Numerous hypotheses and conceptual frameworks relate social issues to energy acceptance, each with its setbacks. However, these frameworks are helpful for gathering, connecting, and condensing a variety of information into one thorough structure. This draws attention to the research inadequacies or faults in much of the literature and common findings that help guide future studies. To properly guide future research, these frameworks must also be revised over time to account for new results or the filling of gaps. As a result, this study aims to review and improve existing frameworks for the acceptability of energy technologies. The literature review will explore aspects related to technology acceptance and/or rejection, emphasizing current models of technology adoption and methods of measuring these values.

The objectives of this review are as follows:

1. To determine the frameworks currently in use for accepting renewable energy technologies and the main difficulties the frameworks are presently facing due to the changing times.
2. To examine the variables that affect energy technology's acceptance (or rejection).
3. To identify and research the current metrics for gauging technology adoption.
4. To identify and assess the strengths and weaknesses of the selected frameworks to improve the current frameworks' applicability and explanatory capacity.

2. Background Study

This study was undertaken to recognize the need for energy technology acceptance, highlight the elements that affect these models, discuss acceptance models and offer comparisons, present methods for gauging energy technology acceptance, and highlight any research gaps.

Renewable energy technologies need to be implemented successfully; we also need to research how well liked they are. However, given the current financial, political, and environmental challenges, choosing an energy source is a crucial decision at the beginning [13].

RET utilizes energy that is replenished from natural resources, including wind, water, solar power, bioenergy, and geothermal heat [14]. RETs are an alternate source of electricity generation that can reduce worldwide emissions of greenhouse gases from energy use as emissions related to fossil fuels rise [15]. RET, as an alternative power generation technology, has increased globally during the past ten years [16]. Financial incentives like FIT, quotas, and responsibilities like the renewable portfolio standard (RPS), which calls for a rise in energy produced from renewable resources, frequently motivate RET investment. However, due to the declining price of RETs, pricing strategies like FIT are becoming less common. Globally, the cost of energy produced from renewable sources is now equivalent to or less expensive than that produced from fossil fuels due to a drop in technology prices [17]. Electricity users can completely unplug from the network or schedule their grid electricity consumption by combining RET with battery energy storage solutions [18]. When the fixed cost of the network is retrieved from a smaller number of grid-based consumers, the lower demand for already-built, taxpayer-funded power distribution networks could result in a rise in electricity prices [19]. When users cannot alter their electricity consumption patterns or install RETs, the cost of electricity can increase. As a result, the demand for grid electricity may be further reduced. Such prospects could position conventional energy generators and grid distributors against renewable energy adoption projects. To achieve the Paris Agreement's goal of mitigating climate change, RET adoption must be at least six times faster, despite such potential (short-term) repercussions on the power network [20].

However, predicting and planning the future in a rapidly evolving environment is difficult, making these frameworks dated. These intricate modifications were recognized by Warren Bennis, who labeled them as VUCA, referring to the volatility, uncertainty, complexity, and ambiguity of circumstances and events. Based on the management philosophies of Warren Bennis and Burt Nanus, it was initially applied in 1987 [21].

The acceptability of technology by the general public is influenced by the media, which can create influence at international or cross-border scales [22]. Based on how developing technologies are portrayed in the media, one can determine how well liked they are in society. Since many of us have little to no direct involvement in the initial stages of energy technology, we depend on the media to inform us of the main problems with new technology. As a result, the media plays a critical role in determining how we view new energy and other technologies [23]. As a result, the level of media coverage of the technology affects its level of social acceptance. Therefore, the way technology is covered in the media may have an impact on social acceptance. For example, people are familiar with low-carbon technologies, like bioenergy, but not with renewable energy sources, such as solar power [24]. From this perspective, it is necessary to review and restructure the frameworks for adopting energy technologies.

3. Methodology

This study utilized a mixed approach to review by employing a semi-systematic approach and integrative literature review [25,26]. The research began with a broad topic that included searching for keywords in the ‘title’, ‘abstract’, and ‘keywords’ of articles from the SCOPUS database. The keywords initially included technology, acceptance, and energy to determine frameworks in a broader energy context. Further, it was narrowed down to renewable energy followed by social as a keyword to achieve the next objective of examining the variables affecting social acceptance of RET. Initially, the use of the operator ‘OR’ broadened the search results by retrieving documents that contained either one or both specified keywords. For example, a search for ‘renewable OR vuca’ retrieved papers that contained either ‘renewable’ or ‘vuca’. However, subsequently, the search was narrowed by the use of an operator ‘AND’ connecting two keywords to find papers containing both words. For instance, a search carried out to identify papers on social media in the context of energy technology acceptance used the keywords ‘technology AND acceptance AND energy OR renewable OR social AND media’. No publication year restrictions were applied to these searches initially to observe the trend in the research. However, to find the most recent articles, a publication year limitation was set from 2020 to achieve the 3rd objective of gauging current metrics for technology adoption. To achieve the last objective, the research was further narrowed down by adding additional keywords such as model, VUCA, social media, limitations, dynamic, and structural equation model (SEM). The year of first publication was noted where applicable during the research.

In Figure 1, a glimpse of the review is shared, summarizing the above. It is observed that as we add more keywords and narrow down the research scope, fewer articles appear. However, the search with VUCA as a keyword, along with other search keywords—‘technology’, ‘acceptance’, ‘energy’, and ‘renewable’—only provides 3 articles highlighting the onset of research into this concept and scope for further research. It is noted that no research has been conducted yet using VUCA in the energy context along with social media, as the search resulted in 0 new papers, as evident in Figure 1. Thereafter, social media seems to have caught researchers’ attention slowly from 2001, only gaining momentum from 2019 onwards, with 2021 being the peak, as most research papers were found in this year. It is further noted that narrowing the scope by using keywords such as model and renewable, along with social media, and broader keywords such as energy, technology, and acceptance provides only 4 research papers with the use of the operator AND. A similar approach of review, beginning with a broad topic review using keywords such as technology, acceptance, and energy and then narrowing it down using additional keywords, was utilized to review the limitations and other approaches that may have been used such as blended models or the use of dynamics or SEM. This approach helps to not only understand the trend in research and identify the current factors affecting renewable energy technology adoption but also highlights the need for further research to accommodate the ever-changing world conditions.

This paper utilizes the findings from the above-mentioned review methodology to achieve its objectives/focus points by providing a comprehensive review and comparison of the most-used technology acceptance models. This paper further attempts to highlight the factors affecting renewable energy technology adoption, the different forms of adoption, political polarization, and the limitations of the technology acceptance model in the view of the current world. This paper ends with an emphasis on future research based on the previous discussion, thus providing valuable insights into current models and altering world conditions for various stakeholders and decision makers.

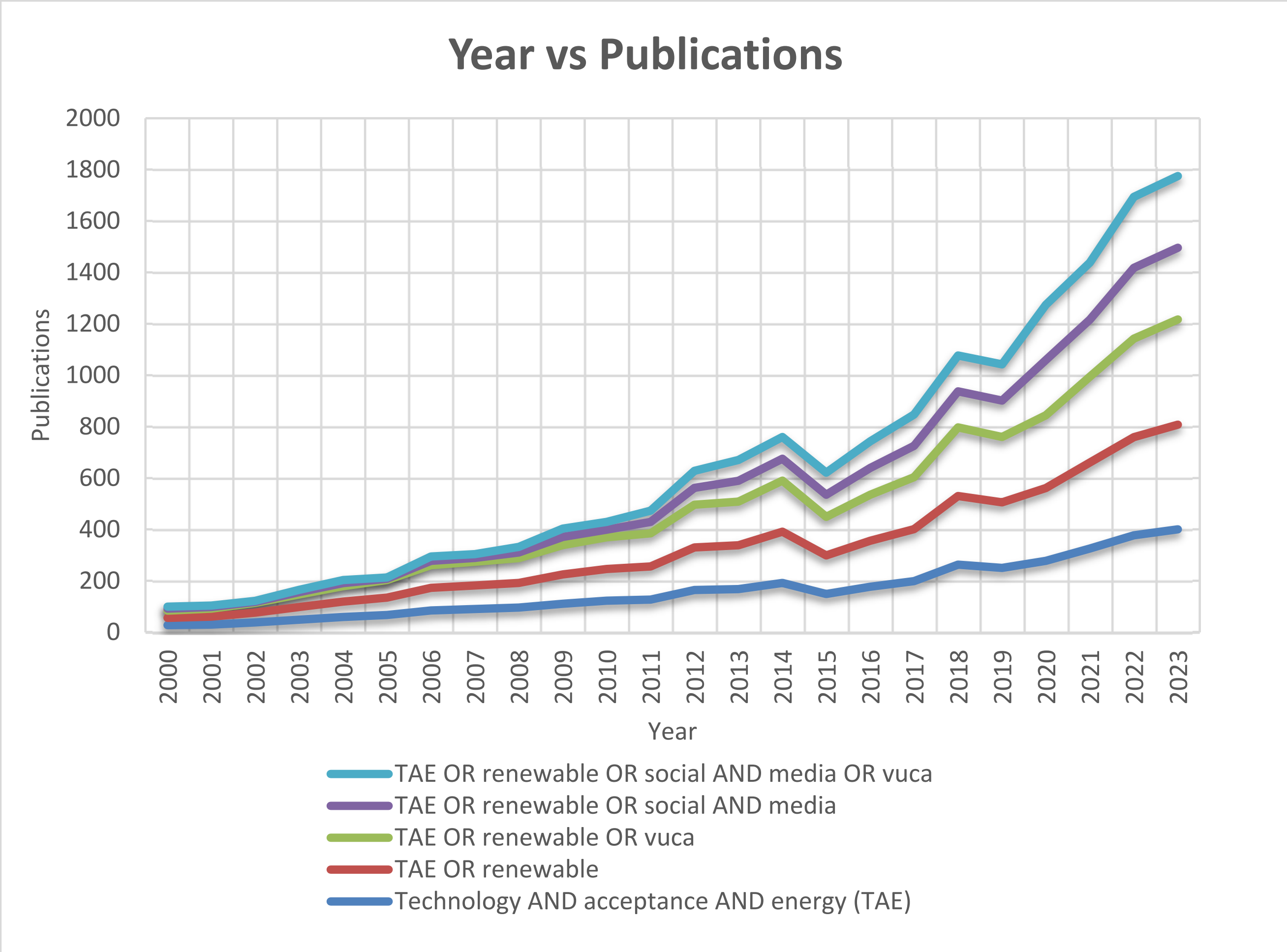

Figure 1. Keywords vs. papers published.

4. Review

To address the need for informed and dynamic energy strategies and frameworks, this paper considers and reviews popular models and underlying theories with a view to understanding their nuances and limitations in the changing VUCA world. A quick glance at the most popular ideas and frameworks of technology acceptance is provided in Figure 2. Acceptance of RET being the crux of this targeted literature review, it is placed in the center of the figure as Acceptance of Renewable Energy. The theories reviewed in this study are stated, beginning with the Theory of Reasoned Action (TRA), placed above the Acceptance of Renewable Energy. This is further developed into the Technology Acceptance Model (TAM) and its extension along with the Theory of Planned Behavior (TPB) and Theory of Interpersonal Behavior (TIB). Other models reviewed in this study are stated clockwise as the Diffusion of Innovation Theory (DOI), the Bass Diffusion Model, Technology, Organization and Environment (TOE), Social Cognitive Theory (SCT), and the Unified Theory of Acceptance and Use of Technology (UTAUT), which are stated around the TRA.

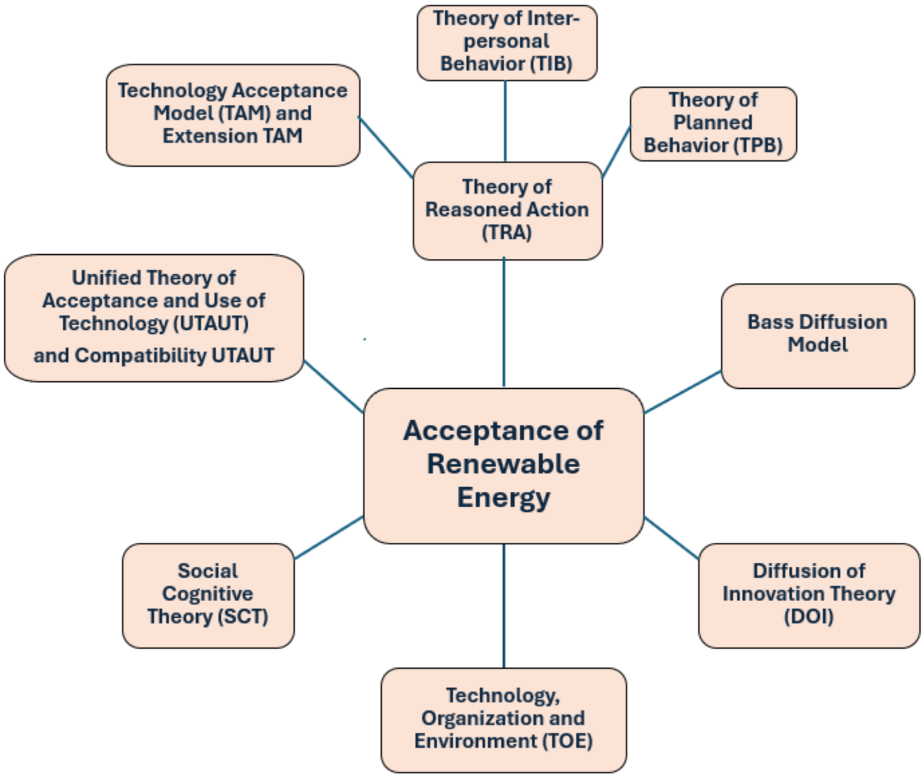

Figure 2. Models and theories for the acceptance of technology, adapted from [27].

4.1. TRA or Theory of Reasoned Action

Many additional hypotheses that were eventually created, including the UTAUT, TAM2, and TAM, had the TRA as their foundation. From a social psychology standpoint, it mostly describes how different people behave when accepting new technologies. According to the TRA [28], user behavior is shaped by two primary variables: personal standards and attitude toward behavior. According to the TRA, people make reasonable decisions based on continual calculation and evaluation of their proper behavioral statements through the development of their attitudes toward behavior. According to Lai P.C [29], attitude refers to the emotions that a person experiences when engaging in the desired behaviors. Another crucial concept in the TRA framework is the subjective norm. As per Fishbein and Ajzen [30], a being's perspective of people who are important to them determines whether they believe that they must act in a particular way.

4.2. TAM or Technology Acceptance Model

The TAM, which Davis [3] created, offers and models a description of how a person embraces and employs technology. The TAM clarifies the technology determining acceptance, which may justify the theoretical and economic viewpoints, while simultaneously explaining the behavior of a user toward several evolving consumer computer technologies utilizing the user population. Behavioral intentions (BIs), attitude toward use (ATT), perceived ease of use (PEU), actual usage (AU), and perceived usefulness (PU) are five variables, each of which establishes a unique TAM component. These constructs are recognized as the primary user determinants of application and technological acceptability. Maturity is the level at which a being claims that applying a specific technology will save time and effort [3]. PU is where a being believes deploying a certain technology will increase their capacity for success at a specific job [3]. A person's attitude about using a specific technology is referred to as their ATT. BI refers to the number of users of a specific technology who have fashioned a plan of purpose to use or not use a certain technology in the future, and AU refers to the application level of a particular technology as a function of frequency (how frequently) and quantified volume when used by consumers [3].

The TAM claims that PEU has an impression on PU. If a technological device is easy to use, there is an excellent likelihood that users will find it useful. The two varieties of PEU and PU, according to the TAM, affect people's attitudes toward using technology. When users feel that technology is user-friendly and beneficial, it results in a high likeliness to adopt a positive attitude about utilizing it. Davis, F.D. [3] found that when using technology, ATT and PU affected consumers' BI. It can be advantageous for users' BI to utilize technology when they see it as useful. The consumers' positive BI toward a certain technology defines the actual utilization of those technological advances, also known as AU. Customers are therefore more inclined to use an item of technology in everyday situations if they have favorable attitudes toward it.

In many earlier studies, the construct of attitude toward adopting a technology was not included [31]. The strong association between PU and BI and the shaky connection that exists between BI and ATT are the key causes of the exclusion. Furthermore, PEU and PU, but not ATT, were directly responsible for driving BI, which resulted in the actual use (AU) of the framework. The conclusions by Davies et al. [32] made this clear. As a result, their research revealed a strong correlation between PU, PEU, and BI, leading the researchers to recommend that the ATT construct be dropped.

4.3. TAM2 and eTAM

In 2000, Davis and Venkatesh [33] created the TAM2. PEU and PU, the fundamental determinants of the first TAM, are preserved in TAM2. It also considers the cognitive utilitarian process and social influence, the eTAM, which considers outcome demonstrability, output quality, and work relevance, as well as the impact of social factors on subjective standards and image. Both the eTAM and TAM2 have been widely utilized to support how different forms of technology are accepted in different organizational environments. According to the TAM2, people use mind mapping to evaluate the relationship between important work objectives and how they utilize a particular system, primarily for the creation of judgments concerning operation contingencies, such as PU.

Potential users often judge a job's relevance through a compatibility test by theories on the corresponding mental process. As a result, the basic definition of an individual assessment of the level to which the system in question is relevant to their employment aim relates to their line of work. According to the eTAM, work relevance has a favorable impact on PU. PU is also affected by output quality. When choosing the system that produces the highest output quality, a specified set of choices holds many systems that are significant to an individual [33]. This assumes the standard profitability test form. The eTAM claims that output quality favorably influences PU. The demonstration of a result is regarded as the third PU determinant. Consequence demonstrability is the actuality of the results obtained through the use of a certain innovation [34].

4.4. UTAUT—Unified Theory of Acceptance and Use of Technology

The UTAUT [35] says "three constructs—expectations of work effort, performance, and social impact—show the key aim of utilizing information technology (IT)". The eight most widely used ideologies and models include these three constructs [36]. Additionally, this model also has a construct of facilitating conditions [36]. The TAM has a crucial part in elucidating the acceptance of technology, paving the way for the emergence of the UTAUT. This model incorporated additional elements like social influence and facilitating conditions, along with consumer-related constructs such as attitude, habit, perceived value, and hedonic motivation [37].

Expectancy of performance is the level to which consumers are certain that utilizing a specific organization would help them enhance their professional performance [38]. The ease of application of a certain system is known as effort expectancy. The extent to which people perceive that using the suggested alternative system is required is known as social influence [39].

An individual's experience and age have a significantly moderate effect on creating favorable conditions for implementing a system [35]. According to Venkatesh et al.'s [35] definition from 2003, an enabling condition is the point when a consumer claims that a technological and organizational setup is typically present to assist the operation of a particular system.

4.5. Compatibility with the UTAUT (C-UTAUT)

In order to increase the UTAUT model's explanatory capacity, Ref. [40] incorporated compatibility beliefs created by Karahanna et al. [41] into it. It also tried to provide a more comprehensive account of how the psychological manifestations of the framework known as the UTAUT are produced by uncovering and testing new boundary conditions. Actual usage patterns were not important to measure because the intent of the study was to inspect how compatibility beliefs and behavioral perceptions related to one another [40]. Furthermore, because it was cross-sectional, a possible drawback of reflective analysis was avoided by evaluating behavioral intention rather than user behavior. The correlations postulated by Venkatesh et al. [35] pertaining to experience were impossible to replicate precisely because the study was longitudinal and did not investigate other periods.

4.6. Theory of Planned Behavior—TPB

The TRA model now includes a new measure called perceived behavioral control, or PBC, to support it. The accessibility of assets, possibilities, and abilities, in addition to how significant those assets, possibilities, and skills are perceived to be in accomplishing goals, are the main factors that affect PBC [42]. Although the TPB and TRA presumed that a person's behavioral intention (BI) was impacting their conduct, the TPB utilizes the PBC for specific behaviors that are not within the voluntary control of the individual. According to Taherdoost et al. [43], the PBC outcomes include a self-efficacy-like component and realistic constraints. Furthermore, PBC influences actual behavior both directly and indirectly via behavioral goals. Thus, according to the TPB model, three primary factors affect BI: PBC, behavioral attitude, and subjective standard. The TPB model has two fundamental issues [44]. The updated TPB could be viewed as the best theoretical framework for explaining how much individual voluntariness affects whether or not they choose to employ information technology at work.

4.7. Theory of Interpersonal Behavior—TIB

This model broadly discusses how emotional and social variables influence the complications of human behavior. To boost its prediction potential, this model includes customs, favorable circumstances, and effects in the accumulation of all characteristics of the TRA and TPB. The idea of social issues, which is analogous to the construction of personal standards in the TRA [45], involves self-perception, standards, and roles. In conclusion, the TIB maintains that the individual is neither wholly automatic nor entirely intentional nor is he or she either wholly social or fully independent. The difference between the TRA and TIB is that whereas the TRA tries to explain the biggest amount of variation as feasible utilizing the fewest number of variables, the TIB aims to explain as many variations as feasible overall since even a little bit of variability may be significant to crucial behavior. Accordingly, emotions, social variables, and the major effects on how intentions are formed come from habits. The TIB uses three layers to defend the behavior [30].

As shown in Figure 3, behavior is tied to emotions, attitudes, and social aspects, which are personal characteristics and past events that shape us. Attitude, social factors, and individual regulating principles affect desires to engage in certain conduct, which is demonstrated as intent. Past behavior frequency resulting in habits, intent, and other enabling factors all factor into predicting a particular behavior [46]. However, the researcher must define the operational meaning of the model variables because the TIB does not offer a straightforward mechanism to this end.

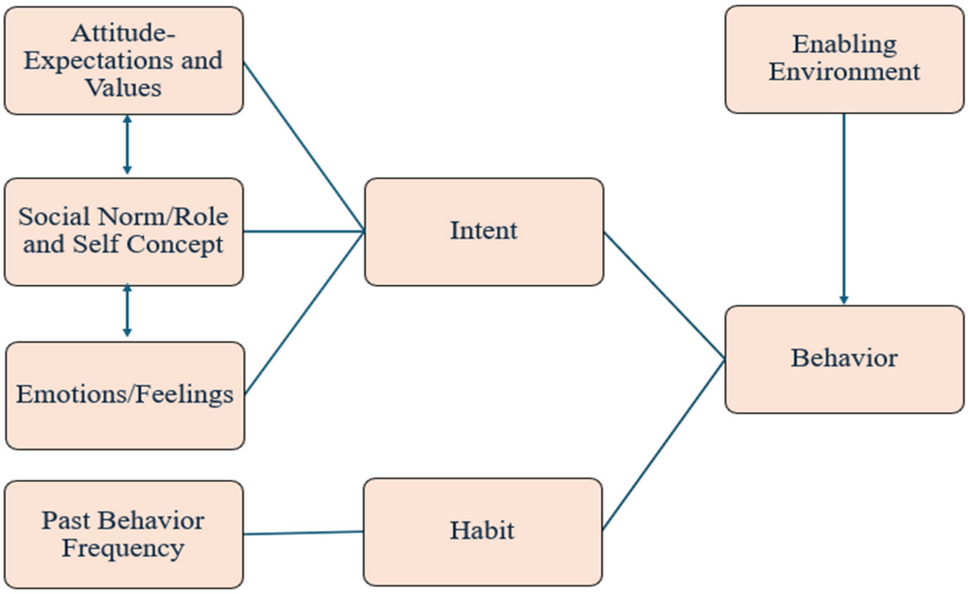

Figure 3. TIB model, adapted from [47].

4.8. Social Cognitive Theory—SCT

The fundamental elements of personal information, behavior, and the environment were used to build the SCT, which was inspired by social psychology. These factors interplay in every direction to predict both individual and societal outcomes and group behavior. Additionally, it can pinpoint strategies for altering and modifying behavior [48]. The usage, effectiveness, and adoption issues are the main focuses of the SCT model's behavior component. Personal aspects include demographics, cognitive skills, and personality [49]. Alternatively, environmental effects include both psychological and physical components that are present outside the individual [49]. The SCT model is used to assess how effectively various factors, particularly self-efficacy, the outcome of performance expectations, stress, influence, and private outcome expectations, lead to the increased relevance of energy technology, resulting in its adoption [50]. The SCT model is shown in Figure 4.

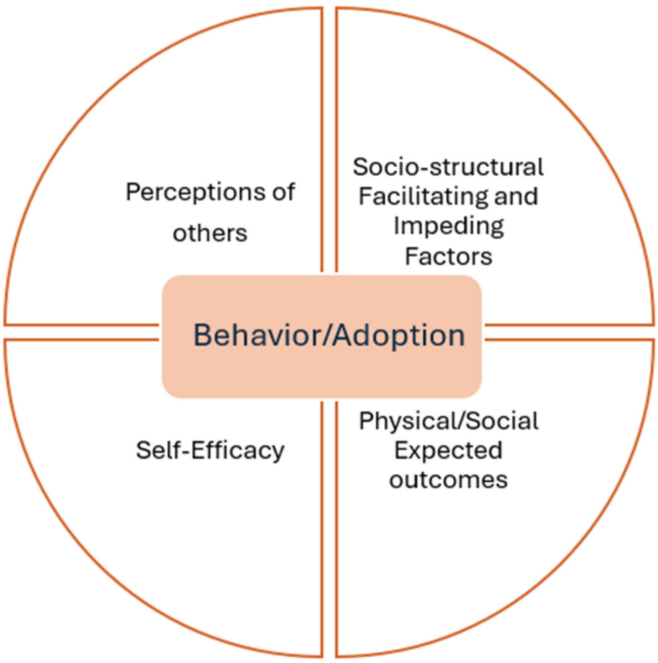

Figure 4. SCT model, adapted from [49].

4.9. Diffusion of Innovations Theory—DOI

The DOI incorporates time, channels of statement, social systems, and innovation, all factors that affect how rapidly a new idea spreads, to examine various inventions. The DOI offers an analytical framework despite being employed across the business and personal levels; this framework is for discussing acceptance on a broader (e.g., geographic) scale. The three key elements of the DOI concept are the creativity determination procedure, user attributes, and innovation features. The participants carried out the five processes of the innovation–decision step—confirmation, expertise, application, choice, and persuasion—over time in a connected social system through various means of communication [51]. Relative advantage, trialability, compatibility, challenge, and visibility are the five primary components determined to substantially affect an idea's acceptability in the innovation [52] stage, as shown in Figure 5. Relative advantage is determined by consumers who perceive that a newfound product or service is superior to existing ones [53]. The higher the relative advantage, the greater the adoption. Acceptance is also affected by how easily a new service or product can be tried. The easier it is to try and test the product or service, the better the acceptance. Similarly, the higher the compatibility, the faster the diffusion. Conversely, complexity and challenges pose a barrier to diffusion. Meanwhile, the higher the visibility or observability of a product, the greater the likelihood of acceptance. The adopter features step defines five types: innovators, those who lose, the late age of the majority, and the early majority [51]. In some cases, there is a useful context for time or temporal factors, social systems, and communication channels to be included in adoption models.

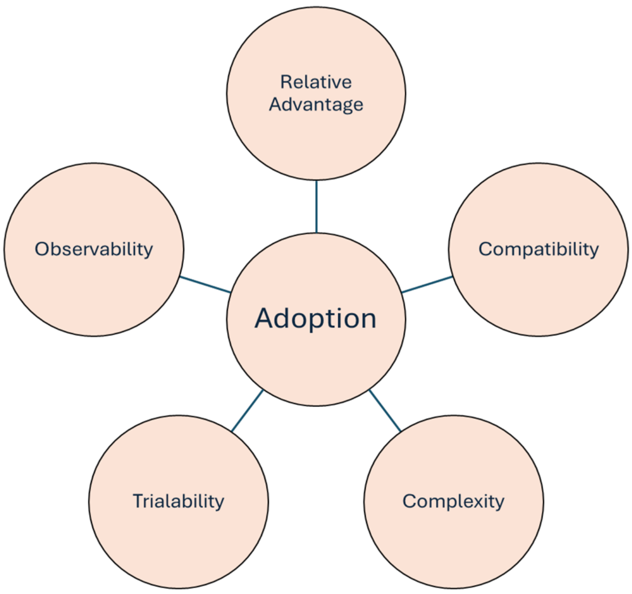

Figure 5. DOI model, adapted from [51].

However, the dynamic treatment of diffusion models, where the temporality of other factors evolves as a function of time, is a unique contribution of the DOI. Not only has this model remained relevant, but researchers in recent years have applied it in energy contexts, such as in the adoption of renewable heating systems, incorporating end-user preferences and attitudes [54–56].

4.10. TOE—Technology–Organization–Environment Framework

The TOE framework considers techno-environmental and organizational factors useful for understanding and analyzing the technology adoption process within an organization [57–66]. Ghobakhloo et al. [67] stated that this framework has been utilized for the e-commerce domain, whereas Cao et al. [57] have applied this framework to the social media domain. Factors significantly affecting the buyer's intention to adopt renewable energy technology are awareness, its sustainability or environmental impacts, one's beliefs of benefits of renewable energy, and opinion of self-effectiveness [68]. The TOE framework encompasses the operations of energy transition to renewable energy [69] while considering the significance of environmental impacts in accepting renewable energy technology [70]. Additionally, the TOE framework has been instrumental in understanding the effects of environmental concerns, religion, and economics [71–73]. Further applications of this framework are in the domain of cloud computing, as stated by Ahmed, 2020 [74]; blockchain, as stated by Bharadwaj et al., 2021 [75]; and mobile health, as stated by Ramdani et al., 2020 [59].

With its application in the organizational domain, the TOE framework can also be utilized in community-based energy systems to understand the complexities involved in renewable energy adoption. Community participation is essential to ensure sustainability and develop ownership of community energy systems [76]. To improve the sustainability, reliability, effectiveness, and efficiency of community energy systems, these systems should be considered part of the global energy system [77].

4.11. Bass Diffusion Models

Like the DOI, Bass diffusion models [78] dynamically describe behavioral elements through empirical adoption curves. Similar to other models, the Bass model was initially applied to the consumer durables marketing context but has been applied to broader markets [79], and even to the diffusion of renewable energy [80], GHG emission reduction potential in buildings [81], the forecast of PV deployment [82], estimation of the utilization potential of PV systems for power generation [83], and the development process of renewable energy price policies [84].

4.12. Summary

Figure 6 shows that the interplay of various theories and models enhances our understanding of the technology adoption process. Theories play a crucial role in shaping technology acceptance models by providing a conceptual framework to understand human behavior and decision-making processes. Thus, the role of theories that interplay with and support the models reviewed here is significant. Hence, the review would be incomplete without addressing these supporting theories. The theories mentioned come from various disciplines, including sociology, psychology, and psychosocial studies.

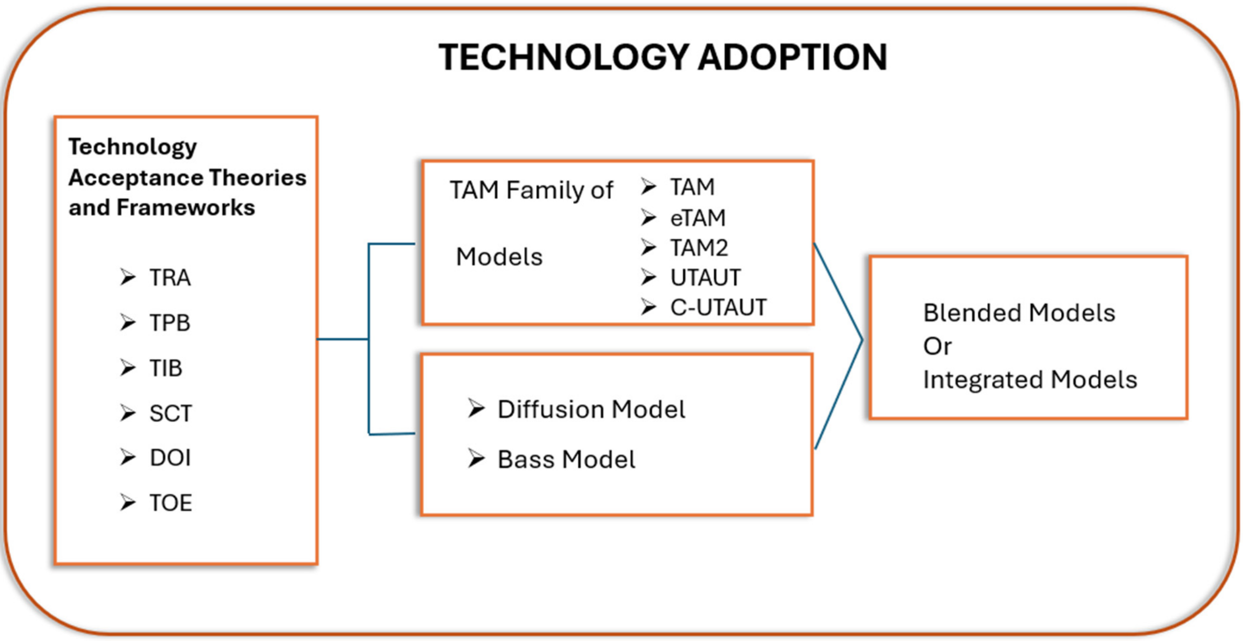

Figure 6. Summary of theories and models.

Table 1 demonstrates some of the theories and frameworks utilized in technology adoption along with their constructs. For instance, the TRA can explain how humans make choices when presented with options by delving into factors such as personal standards and attitudes toward a given behavior. However, they do not consider human emotions during the same process. Moreover, it fails to account for situations in which the intent does not match one's behavior or actions. Similarly, the TPB, developed in 1991 by Icek Ajzen, not only considers factors from the Theory of Reasoned Action [30] but also considers an additional factor of perceived control, which impacts the actual and behavioral intention [43]. The TPB considers perceived behavior control in addition to factors from the TRA, which helps us to understand how behavior can change [42]. However, they do not consider the emotions that contribute to behavior [44]. The TIB considers emotional and social variables, in addition to the factors from the TRA and TPB, and their influence on human behavior. In contrast to the TRA and TPB, the TIB's intricacy and lack of parsimony are its main drawbacks [27]. The SCT is based on the interplay of cognitive, personal, environmental, and behavioral factors [48]. However, the influence of each of these factors on behavior is unclear. The DOI and TPB are predicated on causal connections between environmental influences on psychological assumptions and how we behave and see technology. The SCT focuses on the environment, behavior, and behavioral and cognitive components. However, these causal links are mutually natural [85]. The TPB and TRA concentrate on individual behaviors, whereas the DOI concentrates on organizational traits for adoption decisions. The TOE, although consistent with the DOI [86] (Julies 2021), is limited to its three factors and may not explain all factors that may affect the adoption of technology [86,87] (Tran 2022, Julies 2021). To address this, a blended approach of the TOE with the TAM or DOI has been recommended [86]. It is observed that the adoption of mobile payments was encouraged by independent enterprises promoting business by applying an extended TOE model (TOE with DOI) [88].

The above-mentioned theories are integrated into models like the TAM or UTAUT to capture the complexity of the adoption process and guide empirical studies to better understand and predict user behavior. Table 2 illustrates various adoption models and the factors considered in each model. It also depicts how models have evolved by considering additional factors and displaying a continuum. For example, the TAM considers components such as PEU, PU, ATT, AU, and BI [3], whereas its extension (TAM2) not only considers factors from the TAM but also has additional factors such as output quality, work relevance, and the impact of social factors [33].

The TAM is famous because of its simple mechanics and simplicity of use in predicting adoption. The TAM was initially developed to assess the acceptance of technology such as computers, and it primarily focuses on two key factors, namely perceived ease of use (PEU) and perceived usefulness (PU) [89]. However, over time, the TAM has also been utilized for acceptance in different domains, including energy. A Malaysian study conducted on solar PV adoption stated the factors in the TAM are significant in the adoption of solar PV systems in Malaysia [90]. Similarly, PEU and PU were significant factors that affected the adoption of energy while studying the role of knowledge in adoption [91]. Another study conducted in Italy on fostering energy-efficient buildings and communities highlights the pivotal role of user energy awareness and knowledge along with the importance of people's engagement in energy communities [92]. The limitation of the TAM is that it is useful for personal adoption for its use on behavioral intention. This means that people often decide to like or adopt technology under the influence of word of mouth from their friends or people known to them. The TAM2, an extension of the TAM, attempted to address some limitations of the TAM by considering determinants such as social impact and cognitive instrumental processes, along with PEU and PU [89]. Although PEU has a positive influence on solar adoption, initiatives such as financial support and effective marketing are essential for adoption [93]. Similarly, PEU and PU were found to affect the adoption of solar panels in the northern region of Iran; however, factors such as the absence of apt energy beliefs and unprepared societal structure impeded adoption, surpassing the effect of PEU and PU [94]. However, this may be invalid in situations such as workplaces where choices are governed by company policies [95]. As various studies state, the TAM provides insufficient emphasis on external factors [89,96,97]. For instance, the TAM lacks consideration of factors such as the education and age of a person, which have an important role in their understanding and adoption of technology [98]. To remedy this, gender, age, and experience were incorporated into the UTAUT as moderators for factors such as performance expectancy. The UTAUT also includes factors such as social impact and effort expectancy, along with moderators [36,38,39]. The addition of moderators is useful, as it assists in qualitative inferences. It also makes the model more complex because of the multitude of constructs [35].

Table 1. Adoption theories and framework.

Theories	Factors	References
TRA	Personal standards and attitude about behavior	Fishbein and Ajzen (1975) [30], Samar et al. (2020) [96], Jaiswal et al. (2022) [91]
Theory of Planned Behavior (TPB)	TRA and PBC	White et al. (2015) [42], Taherdoost et al. (2012) [43], Jaiswal et al. (2022) [91]
Theory of Interpersonal Behavior (TIB)	TRA, TPB, emotional, and social	Chang and Cheung (2001) [45], Misbah et al. (2015) [46], Ajibade (2018) [95], Mogaji et al. (2024) [37]
Social Cognitive Theory (SCT)	Behavior, personal, and environment	Rana and Dwiedi (2015) [48], Zhang et al. (2024) [50]
Diffusions of Innovation Theory (DOI)	Time, channels of statement, innovation, and social systems	Rogers (1995) [52], Ajibade (2018) [95], Long and Zhongju (2023) [55]
Technology–Organization–Environment (TOE)	Techno-environmental and organization	Cao et al. (2018) [57], Salmizi et al. (2022) [58], Kabra et al. (2023) [64]

Table 2. Adoption models and factors.

Models	Factors	References
TAM Family of Models TAM eTAM/TAM2 UTAUT	PEU, PU, attitude towards usage, AU, and BI	Davis (1989) [3], Samar et al. (2020) [96], Jaiswal et al. (2022) [91], Mogaji et al. (2024) [37]
	PEU, PU, output quality, work relevance, impact of social factors, and cognitive instrument	Venkatesh and Davis (2000) [33], Samar et al. (2020) [96], Alshammari et al. (2021) [89]
	Expectancy of performance and effort, social impact, facilitating condition, and moderators such as age, gender, etc.	Venkatesh (2003) [35], He et al. (2020) [36], Jaiswal et al. (2022) [91], Mogaji et al. (2024) [37]
Diffusion Model and Bass Model	Innovators, early adopters, early majority, late majority, laggards, imitators, time, communication channel, innovation individual characteristics, and social systems	Turan et al. (2015) [51], Outcault et al. (2022) [53], Bass M (1994) [78], Kim et al. (2020) [81]

The UTAUT model primarily centers on aspects that impact technology acceptance and usage within organizational contexts and does not explicitly address social networks and political polarization. However, the social influence component within the UTAUT may indirectly encompass how social networks influence perceptions and behaviors related to technology adoption.

Similarly, the DOI and Bass models directly relate to social networks but do not deal with social media-induced sociopolitical polarization. Moreover, the diffusion model considers innovation and social networks to provide an understanding of how people adopt new products or innovations [51]. As a result of assigning more weight to system qualities, organizational characteristics, and environmental factors than other adoption models, the diffusion model has a lower predictive ability and is less helpful in the point prediction of outcomes. Similarly, the Bass diffusion model, although dynamic in nature, assumes that market potential is constant, along with product performance (Zhao, 2018) [84]. As observed, these models are based on very similar archetypes, as they have certain factors that affect human intention, which affects the adoption of technology. As most studies utilize or build upon a singular model to explore technology acceptance or adoption, a comparison between single and blended models to recognize the best-fit model for energy adoption is recommended [99]. Thus, no model surpasses all the limitations of its predecessors, and none can be deemed to entirely lack limitations [89].

In the energy context, contemporary models such as the TAM family of models face additional challenges. Energy-related behaviors are deeply entrenched and persuaded by an array of components like habits, attitudes, social norms, and environmental concerns. A Malaysian case study conducted to comprehend the factors affecting residents' adoption of solar energy found that factors like environmentalism and knowledge were the most influential in their adoption decision [90]. Similarly, studies conducted in South Africa [100] and Poland [70] on the adoption of solar technology reiterate environmental concerns as a positive and significant factor for adoption. Attitude is another essential factor that affects adoption [100–102]. Unlike adopting consumer technologies, where the benefits are often immediate and tangible, energy-saving behaviors and technologies may involve upfront costs, long-term benefits, and uncertain outcomes. An electric vehicle adoption study ascertains that adoption is affected by components such as promotion, word of mouth, financial incentives, EV performance quality, and infrastructure preparedness [103]. Another study highlights the significance of the TAM's limitations, stating that the cost and structural requirements drive users to adopt novel energy technologies [104]. A study of smart grid adoption in Ghana identified cost, education, and government policies as key factors influencing smart grid adoption [105]. Furthermore, the energy sector is heavily regulated, and policies play a sizable part in defining technology adoption and energy use patterns. The findings from a survey conducted in Malaysia emphasize the importance of governmental support, highlighting the policy implications for promoting renewable energy adoption [101]. Another study conducted in India indicated that advertising strategies, social influence, buyer awareness, and government enterprises significantly impact purchase intentions, while environmental concern, accessibility, and cost show insignificant influences [106]. Another study conducted in Malaysia on solar thermal heaters indicated that there is a need for tailored policies to enhance the willingness to adopt even with current government support [107]. Additionally, in 2018, it was found that regulatory and structural barriers hindered market adoption of distributed energy systems [108]. Complementing these models for technology acceptance with more comprehensive frameworks is crucial for a holistic understanding of technology adoption in the energy domain.

5. Review of Factors Affecting Models for Energy Technology Adoption

Surveys of stakeholders in the technology and present or potential consumers (focus groups) are used to obtain the data needed to support the theories mentioned above. However, these data have several drawbacks, including the stakeholder's biased opinions, changes in consumer attitudes toward technology after adoption as opposed to before adoption, consumer awareness, and consumption attitudes. As a result, they limit these models' ability to anticipate future events while considering these changes. Therefore, there is a demand for frameworks and models that can predict changes over time (using various situations). Factors such as the presence and influence of social media and the VUCA worldview can be considered to incorporate the changes over time. These models will give decision makers a clearer picture of how the technology will be received over time in various circumstances and help them decide how to apply it.

Numerous variables that can be divided into individual, technological, societal, and contextual aspects affect the acceptance of energy technologies. These elements are essential for determining how users perceive energy technologies, how they feel about them, and how they intend to behave with regard to use. Some essential elements affect the models of adoption of energy technology. Users are more inclined to accept energy if they believe that technology is helpful and advantageous [109].

Perceived Utility and Usability: The extent to which technology meets specific energy needs, boosts efficiency, lowers expenses, or promotes environmental sustainability affects how useful consumers perceive it to be. The user's perception of its simplicity in acquiring information and using the simplicity of its use is a term used to describe technology. Technology is more likely to be embraced and used if it is simple and easy to use [110].

Technology Performance, Cost, and Affordability: The adoption of RET is considerably affected by its efficacy and dependability. Users are more inclined to adopt technologies that produce reliable and satisfactory results over time. The price of power technology and users' capacity to buy it are key factors in its acceptance. Adoption may be hampered by high initial prices or recurring costs, even if the equipment is considered useful [111]. Several variables contribute to the capital limits faced by customers in difficult financial situations, which may result in poor energy technology adoption [112]. For example, Best et al. [113] demonstrated that low-income households are more likely to invest in residential solar systems than high-income households. Many low-income individuals, particularly those who have trouble paying utility bills, lack the resources needed to buy solar energy technology, including access to financing and discretionary personal money [114].

Social Influence, Political Polarization, and Regulations: Social variables that affect technology adoption include peer recommendations, family and friend viewpoints, and community norms. Positive societal pressures can help acceptance, whereas unfavorable attitudes can work against it. Social norms, perceived product attributes, and adoption norms significantly influence individuals' intentions to adopt sustainable energy innovations [115]. Moreover, the adoption of RET is notably influenced by social networks, where information diffusion and social influence play pivotal roles [116]. Interestingly, the structure of these social networks has been found to impact societal polarization, with higher levels of selective exposure leading to increased polarization, although higher user tolerance can serve as a mitigating factor [117]. Additionally, social media, being an integral part of social networks, can exacerbate political polarization, as users are exposed to content that primarily aligns with their interests. Political polarization means that people are growing more divided in their beliefs and ideologies, often because of political parties and different opinions on topics like energy policy [118]. This may lead to contrasting views on the importance of renewable energy initiatives, with some political sections supporting such efforts while others oppose them [1]. Political polarization can influence public perceptions of the effectiveness and necessity of RET, with individuals often aligning their attitudes with their political affiliations rather than objective evidence [119]. Lastly, polarized political debates may hinder collaborative efforts and policy implementation, making it challenging to enact comprehensive energy strategies that address environmental concerns while also meeting societal needs [118]. Energy policies, incentives, and restrictions can strongly influence the acceptance of energy technologies. Supportive laws and incentives like tax breaks can persuade people to use green energy sources [29]. Additionally, studies reveal that landlords are reluctant to renovate rental homes where the tenant will save money by paying less for power. Studies by Hope and Booth [120] from the UK, Melvin [121] from the US, and the International Energy Agency [15] from Japan, the US, the Netherlands, Norway, and Australia look at landlords' willingness to invest in renewable energy measures (which includes but is not restricted to PV systems and building insulation). They discovered little landlord support for spending money on assets, which might reduce tenant energy costs.

Digitalization and Family Structure: Purchasing decisions are now more democratic due to changing family structures and dynamics. The characteristic trait between justified beliefs and opinions in the consumption model and purchase decisions derived from behavioral analysis highlights the evolving nature of consumer behavior [122]. The stress caused by uncertainty in purchasing decisions indicates a shift in the emotional aspects of consumer behavior [123]. Additionally, shoppers who experience a positive and prolific environment while shopping are inclined to speak to store employees, spend more time in the shops, and spend more money on their purchases, thus indicating the role of emotional aspects in purchasing decisions [124]. Because of family dynamics in purchasing decisions, consumer behavior can be unreasonable [125]. Moreover, the influence of digitalization has been observed as one of the factors in purchase decisions directed towards qualitative analysis and empirical investigation of consumer desire to make online purchases [126]. Furthermore, a rising trend in environmentally conscious and ethical consumer behavior is observed, indicating the incorporation of sustainability in consumer purchase behavior [127]. For example, adoption decisions for photovoltaic solar systems are significantly affected by characteristics such as household income, maturity level, household size, household education, access to financing, household ownership, and peer effects [128]. Despite this, people prioritize cost over environmental considerations when choosing whether to adopt solar PV systems [129].

A change in consumer behavior is observed as family structure and dynamics evolve over time. For example, consumer financial decisions are influenced by several factors, one of which is family dynamics, which leads to systematic but irrational behavior [125]. Furthermore, increased awareness within families benefits more conscious and informed consumer behavior, suggesting a relationship between consumer awareness and effective behavior [130]. Another study divided all these factors into four categories: perceived advantage or disadvantage of technology, social influence, complexity of innovation, and understanding of funding and costs [131]. Thus, a significant factor in a household's technology adoption is how it is perceived. Financial, sociodemographic, environmental or biophysical, political, and organizational aspects affect household decision making and acceptance of energy technologies [132]. Thus, they conclude that purchase decisions are more democratic in nature, with an increased emphasis on ethical, emotional, and digitally influenced consumer behavior due to changing family structures and dynamics.

For effective tactics to advocate for acceptance and widespread adoption of RET, it is crucial to comprehend these elements and how they interact. Researchers and decision makers can use this information to create interventions that respond to user concerns, foster user confidence, and aid in the efficient incorporation of sustainable energy solutions into the traditional energy scene.

5.1. Implication of Energy Technology in Society and Politics

The public's behavior or attitude toward installing or accepting new technology is known as social acceptability. Political acceptance, on the other hand, is the reaction of influential figures in a community or society's political structure [133]. In the context of social acceptance of technology, political polarization can influence how different segments of society perceive and adopt technological innovations. This can lead to a situation where people from different political backgrounds have vastly different attitudes towards the same technology. Studies have all highlighted the significant impact of sociopolitical polarization on energy technologies, particularly renewable energy innovations [1,118,119]. Additionally, economic and political polarization can affect voter behavior, potentially influencing energy-related policies and decisions [118]. This is because people respond differently to the infrastructure, energy policies, and technologies established in their nations or regions [134]. For instance, in Lebanon, for a rooftop solar water heater, customer reactions were examined to understand how consumers make adoption decisions [135]. These end-users choose the appropriate technology for their situation, which affects their social acceptance. Other aspects include the ability to pay, income loss, lack of resettlement assistance, per capita income, and comprehension of technology, accessibility, and technological risk, as well as energy consumption, consumption by households, user behavior changes, energy type preferences, and user habits [136].

In general, for acceptance, a broader perception of technology was assessed. Figure 7 shows the total acceptance of an energy supply technology within a country, state, or region, considering factors such as public opinion, policy maker support, and civil society organizations' views. Within community acceptance, the response of local communities, including citizens, stakeholders, and decision makers, affects energy infrastructure projects within their vicinity. The focus is on understanding how communities interact with and perceive the physical presence of energy extraction, production, conversion, or storage infrastructure [137] as well as their engagement with project proposals related to these activities. Finally, the responses of consumers and stakeholders, including householders and investors, towards specific supply and demand side energy applications are included in market acceptance. Stakeholder acceptability is a crucial element of acceptance by society, which significantly affects how energy tools and regulations are bordered and how innovations are implemented [133]. Thus, social acceptance can be evaluated based on an individual's response to a society's political structure or community. At the national or political level, the general public, social organizations, policy makers, private organizations, and experts all have varying degrees of technology acceptance. This technology is often broadly and collectively seen [138].

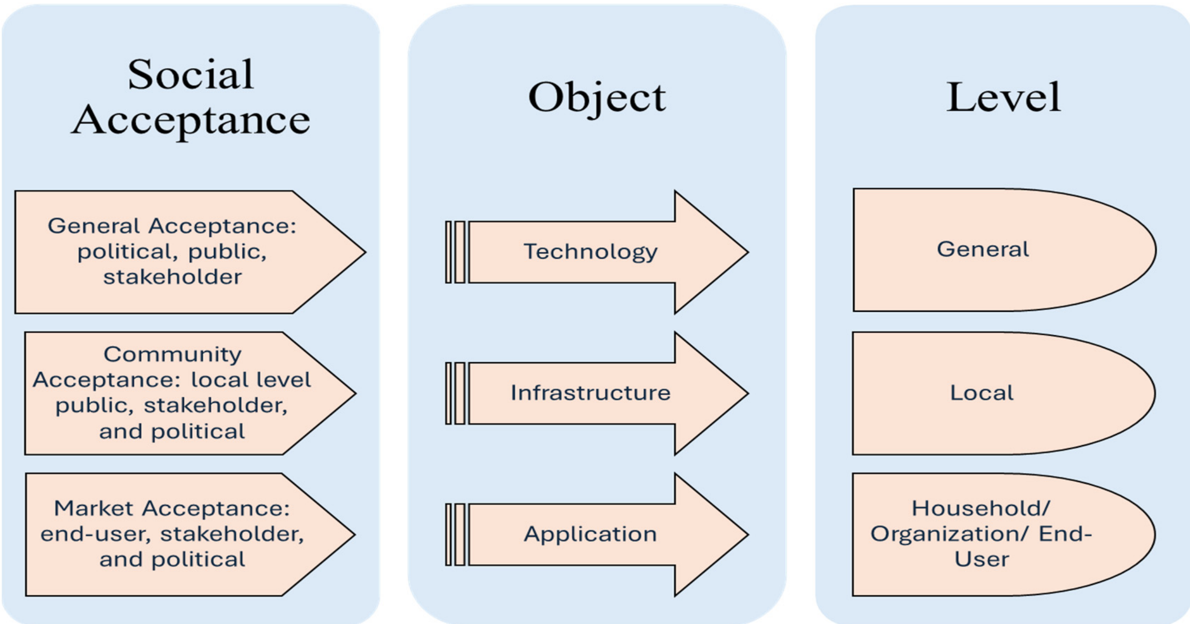

Figure 7. Levels of social acceptance, adapted from [133].

5.2. Implication for Smart Grids

Industries and the government both recognize the critical role that home energy users play in implementing future electricity systems [139]. According to academics, the involvement of these users impedes smart grids [140,141]. It is envisaged that consumers will shell out for smart batteries privately, and this involvement implies some level of acceptability [142]. Acceptability is the last step before an application can be successfully implemented. The phrase "acceptance" is used in scholarship but is not clearly defined. It appears next to the relations "engagement", "involvement", and "participation", which are all used in different ways to embrace technology. However, Davis, F.D. [3] defined acceptance as only achieving "actual system use" in TAM, which is viewed from the standpoint of organizational administration. Scholars have discovered two instances of a TAM variant (Risk-Integrated TAM) used with smart grids [142,143].

5.3. Engagement, Involvement, and Agency

According to earlier research, the phrases "engagement", "participation", and "agency" all refer to an active contribution of the customer in the energy system, frequently involving changes in consumption patterns. Concerning smart grids, both academia and business have looked into involvement and agency [144–147]. According to Chilvers et al. [148], participation is correlated with agency and engagement, and customer involvement and education should be prioritized to prevent disengagement. Gangale et al. [141] contend that the benefits of smart grids cannot be realized without education and engagement. The importance of consumers as the core of a future grid has come into sharper prominence in government and utility reports [14,149]. Therefore, the Australian government is cognizant of consumer risk and investor interest in smart grids [150].

The complexity of smart grids poses a severe threat to customer participation, which is essential for a manageable transition. Integrating internet-based tools frequently utilized for managing, arbitrating, and tracking energy and financial transactions is described as the Internet of Things (IoT). IoT with complexity can result in consumer unwillingness to accept [151]. A poll on smart grids in Portugal with 1084 members illustrates the impact of complexity: 71% of respondents said that if it became too complicated to manage their electricity consumption, they would acquire an IoT device, such as "if [the] tariff varied every hour" [152]. The fact that this suggests a trading agency or contracting of complexity to diminish participant agency is significant.

Now that the concept of behavior may be used in place of agency in the context of smart grids, the impact of agency is indicated to have a greater range. Smart grids adjust to the energy habits of a homeowner. While studying behavior changes, such as changes in energy consumption patterns, is essential for the energy sector, switching to renewable IoT seems to require more agency [140,141,148,152]. Owing to its complexity and automation, smart battery technology will need to be adopted by consumers, and this will occur through technical acceptance.

5.4. Trust, Perceptions, and Attitudes

'Perceptions' are fundamental to the TAM, and there is rising interest in how consumers view successions and smart electricity systems [153,154]. Trust becomes more crucial in uncertain times, such as when the energy industry undergoes structural changes [155], and end-user views are a critical component of utilizing this type of technology [156]. The idea of trust is key to energy transition. According to Gangale et al. [141], people with some knowledge of technology depend on their acceptance decisions for their trust in the technology. Additionally, Büscher and Sumpf [157] discovered that trust, rather than education, is more important for public participation in sociotechnical transition. Similarly, another study on residential electricity consumers highlighted that trust and transparent communication are crucial factors for adoption [158]. Another study underscored factors such as trust and user satisfaction as important factors for pre- and post-biogas fuel adoption [2]. Therefore, trust is an essential foundation for actionability or transformation.

According to Büscher and Sumpf [157], ignorance of smart grid behavior is a significant obstacle to its use. If it works, the technological operation poses the first implementation challenge from a network perspective, followed by the "social operation as communication". Uncertainty underpins this social setup. According to these studies, good communication is inherently unlikely [157]. This describes the considerable implementation hurdle caused by risk and uncertainty.

However, the perception of risk diminishes when trust is present [3,141]. Attention is drawn to the crucial connection between uncertainty and risk by connecting it to trust. Thus, this research helps us understand how a smart grid system affects specific aspects of customer behavior, mainly regarding autonomy and trust. Automation significantly reduces the level of agency necessary. However, because energy systems are an IoT phenomenon, this will mean less agency for consumers. Accepting the underlying automated operation is the key to lowering complexity. Trust is a framework that develops agency and overcomes difficulties.

5.5. Acceptance

The concepts mentioned above, including involvement, trust, agency, and provision of information, do not necessarily correlate with successful implementation. Collectively, these constitute prerequisites for the acceptance of technology. However, in contrast to other scholarly works, the agency is given its own space for study in this research because it is seen as a distinct predecessor. We have attempted to separate the important precursors because other investigations have identified that the consumer acceptability of smart grids is essential for effective placement [14,159]. Ellabban [142], a proponent of the smart grid TAM, contends that user acceptability is fundamental and supports the technology, norms, privacy, cybersecurity policies, prices, and rules. We defined acceptance as the installation and real use of smart batteries, depending on the supporting literature.

6. Scope for Future Research

The specific characteristics and difficulties offered by future energy technologies, including energy storage systems, microgrids, and IoT-enabled devices, may not be fully addressed by the current TAM family of models. Understanding how users' views, opinions, and behavioral intentions vary when thinking about innovative innovations in the context of energy is where there is a study deficit. While the original TAM considers factors at the individual level that affect technological acceptance, it is possible that there is no thorough examination of sociocultural aspects relevant to the energy sector [37,160,161]. Exploring how cultural norms, social media, and context-related variables affect users' willingness to embrace sustainable energy solutions over time is an unmet research need.

Figure 8 shows that the current landscape of technology adoption models primarily revolves around the TAM family of models and diffusion models. However, several challenges persist in the adoption of RET. Key challenges include environmentalism, awareness, and government policies, underscoring the need to address gaps in existing models. These gaps encompass factors such as social influence, digitalization, social polarization, and family dynamics, which play crucial roles in shaping technology adoption behaviors. Addressing these gaps is essential for developing more comprehensive frameworks that accurately capture the complexities of technology adoption in today's evolving sociotechnical landscape.

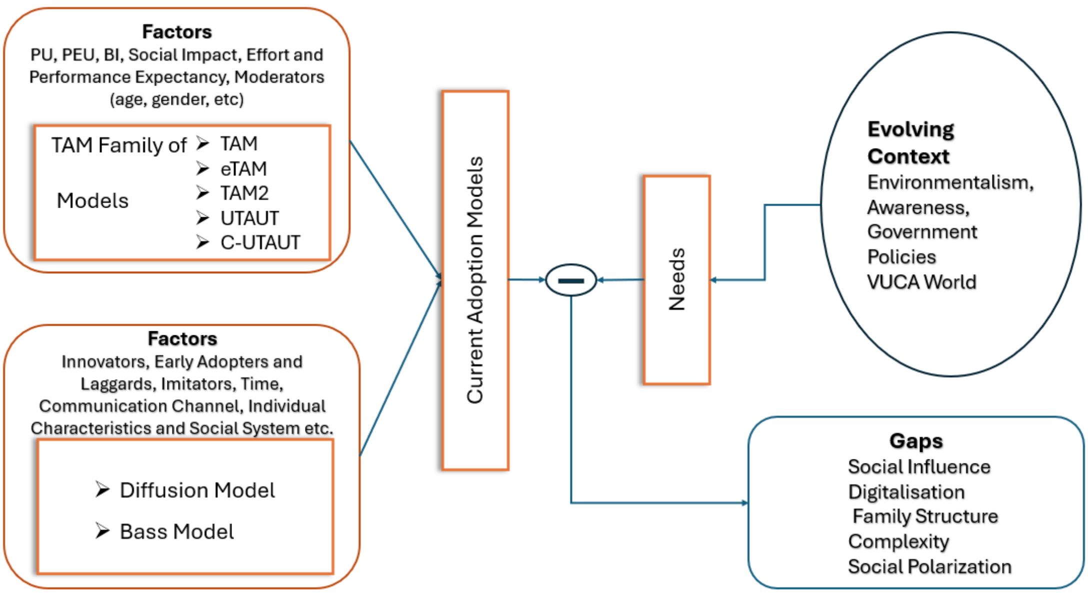

Figure 8. Needs and gaps in current adoption models.

Although the proposed article recognizes the potential policy consequences of reviewing the TAM for technological uptake, there may be a research gap in offering specific and practical advice to decision makers and industry stakeholders [162].

A deeper knowledge of users' attitudes and behaviors toward embracing these advances is necessary given the rapid growth of energy technologies and the necessity of sustainable energy solutions. The TAM has been extensively applied to explore technology adoption across several industries, including the energy industry. To provide more thorough knowledge of RET adoption, it is necessary to reassess and expand the current energy adoption frameworks as the energy environment becomes more complicated and variegated with the emergence of novel energy technologies [37]. First, embracing future energy technologies, such as smart grids, stored energy systems, and IoT-enabled gadgets, presents special difficulties and complexities that the current research may not adequately address. Because of this, the existing model's usability and interpretive capacity in the energy industry may be constrained, making it difficult for academics and policy makers to obtain complete knowledge of the elements influencing or impeding the mainstreaming of such disruptive technologies. Effective tactics for promoting the adoption of renewable energy technologies must be tailored to account for how cultural norms, societal dynamics, and geographical energy legislation affect technological acceptability.

Knowledge gaps also exist regarding how customers experience hardship and perceive energy use. Therefore, qualitative inquiry could be a promising approach for future research to further understand the hardship cohort. Future studies are required to determine whether other approaches, such as alternative government incentives for landlords to use PV systems, could also produce positive net effects. Further investigation might also contrast the opportunities and difficulties faced by different categories of landlords, including those in the public and communal housing sectors and the private rental market. Further quantitative modeling and qualitative analysis in this area would be beneficial for investigating PV adoption barriers that our study did not address, such as data inequalities [163], in addition to the perspectives of many other players, including lawmakers, energy suppliers, and PV firms, who might support or obstruct the shift in emphasis from homeowners to renters as a means of accelerating PV implementation in Australia.

7. Limitation

While this paper sheds light on current adoption models and discusses the possible gaps, it is important to note a potential limitation: the review exclusively utilizes data from SCOPUS. While this approach provides a focused perspective, incorporating additional databases could further enrich the comprehensiveness of the literature review.

8. Conclusions

A key element in deciding whether a technology is successfully implemented is its level of social acceptance, especially in the case of energy technology. This is particularly crucial because the successful usage of technology depends on stakeholders who are interested in the results, as well as the technology's inventors. When developing a framework or constructing a model to forecast user acceptance, it is crucial to consider the VUCA worldview and the impact of media on user decision making. Acceptance models and frameworks are employed to forecast consumer usage and acceptance. Future research should review these frameworks and models and incorporate modern elements, such as social media and shifting worldviews. As a result, it is possible to create a novel structure and quantitative model to forecast technology adoption over time. Future researchers will have the opportunity to use this research to adopt a practical approach to conduct empirical investigations on various technologies. Based on this literature review, this investigation can be used in various sectors to better understand the advantages and disadvantages of each theory.

Author Contributions: Conceptualization, G.B. and T.B.; methodology, T.B.; validation, G.B. and M.P.; formal analysis, investigation, T.B.; resources, T.B.; data curation, T.B.; writing—original draft preparation, T.B.; writing—review and editing, G.B., T.B. and M.P.; visualization, G.B. and T.B.; supervision, G.B. and M.P.; project administration, G.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Wüstenhagen, R.; Wolsink, M.; Bürer, M.J. Social Acceptance of Renewable Energy Innovation: An Introduction to the Concept. *Energy Policy* **2007**, *35*, 2683–2691. [CrossRef]
2. Yasmin, N.; Grundmann, P. Pre- and Post-Adoption Beliefs about the Diffusion and Continuation of Biogas-Based Cooking Fuel Technology in Pakistan. *Energies* **2019**, *12*, 3184. [CrossRef]
3. Davis, F.D. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Q.* **1989**, *13*, 319. [CrossRef]
4. Anser, M.K.; Yousaf, Z.; Zaman, K. Green Technology Acceptance Model and Green Logistics Operations: "To See Which Way the Wind Is Blowing". *Front. Sustain.* **2020**, *1*, 3. [CrossRef]
5. Schoemaker, P.; Heaton, S.; Teece, D. Innovation, Dynamic Capabilities, and Leadership. *Calif. Manag. Rev.* **2018**, *61*, 15–42. [CrossRef]
6. Ginters, E.; Barkane, Z.; Vincent, H. Systems Dynamics Use for Technologies Assessment. In Proceedings of the 22th European Modeling & Simulation Symposium (EMSS 2010), Genoa, Italy, 13–15 October 2010.
7. Giones, F.; Brem, A.; Berger, A. Strategic Decisions in Turbulent Times: Lessons from the Energy Industry. *Bus. Horiz.* **2019**, *62*, 215–225. [CrossRef]
8. Hwang, Y.; Al-Arabiat, M.; Shin, D.-H. Understanding Technology Acceptance in A Mandatory Environment. *Inf. Dev.* **2016**, *32*, 1266–1283. [CrossRef]
9. López-Nicolás, C.; Molina-Castillo, F.J.; Bouwman, H. An Assessment of Advanced Mobile Services Acceptance: Contributions from TAM and Diffusion Theory Models. *Inf. Manag.* **2008**, *45*, 359–364. [CrossRef]
10. Shaheen, S.A.; Martin, E.; Lipman, T.E. Dynamics in Behavioral Response to Fuel-Cell Vehicle Fleet and Hydrogen Fueling Infrastructure. *Transp. Res. Rec. J. Transp. Res. Board* **2008**, *2058*, 155–162. [CrossRef]
11. Michaud, K.; Carlisle, J.E.; Smith, E.R.A.N. Nimbyism vs. Environmentalism in Attitudes toward Energy Development. *Environ. Politics* **2008**, *17*, 20–39. [CrossRef]
12. Gaede, J.; Rowlands, I.H. Visualizing Social Acceptance Research. *Energy Res. Soc. Sci.* **2018**, *40*, 142–158. [CrossRef]
13. Cho, Y.; Shaygan, A.; Daim, T.U. Energy Technology Adoption: Case of Solar Photovoltaic in the Pacific Northwest USA. *Sustain. Energy Technol. Assess.* **2019**, *34*, 187–199. [CrossRef]
14. Arena. Darren Miller: The Energy Revolution Is Happening in Our Homes. 2019. Available online: https://arena.gov.au/blog/darren-miller-the-energy-revolution-is-happening-in-our-homes/ (accessed on 1 November 2023).
15. IEA. *The Latest Trends in Energy and Emissions in 2018*; International Energy Agency: Paris, France, 2019.
16. IRENA. *Renewable Capacity Highlights*; International Renewable Energy Agency: Masdar City, United Arab Emirates, 2019.
17. IRENA. Renewable Power Generation Costs in 2018. Available online: https://www.irena.org/publications/2019/May/Renewable-power-generation-costs-in-2018 (accessed on 1 November 2023).
18. Agnew, S.; Dargusch, P. Effect of Residential Solar and Storage on Centralized Electricity Supply Systems. *Nat. Clim. Chang.* **2015**, *5*, 315–318. [CrossRef]
19. Simshauser, P.; Nelson, T. *The Energy Market Death Spiral-Rethinking Customer Hardship*; AGL Energy Ltd.: Brisbane, QLD, Australia, 2012.
20. Irena. Global Energy Transformation: A Roadmap to 2050. Available online: https://www.irena.org/publications/2019/Apr/Global-energy-transformation-A-roadmap-to-2050-2019Edition (accessed on 1 November 2023).
21. Rath, C.R.; Grosskopf, S.; Barmeyer, C. Leadership in the VUCA World—A Systematic Literature Review and Its Link to Intercultural Competencies. *Eur. J. Cross-Cult. Competence Manag.* **2021**, *5*, 195. [CrossRef]
22. Romanach, L.; Carr-Cornish, S.; Muriuki, G. Societal Acceptance of an Emerging Energy Technology: How Is Geothermal Energy Portrayed in Australian Media? *Renew. Sustain. Energy Rev.* **2015**, *42*, 1143–1150. [CrossRef]
23. Nisbet, M.C.; Scheufele, D.A.; Shanahan, J.; Moy, P.; Brossard, D.; Lewenstein, B.V. Knowledge, Reservations, or Promise? *Commun. Res.* **2002**, *29*, 584–608. [CrossRef]
24. Nuortimo, K.; Härkönen, J. Opinion Mining Approach to Study Media-Image of Energy Production. Implications to Public Acceptance and Market Deployment. *Renew. Sustain. Energy Rev.* **2018**, *96*, 210–217. [CrossRef]
25. Sandberg, M. Sufficiency transitions: A Review of Consumption Changes for Environmental Sustainability. *J. Clean. Prod.* **2021**, *293*, 126097. [CrossRef]

26. Tekmen-Araci, Y. Teaching Creativity in Engineering Schools: A Review of the Literature. *Int. J. Eng. Educ.* **2024**, *40*, 126–143.
27. Taherdoost, H. A Review of Technology Acceptance and Adoption Models and Theories. *Procedia Manuf.* **2018**, *22*, 960–967. [CrossRef]
28. Ajzen, I.; Fishbein, M. *Understanding Attitudes and Predicting Social Behavior*; Prentice-Hall: Hoboken, NJ, USA, 1980.
29. Lai, P.C. The Literature Review of Technology Adoption Models and Theories for the Novelty Technology. *J. Inf. Syst. Technol. Manag.* **2017**, *14*, 21–38. [CrossRef]
30. Fishbein, M.A.; Ajzen, I. *Belief, Attitude, Intention and Behaviour: An Introduction to Theory and Research*; Addison-Wesley: Reading, MA, USA, 1975.
31. Yi, M.Y.; Hwang, Y. Predicting the Use of Web-Based Information Systems: Self-Efficacy, Enjoyment, Learning Goal Orientation, and the Technology Acceptance Model. *Int. J. Hum.-Comput. Stud.* **2003**, *59*, 431–449. [CrossRef]
32. Davis, F.D.; Bagozzi, R.P.; Warshaw, P.R. User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Manag. Sci.* **1989**, *35*, 982–1003. [CrossRef]
33. Venkatesh, V.; Davis, F.D. A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Manag. Sci.* **2000**, *46*, 186–204. [CrossRef]
34. Moore, G.C.; Benbasat, I. Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation. *Inf. Syst. Res.* **1991**, *2*, 192–222. [CrossRef]
35. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User Acceptance of Information Technology: Toward a Unified View. *MIS Q.* **2003**, *27*, 425. [CrossRef]
36. He, K.; Zhang, J.; Zeng, Y. Households' Willingness to Pay for Energy Utilization of Crop Straw in Rural China: Based on an improved UTAUT model. *Energy Policy* **2020**, *140*, 111373. [CrossRef]
37. Mogaji, E.; Viglia, G.; Srivastava, P.; Dwivedi, Y.K. Is It the End of the Technology Acceptance Model in the Era of Generative Artificial Intelligence? *Int. J. Contemp. Hosp. Manag.* **2024**. [CrossRef]
38. Raj, K.B.S. The Role of Social Media Marketing in Ethiopian Tourism and Hospitality Organizations: Applying the Unified Theory of Acceptance and Use of Technology Model. *Cogent Soc. Sci.* **2024**, *10*, 2318866.
39. Recskó, M.; Aranyossy, M. User Acceptance of Social Network-Backed Cryptocurrency: A Unified Theory of Acceptance and use of Technology (UTAUT)-Based Analysis. *Financ. Innov.* **2024**, *10*, 57. [CrossRef]
40. Bouten, M. *Compatibility and Technology Acceptance: Consolidating, Validating and Extending Concepts (Top Thesis)*; Faculty of Economics and Business Administration, Maastricht University: Maastricht, The Netherlands, 2008.
41. Karahanna, E.; Agarwal, R.; Angst, C.M. Reconceptualizing Compatibility Beliefs in Technology Acceptance Research. *MIS Q.* **2006**, *30*, 781. [CrossRef]
42. White, K.M.; Jimmieson, N.L.; Obst, P.L.; Graves, N.; Barnett, A.; Cockshaw, W.; Gee, P.; Haneman, L.; Page, K.; Campbell, M.; et al. Using a Theory of Planned Behaviour Framework to Explore Hand Hygiene Beliefs at the '5 Critical Moments' among Australian Hospital-Based Nurses. *BMC Health Serv. Res.* **2015**, *15*, 59. [CrossRef]
43. Taherdoost, H.; Sahibuddin, S.; Jalaliyoon, N. Smart Card Technology; Awareness and Satisfaction. *J. Comput.* **2012**, *4*, 128–132.
44. Taherdoost, H.; Namayandeh, M.; Jalaliyoon, N. Information Security and Ethics in Educational Context: Propose a Conceptual Framework to Examine Their Impact. *Int. J. Comput. Sci. Inf. Secur.* **2011**, *9*, 134–138.
45. Chang, M.K.; Cheung, W. Determinants of the Intention to Use Internet/WWW at Work: A Confirmatory study. *Inf. Manag.* **2001**, *39*, 1–14. [CrossRef]
46. Misbah, Z.; Gulikers, J.; Maulana, R.; Mulder, M. Teacher Interpersonal Behaviour and Student Motivation in Competence-Based Vocational Education: Evidence from Indonesia. *Teach. Teach. Educ.* **2015**, *50*, 79–89. [CrossRef]
47. Tudela, A.; Habib, K.M.N.; Idris, A.O. Semantic Approach to Capture Psychological Factors Affecting Mode Choice: Comparative Results from Canada and Chile. In *Transport Survey Methods: Best Practice for Decision Making*; Emerald Group Publishing Limited: Bingley, UK, 2013; pp. 625–642.
48. Rana, N.P.; Dwivedi, Y.K. Citizen's Adoption of An e-government System: Validating Extended Social Cognitive Theory (SCT). *Gov. Inf. Q.* **2015**, *32*, 172–181. [CrossRef]
49. John Thogersen, A.G. Electricity Saving in Households—A Social Cognitive Approach. *Energy Policy* **2010**, *38*, 7732–7743. [CrossRef]
50. Zhang, X.; Nketiah, E.; Shi, V.; Cheng, J. Who Will Save Energy? An Extension of Social Cognitive Theory with Place Attachment to Understand Residents' Energy-Saving Behaviors. *Sustainability* **2024**, *16*, 213. [CrossRef]
51. Turan, A.; Tunç, A.Ö.; Zehir, C. A Theoretical Model Proposal: Personal Innovativeness and User Involvement as Antecedents of Unified Theory of Acceptance and Use of Technology. *Procedia-Soc. Behav. Sci.* **2015**, *210*, 43–51. [CrossRef]
52. Rogers, E.M. *Diffusion of Innovations*, 4th ed.; Free Press: New York, NY, USA, 1995.
53. Outcault, S.; Sanguinetti, A.; Nelson, L. Technology Characteristics that Influence Adoption of Residential Distributed Energy resources: Adapting Rogers' framework. *Energy Policy* **2022**, *168*, 113153. [CrossRef]
54. Franceschinis, C.; Thiene, M.; Scarpa, R.; Rose, J.; Moretto, M.; Cavalli, R. Adoption of Renewable Heating Systems: An Empirical Test of the Diffusion of Innovation Theory. *Energy* **2017**, *125*, 313–326. [CrossRef]
55. Long, S.; Liao, Z. Green Relational Capital, Integration Capabilities and Environmental Innovation Adoption: The Moderating Role of Normative Pressures. *Sustain. Dev.* **2023**, *31*, 1570–1580. [CrossRef]
56. Askarany, D. Attributes of Innovation and Management Accounting Changes. *Contemp. Manag. Res.* **2016**, *12*, 455–466. [CrossRef]

57. Cao, Y.; Ajjan, H.; Hong, P.; Le, T. Using Social Media for Competitive Business Outcomes. *J. Adv. Manag. Res.* **2018**, *15*, 211–235. [CrossRef]
58. Salmizi, A.; Aziz, N.; Hazudin, S. Factors Affecting e-Commerce Adoption: A Conceptual Model and Research Propositions. *Int. J. Acad. Res. Bus. Soc. Sci.* **2022**, *12*, 3187–3197. [CrossRef] [PubMed]
59. Ramdani, B.; Duan, B.; Berrou, I. Exploring the Determinants of Mobile Health Adoption by Hospitals in China: Empirical Study. *Jmir Med. Inform.* **2020**, *8*, e14795. [CrossRef] [PubMed]
60. Pérez-Morón, J. Eleven Years of Cyberattacks on Chinese Supply Chains in an Era of Cyber Warfare, a Review and Future Research Agenda. *J. Asia Bus. Stud.* **2021**, *16*, 371–395. [CrossRef]
61. Silva, R.; Mattos, C. Critical Success Factors of a Drug Traceability System for Creating Value in a Pharmaceutical Supply Chain (psc). *Int. J. Environ. Res. Public Health* **2019**, *6*, 1972. [CrossRef]
62. Tomás, S.; Thomas, M.; Oliveira, T. Evaluating the Impact of Virtualization Characteristics on Saas Adoption. *Enterp. Inf. Syst.* **2017**, *12*, 259–278. [CrossRef]
63. Chen, S.; Li, Q.; Liu, B.; Wang, N. Configurational Analysis of the Driving Paths of Chinese Digital Economy Based on the Technology–Organization–Environment Framework. *Sage Open* **2021**, *11*, 21582440211054500. [CrossRef]
64. Kabra, G. Determinants of Blockchain Adoption and Organizational Performance in the Healthcare Sector in india. *Am. J. Bus.* **2023**, *38*, 152–171. [CrossRef]
65. Lihniash, S.; Egdair, I.; Ahmed, S. The Proposed Conceptual Framework to Understand the Effect of the Technology Organization Environment (toe) Model on Internet Financial Reporting (ifr) in Libyan Financial Institutions. *Open J. Bus. Manag.* **2019**, *7*, 339–347. [CrossRef]
66. Ngah, A.; Zainuddin, Y.; Ramayah, T. Applying the toe Framework in the Halal Warehouse Adoption Study. *J. Islam. Account. Bus. Res.* **2017**, *8*, 161–181. [CrossRef]
67. Ghobakhloo, M.; Aranda, D.; Benítez-Amado, J. Adoption of e-Commerce Applications in Smes. *Ind. Manag. Data Syst.* **2011**, *111*, 1238–1269. [CrossRef]
68. Wall, W.; Khalid, B.; Urbański, M.; Kot, M. Factors Influencing Consumer's Adoption of Renewable Energy. *Energies* **2021**, *14*, 5420. [CrossRef]
69. Fayad, M.F.; Sabri, S.; Elmahdy, M.; Kasem, A.A. Managing of Renewable Energy Transformations in Egypt. *Int. J. Sustain. Dev. Sci.* **2020**, *3*, 1–18.
70. Khalid, B.; Urbański, M.; Kowalska-Sudyka, M.; Wysłocka, E.; Piontek, B. Evaluating Consumers' Adoption of Renewable Energy. *Energies* **2021**, *14*, 7138. [CrossRef]
71. Iskandar, A.; Usman, A.; Shaharuddin, S. Role of Islamic Economic and Finance in Renewable Energy: Some Quotation from Quranic Verses and Indonesia Experiences. *Al-Irsyad J. Islam. Contemp. Issues* **2021**, *6*, 583–595. [CrossRef]
72. Gholipour, Y. Future of oil and renewable energy. *Int. J. Frontline Res. Rev.* **2022**, *1*, 14–20. [CrossRef]
73. Majlingová, A.; Lieskovský, M.; Sedliak, M.; Slamka, M. Energy Potential of Biomass Sources in Slovakia. In *Green Energy and Environment*; IntechOpen: London, UK, 2020.
74. Ahmed, I. Technology Organization Environment Framework in cloud Computing. *Telkomnika (Telecommun. Comput. Electron. Control)* **2020**, *18*, 716. [CrossRef]
75. Bhardwaj, A.; Garg, A.; Gajpal, Y. Determinants of Blockchain Technology Adoption in Supply Chains by Small and Medium Enterprises (smes) in India. *Math. Probl. Eng.* **2021**, *2021*, 5537395. [CrossRef]
76. Surya, B.; Suriani, S.; Menne, F.; Abubakar, H.; Idris, M.; Rasyidi, E.S.; Remmang, H. Community Empowerment and Utilization of Renewable Energy: Entrepreneurial Perspective for Community Resilience Based on Sustainable Management of Slum Settlements in Makassar City, Indonesia. *Sustainability* **2021**, *13*, 3178. [CrossRef]
77. Jack, E.K.E.; Jack, K.E.; Obichere, J.-K.C.; Dike, D.O.; Olubiwe, M.; Essien, U.A.; Anunuso, J.C. Development of Human Machine Interface for the Control of the Integrated Hybridized Renewable Energy Resources in Community-Based Power Pool System. *Int. J. Eng. Res. Technol.* **2019**, *8*. [CrossRef]
78. Bass, F.M.; Krishnan, T.V.; Jain, D.C. Why the Bass Model Fits without Decision Variables. *Mark. Sci.* **1994**, *13*, 203–223. [CrossRef]
79. Duretec, K.; Becker, C. Format Technology Lifecycle Analysis. *J. Assoc. Inf. Sci. Technol.* **2017**, *68*, 2484–2500. [CrossRef]
80. Reddy, B.S. Economic Dynamics and Technology Diffusion in Indian Power Sector. *Energy Policy* **2018**, *120*, 425–435. [CrossRef]
81. Kim, S.-H.; Lee, S.; Han, S.-Y.; Kim, J.-H. Scenario Analysis for GHG Emission Reduction Potential of the Building Sector for New City in South Korea. *Energies* **2020**, *13*, 5514. [CrossRef]
82. Dong, C.; Sigrin, B.; Brinkman, G. Forecasting Residential Solar Photovoltaic Deployment in California. *Technol. Forecast. Soc. Chang.* **2017**, *117*, 251–265. [CrossRef]
83. Ashraf, I.; Danish, M.; Fernandez, E. Solar Photo Voltaic for Power Generation in India: Projected Level of Dissemination Using Technology Diffusion Models. In Proceedings of the 41st International Universities Power Engineering Conference, Newcastle upon Tyne, UK, 6–8 September 2006.
84. Zhao, X.-G.; Zhang, Y.-Z.; Li, Y.-B. The Evolution of Renewable Energy Price Policies Based on Improved Bass Model: A System Dynamics (SD) Analysis. *Sustainability* **2018**, *10*, 1748. [CrossRef]
85. Carillo, K.D. Social Cognitive Theory in IS Research–Literature Review, Criticism, and Research Agenda. In Proceedings of the Information Systems, Technology and Management: 4th International Conference, ICISTM 2010, Bangkok, Thailand, 11–13 March 2010.

86. Bryan, J.D.; Zuva, T. A Review on TAM and TOE Framework Progression and How These Models Integrate. *Adv. Sci. Technol. Eng. Syst. J.* **2021**, *6*, 137–145. [CrossRef]
87. Nguyen, T.H.; Le, X.C.; Vu, T.H. An Extended Technology-Organization-Environment (TOE) Framework for Online Retailing Utilization in Digital Transformation: Empirical Evidence from Vietnam. *J. Open Innov. Technol. Mark. Complex.* **2022**, *8*, 200. [CrossRef]
88. Khan, N.A.; Khan, A.N.; Bahadur, W.; Ali, M. Mobile payment adoption: A multi-theory model, multi-method approach and multi-country study. *Int. J. Mob. Commun.* **2021**, *19*, 467–491. [CrossRef]
89. Alshammari, S.H.; Rosli, M.S. A Review of Technology Acceptance Models and Theories. *Innov. Teach. Learn. J.* **2021**, *4*, 12–22.
90. Cheam, W.Y.; Lau, L.S.; Wei, C.Y. Factors Influencing the Residence's Intention to Adopt Solar Photovoltaic Technology: A Case Study from Klang Valley, Malaysia. *Clean Energy* **2021**, *5*, 464–473. [CrossRef]
91. Jaiswal, D.; Kant, R.; Singh, P.K.; Yadav, R. Investigating the Role of Electric Vehicle Knowledge in Consumer Adoption: Evidence from an Emerging Market. *Benchmarking* **2022**, *29*, 1027–1045. [CrossRef]
92. Piselli, C.; Salvadori, G.; Diciotti, L.; Fantozzi, F.; Pisello, A.L. Assessing Users' Willingness-to-Engagement towards Net Zero Energy Communities in Italy. *Renew. Sustain. Energy Rev.* **2021**, *152*, 111627. [CrossRef]
93. Bandara, U.C.; Amarasena, T.S.M. Impact of Relative Advantage, Perceived Behavioural Control and Perceived Ease of Use on Intention to Adopt with Solar Energy Technology in Sri Lanka. In Proceedings of the Conference on the Industrial and Commercial Use of Energy, ICUE, Phuket, Thailand, 24–26 October 2018.
94. Karimzadeh, S.; Salehi, S. A Study of Households' Intention towards Solar Panel Installation Case Study: Villagers of the Northern Regions of Iran. *Environ. Sociol.* **2021**, *7*, 434–446. [CrossRef]
95. Ajibade, P. Technology Acceptance Model Limitations and Criticisms: Exploring the Practical Applications and Use in Technology-related Studies, Mixed-method, and Qualitative Researches. *Libr. Philos. Pract.* **2018**. Available online: http://digitalcommons.unl.edu/libphilprac/1941 (accessed on 1 November 2023).
96. Zaineldeen, S.; Hongbo, L.; Koffi, A.L.; Hassan, B.M.A. Technology Acceptance Model' Concepts, Contribution, Limitation, and Adoption in Education. *Univers. J. Educ. Res.* **2020**, *8*, 5061–5071. [CrossRef]
97. Chin, J.; Lin, S.C. A Behavioral Model of Managerial Perspectives Regarding Technology Acceptance in Building Energy Management Systems. *Sustainability* **2016**, *8*, 641. [CrossRef]
98. Zahid, M.J.A.; Ashraf, M.M.; Malik, B.T.; Hoque, M.R. Information Communication Technology (ICT) for Disabled Persons in Bangladesh: Preliminary Study of Impact/Outcome. In *Grand Successes and Failures in IT. Public and Private Sectors*; Springer: Berlin/Heidelberg, Germany, 2013; pp. 652–657.
99. Ho, J.S.; Tan, B.C.; Lau, T.C.; Khan, N. Public Acceptance towards Emerging Autonomous Vehicle Technology: A Bibliometric Research. *Sustainability* **2023**, *15*, 1566. [CrossRef]
100. Fatoki, O. Determinants of Intention to Purchase Photovoltaic Panel System: An Integration of Technology Acceptance Model and Theory of Planned Behaviour. *Int. J. Energy Econ. Policy* **2022**, *12*, 432–440. [CrossRef]
101. Ahmad, S.; Mat Tahar, R.B.; Cheng, J.K.; Yao, L. Public Acceptance of Residential Solar Photovoltaic Technology in Malaysia. *PSU Res. Rev.* **2017**, *1*, 242–254. [CrossRef]
102. Rezaei, R.; Ghofranfarid, M. Rural Households' Renewable Energy Usage Intention in Iran: Extending the Unified Theory of acceptance and use of technology. *Renew. Energy* **2018**, *122*, 382–391. [CrossRef]
103. Damayanti, S.; Hidayatno, A.; Setiawan, A.D. User Acceptance of Electric Vehicles in Indonesia: A Conceptual Model. In Proceedings of the 3rd Asia Pacific Conference on Research in Industrial and Systems Engineering, Depok, Indonesia, 16–17 June 2020.
104. Malatji, W.R.; Eck, R.V.; Zuva, T. Understanding the usage, Modifications, Limitations and Criticisms of Technology Acceptance Model (TAM). *Adv. Sci. Technol. Eng. Syst. J.* **2020**, *5*, 113–117. [CrossRef]
105. Acakpovi, A.; Abubakar, R.; Asabere, N.Y.; Majeed, I.B. Barriers and Prospects of Smart Grid Adoption in Ghana. *Procedia Manuf.* **2019**, *35*, 1240–1249. [CrossRef]
106. Atulkar, S. Purchase Intention of Indian Customers: A Study on Solar PV technology. *Int. J. Energy Sect. Manag.* **2022**, *16*, 946–964. [CrossRef]
107. Baharom, A.S.; Dahlan, N.Y. Solar Thermal Heating Acceptance among Malaysian Industries Using System Dynamics. *Indones. J. Electr. Eng. Comput. Sci.* **2017**, *8*, 375–381.
108. von Wirth, T.; Gislason, L.; Seidl, R. Distributed Energy Systems on a Neighborhood Scale: Reviewing Drivers of and Barriers to Social Acceptance. *Renew. Sustain. Energy Rev.* **2018**, *82*, 2618–2628. [CrossRef]
109. Meuter, M.L.; Ostrom, A.L.; Roundtree, R.I.; Bitner, M.J. Self-Service Technologies: Understanding Customer Satisfaction with Technology-Based Service Encounters. *J. Mark.* **2000**, *64*, 50–64. [CrossRef]
110. Dapp, T.; Stobbe, A.; Wruuck, P. *The Future of (Mobile) Payments-New (Online) Players Competing with Banks*; Deutsche Bank Research: Frankfurt am Main, Germany, 2012; pp. 1–31.
111. Lai, P.C. Consumers Intention to Use a Single Platform E-Payment System: A Study Among Malaysian Internet and Mobile Banking Users. *J. Internet Bank. Commer.* **2015**, *20*, 1–13.
112. Nelson, T.; McCracken-Hewson, E.; Sundstrom, G.; Hawthorne, M. The Drivers of Energy-Related Financial Hardship in Australia–Understanding the Role Of Income, Consumption and Housing. *Energy Policy* **2019**, *124*, 262–271. [CrossRef]
113. Best, R.; Burke, P.J.; Nishitateno, S. Understanding the Determinants of rooftop Solar Installation: Evidence from Household Surveys in Australia. *Aust. J. Agric. Resour. Econ.* **2019**, *63*, 922–939. [CrossRef]

114. Ameli, N.; Brandt, N. *What Impedes Household Investment in Energy Efficiency and Renewable Energy?* OECD Publishing: Paris, France, 2015.
115. Noppers, E.; Keizer, K.; Milovanovic, M.; Steg, L. The Role of Adoption Norms and Perceived Product Attributes in the Adoption of Dutch Electric Vehicles and Smart Energy Systems. *Energy Res. Soc. Sci.* **2019**, *57*, 101237. [CrossRef]
116. He, P.; Lovo, S.; Veronesi, M. Social Networks and Renewable Energy Technology Adoption: Empirical Evidence from Biogas Adoption in China. *Energy Econ.* **2022**, *106*, 105789. [CrossRef]
117. Haque, A.; Ajmeri, N.; Singh, M. Understanding Dynamics of Polarization via Multiagent Social Simulation. *AI Soc.* **2023**, *38*, 1373–1389. [CrossRef] [PubMed]
118. Autor, D.; Dorn, D.; Hanson, G.; Majlesi, K. Importing Political Polarization? The Electoral Consequences of Rising Trade Exposure. *Nber Work. Pap. Ser.* **2020**, *110*, 3139–3183.
119. Gromet, D.; Kunreuther, H.; Larrick, R. Political Ideology Affects Energy-Efficiency Attitudes and Choices. *Proc. Natl. Acad. Sci. USA* **2013**, *110*, 9314–9319. [CrossRef]
120. Hope, A.J.; Booth, A. Attitudes and Behaviours of Private Sector Landlords towards the Energy Efficiency of Tenanted Homes. *Energy Policy* **2014**, *75*, 369–378. [CrossRef]
121. Melvin, J. The Split Incentives Energy Efficiency Problem: Evidence of Underinvestment by Landlords. *Energy Policy* **2018**, *115*, 342–352. [CrossRef]
122. Sundareswaran, G.; Kamaraj, H.; Sanjay, S.; Devi, A.; Elangovan, P.; Kruthikkha, P. Consumer Behavior Analysis. *Int. J. Res. Appl. Technol.* **2022**, *2*, 82–90. [CrossRef]
123. Moschis, G.P. Stress and Consumer Behavior. *J. Acad. Mark. Sci.* **2007**, *35*, 430–444. [CrossRef]
124. Xia, L. An Examination of Consumer Browsing Behaviors. *Qual. Mark. Res. Int. J.* **2010**, *13*, 154–173. [CrossRef]
125. van Raaij, W.F. Consumer Financial Behavior. *Found. Trends® Mark.* **2014**, *7*, 231–351. [CrossRef]
126. Wu, Y. Research on Factors Influencing Consumer Buying Behavior. In Proceedings of the 2022 4th International Conference on Economic Management and Cultural Industry (ICEMCI 2022), Chongqing, China, 14–16 October 2022; pp. 1113–1120.
127. Kraslanová, M.; Vargová, M.; Poláková, Z. Analysis of Consumer Behavior Zero Waste Consumers. *Math. Educ. Res. Appl.* **2021**, *7*, 50–57. [CrossRef]
128. Guta, D.D. Determinants of Household Adoption of Solar Energy Technology in Rural Ethiopia. *J. Clean. Prod.* **2018**, *204*, 193–204. [CrossRef]
129. Palm, J.; Tengvard, M. Motives for and Barriers to Household Adoption of Small-Scale Production of Electricity: Examples from Sweden. *Sustain. Sci. Pract. Policy* **2011**, *7*, 6–15. [CrossRef]
130. Ishak, S.; Zabil, N.F.M. Impact of Consumer Awareness and Knowledge to Consumer Effective Behavior. *Asian Soc. Sci.* **2012**, *8*, 108. [CrossRef]
131. Vasseur, V.; Kemp, R. The adoption of PV in the Netherlands: A Statistical Analysis of Adoption Factors. *Renew. Sustain. Energy Rev.* **2015**, *41*, 483–494. [CrossRef]
132. De Groote, O.; Pepermans, G.; Verboven, F. Heterogeneity in the Adoption of Photovoltaic Systems in Flanders. *Energy Econ.* **2016**, *59*, 45–57. [CrossRef]
133. Upham, P.; Oltra, C.; Boso, À. Towards a Cross-Paradigmatic Framework of the Social Acceptance of Energy Systems. *Energy Res. Soc. Sci.* **2015**, *8*, 100–112. [CrossRef]
134. Stern, P.C. Individual and Household Interactions with Energy Systems: Toward Integrated Understanding. *Energy Res. Soc. Sci.* **2014**, *1*, 41–48. [CrossRef]
135. Elmustapha, H.; Hoppe, T.; Bressers, H. Consumer Renewable Energy Technology Adoption Decision-Making; Comparing Models on perceived Attributes and Attitudinal Constructs in the Case of Solar Water Heaters in Lebanon. *J. Clean. Prod.* **2018**, *172*, 347–357. [CrossRef]
136. Gozgor, G.; Mahalik, M.K.; Demir, E.; Padhan, H. The impact of Economic Globalization on Renewable Energy in the OECD countries. *Energy Policy* **2020**, *139*, 111365. [CrossRef]
137. Singh, G.G.; Cisneros-Montemayor, A.M.; Swartz, W.; Cheung, W.; Guy, J.A.; Kenny, T.-A.; McOwen, C.J.; Asch, R.; Geffert, J.L.; Wabnitz, C.C.C.; et al. A rapid Assessment of co-Benefits and Trade-offs among Sustainable Development Goals. *Mar. Policy* **2018**, *93*, 223–231. [CrossRef]
138. Baur, D.; Emmerich, P.; Baumann, M.J.; Weil, M. Assessing the Social Acceptance of key Technologies for the German Energy Transition. *Energy Sustain. Soc.* **2022**, *12*, 4. [CrossRef]
139. Finkel, A. *Independent Review into the Future Security of the National Electricity Market*; DCCEEW: Parramatta, NSW, Australia, 2016.
140. Bigerna, S.; Bollino, C.A.; Micheli, S. Socio-Economic Acceptability for Smart Grid Development—A Comprehensive Review. *J. Clean. Prod.* **2016**, *131*, 399–409. [CrossRef]
141. Gangale, F.; Mengolini, A.; Onyeji, I. Consumer Engagement: An Insight from Smart Grid Projects in Europe. *Energy Policy* **2013**, *60*, 621–628. [CrossRef]
142. Ellabban, O.; Abu-Rub, H. Smart Grid Customers' Acceptance and Engagement: An Overview. *Renew. Sustain. Energy Rev.* **2016**, *65*, 1285–1298. [CrossRef]
143. Park, C.-K.; Kim, H.-J.; Kim, Y.-S. A Study of Factors Enhancing Smart Grid Consumer Engagement. *Energy Policy* **2014**, *72*, 211–218. [CrossRef]
144. Energex. *Energex Battery Trials: Preliminary Findings Report*; Energex: Newstead, QLD, Australia, 2017.

145. Abi Ghanem, D.; Mander, S. Designing Consumer Engagement with the Smart Grids of the Future: Bringing Active Demand Technology to Everyday Life. *Technol. Anal. Strateg. Manag.* **2014**, *26*, 1163–1175. [CrossRef]
146. Anda, M.; Temmen, J. Smart Metering for Residential Energy Efficiency: The Use of Community Based Social Marketing for Behavioural Change and Smart Grid Introduction. *Renew. Energy* **2014**, *67*, 119–127. [CrossRef]
147. Burchell, K.; Rettie, R.; Roberts, T.C. Householder Engagement with Energy Consumption Feedback: The Role of Community Action and Communications. *Energy Policy* **2016**, *88*, 178–186. [CrossRef]
148. Chilvers, J.; Pallett, H.; Hargreaves, T. Ecologies of Participation in Socio-Technical Change: The Case of Energy System Transitions. *Energy Res. Soc. Sci.* **2018**, *42*, 199–210. [CrossRef]
149. Isgan. *Phase-Sensitive Enabling of Household Engagement in Smart Grids ISGAN Annex 7 (Smart Grid Transitions) Policy Brief No.1*; Isgan: Beijing, China, 2018.
150. Energy Security Board. *Post 2025 Market Design for the National Electricity Market (NEM)*; Energy Security Board: Sydney, NSW, Australia, 2019.
151. Mani, Z.; Chouk, I. Drivers of Consumers' Resistance To Smart Products. *J. Mark. Manag.* **2017**, *33*, 76–97. [CrossRef]
152. Lopes, M.A.R.; Henggeler Antunes, C.; Janda, K.B.; Peixoto, P.; Martins, N. The Potential of Energy Behaviours in a Smart(er) Grid: Policy Implications from a Portuguese Exploratory Study. *Energy Policy* **2016**, *90*, 233–245. [CrossRef]
153. ARENA. *What Is Renewable Energy*; ARENA: Canberra, NSW, Australia, 2024.
154. Mah, D.N.-Y.; van der Vleuten, J.M.; Hills, P.; Tao, J. Consumer Perceptions of Smart Grid Development: Results of a Hong Kong Survey and Policy Implications. *Energy Policy* **2012**, *49*, 204–216. [CrossRef]
155. Bellaby, P.; Eames, M.; Flynn, R. The Role of 'Trust' in the Transition to Sustainable Energy. *Energy Policy* **2010**, *38*, 2613–2614. [CrossRef]
156. Ponce, P.; Polasko, K.; Molina, A. End user Perceptions toward Smart Grid Technology: Acceptance, Adoption, Risks, and Trust. *Renew. Sustain. Energy Rev.* **2016**, *60*, 587–598. [CrossRef]
157. Büscher, C.; Sumpf, P. "Trust" and "Confidence" as Socio-Technical Problems in the Transformation of Energy Systems. *Energy Sustain. Soc.* **2015**, *5*, 34. [CrossRef]
158. Soland, M.; Loosli, S.; Koch, J.; Christ, O. Acceptance among Residential Electricity Consumers Regarding Scenarios of a Transformed Energy System in Switzerland—A Focus Group Study. *Energy Effic.* **2018**, *11*, 1673–1688. [CrossRef]
159. ACOLA. *The Role of Energy Storage in Australia's Future Energy Supply*; ACOLA: Canberra, NSW, Australia, 2017.
160. Kaivo-oja, J.R.L.; Lauraeus, I.T. The VUCA Approach as a Solution Concept to Corporate Foresight Challenges and Global Technological Disruption. *Foresight* **2018**, *20*, 27–49. [CrossRef]
161. Bagozzi, R.P. The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift. *J. Assoc. Inf. Syst.* **2007**, *8*, 244–254. [CrossRef]
162. Huijts, N.M.A.; Molin, E.J.E.; Steg, L. Psychological Factors Influencing Sustainable Energy Technology Acceptance: A review-Based comprehensive Framework. *Renew. Sustain. Energy Rev.* **2012**, *16*, 525–531. [CrossRef]
163. Fuerst, F.; Warren-Myers, G. Does Voluntary Disclosure Create a Green Lemon Problem? Energy-Efficiency Ratings and House Prices. *Energy Econ.* **2018**, *74*, 1–12. [CrossRef]