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More specific formatting instructions are provided in the template that follows.

Title: Using Text Mining and Topic Modelling to understand the decision criteria in Renewable Energy Project Sanctioning.

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**Abstract:** Renewable energy like solar, wind, geothermal and hydrogen are means by which corporations and government hope to mitigate the effect of climate change. Thus, it is hardly surprising that the renewable energy sector has experienced exponential growth in recent decades. However, literature is rife with examples of outcomes from renewable energy projects being less than stellar, with difficulties like energy transportation and subpar performance of certain renewable energy plants. This paper aims to discuss metrics that go into the definition of “renewable energy project success” but will do so using the data science techniques of text mining and topic modeling. These methods is be applied to a collection of peer reviewed scientific research data and will attempt to rank the most critical factors in renewable energy project success

**One-Sentence Summary:** If renewable energy projects are non-commercial, can they be labelled as successes?

As climate concerns increase, corporations and governments are seen to make increasing investments in renewable energy (RE) technologies in such diverse areas as solar, wind, hydrogen and biomass. The expectation with such renewable technology is that harmful greenhouses gases are reduced, along with other forms of pollution. There is also a secondary consideration driven more by an economic mindset; as fossil fuels become increasing scarce, energy producers are only able to meet the growing demand at an ever-increasing cost. In either scenario however, an increase in contribution of renewable resources into the energy mix is a positive step.

However, several critical challenges still exist, and which reduces the efficacy of widespread RE adoption. First, RE tends to be a less reliable form of energy, due to the unpredictability associated with the natural environment. For instance, it was reported that in India, despite its RE footprint growing by ~20% from 2015-2020, ~15-20% of (wind and solar) projects underperformed during 2019-2020, primarily due to adverse weather conditions [1]. A mitigant to this is to use technology like batteries, but this adds capital and operational expenditures (CAPEX/ OPEX) to projects that are sometimes already financially stressed. Another challenge associated with RE adoption has to do with its effect on legacy electrical grids; without a proper understanding of import capacity limits and load factors, RE can cause a deterioration of power factors and in fact escalate costs for operators [2].

The above are just snippets of issues associated with RE, its challenging path to commerciality and why widespread adoption is sometimes problematic. Despite this, investment in RE continues to build. (Janine to help with links). This is indeed puzzling. Since RE cannot be easily/cheaply stored, transported, has sub optimal production (at times) and is expensive to build, maintain and implement, what are the key motivating factors that are driving private and public sector stakeholders to sanction or fund RE projects? What would be the metric by which a successful RE project is defined? Literature itself is extremely polarized on this, with some authors arguing that economic, financial and technical metrics are key, [3, 4, 5], while others argue that political will, behavioral and social aspects are sufficient, if not more important [6, 7, 8, 9].

**Scope & Methods:** This paper will attempt to understand and rank key determinants in RE project success. Given both the polarization of opinion as well as sheer volume of discourse in academic literature in this area, this question lends itself quite readily to methods in data science related to ‘Text Mining’ and ‘Topic Modeling’ (TM+TM) [10, 11].

Both are part of the Natural Language Processing (NLP) set of tools, and will be used to understand the patterns present in unstructured data sources like words, phrases, sentences, and strings of text. NLP algorithms transform unstructured text formats into structured data, enabling unsupervised machine learning processes to be applied. The algorithms automate procedures of categorising, clustering, tagging, and classifying texts, and can extract information on sentiment, topics or intent, all with the goal to uncover hidden structures or commonalities binding the text [10].

For this paper, NLP is implemented using Latent Dirichlet Allocation (LDA) and Non-Negative Matrix Factorization (NNMF). LDA uses statistics to identify hidden structures within text, while NNMF utilizes linear algebra. By applying weightages to individual words based on their similarities, each algorithm can cluster the family of words into a topic [12, 13]. A key assumption in LDA is that each text block contains ‘*k*’ number of topics, represented by the word distribution [13].

The algorithms are applied to a collated collection of 80 scientific articles with the terms “renewable energy success” present as a subject matter. The selection of scientific articles was based on the criteria that (a) each research article should explain factors of success in renewable energy projects, and (b) the understanding of success was from each article’s own definition of success. Each article was also briefly fact checked to ensure their relevancy to the topic. In order to avoid extended processing times and to ensure that longer articles (with higher word counts) do not unnecessarily skew the evaluation, only text from the abstract and conclusion sections were analysed, the assumption being that they are the most succinct and distilled form of information pertaining to the article. The working hypothesis is that, while brief on detail, these 2 text blocks still contain sufficiently insights to arrive at a meaningful conclusion.

***Data Preparation and Preliminary Exploration:*** A complete flow chart highlighting the NLP process is given in Figure 1. Note that a modified stop word dictionary was created to remove words such as “renewable”, “energy” and “success”, as these would be high frequency words affecting the resulting distribution of words. The process of “tokenization” and “lemmatization” is as done in other NLP processes [12]. The output of this process was visualized using a word cloud where the top 10 most frequent words were highlighted; indeed, a preliminary assessment of the word cloud indicated that the randomly selected articles were suitable for use in the next stage of analysis (Figure 2).

**Diagram, timeline

Description automatically generated**

Figure 1: Flow chart highlighting text processing stages applied to the scientific articles in question.

Text

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Figure 2: Top 10 words with highest frequency.

**Topic Modelling with LDA:** The LDA algorithm is implemented via the use of 2 open-source python libraries, namely “Gensim” and “Mallet” (“MAchine Learning for LanguagE Tootlkit”) (hereafter referred to as ‘Gensim LDA’ and ‘Mallet LDA’ respectively). The former creates a unique dictionary like structure where each word is given a unique id and frequency count of occurrence and also doubles as a visualization library. Mallet is used complementarily to Gensim for coherence analysis. Coherence here is a measure of effectiveness of the topic model. A coherence score measures the degree of sematic similarity between the top scoring words in each topic and also facilitates decisions relating to the optimal value of ‘*k’* (the number of topics). As ‘k varies, so too does the coherence score, with higher coherence scores generally representing better model.

Figure 3 shows the coherence score obtained, as a function of the number of topics. The graph shows that the coherence scores do not varying much between the ranges of 5 to 7 and thereafter decrease. In order to demine topic distinctiveness and prevalence, an intertopic distance map (Figure 4, left) is used, with each bubble representing a topic. Through the use of multidimension reduction scaling (PCA/t-sne), topic’s probability distribution can be visualized to determine the degree of overlap or similarity. Bubble size is a measure of the topic prevalence. From the visualisation, we observe that (a) topics 1-3 and 3-2 overlap very slightly, while topic 4 and 5 are uniquely distinct. For the former, the overlap is statistically insignificant and thus, the 5 topics can be considered distinct enough to take this work forward. Furthermore, topic 1 appears to be the most prevalent topic, constituting 29.9% of the tokens. Figure 4 (right) is a sequence of stack bar graphs with the most prevalent words per topic. In the example shown in the image, the top 3 words to appear under topic 1 are “policy”, “technology”, “industry”, “government” and “environmental”, and are highlighted by the blue bars. However, in topic modelling, the relevance of a word is very important, as it leads to the topic being more obvious. This is where a relevancy metric, , is useful [15].

where is the probability of word w in topic k and is the lift in term’s probability within a topic to its marginal probability across the entire corpus. A lower λ gives more importance to the term , which gives more importance to topic exclusivity. Given in Figure 5 is the effect of reducing by 48%; the word “policy” remains unchanged, but interestingly, words like “industry” and “technology” swap places. Additionally, gone are the words “government” and “environmental” from the top 5 words within the topic, replaced instead with words like “firm” and “adoption”. For this work, we set λ = 1. (QN: IS THIS CORRECT?)

Chart, line chart

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Figure 3: Coherence score as a function of topic number; generally, past 5 topics, the score does not vary significantly.

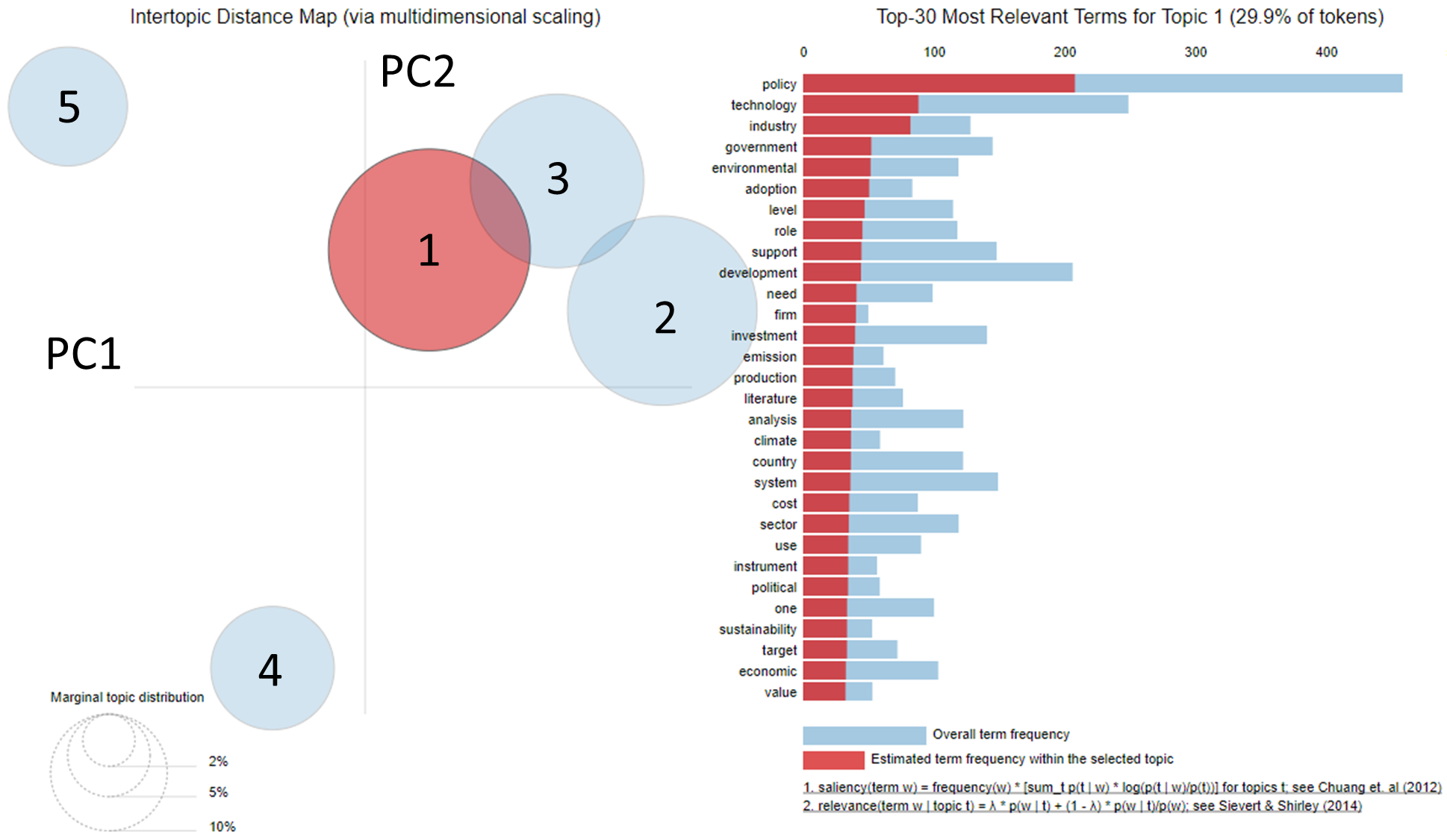


Figure 4: Topic Visualization using a Bubble map and the corresponding top 30 terms in each topic

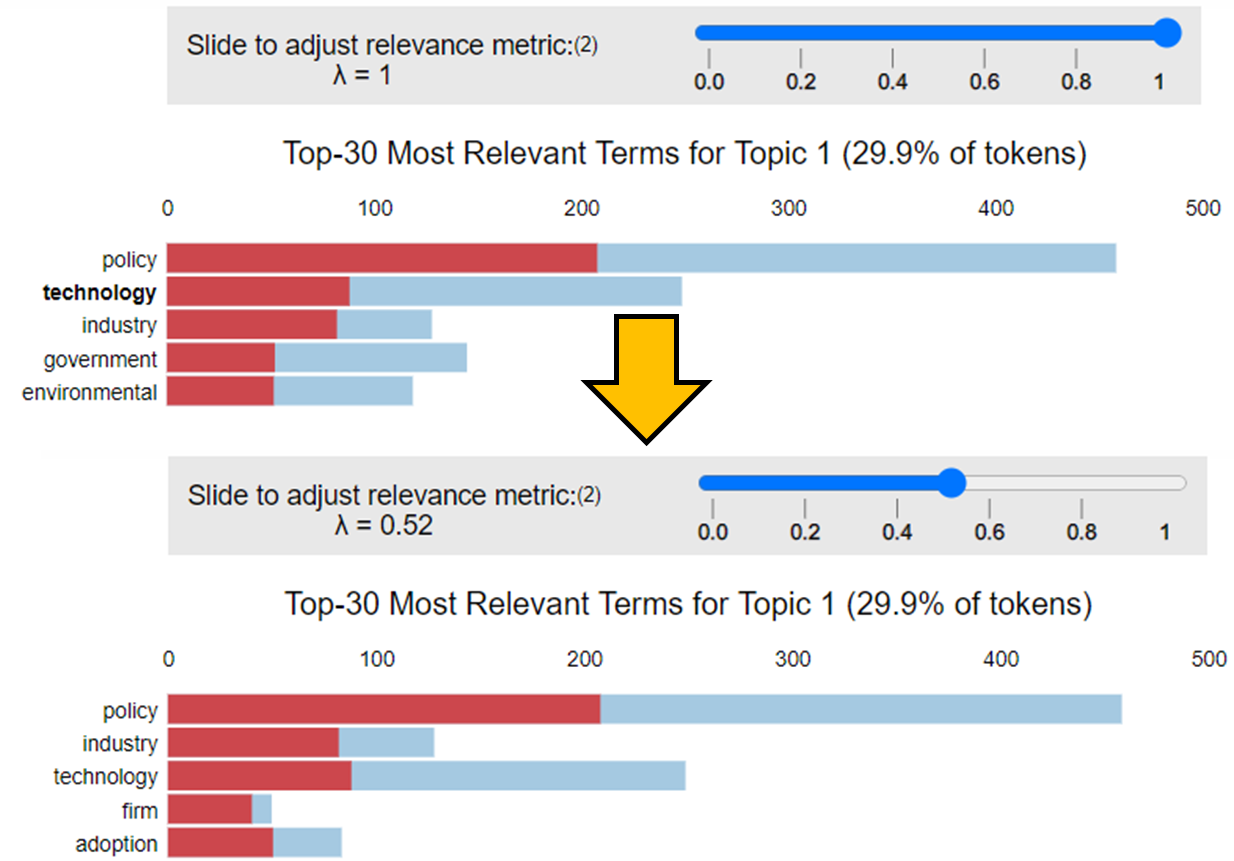


Figure 5: Topic Visualization using a Bubble map and the corresponding top 30 terms in each topic

**Topic Modelling with NNMF:** As another machine learning tool, NNMF is useful as it is able to dimensionally reduce the text data and create topics by grouping words with higher coherence [13]. It does this through a vector multiplication of “*W*” columns and “*H*” rows, with “*W*” representing the weightage of each word in a sentence (‘words-topics’ matrix) and “*H*” represents the words in each column (‘topics-documents’ matrix). The product, “*V*” is referred to as the ‘words-documents’ matrix. In factorizing “*V*” for uses in topic modeling, we are breaking down the corpus into “*W*” and “*H*”. As this approach is based on linear algebraic optimization, the outcome would be an approach that is independent of the probabilistic method utilized by LDA.

**Results:** Given in Table 1 are the top 10 keywords per topic rank, sorted in order of importance. Each of the algorithms presents a slightly different result, although common repetitive words do occur as an output of each algorithm. It is interesting to note the order of the words themselves and how each algorithm places importance on different words.

As an example, the results of the Gensim LDA within Rank 1 has sorted words: 'policy', 'investment', 'community', 'financial', 'performance', 'investor', 'system', 'institutional', 'technology' and 'measure'. These words are plotted in Figure 6 as a function of word count (light blue) and weightage (dark blue. In comparing the words “investment” to “technology”, the algorithm has determined that despite the former having a much lower word count, its importance is greater (i.e. it is more relevant given its exclusivity) and has thus weighted it more, and ranked it higher.

**Chart

Description automatically generated**

Figure 6: Weightage and frequency of top 10 words in Topic 1

However, there is also a need to consider the words collectively to get a sense of whether topics can be categorised as being more ‘quantitative’ or ‘qualitative’. In this example, words like 'financial', 'performance' and ‘investor’ imply quantification, and thus, a subtopic of “financial performance” seems reasonable. This final step is perhaps the most subjective step of this entire process. The human element of interpreting, understanding, and applying a judgement as to the most suitable topic, based on ones understanding of the words, is something that is key to this process. Good topic models therefore require (apriori) that the modeler have some background knowledge of the subject matter.

We repeat this process of (a) considering each line of output, (b) observing for the ranking of the words with respect to count and weightages, (c) determining key words that help categorise the output as either ‘quantitative’ or ‘qualitative’, and (d) deciding on a subtopic for each of the 3 algorithms.

Lastly, we consider all subtopics collectively and then generalise them into several key concepts, which than becomes the final topic model to be discussed in later sections. Generalisation removes some of the bias that may come about from subtopic selection and allows for comparisons between the outputs of the algorithms. The last step was to combine the three methods to give an averaged, ranked topic score.

Table : **Top 10 significand words per algorithm, proposed categorization, subtopic and key concept selection**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Algorithm | Rank of  Topic | Top 10 Words Weighted and Ranked | Categorisation | SubTopic | Key Concept |
| Gensim LDA | 1 | 'policy', 'investment' , 'community', **'financial', 'performance',**  'investor', 'system', 'institutional', 'technology', 'measure' | Quantitative | Financial Performance | Fiscal (Policy/Terms) |
| 2 | 'policy', 'technology', 'industry', **'government'**, 'environmental',  'adoption', 'level', 'role', 'support', 'development' | Qualitative | Environmental Technologies Policies | Government (Policy) |
| 3 | 'policy', **'stakeholder' , 'community'**, 'development', 'process', 'local', 'management', 'support', 'government', 'technology' | Qualitative | Community Development Policies | Community (Support/ Involvement) |
| 4 | '**technology'**, 'policy', 'system', 'development', **'community'**, **'traceability'**, 'group', **'social'**, 'support', 'case' | Quantitative-'Qualitative | Technology and social policies | Technology (Development) & Social (Policy) |
| 5 | **'state'**, 'policy', 'technology', **'investor'**, 'expansion', **'government'**, 'plant', 'country', 'electricity', **'community'** | Quantitative | Technological Policies and investors | Public-Private (Corisking) |
| Mallet LDA | 1 | sector', **'policy'**, 'electricity', 'development', 'country', 'source', **'production'**, 'support', **'data'**, 'emission' | Qualitative | Energy policies | Government (Policy) |
| 2 | technology', **'financial'**, 'impact', **'performance', 'cost', 'measure',** 'plant', 'adoption', 'system', 'importance' | Quantitative | Financial performance | Fiscal (Policy/Terms) |
| 3 | **policy', 'technology'**, 'investment', 'industry', **'environmental'**, 'investor', 'role', 'potential', **'framework'**, 'change' | Quantitative-'Qualitative | Technology investment policies | Technology (Development) & Social (Policy) |
| 4 | **stakeholder'**, 'process', **'social'**, 'management', **'community'**, 'model', **'relationship'**, 'literature', **'analysis'**, 'sustainable' | Quantitative | Stakeholder Perception | Public-Private (Corisking) |
| 5 | **community'**, 'local', 'system', 'government', **'development'**, 'support', **'transition'**, 'policy', **'national'**, 'state' | Qualitative | Community Involvement | Community (Support/ Involvement) |
| Non-Negative Matrix Factorization | 1 | **environmental'**, **'mix'**, 'state', **'government'**, 'country', 'development', 'technology', 'industry', 'sector', **'policy'** | Qualitative | Country Environmental policies | Government (Policy) |
| 2 | **process**', 'development', 'technology', **'management'**, 'program', **'partnership'**, 'social', **'beneficiary'**, 'local', **'community'** | Quantitative | Technology development | Public-Private (Corisking) |
| 3 | **influence', 'green',** 'satisfaction', **'relationship'**, 'proposed', **'network',** **'twomode',** 'method', 'retrofit', 'stakeholder' | Qualitative | Stakeholder Relationship Satisfaction | Community (Support/ Involvement) |
| 4 | market', 'retail', 'portfolio', 'policy', 'performance', **'financial',** 'technology', 'preference', **'investor', 'investment'** | Quantitative | Investor preference | Fiscal (Policy/Terms) |
| 5 | **expansion', 'fit',** 'power', 'state', 'price', 'promotion', 'electricity', **'capacity', 'plant', 'system'** | Quantitative-'Qualitative | Energy systems | Technology (Development) & Social (Policy) |

**Discussion and Implications:** In order from most important to least, the analysis presented above ranked the following success factors for RE projects: (1) Government (Policy), (2) Fiscal (Policy/Terms), (3) Community (Support/ Involvement), (4) Public-Private (Corisking) and (5) Technology (Development) & Social (Policy). In looking at the results, aside from (2), all the other results speak of non-financial factors as being more important in defining success.

*Government (Policy):* Government intervention can be in the form of financial strategies, research and development in renewables, infrastructure building, tracking of consumer adoption rates, influencing socio-economical acceptance of RE, and the overall development of the RE industry. Such involvement is also important as a signaling mechanism to producers, of the strategy towards domestic energy resilience. Governments also act as financial buffers through subsidies and grants (tying this quite closely to the “Fiscal (Policy/Terms)” success factor), which according to the International Energy Agency, has amounted to US$180 billion in 2020 [17].

In the United States, State Energy Programs provide both financial and technical assistance for energy projects that are coherent with nationwide green energy goals. Additionally, federal policies like the 2005 Energy Policy Act, where congress established a legal requirement for federal agencies to derive at least 7.5% of energy consumption from renewable sources, has resulted in renewable energy usage growing by 42% from 2010 to 2020. Thus, the introduction of energy legislation with legal consequence and government financing support has allowed renewables to become the fastest-growing energy source in the country, making up close to 20% of the USA’s energy source [18, 19].

In Singapore, government policies can also include a geopolitical mix, with mooting of a shared regional power grid connecting Singapore to Australia (SUN CABLE literature reference), to more local centric solutions like research and development in space-saving energy storage technologies. At the national level, the government has set a mandate to increase solar usage by 7 times from its measured 2019 usage [20]. In land-scare Singapore, private sector involvement comes in the form of infrastructure construction and maintenance. The construction costs are borne by the government entirely (TENGAH reference, HDB reference).

**Conclusions:** In general, this should include a brief (1-2 paragraph) introduction, followed by a statement of the specific scope of the study, followed by results and then interpretations. Please avoid statements of future work, claims of priority, and repetition of conclusions at the end.

**Main Text:** In general, this should include a brief (1-2 paragraph) introduction, followed by a statement of the specific scope of the study, followed by results and then interpretations. Please avoid statements of future work, claims of priority, and repetition of conclusions at the end.

Subheadings (“Results”, “Discussion”, or more specific subheadings, but not a leading “Introduction”) may be included in Research Articles or Reviews and should be brief and set off by a paragraph break. Up to three levels of subheadings may be used if warranted (bold for level one, bold and italic for level two, and italic for level three). Reports should not have subheadings.

All figures and tables should be cited in order (as, for example, “Fig. 1” and “Table 1”), including those in the Supplementary Materials (which should be cited as, for example, “fig. S1” and “table S1”). You may include line or page breaks if you would like to place figures within the text near where they are referenced. Please do not place figures in text boxes.

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# **References**

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**Acknowledgments:** Munish Kumar would like to thank ERCE for peer review of this work.

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