

Delving into the black box: stochastic ex-post multi-criteria evaluation of net-zero scenarios with an application to Switzerland

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Abstract—Many modeling teams globally have published energy scenarios detailing pathways toward net-zero greenhouse gas emissions. These diverse scenarios are informative but entail a challenge for political decision-makers, utility executives, and citizens. There is limited consensus on how to identify the most important elements in them, interpret, and navigate them. To address this problem, this paper develops a new methodology for comparing energy scenarios based on user-defined decision criteria. Criteria values are first estimated ex-post using stochastic models, which account for uncertainty regarding future technology costs and impacts. Then, a statistical analysis is applied to understand the criteria values’ trends, tradeoffs, and uncertainties. We demonstrate this methodology on Swiss energy scenarios using five sample criteria: investment, domestic land use, material consumption, domestic biodiversity impacts, and social acceptance. The analysis reveals that two classes of technologies drive criteria outcomes: (i) must-have technologies, deployed at large scales in all scenarios, and (ii) emerging technologies, such as hydrogen or biomass, whose role in the energy transition are less well understood. Policies on must-have technologies should enable rapid deployment and reduce uncertainty about costs and impacts. Conversely, policies for emerging technologies should foster further understanding of their impacts and promote public discourse around which impacts are socially desirable. Whilst the method is applied to Switzerland in a case study, it is applicable to other contexts provided sufficient and accurate scenario data. Future work should focus on improving the method’s robustness, including the selection and operationalization of criteria.

Index Terms—energy system optimization, meta-analysis, social impacts, biodiversity, uncertainty

I. INTRODUCTION

Climate change negatively impacts economic growth, migration, health, biodiversity, and food security [1]. To address climate change, research teams worldwide are developing models that analyze how to best achieve net zero greenhouse gas emissions. These models are frequently based on cost

optimization routines and provide optimal scenarios contingent on assumptions about future developments.

The large diversity of modeling assumptions and results provides policymakers and industry experts with a generally helpful yet diverse (and sometimes contradictory) knowledge foundation. On the one hand, model outputs offer a wealth of information on the technologies, policies, and infrastructure required for the sustainable transition. On the other hand, models insufficiently reflect the complexity of real-world decision-making [2], and results from different modeling teams often diverge. Poor documentation and complex model formulations make it challenging for scenario users to understand differences between studies [3]. While novel methods to treat uncertainty and incorporate multiple decision criteria exist [4], [5], [6], these new methods add complexity to the modeling landscape. Moreover, they result in multiple scenarios, which are challenging to communicate to stakeholders. Meta-analyses, which contrast and summarize past modeling findings, are crucial for untangling the confusing modeling landscape.

This paper develops a meta-analysis methodology in which scenarios are evaluated ex-post based on user-defined criteria. It addresses the research question: how can future energy scenarios be meaningfully compared using broad (and uncertain) decision criteria to derive present-day policy recommendations? Advantages of the new method are that it: (i) enables simultaneous consideration of diverse social, economic, and environmental criteria when evaluating scenarios, thereby moving beyond simple cost optimization; (ii) treats parametric uncertainty in criteria values, and (iii) identifies policy-relevant trade-offs between technologies and criteria.

The new methodology is tested using a case study of Switzerland along with five criteria. These criteria are selected to represent diverse social, economic, and environmental

decision factors that can be estimated from data published in scientific literature. Switzerland is a good case study since it is committed to achieving net zero emissions by 2050 [7] and a large number of Swiss net-zero scenarios have been published [8], [9], [10], [11], [12], [13], [14], [15], [16], [17].

Section II describes the three steps of the new methodology while Section III applies this new method to the Swiss context. The conference paper is based on, and modified from, the Working Paper [18], and readers should refer to [18] for more details.

II. METHODS

The developed methodology has three steps (see Fig. 1).

A. Step I: Determine Criteria and Collect Scenario Data

This step (i) determines the criteria to be evaluated, and (ii) selects scenarios to assess. Both choices can be made freely; however, the collected scenario output data must be sufficient to estimate the desired criteria values.

For the Swiss case study, we evaluate five criteria: investment, domestic land use, material consumption, domestic biodiversity impacts, and social acceptance. These represent a diverse sample of economic, environmental, and social decision criteria that can be estimated from existing data. Next, the scenarios for Switzerland are collected using a systematic literature review of the peer-reviewed scientific literature and gray literature based on government studies (see [18] for details). The scope is limited to the net-zero electricity sector in 2050. The final data set includes 54 electricity scenarios from 8 different publications. We collect the annual electricity demand, net imports, generation mix, and capacity mix from each scenario.

B. Step II: Estimate Criteria Values Stochastically

This step uses stochastic models to estimate a distribution of criterion values for each scenario. These models take the data collected in Step 1 as input. They quantify the criteria values and their uncertainty. The latter is critical since future criteria values are highly uncertain and can only be estimated from limited scenario data.

In this paper, we describe only the investment model in detail to demonstrate an example of a stochastic model. The investment model estimates the capital expenditures required to transform the current electricity system into a net-zero system for 2050. These are relevant since renewable energy sources are often capital-intensive. Investment is calculated independently of the original scenario cost assumptions to elucidate the risks associated with targeting each scenario's electricity mix. The analysis thus informs decisions on policies, such as renewable energy deployment targets, which must be made here and now despite future cost uncertainties. We compute investment using the canonical formulation often used in energy system optimization models:

$$I^{(k)} = \sum_{j \in \mathcal{J}} (A_j^{(k)} - A_{j,0}) c_j l_j \frac{i_j (i_j + 1)^{l_j}}{(1 + i_j)^{l_j} - 1} \quad (1)$$

TABLE I
LIST OF SYMBOLS AND PARAMETER DISTRIBUTIONS USED IN THE INVESTMENT MODEL.

Symbol	Definition	Distribution
$k \in \mathcal{K}$	scenario index	–
$j \in \mathcal{J}$	technology index	–
$I^{(k)}$	investment	–
$A_j^{(k)}$	installed capacity in 2050	–
$A_{j,0}$	existing capacity	–
c_j	per unit capital cost (Eur/MW)	PERT
l_j	technology lifetime	uniform
\bar{i}	risk free interest rate	historical bond data
r_j	risk premium	uniform

$$i_j = \bar{i} + r_j. \quad (2)$$

The formulation multiplies the installed capacity by a per-unit capital cost and a financing factor. Symbol definitions are defined Table I. To make the model stochastic, all parameters (c_j , \bar{i} , r_j , and n_j) are repeatedly sampled from distributions ($N_{trials} = 1000$). This yields many investment estimates per scenario, allowing a better uncertainty characterization.

Detailed descriptions of the other criteria models are found in [18]. In our case study, all models take only generation and capacity values as input.

C. Step III: Statistical Analysis

Statistical analysis is used to understand key trade-offs and trends in the scenario outputs and criteria values while also considering the uncertainty in each criterion.

First, the selected scenario outputs (from Step I) and sampled criterion values (from Step II) are collected in two data sets: $X \in \mathbb{R}^{n \times p}$ and $Y \in \mathbb{R}^{n \times d}$, respectively. Here, p is the number of collected scenario outputs, d is the number of criteria. Each row in X contains the collected outputs for one scenario, and each row in Y contains criteria values for the same scenario. To account for uncertainty, the criteria values are repeatedly sampled for each scenario from their distributions established in Section II-B. In the presented Swiss case study, $n = 54000$ since 54 scenarios are each sampled $N_{trials} = 1000$ times. In X and Y , we normalize the columns (mean = 0, standard deviation = 1) to give every column equal weight.

Next, canonical correlation analysis (CCA) [19] is used to analyze the scenario and criteria data. CCA searches for weights $\mathbf{w}_x^0 \in \mathbb{R}^p$ and $\mathbf{w}_y^0 \in \mathbb{R}^d$ which maximize the correlation between the scenario outputs and the criteria values:

$$\max_{\mathbf{w}_x^0, \mathbf{w}_y^0} \text{Corr}(X \mathbf{w}_x^0, Y \mathbf{w}_y^0). \quad (3)$$

Here, the vectors $X \mathbf{w}_x^0 \in \mathbb{R}^n$ and $Y \mathbf{w}_y^0 \in \mathbb{R}^n$ (called *scores*) are projections of the original observations X and Y on to one dimension, respectively. CCA can, therefore, be viewed as an extension of principal components analysis (PCA) to two data sets: while PCA searches for projections that preserve information within a dataset, CCA searches for projections

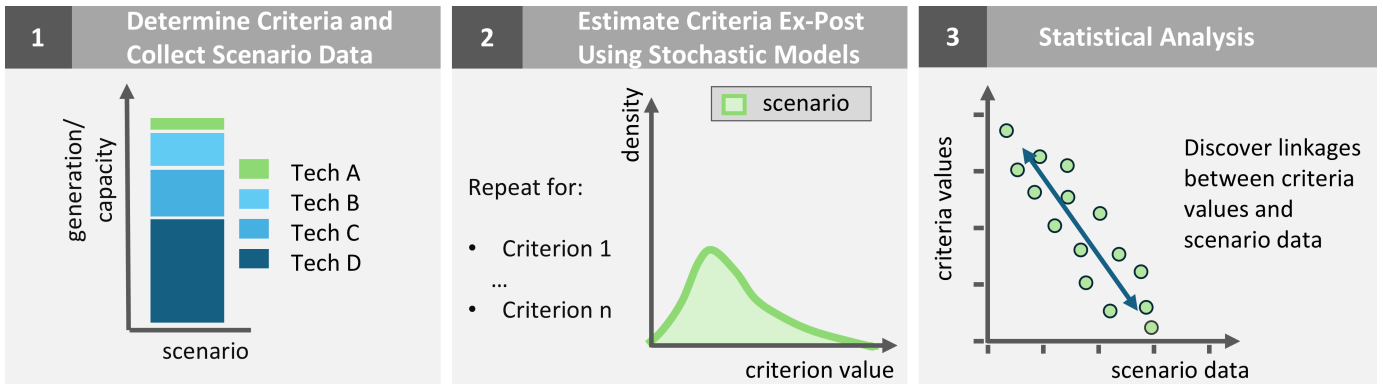


Fig. 1. Outline of the developed method. The method consists of three steps, each described in detail in the text. This figure is modified from [18].

that best preserve correlations between data sets [20], [21]. Like PCA, CCA can be run iteratively to decompose the data fully. Subsequent weights ($\mathbf{w}_x^t \in \mathbb{R}^p$ and $\mathbf{w}_y^t \in \mathbb{R}^d$) are determined by repeating the algorithm on the residual part of the datasets which previously identified scores can not explain. We implement CCA using the Python package Scikit-Learn [22].

The weights of CCA identify salient, independent relationships between scenario outputs and criteria values. Since X compiles multiple model outputs and Y contains information about criteria uncertainty, the obtained relationships are robust under uncertainty.

III. RESULTS

A. Demand and Generation Mix in 2050

Fig. 2 shows the spread of demand and electricity generation in 2050 among different scenarios. Projected electricity demand in 2050 ranges between 61 TWh and 98 TWh, with an average value of 79 TWh. For comparison, Swiss electricity demand in 2023 was 60 TWh [23]. All studies, therefore, project an increase in electricity demand due to the electrification of heating and transportation.

To meet future demand, there is a consensus that solar PV and hydropower will be the dominant electricity supply technologies in 2050. Annual generation from solar PV ranges between 9 TWh and 51 TWh, with an average of 29 TWh. This corresponds to a significant expansion of solar PV from current levels of 4.6 TWh in 2023 [24]. The expansion will come primarily in rooftop solar, although not all modeling studies distinguish between different types of solar PV. Annual generation from hydropower, the other big technological player, has a much smaller spread in the scenarios. Scenario values range between 27 TWh and 40 TWh, with an average of 35 TWh. These values match Swiss hydropower production over the last ten years, which varied between 29 and 38 TWh per year (excluding pumping) [23].

Aside from solar PV generation, the most significant uncertainty comes from net imports, as shown by the large spread of values in Fig. 2. Most studies (78%) foresee Switzerland becoming a net electricity importer in 2050. For context,

Switzerland has been a net exporter of an average of 1 TWh per year over the last ten years [25], with a range of ± 6 TWh per year. Three scenarios are marked as outliers in the violin plot because they have large net imports. Two of these are from a European-scale modeling study that finds it is more cost-effective for Europe to import energy into Switzerland than produce it domestically [26]. Such heavy reliance on neighboring countries could be geopolitically disadvantageous for Switzerland, which was not considered in these scenarios.

Other generating technologies play minor roles in the energy supply. In most scenarios, wind, gas, biomass, geothermal, hydrogen, and batteries generate less than 10 TWh annually. Each of these technologies, except biomass, is also non-essential because scenarios exist where none of the technology is deployed. Biomass includes waste-to-energy, which is already being deployed in Switzerland today and will likely remain deployed in the future.

B. Estimated Criteria Values

Fig. 3 shows the criteria values estimated from the stochastic models. The plot shows two distributions for each criterion: (i) an aggregated distribution over all scenarios, where each scenario is assumed to have equal weight; and (ii) the distribution for a single scenario, “Energieperspektiven 2050+” (EP2050+) [8]. EP2050+ was chosen as a reference since it is at the time of writing the official scenario of the Swiss government. The figure depicts how uncertainty in criteria values for a single scenario compares with the overall range of impacts. Each scenario has impacts on all five criteria, so compromises must be made in the energy transition.

Uncertainty in criteria values, even for individual scenarios, is considerable. This holds for both EP2050+ and the scenarios as a whole. Estimates of investment, for instance, vary by a factor of more than four depending on the sampled parameters, most notably solar PV capital costs. These ranges underscore the importance of a rigorous uncertainty analysis. Modeling studies that do not report uncertainties convey false confidence about claims.

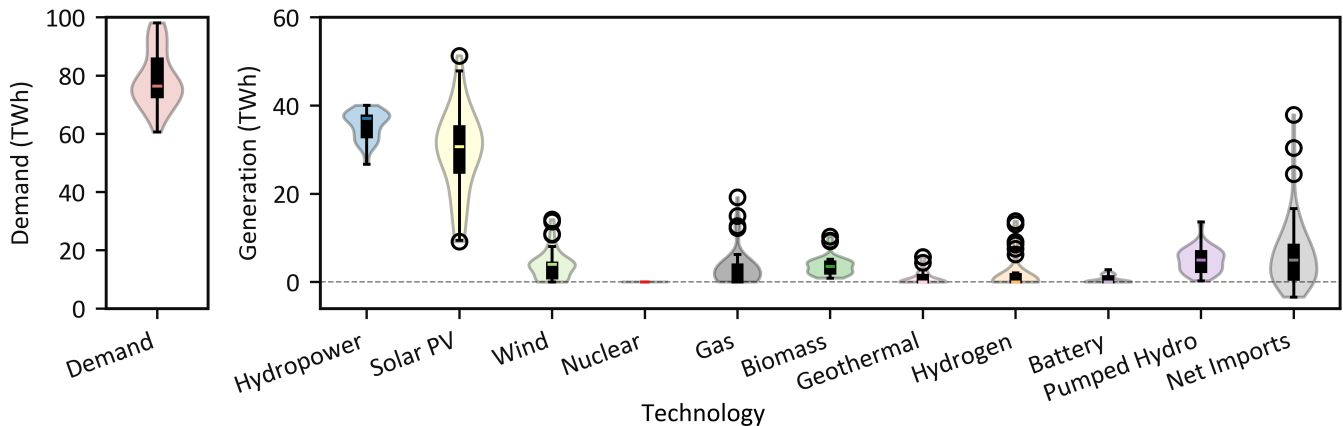


Fig. 2. Spread of annual generation (TWh) by different technologies across all scenarios in 2050. In the box and whisker plots, the lower, middle, and upper boundaries of the box consist of the 25th, 50th, and 75th percentiles, respectively. Circles indicate outliers whose values exceeded the box by more than 1.5 times the interquartile range. This figure is modified from [18].

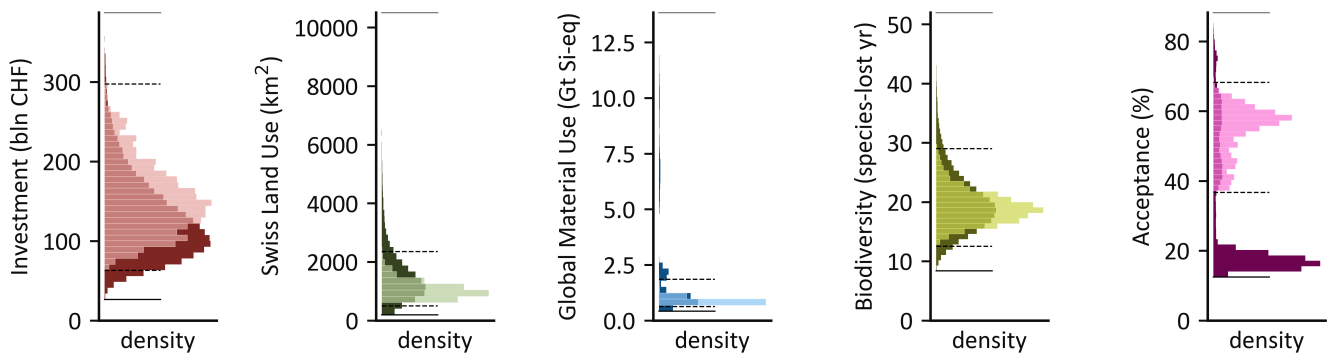


Fig. 3. Distribution of criteria values (i) aggregated over all scenarios and (ii) for the zero basis scenario of EP2050+. In each panel, the light-colored distribution corresponds to EP2050+, while the dark-colored distribution shows the aggregate distribution over all scenarios. The horizontal lines indicate the maximum and minimum estimates for all scenarios (solid, black) and EP2050+ (dashed, black). This figure is modified from [18].

C. Relationships between technologies and criteria values

The CCA shows that emerging technologies, despite limited deployment, are key drivers of electricity system’s social and environmental impacts (Fig. 4). The first CCA weights (w_x^0 and w_y^0 , shown in dark green) indicate a strong positive correlation between hydrogen generation and raw material consumption. This follows from the diagram in which hydrogen and material use are the only variables with high weights. Both weights have the same sign, indicating a positive correlation. Proton exchange membrane fuel cells and electrolyzers require large quantities of rare earth metals like platinum and iridium.

The second set of CCA weights is more complex, with several technological players. The technology weights have positive values primarily for hydropower and pumped hydropower and negative values for net imports, wind, and batteries. These weights describe a trade-off between hydropower and the other, more controversial technologies. Systems with more hydropower have larger domestic biodiversity impacts but are more socially acceptable. In contrast, systems with higher

imports, batteries, or wind power encounter higher social resistance despite lower domestic impacts on biodiversity.

Finally, the third set of weights describes the association between biomass and land use. Systems with more biomass generation are more land-intensive.

Using a linear regression model, the first three CCA technology scores can explain 49% of the total variance in criteria values ($R^2 = 0.49$). This is 70% of the total variance explainable by a linear model using all scenario data as predictors ($R^2 = 0.65$). The identified correlations thus have good explanatory power. Even though several criteria models are linear, perfect correlations do not occur since the analysis accounts for criteria uncertainty.

IV. DISCUSSION

A. Critical Review

The analysis identifies two categories: must-haves and emerging technologies. These categories emerge despite the large scenario diversity resulting from different boundary conditions, assumptions, and methods used by individual studies.

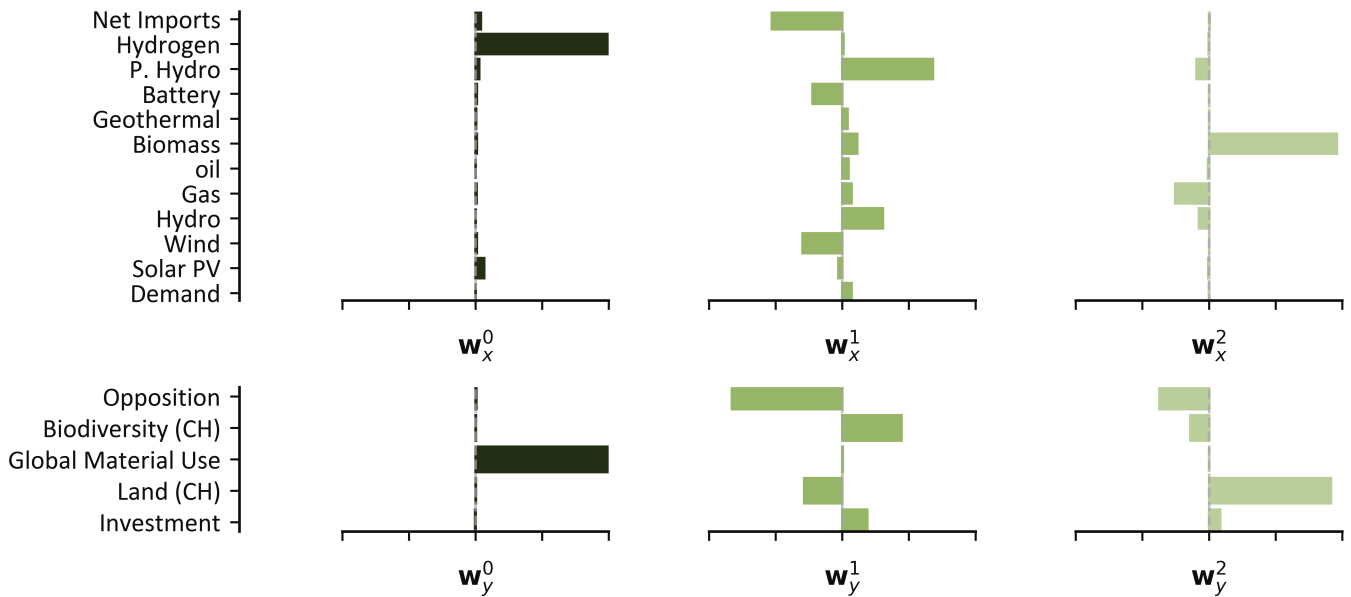


Fig. 4. Weights of technologies (top) and criteria (bottom) resulting from the first three iterations of CCA. Weights from the first, second, and third iterations are shown in dark, medium, and light colors, respectively. Weights between technologies and criteria values are interpretable in a pairwise fashion. In each panel, only the relative magnitudes and signs of the weights are relevant since the correlation function, maximized by CCA, is invariant to the scale of its arguments. Criteria values are plotted so that negative values are advantageous for society and positive values are disadvantageous. This figure is modified from [18].

On the one hand, must-have technologies, such as solar PV and hydropower, are found unanimously (and at large scales) in all energy scenarios. Therefore, these technologies are essential, and government policies should focus on preserving existing units and rapidly building new capacities. On the other hand, technologies that are less developed in the current Swiss energy system, such as hydrogen, wind, and biomass, are identified during the CCA analysis as key determinants of land use, global material use, and social opposition. This holds even though these technologies only have small overall shares in the electricity supply. Research should, therefore, aim to improve our understanding of the system-level effects of these technologies, taking a holistic perspective that moves beyond simple cost optimization.

The analysis extends literature from several fields. First, being a meta-analysis, this work builds on existing Swiss scenario studies. Second, our paper expands on available methods for evaluating energy systems’ social and environmental implications. Integrating non-technical factors into models remains a challenge [27]. Our approach of estimating such criteria stochastically ex-post is generally applicable and could be adapted to new applications in the future.

B. Implications for policy-makers and modelers

Based on our results, several key takeaways remain:

- 1) Policy-makers should seek policies to accelerate the deployment of “must have” technologies. This is particularly true for solar PV, which requires a rapid build-out in all Swiss net-zero scenarios.
- 2) Policy-makers should fund further research on the social, environmental, and economic impacts of emerging

technologies. The goal should be to develop a unified strategy for what technologies are socially desirable.

- 3) Policy-makers and modelers should promote public discourse around emerging technologies to ensure that the public remains informed and involved in decisions regarding the energy transition.
- 4) Modelers should focus on biomass, hydrogen, and other low-carbon fuels, representing sub-technologies and environmental impacts in greater detail.

V. CONCLUSION

Our paper demonstrates a new methodology that evaluates diverse scenarios ex-post based on user-defined decision criteria. This enables scenarios from multiple sources to be easily compared, allows for the incorporation of non-economic factors into scenario comparisons, and rigorously quantifies uncertainties in findings. The energy transition is complex, and a holistic understanding of economic, environmental, and social trade-offs is necessary to make informed decisions.

The results of this have to be seen in light of some limitations. Limitations include (i) the narrow scope of the case study, which only focuses on the electricity supply in a single country, (ii) the reliance on published literature for input data, (iii) the subjective selection of decision criteria, and (iv) uncertainty in parameter distributions for the stochastic models. Addressing these concerns was infeasible in this paper due to time constraints and poor data availability. As demonstrated by this analysis, however, including uncertainty does not prevent meaningful findings. We recommend that future research investigate these topics to expand and refine the results presented in this paper.

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