Strategies for mitigating offshore wind impacts and enhancing data management with AI

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Introduction

The release of more accessible Artificial Intelligence (AI) models such as ChatGPT, emerged new possibilities, uses, and challenges in the field of scientific research and data analysis (Morgan, 2023). Although the use of these tools is already being discussed as a potential facilitator for practices such as document analysis, information systematization, and even scientific and report writing, important limitations have also been identified (Bond et al., 2024; Morgan, 2023). Concerns about data security, risks of plagiarism, and the indiscriminate use of models that can lead to the production of inaccurate or unreliable information have been highlighted (Bond et al., 2024; Fitzgerald & Taylor, 2024).

In the context of Environmental Impact Assessment (EIA), AI presents significant potential for managing a large volume of data in real time, allowing for a quicker and more accurate understanding of the potential environmental impacts and interpreting monitoring data. Real-time analysis of monitoring data can advance environmental management, allowing swift responses in case of critical changes and facilitating compliance with environmental regulations. Such advancements in practice will contribute to evaluate mitigation effectiveness and adapting management strategies as necessary (Bond et al., 2024; Fitzgerald & Taylor, 2024).

Here, the impact assessment of Offshore Wind Farms (OWFs) is investigated, a type of project rapidly expanding in several countries. In Brazil, the OWFs available knowledge is based on international cases and national Environmental Impact Studies (EISs), witch are extensive and complex. Thus, this research aimed to propose to avaluate the impacts and mitigation measures included in OWF in Brazil, as well as to discuss how AI can contribute to the effectiveness of monitoring these impacts.

Metodology

This study was conducted in two stages: (1) reading and extracting information from Environmental Impact Studies (EISs) and systematizing data in an Excel spreadsheet obtained from these sources; and (2) manual analyses of EISs and exploratory testing with the ChatGPT 4 language model (Figure 1).

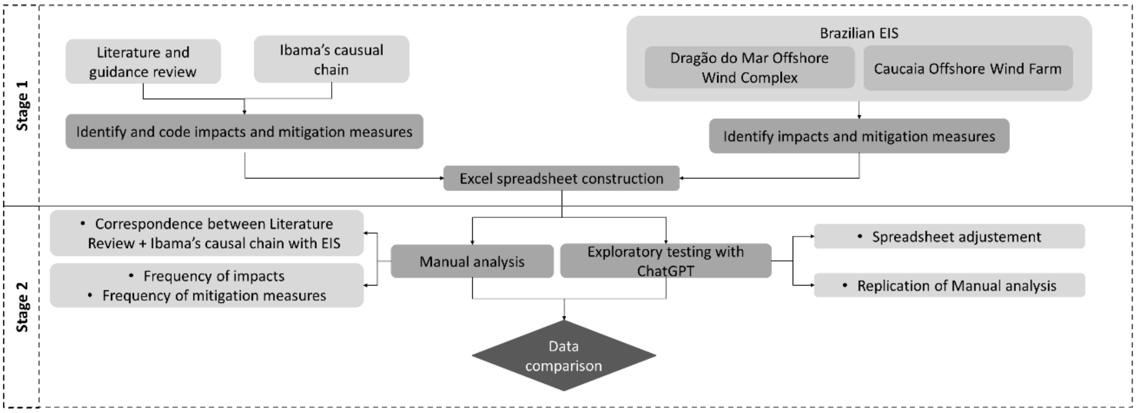

Figure 1. Research steps

In the first stage, the analysis of the EISs was preceded by a literature review aimed at identifying the main environmental and social impacts associated with OWFs. This review included scholarly papers and grey literature, such as Cox (2023), Ipieca (2022), Bennun et al. (2021), Hernandez (2021) and Vasconcelos (2019), as well as a preliminary list of impacts and mitigation measures available in technical documents from the Brazilian federal environmental agency Ibama (Vasconcelos, 2019). The goal of this initial review was to establish a benchmark for comparison between the specialized literature and what has actually been considered and applied in Brazilian EIS. The impact and mitigation information from the literature review was registered in an Excel spreadsheet.

In the sequence, two Environmental Impact Studies (EISs) of OWFs currently undergoing the licensing process were analyzed: the Dragão do Mar Wind Complex and the Caucaia Wind Farm, both in the state of Ceará. Together, the two documents total 4,326 pages, which were thoroughly reviewed to identify and systematically extract data on impacts and mitigation measures.

The analysis of the EISs was conducted in three stages. First, an exploratory reading was carried out to broadly identify the data, resulting in an initial version of an Excel spreadsheet with 482 inputs. Next, a more detailed review was performed to distinguish the impacts and mitigation measures explicitly attributed by the project proponent from those presented solely as theoretical background based on secondary studies. Finally, the data extracted from the EISs were compared with the impacts already systematized from the literature, aiming to identify areas of convergence and divergence (Figure 2). Thus, information from the literature and EISs were inserted into the same excel. Green and red colors were used to facilitate the visualization of correspondences, with green indicating a match and red indicating no match with the reference base ("Literature review" column). The final version for tests of the excel spreadsheet had 356 inputs.

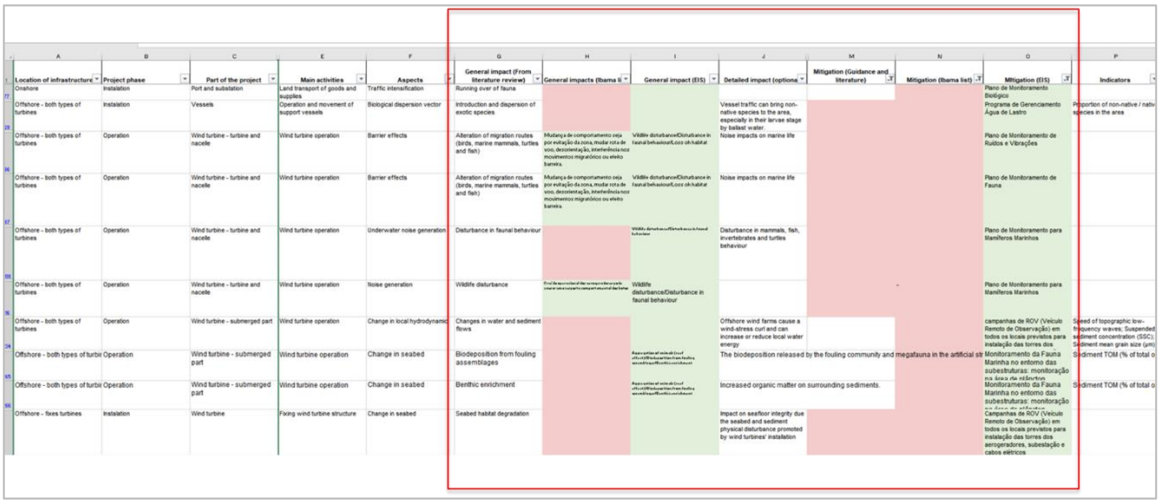

Figure 2. Initial organization of the spreadsheet, highlighting in red box the correspondence between the EISs data and the codes generated in the literature review.

The second stage consisted of manual analyses directly in the Excel spreadsheet and preliminary testing using the ChatGPT language model (version 4 Plus, subscriber access), aimed at evaluating its ability to analyze and synthesize large volumes of structured data. The Excel spreadsheet was inputted in ChatGPT for analyses.

Both manual analyses and those conducted using ChatGPT included this comparison: (i) correspondence between the impacts identified in the literature and the EIS, as well as between the Ibama impacts and the EISs; (ii) the most recurrent impacts across the three data sources (literature, Ibama's casual chain, and EISs) and their associated mitigation measures; and (iii) impacts with the highest number of mitigation measures. A qualitative analysis of the mitigation measure descriptions was also carried out, focusing on understanding the core ideas and proposed solutions.

To facilitate this, minor adjustments were made to the Excel spreadsheet to improve the tool's understanding of the data. These adjustments were made gradually, as the spreadsheet was inserted into the ChatGPT and interpretation issues were identified. The best test version of the spreadsheet included the following modifications: the columns related to impacts identified in Ibama's casual chain and EIS were revised and organized.

The Literature Review column was used as the main reference for comparison. Cells were labeled “corresponding impact” when the impacts reported by Ibama and the EISs matched those found in the literature. When there was no similarity between the sources, the label “no corresponding impact” was applied. In specific cases where certain impacts were not identified in the reviewed literature, the Ibama column was used as the reference for comparison with the EISs. The same procedure was applied to the mitigation columns. Color coding was maintained for clarity: green for corresponding cases and red for non-corresponding ones.

Results

Basic quantitative analyses were initially conducted manually through direct checking of the documents. The primary objective was to verify the correspondence between the impacts and mitigation measures found in the literature, Ibama’s casual chain, and the EISs.

In the manual analysis total of 162 impact inputs from literature (not necessarily 162 distinct impacts), were corresponded to the EISs. These entries represent repetitions of the same impact across different contexts, varying according to the project phase, stage, turbine type, main activity, related aspect, or due to their association with more than one mitigation measure. In the case of mitigation measures, 52 inputs from the literature matched the data in the EISs. Regarding Ibama's casual chain, 8 mitigation measures were identical (Ibama and EISs). The same analysis was conducted using ChatGPT, which correctly identified all 162 impact inputs but overestimated the number of mitigation measures, indicating 70 matches. The model also identified 14 mitigation measures listed by Ibama’s casual chain (not present in the literature) as corresponding to those in the EISs. Ibama’s causal chain includes 14 lines for mitigation measures not identified in the literature. ChatGPT likely included all 14 without checking for alignment.

The manual review also identified 15 impacts that were common across all three sources analyzed (literature, Ibama, and EISs). Among these, notable examples include “Deterioration of water quality,” “Wildlife disturbance,” and “Increased birds and bats mortallity,” which had associated mitigation measures, most of which were related to the construction phase of OWFs (Figure 3). These impacts are widely reported in both offshore and onshore wind projects (Jay, 2011; Juretzek, Schmidt & Boething, 2021; Glasson et al., 2022; Goodale & Stenhouse, 2016), which reinforces the robustness of their identification. On the other hand, “Visual impacts,” although addressed in the international literature, showed a low number of mitigation measures indicated.

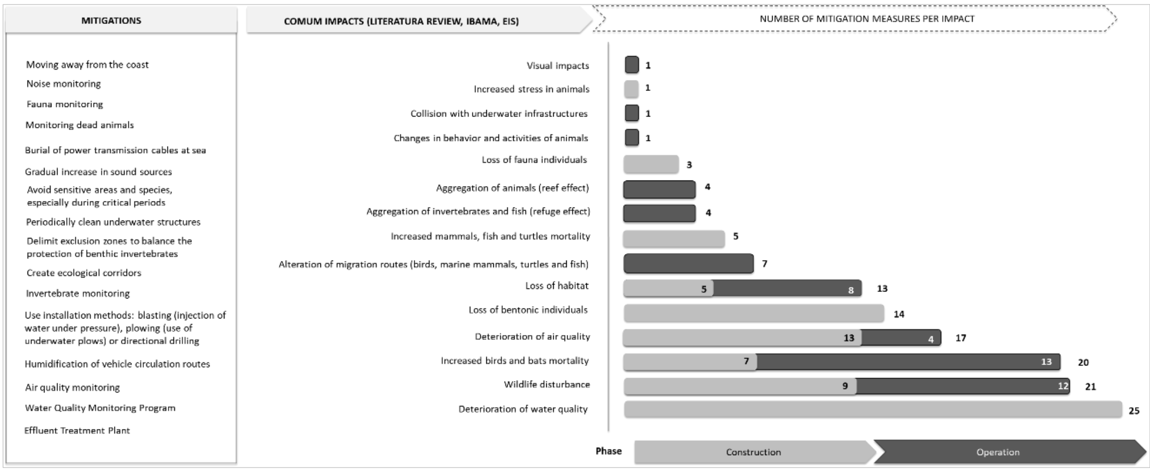

Figure 3. Main impacts, common to the three sources consulted, examples of mitigation and number of mitigation measures associated with the impacts.

The analysis of the common impacts was conducted using ChatGPT, which, in this specific case, correctly identified the 15 impacts shared across all three sources, in alignment with the manual verification. However, the number of mitigation measures associated with these impacts was inaccurately calculated by the tool.

An analysis of the most recurrent impacts in the Excel spreadsheet was also conducted, regardless of their source. From the 356 available inputs, the 15 impacts with the highest number of mitigation measures were highlighted. Once again, “Deterioration of water quality,” “Wildlife disturbance,” and “Increased birds and bats mortallity” were among the most frequently cited, but other impacts (such as those related to benthic fauna and the introduction of non-native organisms) also stood out.

The mitigation measures associated with the 15 most frequent impacts in the EISs generally refer to environmental quality monitoring actions (such as air, marine soil, and water resources), noise and vibration technologies (including bubble curtains, gradual ramp-up of sound sources), solid waste and effluent management, and fauna and flora monitoring programs, however, monitoring does not qualify as a mitigation strategy for environmental impacts. In addition, technologies such as ecological corridors were also considered.

Finally, ChatGPT was asked to perform the same analysis regarding the impacts with the highest number of mitigation measures. However, the results showed significant discrepancies compared to the manual verification (Figure 4). The model followed the logic: (i) creation of a base column with the impacts; (ii) counting of non-empty cells containing mitigation measures; (iii) grouping by impact and summing the corresponding measures; and (iv) displaying the total to the user.

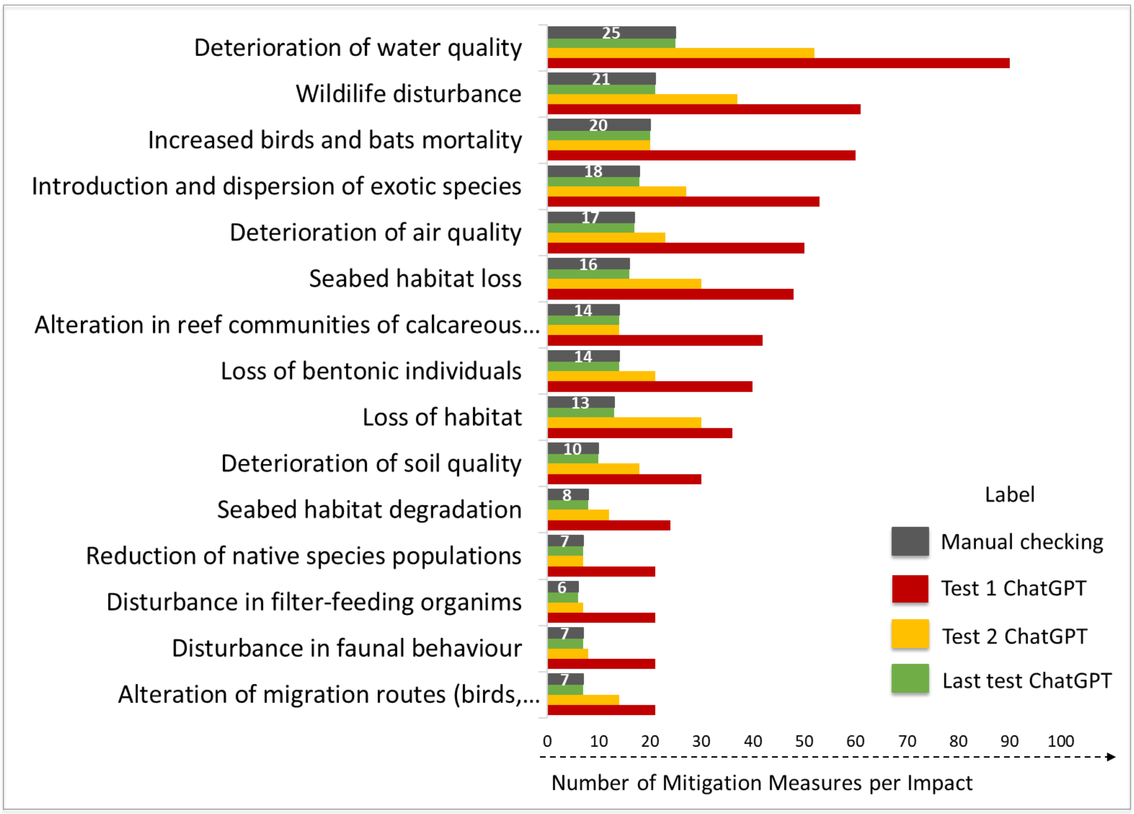

Figure 4. Mumber of mitigation measures for the most reported impacts - comparison between manual checking and the ChatGPT.

In the second test, an additional prompt sent to the model were adjusted by including the instruction: “empty cells should not be counted, and red cells with the text ‘No corresponding mitigation’ should not be counted.” This adjustment significantly improved the results, although discrepancies with the manual verification still remained. Additional tests were conducted using simpler rules, such as: “count one mitigation per row and group identical impacts listed in the ‘General impact (literature review)’ column.” After further reviews and corrections to the spreadsheet, a satisfactory result was achieved, which is shown in the final test in figure 4.

Conclusions

The tests conducted with the ChatGPT 4 Plus (subscriber access) highlighted both the potential and the limitations of using AI in environmental data analysis, particularly in EISs. One of the main challenges identified was the need for careful organization and preparation of the data. It was observed that a significant amount of time was spent on cleaning and standardizing the information in the spreadsheet, which requires considerable effort from the researcher. Cells containing symbols such as “–” or incorrect words, for example, were incorrectly interpreted by the model as valid content, compromising the record count in some analyses. In this study, at least six iterations of modifying the dataset provided to the program were necessary before achieving more reliable results. However, improvements to the data set are still needed.

Another critical point concerns the clarity of the prompts given to the model. Prompts need to be clear and well-structured, and it is advisable to confirm whether the model has understood the request before proceeding with data input. Failing to obtain this confirmation may result in inconsistent responses if the prompt is not correctly interpreted. During testing, it was also observed that the model can produce variations in results even when the same prompts are repeated, which compromises the reproducibility of the analyses. This lack of transparency in analysis and results, as noted by Bond et al. (2023), undermines user confidence. Furthermore, the use of AI does not eliminate the need for human verification, supporting Morgan (2023), Fitzgerald & Taylor (2024) and Bond et al. (2024). A sample check was necessary to validate the automatically generated results. And the greater the volume of data, the more complex this verification process becomes. This study, therefore, reinforces the recommendations of Bond (2024) by highlighting the importance of expanding comparative research between EIA and artificial intelligence, critically evaluating its possibilities and limitations.

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