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RESEARCH PAPER

An Analysis of a ChatGPT Use Case: Can a Large Language Model (LLM) be Used to Plan Artificial Reefs as a Fisheries Management Tool?

Faik Ozan Düzbastılar[1,*], Tevfih Ceyhan[1]

[1]Ege University, Faculty of Fisheries, Department of Fishing and Processing Technology, 35100 Bornova, İzmir, Türkiye.

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Corresponding Author
E-mail: f.ozan.duzbastilar@ege.edu.tr

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Abstract

No studies have examined the appropriateness of artificial intelligence for the planning of artificial reefs used in fisheries management. This study examined ChatGPT's capabilities in planning artificial reef (AR) projects by asking 50 questions and evaluating the answers from five experts. This approach aimed to assess the interactivity of ChatGPT, its contribution to the advancement of marine science and technology, and its potential limitations in the applied marine context. We analysed the experts' ratings using the Likert scale. Specifically, the appropriateness of responses varied between prompts, indicating different levels of relevance and appropriateness. Likewise, the validity of the information presented in the responses varied significantly, suggesting differences in the accuracy and reliability of the content provided. Additionally, assessments of the overall quality of responses yielded analogous results, highlighting differences in the completeness and effectiveness of responses. Using the seven-point Likert scale, the average score of the experts for the first ten questions, which are basic aspects of the ARs, was 4.6 for agreement, 4.7 for relevance, and 4.6 for quality of response. For the remaining 40 questions, which were based on specific phases of the AR project, the average scores were 4.6 for agreement, 4.6 for appropriateness, and 4.5 for quality. Our results suggest that while ChatGPT can effectively address fundamental issues related to ARs and provide accessible information on project planning steps to a wide range of stakeholders, including NGO staff, ministry engineers, private sector officials, and students, it is less reliable for nuanced, high-level scientific inquiries. In summary, while ChatGPT shows promise as an educational and planning aid in the context of ARs, its application should be undertaken cautiously to mitigate the risks associated with its current limitations. Advances in AI and specialized data access are expected to expand their role in research and project planning, improving utility and reliability.

Introduction

Artificial intelligence (AI) originated in a research project at Dartmouth College in 1956 (McCarthy et al., 1956; Gunkel, 2012). Since then, AI has developed significantly, integrating influences from philosophy, fiction, and technology to create systems that mimic human cognition (Abioye et al., 2021; Deng & Lin, 2023). Natural Language Processing (NLP), a pivotal AI branch, involves "Understanding", "Generating", and "Processing" to comprehend and generate human dialogues via algorithms, followed by language processing using statistical, semantic, or hybrid methods (Deng & Lin, 2023). The extensive literature on NLP research covers various sub-areas, often with overlapping advancements that benefit each other (Figure 1.b). AI systems are widely used in the chemical industry, civil engineering, geotechnical engineering, materials engineering, geological exploration, and environmental science (Lu et al., 2012).

It is now an essential tool for engineering design and problem-solving in industries such as transportation (Abduljabbar et al., 2019), healthcare (Jiang et al., 2017), communication (Gunkel, 2012), industry, science, and education (Salehi & Burgueño, 2018; Adetayo, 2023; Tzeng-Ji, 2023). Although small in number, AI has found some applications in marine research, such as conservation of marine ecosystems (Ditria, Buelow, Gonzalez-Rivero, & Connolly, 2022), identification and management of marine protected areas (Kaymaz Mühling, 2023), habitat mapping (Hamylton et al., 2020; da Silveira et al., 2021), artificial reef (AR) detection (Xiong et al., 2021), monitoring coral reefs (González-Rivero et al., 2020), developing autonomous underwater vehicles (Zhang et al., 2023), and extracting ecological information. These applications use acoustic systems to describe ecosystems, identify microorganisms, and quantify marine objects (Song et al., 2023). To aid in ecosystem management decisions, AI also helps predict species richness and distribution (Rubbens et al., 2023). It supports decision-making, conducts assessments, and monitors the marine ecosystem. AI-powered technologies such as remote sensing, underwater sensor networks, and intelligent underwater robots (Song et al., 2023; Ditria et al., 2022) are used to collect data during monitoring. During the assessment phase, machine learning (ML) techniques analyse the collected data and create visual representations and predictive models.

Scientists are increasingly investigating the use of AI algorithms in various areas. For example, using numerical simulations using Computational Fluid Dynamics (CFD) software and laboratory experiments (Jiang et al., 2016) researchers have studied the stability of reef blocks that interact with the seafloor in the context of ARs. The analysis of complex fluid dynamics is carried out using AI algorithms in the interdisciplinary field of CFD, which combines computer science, fluid mechanics, and mathematics (Wang & Wang, 2021). Huge amounts of data from experiments, field observations, and simulations have driven advances in computational techniques (Sofos et al., 2022). To find out how a reef unit interacts with its three-dimensional environment, traditional laboratory experiments in AR research often take days. Conversely, ML and DL applications produce fast results in milliseconds or seconds, while CFD simulations take hours to produce results (Kim et al., 2021).

Artificial Intelligence (AI) is increasingly transforming the fisheries sector by increasing efficiency, sustainability, and decision-making (Mandal, Banerjee, & Ghosh, 2025). Despite this growing interest, there are still relatively few studies, mostly reviews, on the application of artificial intelligence in fisheries and fisheries management (Kim, Lee, & Im, 2024). Current research is generally focused on areas such as the development of artificial intelligence systems for automatic electronic monitoring of catches and bycatch (Khokher, et al., 2022), the use of neural networks for forecasting various aspects of fisheries (e.g., egg distribution, fish growth and age, biomass, and catches) (Suryanarayana, et al., 2008), and the application of machine learning (ML) to improve fishing efficiency, reduce environmental impacts, and support sustainable fisheries management (Mandal, Banerjee, & Ghosh, 2025). Other studies are exploring the integration of data mining and ML in aquaculture and fisheries (Gladju, Kamalam, & Kanagaraj, 2022).

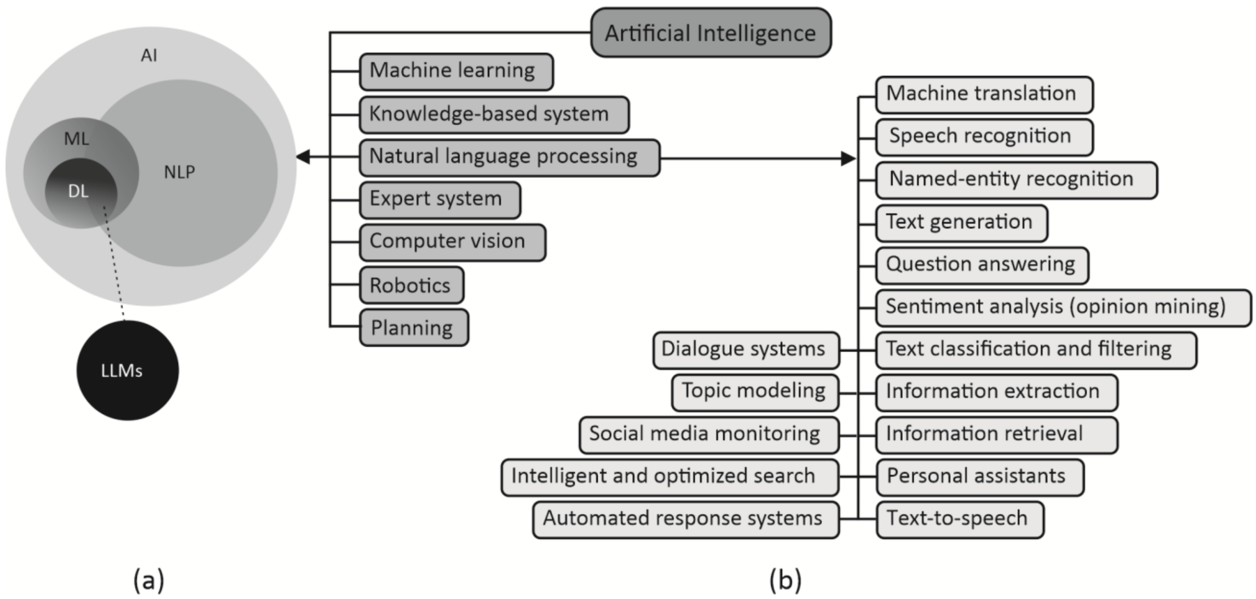

Figure 1. a. Major subfields of artificial intelligence (AI). Relationship of natural language processing (NLP) with artificial intelligence (AI), machine learning (ML), deep learning (DL), and large language models (LLMs), **b.** Sub-areas of NLP according to the researchers (Jones, 1999; Small & Medsker, 2014; Padmanabhan & Johnson Premkumar, 2015; Göksel Canbek & Mutlu, 2016; Arık et al., 2017; Lopez-Martinez & Sierra, 2020; Al-Ghamdi, 2021; Li et al., 2022; Budler et al., 2023; Illia et al., 2023; Surianarayanan et al., 2023).

Research involving LLMs in fisheries is particularly rare. One notable study used life-cycle management techniques to automate the extraction of data from unstructured narrative reports from fishermen, addressing the challenges of low technological literacy and improving data quality for better management decisions and sustainability (Nugraha, et al., 2024). Another study used ML and LLM to improve the classification accuracy of aquaculture disease reports, which contributes to the development of early warning systems and reliable diagnostic tools (Li, Zhang, Cao, Zhang, & An, 2025).

Recent advances in surveillance systems and artificial intelligence have also improved the study of fish behaviour and interaction with fishing gears. DL models now make it easier to analyse large visual datasets with high accuracy, and to achieve near-human-like performance in detecting and classifying fish (Abangan, Kopp, & Faillettaz, 2023). In addition, an AI-based coastal fisheries monitoring system has been developed, using a centralised cloud-based infrastructure to automate data mining and analysis processes (Shedraw, et al., 2024).

Researchers and engineers from various disciplines, including oceanography, economics, marine biology, fisheries science, and civil engineering, must work together to plan, design, build, place, monitor, and evaluate AR projects (Nakamura, 1982; Protocol/UNEP, 2009; FAO, 2015; Seaman & Jensen, 2000). For example, careful material selection and preparation during construction are essential to the longevity of the reef (Lukens et al., 2004). AI predictive models can help with material selection by predicting how a product will behave in different circumstances and using previous data to help engineers select the best materials (Harle, 2024). These models can increase cost efficiency, reduce material consumption, and optimize production sites. AI techniques such as Artificial Neural Networks (ANNs) and support vector machines have been used to predict steel properties (Jung et al., 2020) and concrete compressive strength, taking into account variables such as chemical composition, heat treatment, and construction parameters (Chopra et al., 2016).

ChatGPT (Generative Pre-trained Transformer) is a machine learning tool developed by OpenAI, known for its ability to imitate human experts and act as a subject matter expert in various fields. NLP techniques were used to create ChatGPT, an example of the LLMs which are a subset of NLP (Figure 1. a). Zhu et al. (2023) examined ChatGPT by asking a few questions, and found occasional cases of fabricated and outdated information, although they found that with proper guidance, it was possible to obtain almost error-free information. Similarly, Biswas (2023) examined the advantages and disadvantages of ChatGPT in public health, emphasizing its potential benefits alongside occasional inaccuracies. Deng & Lin (2023) highlighted ChatGPT's capabilities as a powerful NLP system, offering advantages such as higher efficiency, improved accuracy, and cost savings. Additionally, Tao & Xu (2023) experimented with ChatGPT for creating thematic maps, acknowledging its value despite some limitations, including uneven benefits for users and the need for user intervention in quality control. However, the use of artificial intelligence, particularly ChatGPT, in writing articles raises ethical concerns, particularly regarding potential plagiarism (Curtis & ChatGPT, 2023). Some authors have even faced criticism for employing ChatGPT as an author in their manuscripts (O'Connor, 2023). Despite its strengths in natural language processing and instruction, Cheng & Yu (2023) found room for improvement, especially in handling elementary-level arithmetic and logic problems.

These AI tools can help researchers uncover new insights that can then be used to improve knowledge management systems through data-driven recommendations. Among these tools, chat-based AI systems can also aid researchers in managing critical information by facilitating the construction and maintenance of a knowledge base. This is the first time that LLM, one of the artificial intelligence applications used in various fisheries management applications, is assessed in the planning of an artificial reef project. In this study, we aimed to develop a feasible design for an AR project by utilizing a provided flowchart and leveraging ChatGPT, which integrates several state-of-the-art technologies, including NLP, ML, and DL. Specifically, we employed ChatGPT 3.5 (https://chat.openai.com/), developed by OpenAI, to efficiently and accurately access information from the vast repository of knowledge on AR applications accumulated by scientists over decades.

Materials and Methods

We employed an exploratory methodology to assess the potential application of ChatGPT in augmented reality (AR) technology within applied marine sciences. This approach was designed to comprehensively examine the following areas: (1) the interactivity level of ChatGPT; (2) the benefits of ChatGPT and associated generative AI in improving marine science and technology; and (3) the potential limitations of ChatGPT and associated generative AI in applied marine science and its technologies. To thoroughly analyse all aspects of ARs and take appropriate actions during the planning phase, we asked a series of both simple and complex questions based on extensive studies (Nakamura, 1982; Seaman & Sprague, 1991; Seaman & Jensen, 2000; Seaman et al., 2011) in the context of AR project planning. ChatGPT-3.5 (accessed March 20–21, 2024) responded to these requests.

The requests cover two different topics: the fundamental aspects of ARs, consisting of fundamental questions (Table 1), and the specific phases of project planning (Figure 2). Each set of questions addresses different facets of AR implementation, with the former

Table 1. Fundamental questions asked to ChatGPT

Questions	
Prompt 1	Can you define an AR?
Prompt 2	How long have ARs been in use around the world?
Prompt 3	In which country did the concept of ARs or similar practices first emerge?
Prompt 4	Can you list the main uses of benthic ARs worldwide?
Prompt 5	What AR practices are used to support artisanal fisheries?
Prompt 6	Which AR model is most commonly used to improve fisheries?
Prompt 7	What AR design is most commonly used to improve fisheries?
Prompt 8	Can you provide a valid reference for AR planning?
Prompt 9	Are tire modules still actively and efficiently used as ARs?
Prompt 10	Can ARs be categorized by increasing size?

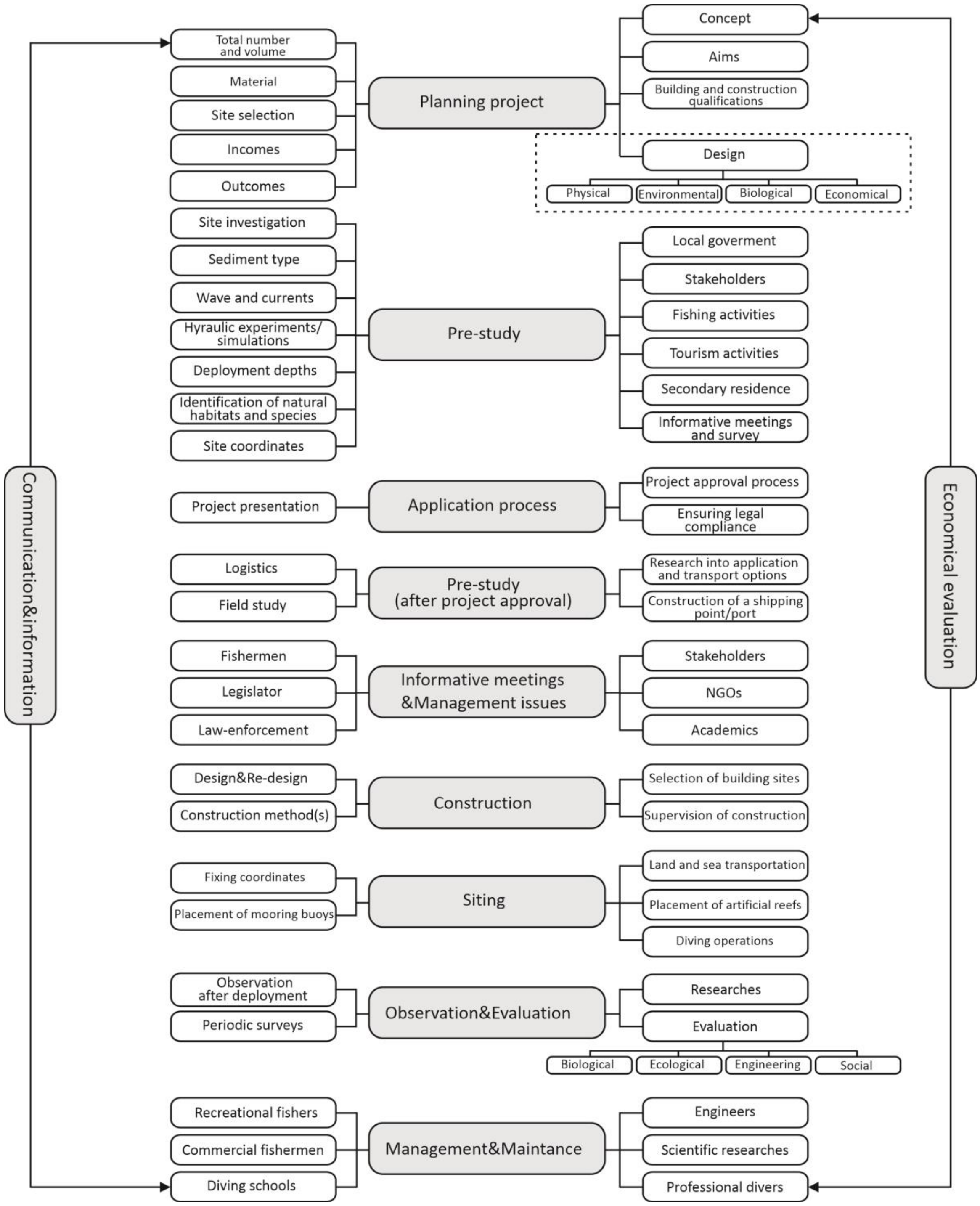

Figure 2. The process of planning an AR project is developed based on pertinent literature (Nakamura, 1982; Seaman & Sprague, 1991; Seaman & Jensen, 2000; Grove, Sonu, & Nakamura, 1991; Ohshima, 1982; Seaman, et al., 2011; FAO, 2015).

focusing on fundamental knowledge and the latter addressing logistical and strategic considerations in project development. After rigorous evaluation by five experts holding doctoral degrees in ARs and their applications, the validity, appropriateness, and quality of responses generated by ChatGPT were meticulously assessed.

The five experts involved in this evaluation were selected based on their academic credentials and demonstrated expertise in artificial reef (AR) research. Each held a doctoral degree in marine sciences and had authored peer-reviewed publications specifically focused on AR design, implementation, or evaluation. Their selection was constrained by the limited number of researchers in Turkey with such qualifications and availability, as well as logistical challenges in engaging international reviewers. The 50 questions presented to ChatGPT were newly developed for this study, as no prior framework or standardized questionnaire was available for assessing AI capabilities in AR planning. To ensure scientific robustness, the questions were grounded in established technical and academic sources such as Nakamura (1982), Seaman and Jensen (2000), and FAO (2015), covering both foundational principles and advanced project design considerations. Although the questions were not formally pilot-tested, they were reviewed for clarity, scope, and relevance by two independent researchers before being finalized. Responses from ChatGPT were evaluated using a seven-point Likert scale across three dimensions: agreement with established scientific knowledge, contextual appropriateness, and overall quality (Table 2). Each scale ranged from 1 (very poor/strongly disagree/absolutely inappropriate) to 7 (excellent/strongly agree/absolutely appropriate), following established Likert scoring practices (Boone & Boone, 2012). Statistical analysis was performed in R (R Core Team, 2021), using the likert (Bryer & Speerschneider, 2016) and ggstatsplot (Larmarange, 2023) packages. As the data were ordinal in nature and did not satisfy parametric assumptions, Kruskal–Wallis rank sum tests were used to identify significant differences in expert evaluations across the set of 50 prompts ($P<0.05$).

The approach of the next part of the study is solely to interact with ChatGPT and request information on the planning and application of an AR project based on a flowchart prepared by the authors (Figure 2). In this framework, we conducted the question–answer interaction based on four different design criteria (physical, environmental, biological, and economical) in the design phase in the planning section (see Figure 2). To achieve this, we relied on support from relevant literature to systematically plan the project, beginning from fundamental stages, and subsequently assessed the accuracy of the provided information. For this purpose, a total of 40 questions were prepared on various topics related to AR planning. By posing a total of 50 distinct questions, the significant advantages and limitations of employing ChatGPT for planning an AR project are summarized and critically examined. Finally, we discuss the implications and potential of ChatGPT for future AR projects with varying objectives, utilizing AI. In this respect, one of the aims of the possible AR project was to plan for the promotion of artisanal fishermen.

In this study, we used text mining techniques to pre-process and analyse the text data. Pre-processing included converting the text to lowercase, deleting numbers, deleting common English stop words, and deleting extra spaces to ensure consistency. We then calculated the correlation between words and word occurrence frequency. These tasks were performed using a combination of R packages: qdapTools for data manipulation (Rinker et al., 2023), tm for text mining (Feinerer & Hornik, 2024; Feinerer et al., 2008), SnowballC for word stemming (Bouchet-Valat, 2023), wordcloud for visual representation (Fellows, 2018), and RColorBrewer for enhancing the visual appeal of the word clouds (Neuwirth, 2022). This comprehensive pre-processing and analysis has allowed for a thorough examination of the text and provided valuable insights into the patterns and relationships within the text.

Results

In the first phase of the study, ten questions were asked about ARs related to the definition, concept, and use of ARs (S1 Appendix contains detailed answers). Prompts 1, 6, and 9 were rated very satisfactory by the experts in many respects. In the second step, the five experts found nine answers to forty questions about planning and implementing an AR project to be entirely acceptable. Due to the length of the answers given by the AI, some answers are included. Detailed answers can be found in the S1 Appendix, S2 Appendix, S3 Appendix, S4 Appendix, and S5 Appendix. Further investigation

Table 2. 7-point Likert scale

	Quality		Agreement		Appropriateness
1	Very poor	1	Strongly disagree	1	Absolutely inappropriate
2	Poor	2	Disagree	2	Inappropriate
3	Below average	3	Somewhat disagree	3	Slightly inappropriate
4	Average	4	Neither agree or disagree	4	Neutral
5	Above average	5	Somewhat agree	5	Slightly appropriate
6	Good	6	Agree	6	Appropriate
7	Excellent	7	Strongly agree	7	Absolutely appropriate

revealed specific trends: Prompts 13, 13a, 25, 26, 27, 28, and 29 received poor scores, in stark contrast to prompts 1, 21a, 42, and 43, which received excellent results in response quality (Figure 3). Similarly, prompts 10, 13, 13a, 25, 26, 27, 28, and 29 were associated with levels of mismatch. In contrast, prompts 1, 9, 13b, 15, 16, 21a, 22, 42, and 43 were related to high levels of agreement in the alignment shown with current literature, the precision of the terminology, and the presence of cited references (Figure 4). Additionally, prompts 8, 13, 13a, 25, 26, 27, 28, 29, 30, and 31 were deemed inappropriate, as opposed to prompts 1, 6, 9, 15, 21a, 24, 42, 43, and 45 which had high percentages of appropriateness (Figure 5).

Our analysis examined the appropriateness, validity, and overall quality of answers generated by ChatGPT in response to inquiries about artificial reefs. Utilizing Kruskal-Wallis tests, we found significant differences in all three response dimensions. In particular, the appropriateness of responses varied

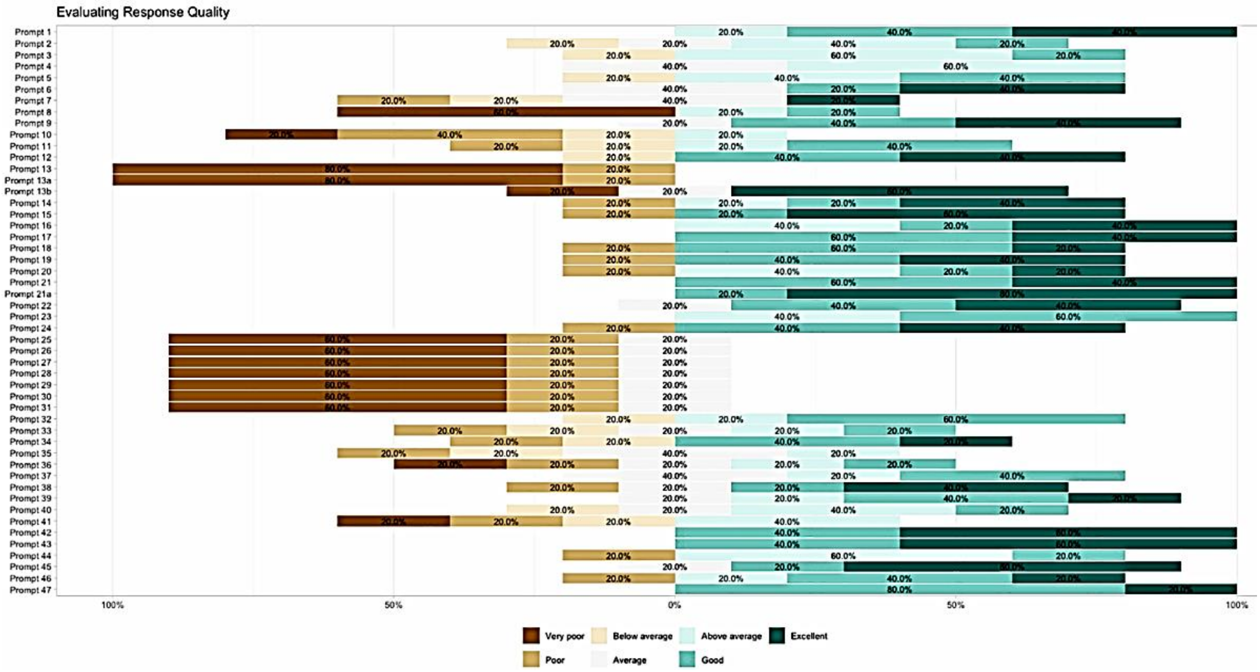

Figure 3. Analysis of the quality of the answers given by the LLM.

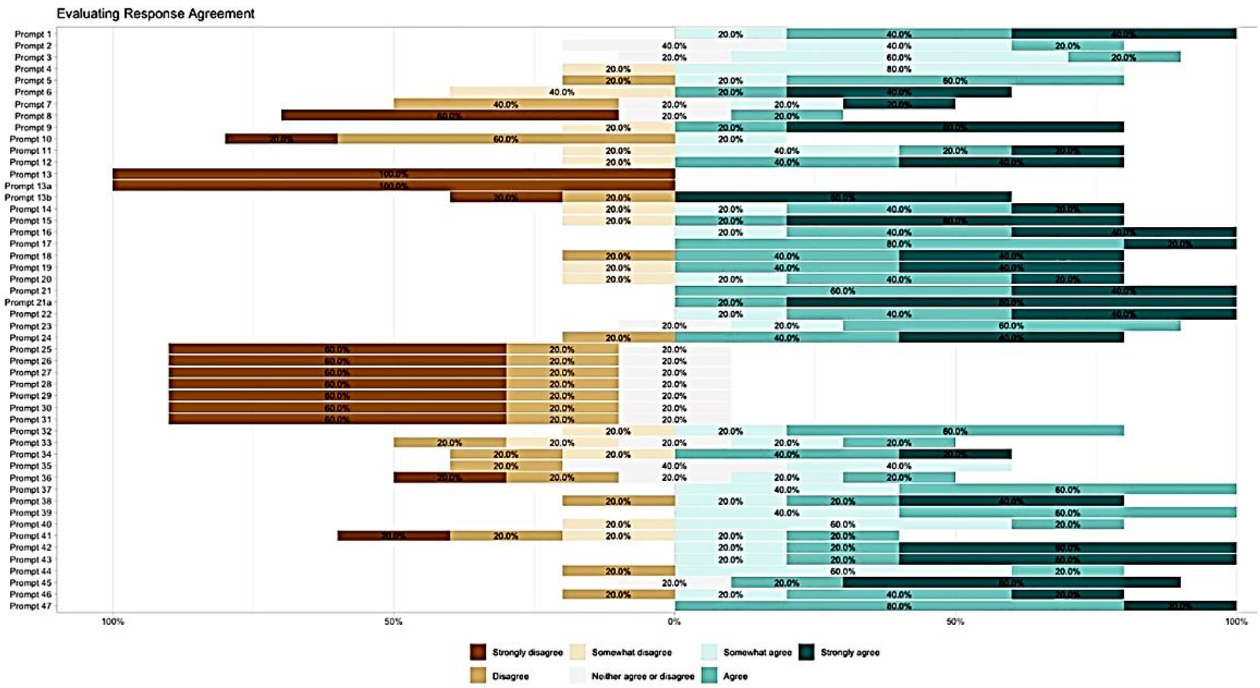

Figure 4. Analysis of the agreement of the answers given by the LLM.

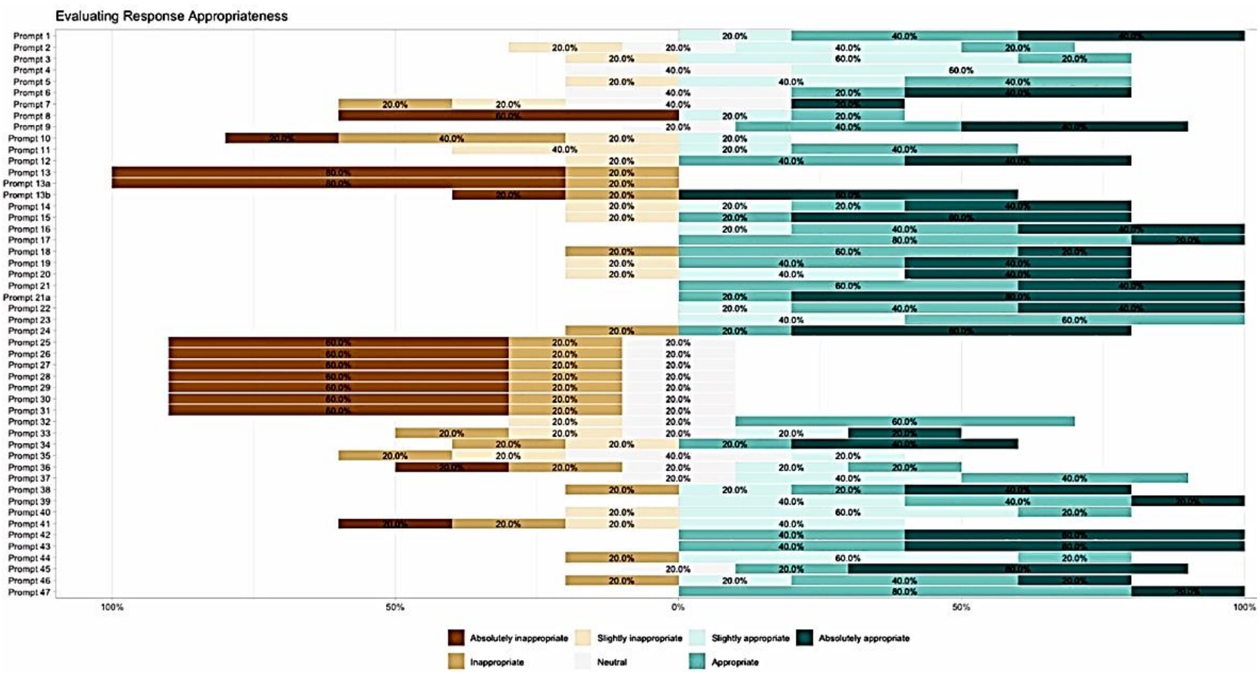

Figure 5. Analysis of the appropriateness of the answers given by the LLM..

between prompts (Kruskal-Wallis chi-squared= 148.27, df= 49*,* P<0.05), indicating different levels of relevance and appropriateness. Likewise, the validity of the information presented in the responses varied significantly (Kruskal-Wallis chi-squared= 147.45, df= 49, P<0.05), suggesting differences in the accuracy and reliability of the content provided. Additionally, assessments of the overall quality of answers yielded analogous results (Kruskal-Wallis chi-squared= 147.28, df= 49, P<0.05), highlighting differences in the completeness and effectiveness of responses. These results underscore the nuanced nature of AI-generated responses and emphasize the importance of considering multiple dimensions when evaluating their performance.

Physical Design and Construction

The design of ARs took into account physical aspects such as shape (openings, space, etc.), size (volume, weight, etc.), material properties (durability, structure, structural integrity, etc.), and type of reef (production, mixture, etc.). A total of 14 questions (Prompt 11…., Prompt, 13, Prompt 13a, Prompt 13 b, ….., Prompt 21a) were prepared to ask ChatGPT about physical design and construction processes (Table 3, see S2 Appendix).

Prompt 13: "If a hollow cube reef model with a side length of 1 m has a 60 cm wide square window on each surface, what will be the solid volume of the reef?" ChatGPT calculated the volume of a solid cube using the following equations, where V_{cube} is the volume of the cubic AR including all spaces, $V_{window(s)}$ is the volume of the window, A_{window} is the area of the openings of the cubic reef module, T_{window} is the wall thickness of the window, and a_{window} is the side length of the window.

$$V_{cube} = 1\ m^3$$

$$V = A_{window} \times T_{window}$$

$$A_{window} = (a_{window})^2 = (0.6\ m)^2 = 0.36\ m^2$$

Given that the thickness of the window is 1 m (since it is a hollow cube), the volume of each window is 0.36 m^2. Since there are 6 windows on the cube (one on each surface), the total volume of the windows is 6 x 0.36 m^3 = 2.16 m^3. Finally, we subtract the volume of the windows from the volume of the solid cube to find the solid volume of the reef (V_{solid}):

$$V_{solid} = V_{cube} - V_{windows} = 1\ m^3 - 2.16\ m^3 = -1.16\ m^3$$

ChatGPT noticed the error and issued the following statement: "*However, it seems there's a discrepancy because the volume of the windows exceeds the volume of the solid cube, which doesn't make sense physically. This may be due to the dimensions provided. Please double-check the dimensions or clarify if there's a mistake.*".

After this erroneous action, the question was asked again with more details. Prompt 13a: "If a hollow cube reef model with a side of 1 m has a 60 cm wide square window with a thickness of 20 cm on each surface, what is the volume of the reef?". Although ChatGPT correctly calculated the volume of six windows which is 0.432 m^3 in this experiment, it forgot to consider the 60 cm^3 space inside the cube and found that the result (0.568 m^3) was incorrect. Then the final prompt was made. Prompt 13b: "If a hollow cube reef model with a side of 1 m has a 60 cm wide square window with a thickness of 20 cm on each surface, what is the volume of the reef? Imagine that the cube's inside with a side of 60 cm is empty. So you need to subtract the volume of the interior from the total volume, just like you did with the windows.”. ChatGPT finally found the correct answer using the following equation ($V_{interior}$ = All spaces in the reef module except for windows):

$$V_{solid} = V_{cube} - (V_{interior} + V_{windows})$$

$$V_{solid} = 1\ m^3 - (0.216\ m^3 + 0.432\ m^3)$$

$$V_{solid} = 0.352\ m^3$$

Prompt 21 aimed to determine the amount of concrete and reinforcing steel in terms of the solids volume of an AR module, which was calculated to be 0.352 m^3 due to ChatGPT's poor mathematical skills. So, Prompt 21 was: “What amount of cement and reinforcing steel would be required to build an AR that can be utilized in the ocean for at least 30 years, in a hollow cube block with a volume of 0.352 cm^3?”. ChatGPT suggested a typical mix ratio of 1:2:4 (cement: sand: aggregate) for concrete by volume. Additionally, ChatGPT found that cement volume accounts for approximately 15% of the total concrete volume:

$$V_{cement} = 0.15 \times V_{concrete}$$

A common ratio of reinforcing steel to concrete was estimated by ChatGPT to be around 1-2 percent by volume:

$$V_{reinforcing\ steel} = \text{Reinforcement ratio} \times V_{concrete}$$

Calculations carried out by ChatGPT were given:

$$V_{concrete} = 0.352\ m^3$$

$$V_{cement} = 0.15 \times 0.352\ m^3 = 0.0528\ m^3$$

$$V_{reinforcing\ steel} = 0.01 \times 0.352\ m^3 = 0.00352\ m^3$$

At the end of the calculation, ChatGPT wanted us to provide units for the densities of the materials. Prompt 21a was then designed to provide density and unit information for the materials. Prompt 21a: “As you want, the density of reinforcing steel is 7850 $kgm^{-3,}$ and the density of cement is 2400 kgm^{-3}”. ChatGPT calculated the mass of cement (m_{cement}) and mass of reinforcing steel ($m_{reinforcing\ steel}$) using the following equations:

$$m_{cement} = 0.0528\ m^3 \times 2400\ kgm^{-3} = 126.72\ kg$$

$$m_{reinforcing\ steel} = 0.00352\ m^3 \times 7850\ kgm^{-3} = 27.632\ kg$$

In this prompt, the question was revised and re-asked several times to ensure that all details were correctly recognized by ChatGPT (Prompt 25, …., Prompt 30). Finally, we designed Prompt 31: According to JCFPA (1986), the deployment area of reef blocks should not exceed 20 times the aggregate shade areas of all individuals (S <20 x N x X). The relationship is expressed mathematically as the circular area (S) should be less than multiplying the number of reef blocks (N), the coefficient (20), and the surface area of the AR block with one side (only one face) touching the seabed ($X = a^2$). If we planned to use a hollow cubic reef block with a side of 1.5 m to create an AR area with a total volume (bulk volume) of 400 m^3 (J), what should be the radius of the circular area (r)? According to the given formulae (JCFPA, 1986), how many reef blocks (N) would be required for this area (S) (Additional information: $N = J.a^{-3}$; pi is approximately 3.14)? ChatGPT responded to complex questions using the equations given above. While almost all operations were performed with the correct formulas, the radius of the circular area (r) and the number of AR blocks (N) required to form that area were incorrectly calculated due to a simple division error (Incorrect ChatGPT answers: r= 50.5 m, and N= 178).

Table 3. Examples of prompts to ChatGPT on the physical design and construction of artificial reefs and responses received (Ag: Agreement; Approp: Appropriateness; Qlt: Quality-Scores: 1 to 7)

Prompts		Responses summarised	Scores (Mean)		
No	Content		Ag	Approp	Qlt
11	What shape and design of ARs is most commonly used or manufactured?	ChatGPT summarised five commonly used AR designs concrete modules (tetrahedrons, pyramids, cubes, or balls), shipwrecks, tire reefs, and submerged rock piles	5.4	5.0	4.4
22	Is complexity in the design of ARs a design criterion that increases their efficiency?	ChatGPT defined the complexity in the design of ARs, which refers to creating structures with different shapes, sizes, and characteristics that provide diverse habitats and niches for marine species, as a common key design criterion that can increase their efficiency and effectiveness. ChatGPT stated the importance of the complexity of reef designing by stating some important points such as biodiversity, food chain support, coral growth, habitat resilience, recreation and tourism, fishing enhancement, and ecological functionality.	6.2	6.2	6.0

Environmental Design

When designing an AR unit, we considered from an environmental perspective the design of waves and currents, determination of environmental forces, local scours, and embedment process, selection of appropriate deployment depths, sediment properties, laboratory experiments, and numerical simulations using complex software such as CFD. and field/case studies. ChatGPT asked 7 questions (Prompt 32, ……, Prompt 38) about environmental design considerations for AR planning (Table 4, see S3 Appendix).

Biological Design

In the biological design of the AR, we evaluated reef design based on fish behaviour (size and shape of structural elements), hydrodynamics, and aggregation aspects (vertical profile, protected area, etc.). Regarding the biological design of ARs, 6 questions (Prompt 39, ….., Prompt 44) were prepared for ChatGPT (Table 5, see S4 Appendix).

Prompt 42: "According to Nakamura (1980), the product of the minimum column width (W_{min}, cm) of a hollow cubic AR and the minimum current velocity (U_{min}, cms^{-1}) should be greater than 100. Accordingly, in an environment with a current velocity of 10 cm per second, how many centimetres should the minimum column width be?". This is a prompt to calculate the minimum column width of an AR unit by specifying a formula based on the reference using ChatGPT. In this Prompt, ChatGPT found the result (W= column width is 10 cm) in a few seconds using the formula given below (Nakamura, 1980; Grove et al., 1991):

$$W_{min} \times U_{min} > 100$$

Table 4. Examples of prompts to ChatGPT on the artificial reef environmental design and responses received (Ag: Agreement; Approp: Appropriateness; Qlt: Quality-Scores: 1 to 7)

Prompts		Responses summarised	Scores (Mean)		
No	Content		Ag	Approp	Qlt
32	The size and positioning of the openings can affect water flow and circulation in the reef. This can impact sediment transport, oxygen levels, and nutrient distribution, all of which are important to the health of marine ecosystems. From this perspective, what is your design of an AR unit to meet these variables and ensure longevity?	ChatGPT evaluated the following factors that influence AR design: (1) Placement and size of openings influence sedimentation, water flow, and nutrient distribution; (2) Reef shape and turbulence; (3) Material selection ensures structural integrity and supports attachment of marine life. (4) Flexibility in deployment is ensured by the modular design; (5) Hydrodynamic modelling optimizes reef efficiency, and (6) Ecological features such as textured surfaces promote biodiversity.	5.2	5.0	5.2
34	Can you provide information on local scour formation affecting the stability of structural elements of underwater structures such as benthic ARs?	ChatGPT defined that local scouring refers to the erosion or removal of sediment from the seabed around submerged objects due to water flow and can significantly affect the stability of structural elements of underwater structures, including benthic ARs. ChatGPT then summarised several factors that contribute to the formation of local scour around subsea structures: (1) Flow velocity, (2) Sediment characteristics, (3) Structure/reef geometry, and (4) Environmental conditions.	4.8	5.0	4.8

Table 5. Examples of prompts to ChatGPT on biological design of artificial reefs and responses received (Ag: Agreement; Approp: Appropriateness; Qlt: Quality-Scores: 1 to 7)

Prompts		Responses summarised	Scores (Mean)		
No	Content		Ag	Approp	Qlt
39	How large should the openings in the body of the AR be so that it can attract fish?	ChatGPT explained that the size of the openings in the body of an AR depends on various factors, including the targeted fish species, local environmental conditions, and the purpose of the reef. ChatGPT described that openings, which are typically sized to match the body size of the target species and its swimming behaviour, should be large enough to allow fish to enter and exit the structure easily while providing suitable habitat and refuge. ChatGPT warned that the openings should be large enough to attract fish but not so large that they threaten the structural integrity of the reef.	5.6	5.8	5.6

Prompt 43: "When designing ARs, we aim for the reef to provide interior habitat for tenant fish. In addition, the reef should be designed so that the leeward current speed remains acceptable for small fish individuals. So we have to design or arrange the reef in such a way that it can reduce the current velocity in the leeward direction. Can you provide a formula or design suggestion for this theme?". Prompt 43 is for calculating the current velocity at the leeward side of the reef using ChatGPT. ChatGPT explained that reducing current velocity in the wake zone could be possible through structures, spacing, and orientation of ARs. ChatGPT added that a common approach is to incorporate porous or permeable materials into the reef design to allow water to flow through and dissipate energy. Finally, ChatGPT expressed that creating irregular shapes or incorporating vertical structures can help create turbulence and reduce current velocity. ChatGPT has given a simple formula to estimate the reduction in current velocity due to the presence of ARs:

$$V_{\text{reduced}} = V_{\text{initial}} \times (1 - A_{\text{reef}} \times A_{\text{total}}^{-1})$$

Where, V_{reduced} is the reduced current velocity within the reef, V_{initial} is the initial current velocity outside the reef, A_{reef} is the cross-sectional area of the AR, A_{total} is the total cross-sectional area of the waterway

ChatGPT explained that the formula provides an estimate of current velocity reduction based on the ratio of the cross-sectional area of the reef to the total area of the waterway. Additionally, ChatGPT emphasized that it is important to note that reductions may vary depending on factors such as reef density, shape, and environmental conditions. Similarly, ChatGPT suggested that for specific designs tailored to project requirements, consultation with ocean engineers or marine scientists with experience in AR design would be advisable, as they can provide detailed simulations, modelling, and field studies to design reef configurations for desired reductions optimize flow speed and maximize habitat suitability for fish populations.

Economical Design

Although economic design covers all steps of AR planning, the main elements are summarized as construction costs (mould, labour, materials, etc.), transportation costs, deployment and arrangement costs, and project costs (preliminary studies, pilot study, etc.), the balance between expenditure and income, fishing income, and other incomes (fishing, diving, tourism, etc.). In this section, ChatGPT was asked three questions about the economics of ARs. Regarding the biological design of ARs, 3 questions (Prompt 45, ….., Prompt 47) were prepared for ChatGPT (Table 6, see S5 Appendix).

ChatGPT's answers to AR design questions in various domains were analysed to reveal word frequencies using text cloud graphics. Text mining analysis revealed that the dataset contained 378 unique words that were repeated at least four times (Figure 6). The most frequently occurring word was "reef" with a frequency of 293 times, followed by "artificial" 199 times. This distribution aligns with our expectations given the context of the study. Among the 20 most common words, "conditions" was the least frequently occurring word, appearing 25 times. These results highlight the importance of certain key terms and concepts in the text and clearly indicate the main focuses and recurring themes in the responses.

Discussion and Conclusion

The use of AI systems in the natural sciences and, ultimately the LLMs have made significant progress with the continuous development of digital technology. Particularly in marine sciences, in addition to monitoring

Table 6. Examples of prompts to ChatGPT on the economic design of artificial reefs and responses received (Ag: Agreement; Approp: Appropriateness; Qlt: Quality-Scores: 1 to 7)

Prompts		Responses summarised	Scores (Mean)		
No	Content		Ag	Approp	Qlt
47	What examples can you give of the economic benefits of ARs? And how can the economic value of ARs be measured?	ChatGPT summarised the benefits of AR applications as given: (1) Fisheries Enhancement (benefits of commercial and recreational fishing, resulting in increased yields and economic gains for fishermen and the fishing industry as new AR habitats are created), (2) Tourism and recreation (new habitats attract divers, snorkelers, and anglers, stimulating tourism and recreational activities), (3) Ecosystem services (New ARs have economic value in terms of reducing coastal erosion, supporting marine biodiversity, and maintaining ecosystem functions), (4) Research and education (ARs serve as research platforms with research grants, educational programs, and scientific collaborations related to ARs and contribute to economic activity in the academic and research sectors).	6.2	6.2	6.0

studies (Ditria, Buelow, Gonzalez-Rivero, & Connolly, 2022; da Silveira, Strenzel, Maida, Gaspar, & Ferreira, 2021; da Silva, et al., 2023), researchers, contractors and regulators want artificial intelligence to provide guidance and solutions (Ditria et al., 2022) in phases such as planning, implementation and post-implementation (Rubbens et al., 2023). In this study, we conducted artificial reef planning using LLM to measure the extent to which this is possible and obtained the results.

The integration of ChatGPT and related generative AI systems has gained traction among researchers in a range of areas such as supply chain management, risk assessment and safety, sustainable building design, civil engineering, and construction automation. According to Rane (2023), this integration promises to increase the quality of life, modernize urban infrastructure, and improve sustainability. In addition, scientists have investigated ChatGPT's language translation capabilities and its potential uses in climate research (Biswas, 2023). Verma (2023) used ChatGPT to study how deep-sea mining impacts biodiversity, marine ecosystems, and ocean health. This analysis helped with regulatory tracking and environmental impact assessment. However, difficulties have been identified, including around understanding complicated scientific ideas and biases in training data. Agathokleous et al. (2023) examined the impact of ChatGPT on biology and environmental sciences and recognized its benefits and risks, which they continue to investigate.

Historically, ARs consisting of various structures using natural and manufactured materials (from rocks, and logs to complex AR constructions) have been used around the world in a variety of ways to protect ecosystems and fisheries production (Seaman & Sprague, 1991; Seaman & Jensen, 2000; Seaman et al., 2011). Today, the appropriate and rational planning, design, and management of ARs is crucial as one of the most productive tools for manipulating the ecosystem. In this study, we were interested in how a LLM could help us design artificial reefs. In this context, the answers to the questions posed to ChatGPT about artificial reef technology and the planning stages of artificial reefs were evaluated by five experts. This assessment allowed us to get an idea of the reliability of the information provided by artificial intelligence tools.

Sohail et al. (2023) examined 109 Scopus-indexed publications dominated by some fields such as

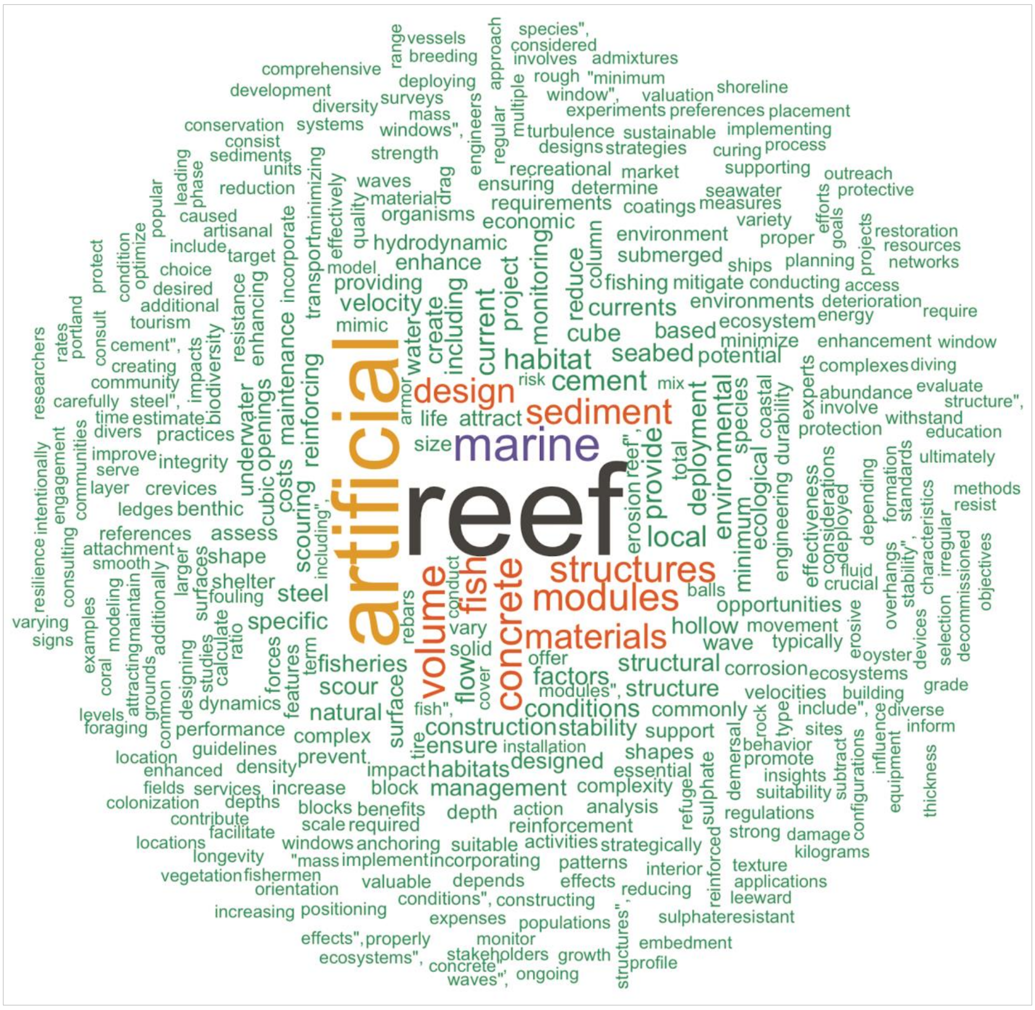

Figure 6. Word cloud represents the most common words in the dataset, with words appearing at least four times. Stop words, numbers and special characters have been removed from the text.

medicine, social sciences, computer science, multidisciplinary studies, health professions, engineering, nursing, decision sciences, immunology and microbiology, biochemistry, genetics and molecular biology, and others on ChatGPT. They found that a total of 68 articles were published to evaluate ChatGPT's capabilities, its ability to provide accurate answers, or the depth of its knowledge, as we did in our study. According to Deng & Lin (2023), ChatGPT increases efficiency by automating conversations, saving time and money. ChatGPT's pre-trained language model helps understand questions and provide meaningful answers. This effectiveness was demonstrated in this study by the speed with which ChatGPT responded to complex and targeted artificial reef planning requests within seconds. When analysing the high scores obtained by the experts, the most common questions for the three different concepts (quality, agreement, and appropriateness) are 1, 21a, 42, and 43, respectively. The experts also agreed on the questions for these three different concepts and gave low ratings of 13, 13a, 25, 26, 27, 28, and 29.

Analysis of the questions in this framework revealed that ChatGPT fabricated answers on some, had difficulty on others, and had problems at all on some topics. In this study with prompts 13, 13a, and 13b, we asked ChatGPT to calculate the solid volume of a hollow cube reef model with a side length of 1 m and a window width of 60 cm. However, with our help, it was only on the third attempt that we managed to find the correct answer. In another experiment (prompts 21 and 21a), we asked ChatGPT to calculate the optimal mix for building a reinforced concrete reef block. The mixing ratio was determined by ChatGPT, but ChatGPT wanted us to provide units for the densities of the materials, and finally, the mass of the materials was calculated. Zhou et al. (2023) reported that ChatGPT actively responds to user feedback by quickly correcting errors and filtering out incorrect questions. In addition, it requests additional information (e.g. material density) for precise calculations when necessary to ensure the accuracy of its answers as in our study.

We asked ChatGPT to calculate the area on which a certain number of artificial reef blocks of known dimensions would be placed. Each time we reworded the question (prompt 25, ..., 31) by making it a little more meaningful. Although the formulas were given, it still made errors in mathematical operations and could not achieve the result. In another experiment (Prompt 42), we used Nakamura's (1980) formula to calculate the minimum column width according to the current velocity, and ChatGPT was correctly determined based on the equation result in a few seconds. The following prompt was for the current velocity on the leeward side of the reef. ChatGPT explained this in detail and gave a simple formula to estimate the reduction in current velocity due to the presence of ARs. Frieder et al. (2023) analysed different versions of ChatGPT for math skills ranging from simple math problems to Math Olympia tasks and rated them from 1 to 5 depending on satisfaction with the answer. They explained that ChatGPT did not provide as satisfactory and accurate answers as exaggerated in the media, but also emphasized that the answers received were promising. They claimed that although its ability generally decreases as the mathematical difficulty of a prompt increases, it occasionally provides perceptible evidence (Frieder et al., 2023). Zhou et al. (2023) argued that ChatGPT cannot solve precise reasoning problems (e.g., mathematics) and that ChatGPT often offers erroneous solutions for arithmetic or logic problems with probabilistic rather than definite answers.

The question about the definition of an artificial reef (Prompt 1) was rated as very satisfactory by all experts. Other questions (Prompt 21a, 42, and 43), which involved formulas and calculations, also received high ratings from five experts. In our study, ChatGPT gave completely or partially incorrect answers to some questions (e.g. 10 and 23). Zhou et al. (2023) found that ChatGPT still produces biased or factually inaccurate answers. They stated that ChatGPT could not search the site for current and new information in real-time. For this reason, ChatGPT can be persistent about incorrect answers. In prompt 8, we asked ChatGPT to suggest a valid source for artificial reef planning, but the literature it gave us was a complete fabrication. Although the answer consisted of the name of the journal, the title and authors of the publication, the pages, and the publisher we found no such publication exists. Zhu et al. (2023) stated that LLM could generate false or fabricated information such as DOI and URL links. Similarly, Agathokleous et al. (2023) have drawn attention to some risks of ChatGPT, such as misleading the public and providing false and inaccurate information about environmental sciences and biology. In the same scientific area, they stated that the benefits of ChatGPT are to enable access to information, support research and risk assessment, educate the public, provide insights and recommendations, facilitate communication, and improve efficiency.

We asked ChatGPT quite a few questions (Prompts 7, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 24, 35) about design aspects (shape, openings, type, etc.), material properties (durability, structure, structural integrity, etc.), and reef type in the construction phase of artificial reef units. ChatGPT offered many logical solutions that were rated above average by experts in planning an artificial reef project. The potential uses, benefits, and challenges of integrating these AI technologies into construction practice were examined by Rane (2023). Rane (2023) examined the role of ChatGPT in the construction industry and summarised the advantages and challenges of ChatGPT for some aspects such as design optimization, material selection, environmental impact assessment, innovation, and concept development. In our study, we asked ChatGPT about the potential economic costs of planning an artificial reef and received information about the environmental impacts (i.e. regulatory requirements to mitigate potential negative effects of the reef system on the marine environment) and their assessment (Prompt 45). Verma (2023), as mentioned in Rane (2023), claimed that ChatGPT can help produce reports and summaries from environmental impact data (e.g., destruction of benthic ecosystems, loss of biodiversity, potential chemical contamination) occurring during deep-sea mining collected.

Conclusion

Many researchers have addressed the positive and negative aspects of ChatGPT (Agathokleous et al., 2023; Baidoo-anu & Ansah, 2023; Biswas, 2023; Deng & Lin, 2023; Rane, 2023; Sohail et al., 2023; Verma, 2023; Zhou et al., 2023). In the study, we used targeted questions to determine ChatGPT's ability and access to information for artificial reef planning. Five experts, each with a doctorate in ARs, evaluated answers of LLM to a series of questions about AR technology. Although the LLM satisfactorily answered general questions about AR applications, it performed less well on more complex, expert-level questions. This is particularly due to the lack of access to resources containing the knowledge and experience of Japanese scientists on AR technology. Therefore, it may be advisable to be careful when evaluating the information provided by AI, especially in scientific research, and to verify the information. There is an obvious information barrier: ChatGPT's latest education data is three to four years out of date because ChatGPT does not have real-time Internet access. Therefore, events or developments after this date are unknown. For example, it would be pointless to ask about the prices of materials needed to build an artificial reef. This particular limitation requires users to review and verify all data, especially when it relates to current events. Although it can generate content, human intervention is sometimes required to obtain more accurate and useful information. In some cases, it is possible to improve the prompt and instruct the AI to provide a more accurate answer with a more specific prompt. The questions asked in our study are evidence that AI is being positively manipulated. The questionnaire can help the AI with more detailed information, while the non-repeater can draw the line at clearer and more concise information. One limitation of the study is the small number of experts. But the reluctance of the experts to respond to the very long texts of the foreign experts and the lack of time limited us to the expertise of the academics working in these waters. Although the experts are local, the questions asked of the AI are based on globally accepted, tested, practised, and published sources, so that the results apply to all those involved in AR planning.

ChatGPT can be integrated as a workflow assistant for a user who already has sufficient knowledge to determine whether the output of ChatGPT is correct. However, basic topics on artificial reefs and information on project planning steps are easily accessible through AI to all stakeholders, including NGO staff, ministry engineers, private sector officials, and undergraduate and graduate students. Shortly, researchers will be able to quickly access AI's vast knowledge base by uploading both new and old data to the cloud. Therefore, the planning of artificial reefs using such artificial intelligence applications should be reviewed, literature studies should be carried out and, finally, expert advice should be sought. However, these applications will do more productive work in the future.

Ethical Statement

Ethical Statement Local Ethics Committee Approval was not obtained because experimental animals were not used.

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Author Contribution

(FOD): Conceptualization, methodology, investigating, writing - original draft, writing - review & editing, visualization. (TC): Investigating - original draft, writing - review & editing, visualization.

Conflict of Interest

The authors declare that they have no known competing financial or non-financial, professional, or personal conflicts that could have appeared to influence the work reported in this paper.

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