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AI in Biodiversity Education: The Bias in Endangered Species Information and Its Implications

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Abstract

The use of AI-generated content in education is significantly increasing, but its reliability for teaching natural sciences and, more specifically, biodiversity-related contents still remains understudied. The need to address this question is substantial, considering the relevance that biodiversity conservation has on human sustainability, and the recurrent presence of these topics in the educational curriculum, at least in Spain. The present article tests the existence of biases in some of the most widely used AI tools (ChatGPT-4.5, DeepSeek-V3, Gemini) when asked a relevant and objective research question related to biodiversity. The results revealed both taxonomic and geographic biases in all the lists of endangered species provided by these tools when compared to IUCN Red List data. These imbalances may contribute to the perpetuation of plant blindness, zoocentrism, and Western centrism in classrooms, especially at levels where educators lack specialized training. In summary, the present study highlights the potential harmful impact that AI's cultural and social biases may have on biodiversity education and Sustainable Development Goals-aligned learning and appeals to an urgent need for model refinement (using scientific datasets) and teacher AI literacy to mitigate misinformation.

Keywords: AI bias; biodiversity education; endangered species; sustainable development goals (SDGs); taxonomic bias; geographic bias

Academic Editors: Ebba Ossiannilsson and Aras Bozkurt

Received: 21 May 2025
Revised: 15 July 2025
Accepted: 16 July 2025
Published: 18 July 2025

Citation: de Pedro Noriega, L.; Bobo-Pinilla, J.; Delgado-Iglesias, J.; Reinoso-Tapia, R.; Gallego, A.M.; Quirós-Alpera, S. AI in Biodiversity Education: The Bias in Endangered Species Information and Its Implications. *Sustainability* **2025**, *17*, 6554. https://doi.org/10.3390/su17146554

1. Introduction

1.1. Artificial Intelligence and Education

The genesis of artificial intelligence (AI) can be traced back to the mid-20th century, when pioneering figures such as Alan Turing introduced the concept of machines capable of performing cognitive tasks [1]. The term "artificial intelligence" was officially coined in 1956, marking the establishment of AI as a distinct field of study [2]. In recent decades, significant advancements in machine learning algorithms, deep learning techniques, and access to extensive datasets have contributed to the rapid progress of the field [3]. The sophistication of AI has reached unprecedented levels, as evidenced by applications such as ChatGPT, Gemini and, more recently, DeepSeek ([4]; among many others). These systems exhibit advanced capabilities in human-like interaction, complex reasoning, and content creation. They are enabled by sophisticated language models that have been trained on extensive datasets, thereby facilitating a wide range of capabilities, including text processing, multimedia generation, and the resolution of complex challenges such as medical diagnostics, autonomous vehicle navigation, and personalized services [5,6].

In the field of education, the integration of AI has led to significant advancements in the realm of learning solutions. These solutions are characterized by their personalized approach and accessibility, spanning diverse academic domains [7,8]. These tools can function as virtual tutors, delivering tailored explanations based on individual student needs [9,10]. Ref. [11] posit that AI-powered education facilitates personalized learning, thereby enhancing knowledge retention and student engagement. AI applications also support educators by automating administrative tasks such as grading assessments and generating instructional materials, thereby allowing teachers to allocate more time to direct student interaction [12]. Furthermore, these tools have the potential to democratize access to high-quality education, particularly in regions facing resource constraints. In this regard, ref. [13] have asserted that AI has the capacity to bridge educational gaps by providing real-time tutoring through chatbots, thereby mitigating geographic and economic barriers.

Nevertheless, the integration of AI into education is not without challenges [14,15]. A significant concern pertains to the potential overreliance on technology, which may impede the cultivation of critical cognitive abilities such as independent thinking and problem-solving [16,17]. Ethical concerns also arise, particularly regarding data privacy, bias in algorithmic decision-making, and the risk of diminishing the role of educators in the learning process [18–21]. Consequently, as Ref. [16] contends, the key to effective AI integration in education is its role as a complementary instrument, not a substitute for teachers and human interaction.

1.2. AI in Natural Sciences Education and Research

In the domain of the natural sciences, which encompasses disciplines such as biology, physics, chemistry, and earth sciences, the application of AI is facilitating the emergence of novel pedagogical and research opportunities. These tools have the capacity to enhance the learning experience by providing innovative resources, including customized explanations, interactive simulations, and conceptual diagrams to elucidate complex scientific phenomena. Furthermore, AI facilitates the creation of thematic questions and exercises, thereby enhancing classroom engagement [22,23]. In addition, AI can also serve as an instrumental tool in incorporating research methodologies into educational settings [24].

Additionally, and in line with the abovementioned limitations of AI, its indiscriminate use in scientific education also brings significant concerns. A primary risk is that students may employ AI primarily as a problem-solving or text-generation tool rather than as a means of fostering deeper analytical engagement with scientific concepts. This reliance may pose a challenge to the development of critical thinking and scientific literacy [25,26]. Furthermore, it is imperative to assess whether the information generated by AI aligns with current scientific knowledge [27,28]. A crucial question remains: Do widely used AI applications provide scientifically accurate and unbiased information, or do they introduce distortions that could mislead both educators and students?

1.3. Biodiversity Education and Sustainable Development

Biodiversity is a critical subject in education and plays a fundamental role in advancing the Sustainable Development Goals (SDGs) outlined in the United Nations' 2030 Agenda. The significance of biodiversity stems from its function as the foundation of life on Earth and its interconnectedness with social, economic, and environmental sustainability [29,30]. Integrating biodiversity education into curricula has been demonstrated to foster environmental awareness from an early age. Students are able to gain insights into the interdependence of ecosystems and the consequences of human actions on the environment [31,32].

According to [33], environmental education is essential for cultivating responsible global citizens committed to sustainability. Moreover, biodiversity loss is recognized as one of the most pressing environmental challenges of the 21st century [34]. Education in this domain provides students with the knowledge and skills necessary to address critical issues such as climate change, deforestation, and species extinction [35].

Biodiversity is closely linked to several SDGs, as it is vital for human well-being and ecological balance. Specifically, it aligns with SDG 13 (Climate Action), given that biodiverse ecosystems—such as forests and oceans—serve as carbon sinks, thereby mitigating climate change. The importance of education in promoting the conservation of these ecosystems to reduce greenhouse gas emissions is also emphasized [36]. Furthermore, biodiversity is intricately linked to both SDG 14 (Life Below Water) and SDG 15 (Life on Land), underscoring the necessity for biodiversity conservation and the mitigation of desertification [37]. Moreover, within the educational context, biodiversity is integral to SDG 4 (Quality Education) as it constitutes a cross-disciplinary theme that interlinks biology, geography, and social sciences [33]. The integration of biodiversity education within curricula is a key strategy that fosters a holistic educational approach, one which is aligned with the principles of sustainability [33].

In Spain, the treatment of environmental education in general and biodiversity in particular is recurrent throughout the educational curriculum, but with obvious differences between the different educational stages. In Early Childhood Education (aimed at children up to 6 years of age), the legislation establishes objectives related to the observation and respect for the environment, without going into more detail due to the young age of the learners [38]. As students progress through the educational system, the curriculum becomes more intricate. In Primary Education (ages 6–12), two key competences, STEM and Citizenship, are introduced. These competences emphasize the importance of preserving the environment and living beings, as well as adopting sustainable lifestyles to contribute to biodiversity conservation. This term is first mentioned in educational legislation. In the section of basic knowledge entitled "Life on our planet", the study of living beings, their classification, their relationships within ecosystems, and the importance of preserving their diversity is proposed; and in other sections such as "Sustainable development and environmental ethics", the conservation of biodiversity is addressed as an eco-social problem to be solved [39]. Secondary education is arguably the one in which the treatment of biodiversity and its conservation is most intensified. This phenomenon is exemplified by the operational descriptor CC4 of the Citizenship Competence, which states that students should "begin to adopt sustainable lifestyles, to contribute to the conservation of biodiversity" [40]. Furthermore, various sections of basic knowledge refer to this issue and its eco-social relevance, particularly in the subjects of "Biology and Geology" and the first three courses [40]. Finally, in the Baccalaureate stage (16–18 years; non-compulsory), the subjects "Biology, Geology and Environmental Sciences" and "General Sciences" also address aspects such as sustainable development, the loss of biodiversity as a socio-environmental problem and the causes and consequences of this phenomenon [41].

According to this background, the present study investigates the accuracy and reliability of AI-generated information in the framework of biodiversity education, specifically aiming to determine if AI applications provide scientifically valid data on endangered species or exhibit biases that could misinform both educators and students.

2. Materials and Methods

To formulate an objective research question that would allow us to determine whether AI-generated responses exhibit bias, it was essential to pose a straightforward query while avoiding explanations that students or educators would be unlikely to request.

Specifically, the initial question presented to AI applications was the following: "Generate a list of 100 living species that are endangered". In total, 100 species were requested since higher numbers generate a volume of data that future teachers are unlikely to analyze for educational purposes, and lower numbers limit, taking into account the high number of species in real danger, the capacity to perform an efficient analysis; moreover, the question aimed to assess whether the responses provided by AI systems align with scientific data or whether they reflect societal biases, geographical biases, or preferential biases. For this study, three of the most relevant AI-based text generation tools to date were selected: ChatGPT-4.5 (based on GPT-4-turbo, OpenAI), DeepSeek-V3-chat (DeepSeek AI), and Gemini 1.5 Flash (Google), all accessed in February 2025. As an initial approach, to avoid influencing the chatbots' responses, three runs were performed for each AI bot, and fresh accounts were used.

The species obtained were categorized by two biodiversity experts into taxonomic groups (predominantly at the class level but, in some cases, at the kingdom level, e.g., plants) and geographic region; in order to analyze the taxonomic bias (uneven phylum coverage and over/underrepresentation of specific taxa) and geographic bias, respectively. The findings were expressed as percentages to enable comparison with real-world extinction risk percentages reported by the International Union for Conservation of Nature (IUCN) and descriptive analyses, including mean and standard deviation, were conducted using R statistical software (version 4.4.0). To minimize potential biases in the comparison, IUCN values were adjusted based on the proportion of evaluated species relative to the total estimated species count (the IUCN estimates that there may be approximately 8 million species of which only 169,410 have been evaluated and of these 47,187 are in danger of extinction), and this adjustment accounts for discrepancies in assessment coverage across taxa (e.g., 84% of mammal species have been evaluated compared to only 1.2% of insect species).

The data of the geographic distribution of the species was also obtained from the IUCN (https://www.iucnredlist.org/es/statistics, accessed on 4 February 2025). The data of the absolute number of endangered species is variable along time, but the percentages are quite stable; to establish clear geographical entities, 8 areas were defined, with some of them being created by combining several IUCN areas ("Caribbean Islands" and "Mesoamerica" in Central America; "East Asia", "North Asia", "West and Central Asia" and "South and Southeast Asia" in Asia; "North Africa" and "Sub-Saharan Africa" in Africa) while others were obtained directly ("Europe", "North America", "South America", "Oceania" and "Antarctica").

To assess the consistency and magnitude of systematic error in the results, two complementary indicators were calculated using R statistical software (version 4.4.0): the taxonomic and geographic Bias Ratio and the Magnitude Error Bias. The Bias Ratio was computed as the mean of the signed differences between the values generated by the AI chatbots and the reference values (IUCN dataset), divided by the standard deviation of those differences; this ratio provides an indication of the directional consistency of the bias (higher absolute values indicate stronger and/or systematic bias, while values close to zero indicate either accuracy or random errors); when the standard deviation of the bias was zero (same percentage values for the three runs) the Bias Ratio was undetermined and noted as "na"; the Magnitude Error Bias is calculated as the mean of the absolute bias values.

Furthermore, considering that the differences between the actual IUCN data and the AI responses could be due to sampling error (this would be the case if the AI performed random sampling among the IUCN databases), three random samplings were performed on the IUCN database to calculate the mean and standard deviation values for both the taxonomic groups and the geographical areas.

3. Results

In the case of ChatGPT, the responses included 43.3 mammals (SD = 1.5), 15 birds (SD = 4.6), 6.7 plants (SD = 6.1), 10 reptiles (SD = 1.5), 6.3 amphibians (SD = 2.1), 6.7 fish (SD = 1.2), and 5.7 insects (SD = 1.5), as well as 1.7 mollusks (SD = 0.6), 1.3 arachnids (SD = 0.6), 1.3 cnidarians (SD = 1.2), one crustacean (SD = 1), and 0.7 fungus (SD = 1.2) (Appendix A and Table 1). Within its response, the AI tool explicitly stated "Below is a representative list of 100 species (including animals, plants, and other living organisms) that are classified as threatened or endangered according to various assessments (e.g., IUCN). It is important to note that conservation status may vary by region and that some species fall under categories such as Critically Endangered, Endangered, or Vulnerable. This list is illustrative and not exhaustive."

Table 1. Values of endangered species obtained by taxonomy for the three IA applications. The data are segregated by the main taxonomic groups and are expressed in percentage and standard deviation (between parenthesis). The random values were obtained from the current IUCN database. The Endangered % data are extrapolated from the IUCN database giving the size of the taxonomic group, the species evaluated, and the percentage of species evaluated endangered (see text).

	GPT-4.5% (SD)	DeepSeek-V3% (SD)	Gemini % (SD)	Random Selection from IUCN; % (SD)	Endangered % (Extrapolated from IUCN)
Insect	5.7 (1.5)	2.7 (2.5)	4.5 (0.6)	5.7 (1.2)	36.37
Plant	6.7 (6.1)	6.1 (1.9)	12.3 (2.5)	63.3 (3.1)	29.6
Fungus	0.7 (1.2)	0	4.7 (4.7)	0.3 (0.6)	11.9
Arachnid	1.3 (0.6)	1 (1)	1 (0)	2 (1.4)	6.26
Mollusk	1.7 (0.6)	1 (1)	2 (1)	5.3 (4.2)	4.26
Crustacean	1 (1)	0.7 (1.2)	2.7 (0.6)	1.3 (0.6)	3.84
Fish	6.7 (1.2)	2.7 (2.5)	10.7 (1.2)	7.7 (1.2)	0.95
Amphibian	6.3 (2.1)	5.7 (5.5)	7.3 (2.5)	0.7 (1.2)	0.57
Reptile	10.3 (1.5)	7.7 (6.8)	10.3 (0.6)	3.3 (0.6)	0.39
Cnidarian	1.3 (1.2)	4.1 (3.6)	0.7 (0.6)	0	0.37
Mammal	43.3 (1.5)	53.1 (26.2)	23.8 (5.5)	2.7 (1.2)	0.27
Bird	15 (4.6)	15.3 (13.3)	20 (0)	1.5 (0.7)	0.23
Other	0	0	0	0.7 (1.2)	15.87

Additionally, some of the responses did not refer to specific species (e.g., "orchids," "crayfish," "ferns," or "certain species of beetles").

About the ChatGPT taxonomic Bias Ratio, it showed a wide range (Table 2), from a minimum of −20.1 (insects) to a maximum of 28.2 (mammals). Notable underrepresentations include insects (−20.1), fungi (−9.7), and arachnids (−8.5), while mammals are strongly over-represented (28.2), followed by reptiles (6.5) and fish (5.0).

Regarding the geographical distribution of the mentioned species (Table 3), the region with the highest number of species listed was Asia (30.5), followed by Africa and South America (16.7 and 15.7%, respectively), Europe (10.2%), North America and Oceania (10.1 and 9.5%, respectively), Central America (6.9%), and finally, Antarctica (1%). It is important to note that some species were found in multiple regions, while others could not be precisely located due to the general nature of the response (e.g., "orchids").

Table 2. Taxonomic and geographic Bias Ratio values. Positive values indicate over-representation; negative values indicate underrepresentation.

	Taxonomic Bias Ratio		
	GPT-4.5	**Gemini**	**DeepSeek-V3**
Insect	−20.1	−55.5	−13.4
Plant	−3.8	−6.9	−12.3
Fungus	−9.7	−1.5	na
Arachnid	−8.5	na	−5.3
Mollusk	−4.5	−2.3	−3.3
Crustacean	−2.8	−2.0	−2.7
Fish	5.0	8.4	0.7
Amphibian	2.8	2.7	0.9
Reptile	6.5	17.2	1.1
Cnidarian	0.8	0.5	1.0
Mammal	28.2	4.2	2.0
Bird	3.2	na	1.1
	Geographic Bias Ratio		
	GPT-4.5	**Gemini**	**DeepSeek-V3**
Asia	3.3	−1.4	0.0
Africa	−2.6	−3.3	−3.0
South America	−0.5	−0.7	−3.1
Central America	−2.3	−6.0	−0.4
Oceania	−0.4	0.9	−0.5
Europe	4.2	1.8	0.2
North America	2.3	13.3	0.8
Antarctica	0.9	0.4	0.9

"na" values represent undetermined Bias Ratio.

The geographic Bias Ratio showed the highest positive bias towards Europe (4.2) and Asia (3.3), followed by North America (2.3) and Antarctica (0.9). Negative biases were observed for Africa (−2.6) and Central America (−2.3), with smaller deviations for South America (−0.5) and Oceania (−0.4).

In the case of DeepSeek, the first response included a total of 120 items (including both species and subspecies, Appendix A and Table 1). Among them, 100 were mammals, of which 46 were subspecies of the insular grey fox (*Urocyon littoralis*); of these 46, only 7 different subspecies were listed, 4 of them being listed multiple times. Additionally, the tool listed 10 plant species and 10 coral species. The second and third run included 100 species each; considering the three runs together, the results included 53.1% of mammals (SD = 26.2), 15.3% of birds (SD = 13.3), 7.7% of reptiles (SD = 6.8), 6.1% of plants (SD = 1.9), 5.7% of amphibians (SD = 5.5), 4.1% of cnidarians (SD = 3.6), 2.7% of insects and fish, both with a SD = 2.5, 1% of arachnids and mollusks (SD = 1), and 0.7 crustaceans (SD = 1.2). The application also provided the following statement: "Here is a list of endangered living organisms. This list includes animals, plants, and other organisms facing serious threats to their survival. Some of these species are critically endangered, while others are classified as vulnerable or endangered according to the International Union for Conservation of Nature

(IUCN) and other sources. This list is only a sample of the many species currently at risk of extinction worldwide."

Table 3. Values of endangered species obtained by regions for the three IA applications. The data are segregated by geographic area and expressed in percentages. The random values were obtained from the current IUCN database.

	GPT-4.5% (SD)	DeepSeek-V3% (SD)	Gemini % (SD)	Random Selection from IUCN; % (SD)	Endangered % (IUCN)
Asia	30.5 (1.3)	26.6 (9.5)	21.8 (3.2)	30.3 (4.9)	26.17
Africa	16.7 (2.6)	13.1 (3.4)	17.4 (1.8)	23.7 (2.1)	23.32
South America	15.7 (5.4)	9.5 (2.8)	16.1 (3.2)	18.7 (4)	18.39
Central America	6.9 (2)	9.2 (6.5)	4.6 (1.2)	10.7 (3.2)	11.56
Oceania	9.5 (1.3)	7.2 (5.4)	14.8 (5.6)	9 (1)	9.97
Europe	10.2 (0.9)	7.5 (5.4)	12.5 (3.5)	4.7 (2.3)	6.31
North America	10.1 (2.6)	26.0 (26.5)	12.5 (0.6)	2.7 (1.5)	4.17
Antarctica	1 (1)	1 (1)	0.4 (0.6)	0	0.11

The DeepSeek chatbot showed a comparatively narrower taxonomic Bias Ratio range, with bias ratios ranging from −13.4 (insects) to 2.0 (mammals). It demonstrated underrepresentation in plants (−12.3), and mild over-representation in birds (1.1) and reptiles (1.1).

Regarding distribution, 26,6% of the mentioned species were from Asia and 26.0 were from North America, 13.1% were from Africa, 9.5% from South America, 9.2% from Central America, 7.5% from Europe, 7.2% from Oceania, and 1% from Antarctica (Table 3).

The geographic Bias Ratio presented the narrowest range of geographic bias, with values spanning from −3.1 in South America to 0.9 in Antarctica. It showed near-neutral bias for most regions (e.g., Asia: 0.0, Europe: 0.2, North America: 0.8), although some underrepresentation appeared for Africa (−3.0) and South America (−3.1).

The Gemini chatbot mentioned 100 species in each query: 23.8 mammals (SD = 5.5) and 20 bird species (SD = 0), 12.3 species of plants (SD = 2.5), 10.7 species of fishes (SD = 1.2), 10.3 species of reptiles (SD = 0.6), 7.3 species of amphibians (SD = 2.5), 4.7 species of fungus (SD = 4.7), and a few species of invertebrates (4.5 insects (0.6), 2 mollusks (SD = 1), 2.7 crustaceans (0.6), 1 arachnid (SD = 0), and 0.7 cnidarians (SD = 0.6)) (Appendix A and Table 1). Gemini also provided the following statement: "It's important to remember that this list is just a sample, and there are many more species in danger of extinction around the world. Biodiversity conservation is crucial to the balance of our planet."

In this case, the taxonomic Bias Ratio showed the most extreme bias overall, with a minimum of −55.5 (insects) and a maximum of 17.2 (reptiles). Underrepresentation was also observed in plants (−6.9), mollusks (−2.3), and amphibians (−2.7), while mammals (4.2) and fish (8.4) were over-represented. Data for arachnids and birds were undetermined (na).

Geographically, these species are distributed as follows: 21.8% of the species were native to Asia, 17.4% to Africa, 16.1% to South America, 14.8% to Oceania, 12,5% to North America and Europe, and 4.6% to Central America.

Regarding the geographic Bias Ratio, Gemini exhibited the most extreme geographic bias overall, ranging from −6.0 in Central America to 13.3 in North America. Other regions showing positive bias include Europe (1.8), Oceania (0.9), and Antarctica (0.4), while negative values were found for Africa (−3.3), Asia (−1.4), and South America (−0.7).

Regarding the data obtained from the International Union for Conservation of Nature (IUCN), the estimated percentages of endangered species vary significantly by taxonomic group, ranging from 36.37% of the total for insects to 0.23% for birds (detailed values can be found in Table 1).

Regarding geographical distribution, the total number of assessed species in each of the regions considered was also obtained from the IUCN, and the corresponding percentage of endangered species in each area was calculated (Table 3); the values ranged from 26.17% of endangered species found in Asia to 4.17% of the endangered species found in North America.

The results for the taxonomic Magnitude Error Ratio ranged from 11.3 (Gemini) to 13.9 (DeepSeek), and an intermediate value for ChatGPT (13.0). Geographic Magnitude Error Ratio: Given the Geographic Magnitude Error Ratio, DeepSeek also showed the highest value, with 7.7, while Gemini had a moderate Geographic Magnitude Error Ratio (5.0), and ChatGPT showed the lowest value (4.0).

The results of the random selection of species from the IUCN endangered species database showed taxonomic values of 63.3% (SD = 3.1) for plants, 7.7% (SD = 1.2) for fish, 7.3% (SD = 2.5) for amphibians, 5.7% (SD = 1.2) for insects, 5.3% (SD = 4.2) for mollusks, 3.3% (SD = 0.6) for reptiles, 2.7% (SD = 1.2) for mammals, 2% (SD = 1.4) for arachnids, 1.5% (SD = 0.7) for birds, 1.3% (SD = 0.6) for crustaceans, 0.7% (SD = 1.2) for the Other category, and 0.3% (SD = 0.6) for fungi. The cnidarian group was not represented. Regarding the geographical results, values of 30.3% (SD = 4.9) were obtained for Asia, 23.7% (SD = 2.1) for Africa, 18.7% (SD = 4) for South America, 10.7% (SD = 3.2) for Central America, 9% (SD = 1) for Oceania, 4.7% (SD = 2.3) for Europe and 2.7% (SD = 1.5) for North America, Antarctica did not obtain results. It is important to note that these results are based on the IUCN Endangered Species Database, and these values do not take into account the percentage of species assessed in each group.

4. Discussion

4.1. Bias in the Results of the AI

At present, AI applications are ubiquitous in both daily life and educational environments ([42], among many others); however, despite their numerous benefits and utilities, the results of this study suggest that caution should be exercised when using them, since the problems of their use are not limited to ethics, as is often highlighted. Both taxonomic and geographic bias have the potential to generate significant issues with teaching effectiveness and the self-taught capacity of students. In both instances, the absence of fundamental technical training can serve as a catalyst for the emergence of these biases (e.g., plant blindness) and perpetuate the associated challenges. This phenomenon has been previously observed in several domains [43].

4.1.1. Taxonomic Bias

With regard to the field of biology and the study of biodiversity, the human predilection for animals over other groups of living organisms, such as plants, fungi, and microorganisms, is a well-documented phenomenon [44]. This tendency, termed "zoocentrism," signifies a cultural and psychological predisposition to assign greater value to animals than other forms of life. This bias influences not only daily interactions but also scientific research, environmental legislation (which tends to prioritize conservation efforts disproportionately on animals—particularly on charismatic species such as mammals and birds [45–47]), and education [27,48]. The findings of this study demonstrate that artificial intelligence applications also exhibit this phenomenon, which, as would be expected, reflect societal tendencies.

Furthermore, it is imperative to consider factors other than zoocentrism. As demonstrated in the results, both AI applications manifest a marked bias, not only towards animals but specifically towards mammals [47]. This bias becomes even more apparent when compared to objective data from the IUCN, which indicates that mammals represent a relatively small taxonomic group, especially among species classified as endangered. This phenomenon is also part of a well-documented cognitive bias known as Plant Blindness, or more recently, Plant Awareness Disparity [49]. This term describes the human tendency to overlook or undervalue the ecological significance of plants [50]. One contributing factor is the perception of plants as static, silent, and less interactive than animals [51]. Intriguingly, a juxtaposition of the IUCN data with the findings derived from AI applications reveals that plants do not constitute the most underrepresented group. As other authors have stated in similar studies, fungi, insects, and arachnids are even more significantly overlooked [52]. Despite the assertions of AI models that their lists encompass a broad taxonomic range, the outcomes evidently do not align with scientific reality. The paucity of species mentioned in the article makes the breakdown of the data impractical.

Regarding the exclusion of fungi, this is most likely a consequence of the ambiguity surrounding their classification. Fungi do not conform easily to the conventional categories of "animal" or "plant". This has resulted in a lack of recognition concerning their ecological importance, including their role in decomposition, as well as their significance in medicine and food production [52]. Given that no fungal species were included in one of the three AI-generated lists (and in GTP-4.5 the mean value is 0.7%) and considering that fungi are rarely considered in discussions of endangered species, it is unsurprising that this bias remains largely unchallenged.

As for insects, despite the similarities between the AI results (specifically with ChatGPT) and the random selection, their underrepresentation is particularly concerning. This group exhibits the highest negative taxonomic Bias Ratio, which means a great underrepresentation in comparison with the IUCN data. This is especially shocking considering that they represent the most diverse group within the animal kingdom [53] and the fact that invertebrates—and insects in particular—exhibit higher rates of extinction and threatened species than more well-known taxa [54]. Furthermore, insects are recognized as being of paramount importance to human survival, given their pivotal role in agriculture, human health, and natural resources, among other aspects [55]. The observed underrepresentation may be attributed to society's negative perception of this group, evoking responses such as fear or disgust more than other types of animals [56,57]. This is probably due to factors such as their unpredictable movements, their non-human morphology, or their ability, in some cases, of biting, stinging, and transmitting infection or disease [58,59].

4.1.2. Geographic Bias

In addition to the taxonomic classification of organisms, their geographical origin was also taken into account in order to study the potential existence of bias. In the case of ChatGPT, an underestimation (as a representation of taxa lower than their % of endangered species compared to the world total data) of Africa and Central America has been observed, while other continents such as Asia, North America and, especially, Europe show a notable overestimation. This phenomenon can be attributed to the historical and cultural influence of Western civilization [60], particularly in North America, which is also the geographical origin of the company developing ChatGPT. Indeed, other studies conducted with ChatGPT in various fields (e.g., education, culture) have demonstrated similar biases [61,62]. A similar trend was observed for Gemini, also of North American origin, with its list underestimating areas such as Asia, Africa, and Central America, and significantly overestimating Europe, North America, and Oceania. The findings obtained by these two tools also appear to suggest an influence of societal tendencies on the geographical variable. In the case of DeepSeek, a clear underrepresentation of Africa and

South America can be mentioned. The variation in the different runs performed makes it difficult to decide if the representation in the other areas is fair or not. Moreover, the results are difficult to explain in terms of taxonomy and origin and are completely conditioned by the presence of seven subspecies (repeated 46 times in the first run performed with DeepSeek) of the same North American fox species (*Urocyon littoralis*). This finding appears to lack practical relevance, as the prompts provided were unambiguous in requesting the specified taxonomic category (species), and it is impractical to include subspecies within an extensive list such as that of endangered living beings. The most plausible explanation for this occurrence is the lack of internal mechanisms to ensure uniqueness unless explicitly requested; models do not always have the memory to remove duplicates, especially with long lists (>20 items) [63,64].

4.1.3. Biases and AI Applications

The statistical analyses conducted in this study have shown that the widest ranges for both taxonomic and geographic Bias Ratio were observed in Gemini, with broad differences between the most over- and underrepresented groups and areas, respectively. However, globally (i.e., for the whole set of taxonomic groups and/or geographic areas) the greatest bias, measured through the Magnitude Error Ratio, was observed for DeepSeek both from a taxonomic and geographic perspective, making it “the most biased” AI application in our study.

In any case, the results obtained, although simple, clearly show that the answers generated by generative artificial intelligence systems can reflect and amplify pre-existing biases (in this case both geographic and taxonomic) in the data they have been trained on (e.g., [65,66]), this situation was already detected in searches on regular search engines before the appearance of artificial intelligence chats [27]. The AI models rely on massive databases harvested mostly from the internet, which includes both academic sources and a large amount of unverified, popular, or socially biased content [67–69]. Since the majority of the corpus comes from data available online until 2024, there is a real risk that the models not only reproduce stereotypes, inequalities, and/or taxonomic/geographic bias, but reinforce them through a cumulative effect each time the system generates similar content based on previous interactions [70,71].

Added to this is the mechanism of user reinforcement, whereby popular or most accepted answers tend to be prioritized by the system, further reinforcing dominant biases [72]. Although the user can explicitly influence content through the use of prompts, these can also induce biased responses if they contain implicit assumptions or if the AI fails to recognize taxonomic, geographic, or social ambiguities [73].

Furthermore, each AI system implements its own filters, alignment models, and architectures, resulting in differences in the type and degree of bias across platforms. In this regard, probably the best known AI chatbot is ChatGPT, whose training process consists of four well-known steps [74]; it starts by training the model on large amounts of unlabeled data from different internet databases, thus allowing the learning of general patterns and data relations; after that, the pre-trained model is fine-tuned by using a small dataset, linked to a specific task, thus becoming more efficient and appropriate for it. This step is mainly performed by human AI trainers, who also assess the accuracy and quality of responses in the following step by assigning scores to each pair of “prompt-response”, prior to the final optimization process. The fact that the GPT model is pre-trained on presumably non-cleaned/refined data, together with the human dependency for fine-tuning and model training, increases the risk of obtaining wrong, biased, or inaccurate responses by this tool [74]. In the case of Gemini, a comparative study with ChatGPT was conducted by [75], who concluded that the model type of Gemini (Multimodal Language Model), together with its particular architecture (which, for example, includes Retrieval-Augmented Generation (RAG)) and the use of datasets curated by Google allow the production of more precise and informative responses. However, these features also seem to limit the creativity and conversational flow of the outputs and are not capable of avoiding the biased responses which derive from the human-conditioned training data mentioned for ChatGPT. Our results reveal the same weakness for the case of DeepSeek-V3, even though it has been found to be a high-performance tool that offers accurate responses at lower input costs than other chatbots [76]. The same study also concluded that the efficiency of this and other AI tools (including ChatGPT and Gemini) depends on the specific task requested by the user, which strongly limits the conclusions we can draw in our particular work where, as we mentioned before, DeepSeek offered the highest bias levels.

Taking into account the complexity of the models and the different architectures, understanding how these models are trained, how they prioritize responses, and what data they rely on is key to critically evaluating their use in educational, scientific, or social contexts.

4.2. AI Implications for Biodiversity Education

The findings of this study hint the challenges associated with the utilization of AI applications for self-directed learning and for non-specialist teachers. Educators who rely on these tools for classroom instruction may also encounter difficulties due to their inherent biases [44,77]. While AI applications offer significant benefits, they may also reinforce existing biases, particularly the disproportionate emphasis on mammals, rather than contributing to their correction. Consequently, these technologies still do not seem to be an optimal way to meet the biodiversity-related challenges outlined in the previously mentioned Sustainable Development Goals (SDGs), particularly regarding the conservation of endangered species, where biases may be maintained, both geographical and taxonomic. This is particularly salient in the context of Spain, where the recurrent presence of biodiversity in the educational curriculum has been previously highlighted [38–41]. A particularly problematic scenario emerges in the context of Primary Education, as educators at this level are not equipped with specialized training in scientific disciplines. This may result in a heightened inclination to rely on AI tools for the preparation of their lessons.

During Primary Education, complex content is already addressed, such as the identification and classification of living beings, the human relationship with ecosystems, the relevance of biodiversity, eco-social responsibility, or climate change. This can pose a challenge for those teachers less familiar with these topics. This problem is hypothesized to be less acute in the Early Childhood Education stage, due to the greater simplicity of its content, and in the Secondary and Baccalaureate stages, where teachers are expected to have specific training to access their job position. However, studies have revealed an increasing inclination towards AI among teachers at these levels [78], and the greater autonomy afforded to students in completing their tasks may also influence their utilization of AI. The findings of this study suggest that these trends could potentially contribute to the perpetuation of social trends concerning biodiversity, particularly with regard to species at risk of extinction, from both taxonomic and geographical perspectives. There is a lack of studies applied to these groups in which the teachers themselves are the focus; it is necessary to analyze the variations in the biases present to identify the depth of the problem and propose possible solutions.

5. Conclusions and Limitations

To summarize, the findings of this study demonstrate that AI applications not only replicate ethical biases, but also taxonomic and geographical biases, which have the potential to impede educational effectiveness and self-directed learning. The dearth of rudimentary technical training among pedagogues and pupils can intensify these biases, perpetuating issues such as zoocentrism and plant blindness. The prevailing cultural inclination towards the preference for animals, particularly mammals, at the expense of other organisms such as plants, fungi, insects, and microorganisms, is a salient concern. This bias is perpetuated by the predominance of artificial intelligence in various fields, despite the ecological significance of these other organisms. This imbalance is incongruent with scientific reality, as evidenced by IUCN data, and contributes to a distorted perspective of biodiversity in education and conservation. Furthermore, the geographical bias is indicative of the influence of sociocultural trends and the geographic origin of the developing companies, thereby limiting a balanced global perspective.

The integration of AI in educational settings, particularly at primary school levels where educators may not possess specialized scientific training, can perpetuate stereotypes rather than rectifying them. This hinders the achievement of the Sustainable Development Goals (SDGs) related to biodiversity and perpetuates a biased view of endangered species. To mitigate these biases, it is crucial to enhance the training of AI models with rigorous scientific data and to promote critical teacher training that encourages the responsible use of these tools.

Further research is required to develop solutions that have a tangible impact on teachers at these levels. It is also necessary to evaluate how learning models correct these biases, in the event that such progress occurs, and how other (and new) models reflect them.

Author Contributions: Conceptualization, J.B.-P. and L.d.P.N.; methodology, J.B.-P. and L.d.P.N.; formal analysis, J.B.-P., L.d.P.N., and S.Q.-A.; investigation, J.B.-P. and L.d.P.N.; data curation, J.B.-P., L.d.P.N., and A.M.G.; writing—original draft preparation, J.B.-P. and L.d.P.N.; writing—review and editing, all the authors; visualization, J.B.-P. and L.d.P.N.; supervision, J.D.-I. and R.R.-T. All authors have read and agreed to the published version of the manuscript.

Funding: This study has been developed within the framework of the research project TED2021-130300B-C21 funded by the Ministry of Science and Innovation.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Acknowledgments: Taking into account that it forms the basis for this study, the authors have used IA tools to obtain data (see text). The authors have reviewed and edited the output and take full responsibility for the content of this publication.

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

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
SDG	Sustainable Development Goals
IUCN	International Union for Conservation of Nature

Appendix A

Table A1. Example of the full list of the species provided by the IA chatbots (first run).

Nº	GPT-4.5	DeepSeek-V3	Gemini (v.2025)
1	Harlequin Frog	Sumatran tiger	Polar Bear
2	Panama Golden Frog	Mountain gorilla	*Xerocomellus porosporus*
3	Central American Glass Frog	Bornean orangutan	Asian Elephant
4	Darwin's Frog	Sumatran Orangutan	Western Chimpanzee
5	Woodland Salamander	Javan rhinoceros	Darwin's Fox
6	European Woodland Salamander	Black rhinoceros	North Atlantic Right Whale
7	Tiger Salamander	Sumatran Elephant	Mexican Fishing Bat
8	Scorpion Endemic to Certain Islands	Snow leopard	Iberian Lynx
9	Antarctic Albatross	Iberian lynx	Brown-headed Spider Monkey
10	Laysan Albatross	Polar bear	Tibetan Bear
11	Black Stilt	Giant panda	Irrawaddy River Dolphin
12	Philippine Blue-winged Cockatoo	Chinese pangolin	Javan Rhinoceros
13	Moluccan Cockatoo	Sunda Pangolin	Omiltemi Rabbit
14	California Condor	Vaquita	Venezuelan Red Siskin
15	Cock-of-the-Rock	North Atlantic Right Whale	Kakapo
16	Spix's Macaw	Blue Whale	California Condor
17	Northern Bald Ibis	Leatherback Sea Turtle	Northern Bald Ibis
18	Kakapo	Hawksbill Sea Turtle	Ivory-billed Albatross
19	Okarito Kiwi	Green Sea Turtle	Amsterdam Albatross
20	Storm Petrel	California Condor	Helmeted Hornbill
21	Darwin's Finch	Philippine Eagle	Spix's Macaw
22	Bannerman's Turaco	Hyacinth Macaw	North Island Brown Kiwi
23	Crayfish	Scarlet Macaw	Amur Leopard
24	Franklin's Bumblebee	Tanimbar Cockatoo	Galapagos Penguin
25	Stag Beetle	Northern White Rhinoceros	Bearded Vulture
26	Blue Butterfly Morpho	Sumatran rhinoceros	Red-cockaded Woodpecker
27	Karner butterfly	Malayan tapir	Balearic Shearwater
28	Monarch butterfly	Mountain tapir	Albert's Lyrebird
29	Axolotl	Baird's tapir	Capercaillie
30	Blue whale	Amazonian tapir	Nicobar Pigeon
31	North Atlantic right whale	Jaguar	Mauritius Parakeet
32	European bison	Red panda bear	Black-bellied Sandgrouse
33	Bonobo	Spectacled bear	Shoebill
34	Common chimpanzee	Sun bear	Mountain Gorilla
35	Amazon river dolphin	Sloth bear	Floreana Thrush
36	African forest elephant	Red wolf	Hawksbill Turtle
37	Asian elephant	Mexican Grey wolf	Malagasy Tortoise
38	Gharial	Northern lynx	Orinoco Crocodile
39	Mountain gorilla	Canadian lynx	Tuatara
40	Indri	Eurasian lynx	Round Island Python
41	Greater bamboo lemur	African lion	Vietnamese Box Turtle
42	Bamboo lemur	Asiatic lion	Tarzan's Chameleon
43	Mantilla lemur	Cheetah	Anegada Iguana
44	Crowned skull lemur	Asiatic cheetah	San Francisco Garter Snake
45	Gray mouse lemur	Striped hyena	Sumatran Tiger
46	Ruffed lemur	Brown hyena	Howe Island Giant Gecko
47	Sand lemur	Spotted hyena	Axolotl
48	Asiatic lion	Darwin's Fox	Golden Poison Frog
49	Amur leopard	Sierra Nevada red Fox	Carriqui Harlequin Toad
50	Snow leopard	Arctic Fox	Manduriacu glass frog
51	Iberian lynx	Argentine Grey Fox	Chinese giant salamander
52	Ethiopian wolf	Patagonian Grey Fox	El Tambor marsupial frog
53	Mexican wolf	Pampas Grey Fox	Betic midwife toad

Table A1. *Cont.*

Nº	GPT-4.5	DeepSeek-V3	Gemini (v.2025)
54	Barbary macaque	Island Grey Fox	Sagalla caecilians
55	Northeastern howler monkey	Channel Islands Grey Fox	Table Mountain ghost frog
56	Bornean orangutan	San Miguel Islands Grey Fox	Chinese pangolin
57	Sumatran orangutan	Santa Rosa Islands Grey Fox	Apennine fire-bellied toad
58	Giant panda	Santa Cruz Islands Grey Fox	Chinese sturgeon
59	Pangolin	San Clemente Islands Grey Fox	Freshwater sawfish
60	Palm Pangolin	San Nicolas Islands Grey Fox	Giant grouper
61	African Wild Dog	San Miguel Islands Grey Fox	Great white shark
62	Javan Rhinoceros	Santa Catalina Islands Grey Fox	Atlantic bluefin tuna
63	Sumatran Rhinoceros	San Clemente Islands Grey Fox	Australian lungfish
64	Black Rhinoceros	San Nicolas Islands Grey Fox	European eel
65	Saola	San Miguel Islands Grey Fox	Mekong giant catfish
66	Verreaux's Sifaka	Santa Catalina Islands Grey Fox	Danube salmon
67	Malayan Tapir	San Clemente Islands Grey Fox	Blue-eyed black lemur
68	Bengal Tiger	San Nicolas Islands Grey Fox	Baxter Springs trout
69	Sumatran Tiger	San Miguel Islands Grey Fox	Lord Howe Island land snail
70	Red Uakari	Santa Catalina Islands Grey Fox	Swellendam crayfish
71	Vaquita	San Clemente Islands Grey Fox	Queen Alexandra birdwing butterfly
72	Chinook (Pacific Salmon)	San Nicolas Islands Grey Fox	Giant Wallace's bee
73	Atlantic Sturgeon	San Miguel Islands Grey Fox	Stag beetle Kempsey
74	Giant Manta Ray	Santa Catalina Islands Grey Fox	Maratus elephans peacock spider
75	Asian Catfish	San Clemente Islands Grey Fox	Staghorn coral
76	Mekong Catfish	San Nicolas Islands Grey Fox	Gulf Coast freshwater mussel
77	Napoleon Wrasse	San Miguel Islands Grey Fox	Murray freshwater lobster
78	Fraser Fir	Santa Catalina Islands Grey Fox	Saola
79	Widdringtonia Cedar	San Clemente Islands Grey Fox	Lord Howe Island tree cricket
80	Cedar of Lebanon	San Nicolas Islands Grey Fox	Coast redwood
81	*Cyanea micronesica*	San Miguel Islands Grey Fox	Wollemia
82	Socotra Dragon Tree	Santa Catalina Islands Grey Fox	Lord Howe pine
83	Tree Fern of Certain Rainforests	San Clemente Islands Grey Fox	Jellyfish tree
84	European Elm	San Nicolas Islands Grey Fox	Victoria giant water lily
85	Wild Orchid	San Miguel Islands Grey Fox	*Rafflesia arnoldii*
86	Madagascar Palm	Santa Catalina Islands Grey Fox	Venus flytrap
87	*PuyarRaimondii*	San Clemente Islands Grey Fox	Jade tree
88	*Rafflesia arnoldii*	San Nicolas Islands Grey Fox	Ghost orchid
89	Wollemia Cuban alligator	San Miguel Islands Grey Fox	Tapanuli orangutan
90	Orinoco alligator	Santa Catalina Islands Grey Fox	Chilean pine
91	Philippine crocodile	San Clemente Islands Grey Fox	*Amanita liquii*
92	Komodo dragon	San Nicolas Islands Grey Fox	*Boletus regineus*
93	Ricord's iguana	San Miguel Islands Grey Fox	*Clavaria zollingeri*
94	Caribbean iguana	Santa Catalina Islands Grey Fox	*Geastrum britannicum*
95	Hawksbill turtle	San Clemente Islands Grey Fox	*Hygrophorus erubescens*
96	Mekong river turtle	San Nicolas Islands Grey Fox	*Mycena interrupta*
97	Leatherback turtle	San Miguel Islands Grey Fox	*Ramaria Botrytis*
98	Oryctes	Santa Catalina Islands Grey Fox	*Sarcosoma globosum*
99	Northeastern howler monkey	San Clemente Islands Grey Fox	*Tricholoma caligatum*
100	Some Beetle species	San Nicolas Islands Grey Fox	Vaquita
101		Ghost orchid	
102		Hawaiian passionflower	
103		Copal resin tree	
104		Wollemi Pine	
105		Giant sequoia	

Table A1. *Cont.*

Nº	GPT-4.5	DeepSeek-V3	Gemini (v.2025)
106		Redwood	
107		Cinchona tree	
108		Cinnamon tree	
109		Tree Vanilla	
110		Nutmeg tree	
111		Elkhorn coral	
112		Brain coral	
113		Star coral	
114		Fire coral	
115		Mushroom coral	
116		Finger coral	
117		Table coral	
118		Column coral	
119		Pillar coral	
120		Brain coral	

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