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Citizen Science Apps in a Higher Education Botany Course: Data Quality and Learning Effects

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Abstract: Although species identification apps are becoming increasingly popular in citizen science, they are hardly used in university courses on biodiversity literacy. In this study, we investigated whether the use of a plant identification app by students provides similar data quality to the use of scientific keys and whether it improves the process of knowledge acquisition. To this end, dry grassland plots were monitored in Berlin to record plant species diversity by two groups, Bachelor's and Master's students, with different experience in plant identification. Both groups were asked to survey the plots once in April and once in June, the first time with the app Pl@ntNet, and the second time with scientific keys commonly used in teaching. To evaluate their performance and the respective tools, the results were compared with those of experts from the same plots. The students identified, on average, only half of the plants per plot and misidentified or failed to identify a high proportion of species compared with the experts, regardless of the identification tool. In addition, the number of plants identified that did not occur at all in the region or in the considered habitat was alarmingly high. In view of the worldwide loss of species knowledge, it is becoming clear that apps can trigger the study of a species group, but do not solve the fundamental problem of neglecting biodiversity courses at universities.

Keywords: species literacy; biodiversity literacy; citizen science; artificial intelligence; higher education

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1. Introduction

Citizen science (CS), recently also discussed under the name community science [1], is the active involvement of the public in the whole or parts of the research process. The bipartite promise of CS for science and society is that CS can both contribute to science, for example, by providing valuable scientific data, and increase the knowledge and the social capital of participants from the public. The scientific contribution of CS programs, with data quality studies being in the foreground, has been the focus of the scientific community for a long time. Due to the advent of smartphone and internet technologies [2], especially in biodiversity-related programs, the amount of data collected by amateur naturalists has rapidly increased and, with it, investigations on the usability of CS data. Particularly in projects appropriate for the masses, like eBird, eButterfly, or Mückenatlas, bias originates from the diverse recording behavior and level of identification skills of the citizen scientists [3–5]. Over the last few years, strategies to mitigate bias and to increase data quality have been developed. These strategies target either project design and protocol [6–8] or statistical analysis [9–12], and are now widely used by the scientific community, such that there is already talk of CS becoming mainstream [13].

The recognition of the direct dependence of CS biodiversity data on the observation performance of the citizen scientists led to the research focus of the science of citizen science slowly shifting from the data aspect to the participants—also in the light of the second part of the CS promise of benefitting society. Expectations are high that public involvement will result in better dialogue between the public and scientists, a research agenda that is more relevant to the public, a better understanding of scientific methods and timeframes, an increase in scientific literacy, and, with regard to biodiversity-related projects, raised awareness of environmental issues or changes in attitudes or behavior [14]. In order to investigate these expectations, studies have been conducted on participants of biodiversity-related programs, focusing on their motivation [15–17], their behavior [18–20], and their demographic background [21,22].

Of growing interest in recent years has also been the question of the educational power of CS and whether or what people get out of their participation (e.g., an increase in knowledge or skills). Most studies report gains in knowledge and skills related to the project topics and, moreover, improved quality of life [21,23–26], but less so in relation to the understanding of scientific processes [27]. However, most studies relate to informal learning environments. The literature on the implementation of CS in formal education is sparse; hence, little is known about the integration practices and beneficial outcomes of applying CS in higher education.

A review by Vance-Chalcraft and colleagues [28] found, in 15 papers and 79 instructor survey responses, that CS projects are mostly used in smaller classes (fewer than 30 students) for collecting and submitting data for ecological and environmental studies. They reported that students benefit from positive feelings toward being engaged in CS, improved scientific practices, and increased knowledge and engagement. Paradise and Bartkovich [29] found that the majority of students in an undergraduate entomology course perceived CS tools as helpful for identifying insect specimens and that their comprehension and valuation of biodiversity improved, as well as their species literacy.

The challenges recognized are the different levels of engagement with CS, logistical and data quality problems, and difficulties when referencing the scientific literature and other sources [28,30,31]. Interestingly, the COVID-19 pandemic facilitated or even accelerated the inclusion of CS approaches and tools in many higher education courses to engage students working from home [28]. For example, free apps were used in some courses to investigate specific research questions [32–34], there was a shift toward CS methods and tools for biodiversity monitoring and literacy courses [35,36], and with BotanizeR [37], even an R package was developed to teach botany skills remotely.

The successful application of CS in biodiversity and species literacy classes is of particular interest, given the low knowledge about native species among students [38,39], also in Germany, be they plants [40], vertebrates [41], or insects [42,43]. The same trend is measurable among adults, who are becoming more and more getting disconnected from nature [44], and lay experts, for example, hobby naturalists, who overage without a new generation coming along [45]. At the same time, professional experts from institutional science are becoming older and fewer [46,47], with the same problem of replacement by younger researchers. This is an extremely negative development in the face of the biodiversity crisis [48], in which taxonomic expertise is urgently needed to assess global biodiversity data, which can only be sufficiently collected by involving the entire public [49]. Scientists can only cover a certain number of places and only have the resources to do so. The idea of increasing species literacy and, therefore, also of laying the foundation for civic engagement through CS in higher education is highly relevant to a future sustainable society.

CS platforms and apps that support species observation and identification (e.g., iNaturalist) have found their way into higher education in North American colleges and universities [50,51], because these easy-to-use apps are both adequate for first and advanced users from the digital native generations [31]. In contrast, mastering the skills to identify species with field guides and scientific literature is challenging and takes years, if not decades. The process of using scientific identification keys and the terminology knowledge it requires can make frustrated students reluctant to enter the field of taxonomy in the first place [52]. To overcome this initial barrier, image-based species identification via deep learning for plants, fungi, insects, and other taxa has constantly improved in accuracy and application area [53–55]. Corresponding smartphone and web apps have become very practical for beginners and advanced users, and are growing in number. However, a test with nine apps for plant identification showed very different results in the performance of the respective tool, so incorrect determinations can occur, especially with beginners, and thus lead to a counterproductive learning effect [56].

It is slow for apps to find their way into university seminars and courses, and whether they actually help to build species literacy in higher education—and provide useful data in the process—has not yet been sufficiently investigated. In this comparative analysis, Bachelor's and Master's students with different levels of experience and knowledge in plant identification recorded plant species diversity in urban dry grassland sites. To assess the students' identification accuracy, their results were compared with those of expert botanist collections for the same plots. The students worked alternating with both a plant-specific identification app (Pl@ntNet) and standard identification keys, and before and after classical botany identification courses. The study aims to answer the following questions:

1. Does the use of a plant identification app by students provide useful data in comparison with conventional species identification resources (field guides, scientific literature)?
2. Does a plant identification app enhance the process of knowledge acquisition for species identification?

2. Methodology

2.1. Study Context

The long tradition of the Technische Universität Berlin in plant ecology, especially in the context of urban ecology, is reflected in the botany courses offered by the university. Within two separate courses during the COVID-19 pandemic in 2021, two groups of students from the study programs Ecology and Environmental Planning (Bachelor's) and Urban Ecosystem Sciences (Master's conducted rounds of vegetation surveys as part of their training in botany. As an innovative element, the Pl@ntNet app for plant identification was employed for the first time in both of these courses for mapping flora in the field. In order to evaluate its effectiveness, it was only applied in the first round of vegetation surveys, and in the second round, the scientific keys by Jäger and Rothmaler [57,58] were used—both classic field guides for teaching. To assess the results from the two survey rounds and to compare the performance of both the identification tools and the differently experienced student groups, their observations were compared with those of an expert botanist. In the following, we provide background information on the tools used for plant identification, the student participants and the corresponding university courses, the data collection protocols of the students and the expert, and the data analysis methods.

2.1.1. Pl@ntNet App

One of the earliest and most widely used apps dedicated to plant species identification is Pl@ntNet (https://plantnet.org/en/ (accessed on 20 April 2022)), referred to as PlantNet or simply the App in the following. It was developed in France in 2009, and 320 million identification requests have since been identified via the App. PlantNet is among the most accomplished plant identification apps on the market [56] and performs especially well when provided with more than one picture of the same plant—a feature that only a few other apps contain. It is also free to use, even for non-registered users, and works in two steps. First, one or more images of the same plant are uploaded, labeled leaf, flower, etc., and the artificial intelligence provides a list of plant species candidates. Each candidate comes with a score that can be interpreted, like confidence levels or probabilities. According to the programmers of the App, the accuracy measured for the first five species suggested for each image ranges from 89% to 63%, depending on the difficulty of the tested datasets [59]. If the user is registered, in the second step, the picture can be saved with the selected species suggestion, which is then confirmed or substituted with the right species name by the PlantNet community. In return, the images labeled with the correct species name are regularly fed back into the training database to improve the algorithm.

2.1.2. Scientific Keys for Plant Determination

The “Exkursionsflora von Deutschland” (excursion flora of Germany) is a classic guide to plant identification and, along with another popular book [60], the most commonly used textbook in botany courses. The book is already in its 22nd edition at the time of writing and works, like many other scientific identification books, via a step-by-step determination from the main groups to the family and genus and then to the species via a dichotomous key system with numbers. Although the book provides many illustrations, an extensive glossary, and a very good index, it can be a challenge for beginners, especially in field work, with its several hundred pages (depending on the edition).

2.2. Study Participants

2.2.1. Students

Both Bachelor’s and Master’s students participated in the study within their two differently designed botany courses in the summer semester of 2021. The Master’s course was offered online due to social contact restrictions during the COVID-19 pandemic. In addition to learning plant identification, the course aimed to provide a broader understanding of urban habitats and their monitoring, and of plants in the urban environment in general. Twenty students were enrolled at the beginning, and nineteen completed the program. These Master’s students also had previous experience acquired in botanical identification exercises. In addition to the theoretical content, an important part of the course was the application of knowledge during vegetation surveys in the field. The survey protocol (2.3.2) was explained in detail in a course handout. The use of the PlantNet app was not explained in this handout, but reference was made to the corresponding website where all the necessary information was summarized and students were expected to acquire the knowledge on their own. Students received a course script and a video on how to use the scientific identification key. However, they were asked to provide feedback and to contact the instructor with questions if they were unclear. In addition, fixed office hours and a forum on ISIS (Information System for Instructors and Students) were offered to answer questions, but both were hardly used. All materials were provided through ISIS.

In the Bachelor’s course, the same instructions for conducting the vegetation survey were given. Similarly, 20 students enrolled, but the course structure was different compared with that of the Master’s class. Instead of a continuous course sequence, there was a block unit between the first and the second vegetation surveys in which the basics of plant identification were taught. As a result, the students approached the first and second rounds of data collection with different levels of knowledge. However, in contrast with the Master’s students, when entering the course, these Bachelor’s students were at the beginning of their second semester, with no previous experience in vegetation science or botany.

2.2.2. Experts

Due to contact restrictions during the COVID-19 pandemic, botanical identification exercises could not take place as usual at the university. This gave rise to the idea of qualitatively testing the practical use of identification apps in teaching by using a data set of botany experts as a reference, which had been recorded the year before as part of a research project. In our case, the expert in botany is the co-author B.S., who is one of the leading botanists for the Berlin and Brandenburg region (e.g., [61]) and has authored key baseline studies, such as the Red List [62] and the atlas of Berlin’s flora [63].

2.3. Data Collection

2.3.1. Study Sites

The study area was Berlin, the largest city in Germany, with a surface area of 891 km^2 and a population of 3.8 million inhabitants in 2021. About 59% of Berlin is developed with built-up areas and streets, whereas green and blue spaces cover 41%, including forests (18%) and grassland (5%) [64]. We selected 20 study sites from the dry grassland plots that were established within the CityScapeLab Berlin, an experimental research platform to untangle urbanization's effects on biodiversity and biotic interactions [65]. These sites extend across the outskirts of Berlin and were developed on sandy soils on ruderal sites, on roadsides, in forest clearings, or near forests. They are extensively managed by mowing a maximum of once per year, without fertilization or irrigation. All patches belong to the same phytosociological vegetation type (Sedo–Scleranthetea communities [66]). Each site encompasses one randomly located plot with a standardized size (4 m × 4 m), which was calibrated with GPS and marked with four colored marker points to facilitate recognition during the different vegetation periods.

2.3.2. Task Description and Vegetation Surveys

Students and experts followed the Braun–Blanquet method [67] for vegetation mapping. All participants recorded the species community and species richness, and assessed the degree of coverage of all and single species on the 4 m × 4 m plot at the site.

The students worked alone or in teams of two and were responsible for one study plot. The students organized themselves in a way that every plot was only surveyed by one team or individual, so that no duplication occurred. In both courses, the students surveyed their dedicated plot(s) twice, once in April and once in June. In the first round in April, they were only allowed to use the PlantNet app and internet sources (in the analysis referred to as Bachelor I and Master I); in the second round in June, they carried out the survey with scientific literature and expert field guides (Bachelor II and Master II). The expert also surveyed the 20 sites and corresponding 20 plots in 2020 two times: once between April and May and a second time in August. The outcomes provide the benchmark to validate the students' findings. The expert recorded all vascular plants, and species coverage was visually estimated in 10% increments [68] following the same protocol as the students; the nomenclature followed Jäger and Rothmaler [57,58]. Table 1 provides an overview of the student and expert participants of the study.

Table 1. Overview of the research design.

	Bachelor Students	Master Students	Expert
Study program	Ecology and Environmental Planning	Urban Ecosystem Sciences	-
No. students enrolled	20	20	-
Course form	Block (1st vegetation survey, two-week identification course, 2nd vegetation survey)	Continuous (weekly plus 1st and 2nd vegetation surveys)	-
Survey plots (one plot per site)	20	19	20
Working form (no. of plots)	Individually (1)/pairs (2)	Individually (1)/pairs (2)	Individually (20)
Survey year	2021	2021	2020
1st vegetation survey in	April	April	April/May
1st survey identification tools	PlantNet app	PlantNet app	Scientific keys [57,58]
2nd vegetation survey in	June	June	June
2nd survey identification tools	Scientific keys [57,58]	Scientific keys [57,58]	Scientific keys [57,58]

2.4. Data Analysis

In the first step, the species numbers obtained with the different experience levels were compared with those of the expert mapping (Bachelor I vs. Bachelor II vs. Master I vs. Master II vs. Expert). After testing for normal distribution and variance homogeneity, an ANOVA (analysis of variance) was performed. Pairwise multiple comparison was performed afterward using Holm–Sidak post hoc tests.

In the second step, we pooled the surveys of the Bachelor's students and those of the Master's students and analyzed possible differences using ANOVA and Holm Sidak post hoc tests (Bachelor's vs. Master's vs. Expert). To compare the species compositions of the different study sites, we performed non-metric multidimensional scaling (NMDS). The Bray–Curtis Index was used as a distance measure. The vegetation data were square-root-transformed beforehand. To determine the best possible model (local optimum of the stress value), a total of 100 computational runs for the NMDS were preset.

In the final step, we calculated the number of misidentifications by checking whether the identified plants were known for Berlin [62,63] and for dry grassland habitats [69]. In addition, the percentage of missed species and misidentifications compared with the expert surveys was calculated to be the benchmark (100%). These two error rates were used as proxies to answer our research questions because we intended to quantitatively evaluate the usability and usefulness of PlantNet and of scientific keys based on the results of the plant identifications. We took the first error rate, i.e., the proportion of incorrectly identified plants because they did not occur in Berlin or in the corresponding habitat, as a proxy for whether the App or the scientific field guides had an influence on data quality. Should this error rate change significantly between the two survey rounds within the groups, we could infer differences in the students' performance in handling the corresponding identification tool (e.g., to double-check with available information on distribution and habitat). The second proxy applies to the students' overall ability to identify plants and results from measuring the students' error compared with the species identified by the expert. If the proportion of overlooked and incorrectly determined species did not change between the two survey rounds within the groups, there would be no learning effect from using the App. *t*-tests and chi-square tests were performed to reveal differences in the error rates between the first and second runs for both Bachelor's and Master's students, or just both groups, respectively.

All statistical and multivariate analyses were performed in R version 4.1.2 [70] using the 'vegan' package [71] for multivariate analysis. The statistical analyses were accompanied by a descriptive analysis of how many of the plant species found by the student groups did not occur in Berlin or which plant species did not normally occur in the habitat studied [62,63] (Table S1).

3. Results

Considering the total of 20 plots, 330 vascular plant species were recorded. Of this total number of plant species on all plots, the Bachelor's student surveys yielded 182 species, whereas the Master's students recorded 188 species. The expert surveys resulted in 185 plant species in total. We found significant differences in the number of plant species recorded by those with different levels of experience. Students recorded significantly fewer species per site than the expert ($F = 44.47$, $p < 0.001$, ANOVA) (Figure 1A). The Bachelor's student surveys recorded 6 to 22 species per plot (mean = 13 ± 1 SEM) in the first round and 5 to 21 species (12 ± 1) per plot in the second round. The Master's students recorded 5 to 28 species per plot during their first survey (14 ± 1) and 6 to 24 per plot in the second one (14 ± 2). The expert recorded 17 to 59 species (37 ± 3) per plot. Differences among experience levels were also significant when combining the Bachelor's and Master's surveys ($F = 23.67$, $p < 0.001$, ANOVA) (Figure 1B). The ranges were 9 to 30 species (20 ± 1) for Bachelor's students and 10 to 40 species (20 ± 2) for Master's students per plot, combined for the first and second runs.

The species composition varied among the study sites (Figure 2). The differences in species composition were lower in the expert surveys than those in the Bachelor's and Master's surveys. Both Bachelor's and Master's students recorded several species that neither occurred in Berlin. nor in the habitat type dry grassland (Figure 3). The numbers of species that did not occur in Berlin was 34 species (18.7%) for Bachelor's and 24 (12.7%) for Master's students. The numbers of species that did not occur in dry grasslands were higher, with 59 species (32.4%) and 53 species (28.2%) for Bachelor's and Master's surveys, respectively.

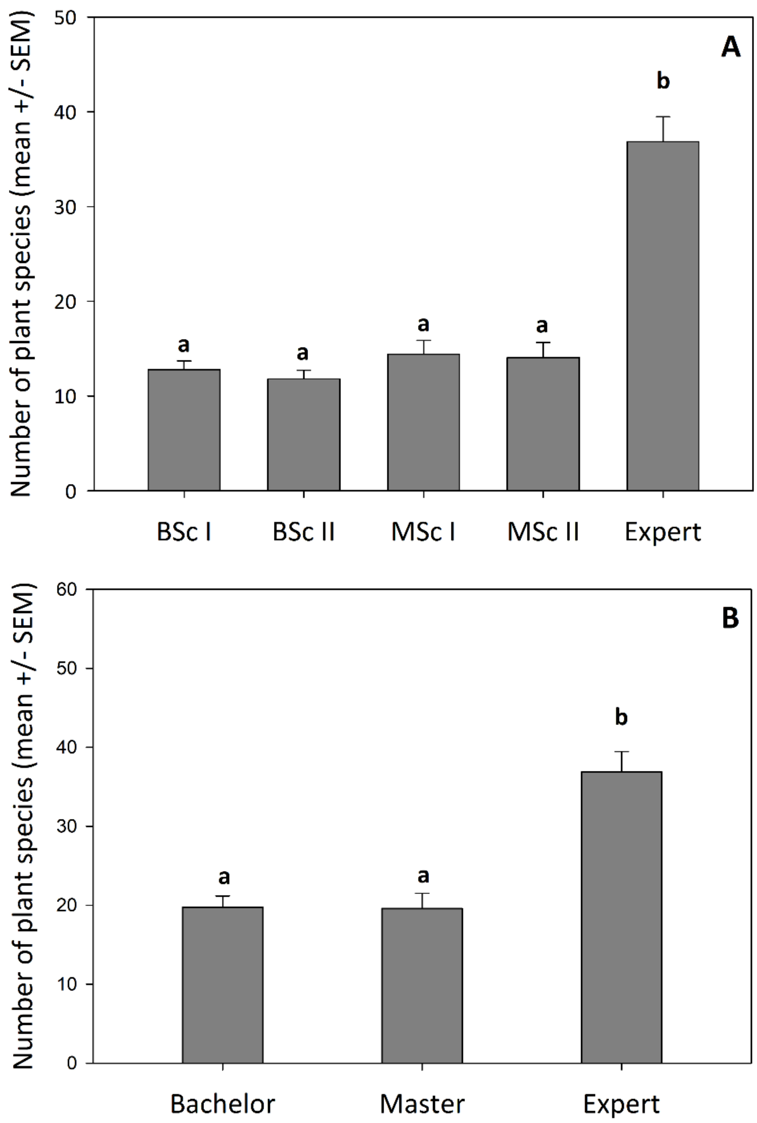

Figure 1. The number of plant species recorded by those with different levels of experience (**A**), which differed significantly between the students and the expert (F = 44.47, $p < 0.001$, ANOVA). The numbers of species also differed significantly (F = 23.67, $p < 0.001$, ANOVA) when comparing Bachelor's students, Master's students, and the expert (**B**). Different lower-case letters indicate significant differences among groups, with $p < 0.001$.

The Bachelor's students who had no prior knowledge, but attended a plant identification course between the two data collection dates, had significantly lower error rates with regard to species not known in Berlin or in dry grassland habitats in the second round (Berlin: t = 3.14, $p < 0.003$/habitat type: t = 3.43, $p < 0.001$, *t*-test). No significant changes in error rates were reported for the Master's students, who had experience in plant species identification prior to data collection (Berlin: t = 1.34, $p < 0188$/habitat type: t = 1.31, $p < 0.198$, *t*-test). Compared with the data from the expert surveys, the students overlooked or misidentified a large number of species (Table S1). Between 77.5% and 81.2% of the species determined by the expert were not detected by the students in all runs, and between 12.4% and 22.6% of the species identified by the students were incorrect (Figure 4). These error rates were not significantly different between student groups.

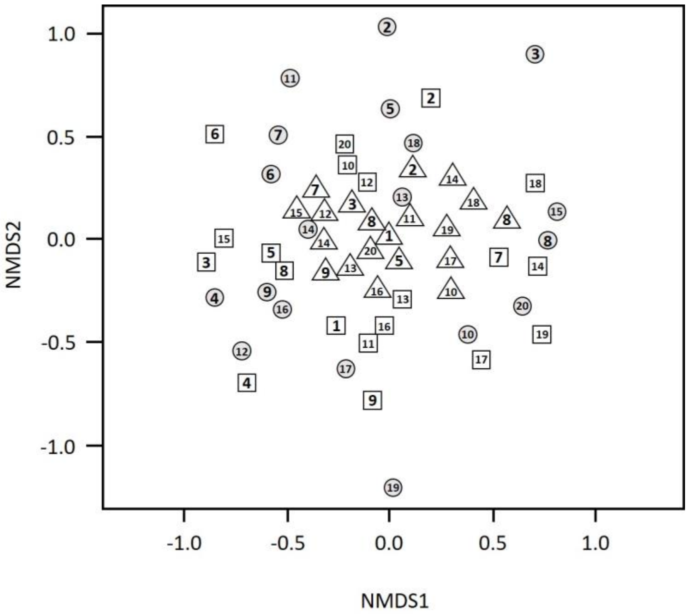

Figure 2. The comparison of the plant species composition revealed a wider dispersion among the results of the Bachelor's (square) and Master's (circles) surveys than that of the expert (triangle) (NMDS, stress = 0.19).

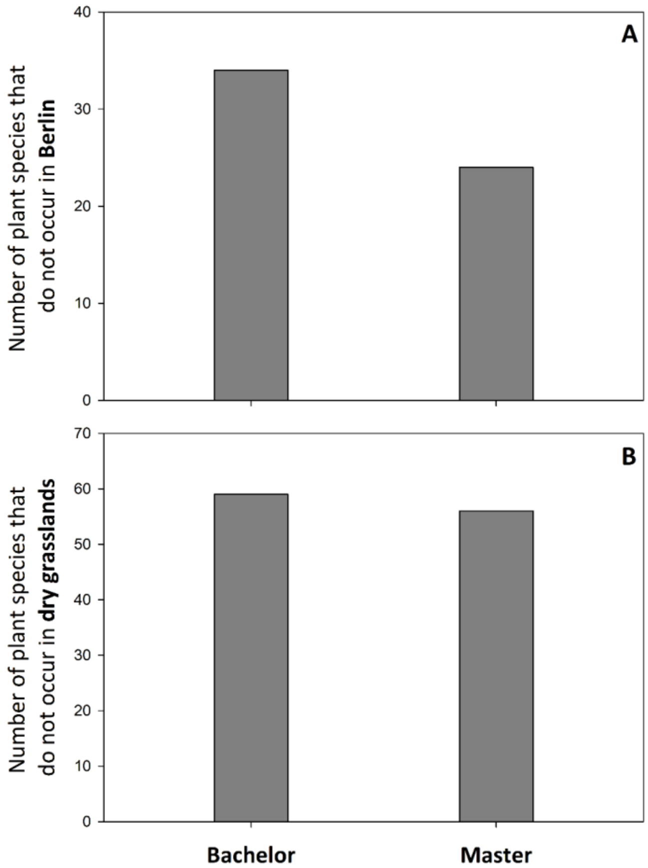

Figure 3. Both Bachelor's and Master's students recorded several species that neither occurred in Berlin (**A**), nor were found in the habitat type dry grassland (**B**). No significant differences ($\chi 2$ (1, N = 173) = 0.56, $p > 0.05$) were found between groups.

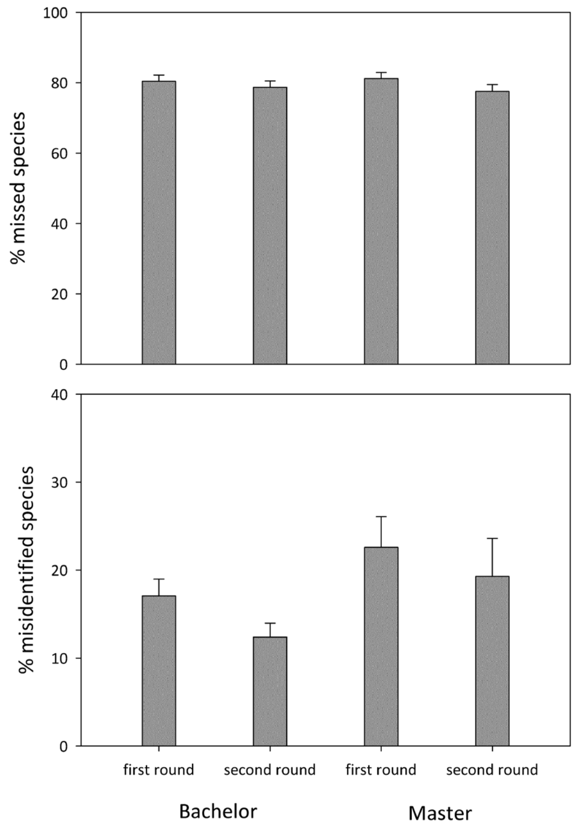

Figure 4. Percentage of missed and misidentified species by Bachelor's and Master's students in relation to the expert surveys for both the first and second rounds of surveys.

4. Discussion

In this study, we compared the data quality and potential learning effects of the use of different plant species identification tools by Bachelor's and Master's students using expert knowledge for reference. With respect to our first question, we started by looking at species richness. The expert recorded, on average, twice as many species per site as the students. Likely due to their greater experience, experts can identify vegetation very quickly and less time is needed to consult a scientific identification key. In contrast, the different levels of performance of the students, that is to say, not all students have the same skills or experience, may have led to a lower average and a wider range in the number of species identified per site. Without expert knowledge, it is, in general, harder to identify species and, in addition, students overlooked or misidentified many species (Table S1).

The misidentified and overlooked species were mainly grasses or non-flowering specimens that were difficult to recognize from photos or without expert knowledge (e.g., rosettes and seedlings). The level of student commitment to completing the task may have also been a factor influencing the species richness. Students' intrinsic motivation has been shown to correlate positively with performance in species identification [72]. Lastly, when accumulating the plant species across sites, there was nearly agreement on the total number identified between the expert and student groups. However, this result was misleading, because the students made a high proportion of incorrect determinations.

The first indication of possible misidentifications in the students' data collection was the higher dissimilarities in species composition between sites shown in the NMDS (Figure 2). The dispersion in the plant assemblages between sites was much wider in the students' vegetation collections compared with the expert's. A difference in the species composition between the sites could be expected, for example, to be affected by the different degrees of urbanization per sample location [73,74] or correlations between phenology and microclimatic conditions [75]. However, these factors applied to all groups and could not account for the large difference in dispersion between student and expert surveys, because species composition would not change that dramatically from 2020 to 2021.

A more direct measure, but independent of the expert's result, is whether the identified species had already been documented for Berlin or in urban dry grasslands. This measure would represent how accurately the students worked and what local species knowledge they had. Between 12.7% and 32.4% of the plants identified by the students did not fall into these two categories. These values could be interpreted like an error rate, given the excellent documentation of the flora of Berlin [62,69] and the vegetation of dry grasslands in this region [76–79]. Consequently, a change in the error rate in plant identification between the students' first and second data collections would provide indications of whether the use of the App or the scientific literature had any influence on data quality.

We considered the Master's students to be the control group and the Bachelor's students to be the experimental group, because the latter attended an additional botanical identification course between the two sampling rounds. A significant decrease in the error rate between the samplings was demonstrated for the Bachelor's students. The Master's students had more experience in general and, therefore, performed better than the Bachelor's students, but there was no change in the error rate between the two data collections. Presumably, the traditionally taught plant identification course, where they learned to use scientific determination keys and to identify the characteristics of selected plant families, was responsible for the Bachelor's students' improved identification skills. They probably had a better understanding of the terminology and plant characteristics after the course.

Finally, by measuring the error of the students in comparison with the species identified by the expert, the results revealed high percentages of missed and incorrectly determined species. This measure can be interpreted like an error rate representing the students' overall ability to identify plants. The visible, but non-significant, decrease in misidentifications between the two survey rounds for both the Bachelor's and Master's courses could be due to the Bachelor's botany course or the use of scientific literature. However, considering that the supposedly more experienced Master's students fared even worse than the Bachelor's students, the overall performance of the students was humbling.

To use the data for further research beyond the teaching obligation, misclassifications have to be ruled out. One possibility would be to filter student's data by matching them with already existing, excellent databases (as performed here), but also, other approaches that have been developed in the context of citizen science in recent years could be applied, for example, automated filtering, consensus methods, or expert validations [80,81]. In fact, PlantNet has an advantage over the handed field guides in that users can view a world map to explore whether the species has already been recorded for this place or region, or find out information about its distribution via direct links to further information, for example, Wikipedia or GBIF (Global Biodiversity Information Facility). In addition, students should be made aware that PlantNet has set its own accuracy threshold above 0.9 (one criterion to be automatically uploaded to GBIF) and that they should take extra care when adopting the App's suggestions if the score is lower. It is possible that the students were not aware of these functions, which would have helped them to assess the correctness of their determination themselves. For future field work with students using PlantNet or another mobile application that specifically maps the German flora, for example, Flora Incognita [82], a more thorough introduction to the functionalities seems necessary.

Considering not only the first, but also our second research question, whether the App may enhance knowledge acquisition, our results show two consequences, firstly for the use of plant identification apps in teaching and beyond, and secondly for species identification courses in general. With regard to identification apps in teaching, Thomas and Fellowes [83] reported similar performances in bird species identification, whereas Jeno and colleagues [72] reported higher performance in identifying plant species with a corresponding mobile application compared with traditional field guides. Noncomparative studies have shown that students using citizen science apps, like iNaturalist, can generate a high percentage of high-quality data [31,50]. Apps for species identification in higher education, therefore, have their justification, given that they seem to provide useful data for different applications, even when users are novice botanists. In our case, the proportion of incorrectly identified species does not fully support the idea that species identification apps, in the way that they were used in our course, help to develop better skills, or generate high-quality data. However, it can be assumed that the students would have been able to identify far fewer plants without PlantNet and that their performance and learning progress—in contrast with other studies—were assessed on the basis of expert knowledge and in the context of a very specific type of biotope with species that are difficult to identify, for example, grasses.

Even though we could not demonstrate in our investigation that the use of PlantNet led to immediate learning effects, other cases showed positive impacts by allowing the students to use of apps instead of books or printed handouts. Mobile applications have been found to increase motivation to complete species identification tasks [72,83]. This is also true for applications that do not contain automated image recognition, but only a digital version of a scientific key that appears to be more user-friendly than turning pages in a book [84,85]. In general, students in higher education found the use of a citizen science-based mobile application to support species identification motivating [30,51]. The not significant, but still higher average number of species identified in the first round, when Bachelor's and Master's students were allowed to use PlantNet, could be an indication that this was true for our student groups as well, although many plants could also have dried out until June due to the limited rainfall in spring 2021. However, it cannot be ruled out that the higher number was caused by the faster and more convenient use of an app that immediately identified the species, perhaps even without double-checking with further resources.

In assessing the usefulness of courses for species identification in general, the error rates highlighted how difficult the task of identifying plant species is and how little can be taught at university. Developing these skills takes time and patience, and often requires not only experience in field data collection and working with scientific literature, but also an expert mentor to receive feedback and improve [86,87]. Apps can stimulate interest in learning about plants more easily and straightforwardly, and help to achieve initial success more quickly. This is also one of the core tasks of these apps, which is to motivate the general population to concern themselves with the environment and its protection [59]. But learning one or more species groups is a lengthy process that cannot be shortened via digitization either. Human experts are extremely important, also for the capabilities of the apps, for example, for validating or labeling images to improve accuracy [53]. Therefore, the teaching of species knowledge should be given a higher priority at university, not to mention in the context of global biodiversity loss. Given the possibilities and limitations of plant identification apps, combining them with scientific literature and digital identification keys would probably be the best way to improve the accuracy of students' performance and, at the same time, avoid frustration.

The results of this study should only be understood to be preliminary, because they are subject to some limitations. To assess the learning effect through the use of an app, it would be advisable to separate the groups further, for example, into teams working only with PlantNet or only with the field guides before and after the botany course. A control group that does not participate in the botany course is not feasible, because the species identification course is mandatory for all students and would also contradict the educational mission. In addition, it would be better to measure learning effects with quizzes or surveys before and after the course, in addition to estimating error rates. Simultaneously, other factors, like the impacts of the App use on motivation, attitudes toward the task and the environment, and effects on social engagement, could be examined with accompanying questionnaires or interviews [83]. It is not clear to what extent students were familiar with the various features of the App. There was a possibility that not all helpful information was exploited to assess whether the identified plant was a realistic selection. Including a community-validated digital herbarium or collection that could be accessed as a registered user of PlantNet could have helped students build the knowledge base needed for the second round of sampling. Last, but not least, this study was also limited by the randomness of the field work, which confronted both the students and the expert with different conditions—the respective weather patterns during the recording, the phenology, and other unknown factors influencing the occurrence and seasonal appearance of plant species.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su151712984/s1, Table S1: Top misidentified and missed species.

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