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Scientific reasoning skills predict topic-specific knowledge after participation in a citizen science project on urban wildlife ecology

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Abstract

In citizen science (CS) projects, citizens who are not professional scientists participate in scientific research. Besides serving research purposes, CS projects provide participants opportunities for inquiry-based learning to promote their topic-specific knowledge and scientific reasoning skills. Previous research suggests that participants need scientific reasoning skills to engage in scientific activities and to learn from inquiry in CS projects. Participants' scientific reasoning skills, therefore, might enhance the resulting topic-specific knowledge at the end of a CS project. On the other hand, scientific reasoning skills themselves are a learning outcome of CS projects. Hence, they might play a *double role* in CS projects: as a learning outcome and as a prerequisite for acquiring knowledge. In the informal education context of CS, it has not yet been investigated whether scientific reasoning skills predict topic-specific knowledge or vice versa. To address this question, the research presented here used a cross-lagged panel design in two longitudinal field studies of a CS project on urban wildlife ecology ($N = 144$ participants). The results indicated that participants' scientific reasoning skills positively influenced their topic-specific knowledge at the end of the project, but not vice versa. Extending previous research on individual learning outcomes of CS projects, the results showed that inquiry-based learning in CS projects depends on certain prerequisites, such as participants' proficiency in scientific reasoning. We discuss the implications for future research on inquiry-based learning in CS projects and for further training of CS participants in acquiring scientific reasoning skills.

KEYWORDS

citizen science, ecology, knowledge, longitudinal study, scientific reasoning

In citizen science (CS), citizens and scientists collaborate in research projects. Besides their scientific outcomes, many CS projects promote citizens' individual learning outcomes (Phillips et al., 2018) by using inquiry-based learning approaches (Herodotou et al., 2017; Mitchell et al., 2017). Topic-specific knowledge has been up to now the most prominently investigated learning outcome of CS projects (Groulx et al., 2017; Peter et al., 2019). In contrast, scientific reasoning skills and epistemological beliefs about scientific knowledge have received much less attention in this context (Aristeidou & Herodotou, 2020; Stylinski et al., 2020). Moreover, participants' topic-specific knowledge, scientific reasoning skills, and epistemological beliefs have so far been investigated only separately, and little is known about their mutual relationship (Aristeidou & Herodotou, 2020; Crain et al., 2014).

Concerning scientific reasoning, current research suggests that scientific reasoning skills are not only a learning outcome but also a prerequisite for inquiry-based learning (Stylinski et al., 2020). This means that participants may need scientific reasoning skills in order to effectively engage in scientific activities in inquiry-based learning (Edwards et al., 2017). These activities are in turn positively related to topic-specific knowledge (Masters et al., 2016). Thus, for inquiry-based learning in CS projects, the *double role* of scientific reasoning skills needs to be examined. Additionally, the role of epistemological beliefs needs to be explored, because they are conceptually related to scientific reasoning skills. This is the case because scientific reasoning skills involve solving problems using scientific methods, while epistemological beliefs involve reflecting on this inquiry process at a meta-level (Reith & Nehring, 2020). If participants have more elaborate epistemological beliefs about how scientific knowledge is constructed, they might choose more adequate scientific methods to solve problems (Reith & Nehring, 2020). Thus, more elaborated epistemological beliefs may also be a prerequisite for inquiry-based learning (Kremer et al., 2014; Michel & Neumann, 2016). Therefore, the present longitudinal study investigated the relationship between scientific reasoning skills, epistemological beliefs, and topic-specific knowledge during an informal, inquiry-based learning experience in an urban wildlife CS project. A cross-lagged panel design was used that allowed for testing cause-effect relationships.

1 | LEARNING FROM INQUIRY IN CITIZEN SCIENCE

Scientific inquiry is inherent to CS projects, because participants get involved with scientific activities (Peterman et al., 2017; see Stylinski et al., 2020, for an overview), such as collecting and analyzing data (e.g., iSpot; Silvertown et al., 2015). CS projects allow citizens to involve themselves in scientific activities to varying degrees (e.g., Bonney et al., 2009; Shirk et al., 2012). These different degrees of involvement provide distinct opportunities for inquiry-based learning (Bonney et al., 2016; Edwards et al., 2017; Mitchell et al., 2017). For example, in a contributory CS project, citizens can participate in scientific activities of data collection and data processing, but this involvement in itself might not help them understand the scientific inquiry of the project (Aristeidou et al., 2020). In contrast, in a collaborative CS project, citizens can collect and process data but also form hypotheses, test hypotheses, analyze data, and discuss evidence with other participants and professional scientists. This degree of involvement integrates an inquiry-based learning approach and is based on previous suggestions that involvement with different scientific activities will increase participants' learning outcomes (Bonney et al., 2016). Inquiry-based learning approaches, and especially those approaches that employ structural guidance (Carolan et al., 2014; Lazonder & Harmsen, 2016), are highly relevant for promoting learning outcomes such as topic-specific knowledge (Alfieri et al., 2011; Furtak et al., 2012), scientific reasoning skills (Arnold et al., 2017; Lazonder & Harmsen, 2016), and epistemological beliefs (Furtak et al., 2012).

2 | SCIENTIFIC REASONING SKILLS, TOPIC-SPECIFIC KNOWLEDGE, AND EPISTEMOLOGICAL BELIEFS

All three constructs—that is, scientific reasoning skills, topic-specific knowledge, and epistemological beliefs—have previously been identified as potential learning outcomes in a framework for individual learning outcomes in CS projects (Bonney et al., 2016; Phillips et al., 2018). We define all three constructs by referring to frameworks of scientific literacy that have previously been adopted in CS projects (e.g., Bonney et al., 2009). Within such frameworks for scientific literacy (see Kampa & Koeller, 2016, for an overview), scientific reasoning skills represent the processes in science (*knowing how*, procedural knowledge), whereas topic-specific knowledge represents the facts and concepts of specific domains (*knowing that*, declarative knowledge). In addition to declarative and procedural knowledge, epistemic knowledge is a third knowledge type that includes epistemological beliefs about how knowledge is generated (Kampa & Koeller, 2016; She et al., 2019).

In the natural sciences, the skills necessary to solve problems in a scientific way are referred to as skills of scientific reasoning (e.g., Drummond & Fischhoff, 2017; Lawson et al., 2000). We will, therefore, draw upon previous models that conceptualize scientific reasoning as a context-specific, scientific problem-solving process (Fischer et al., 2014; Hartmann et al., 2015). In this conceptualization, scientific reasoning is concerned with the processes of scientific discovery (e.g., Klahr & Dunbar, 1988; see Engelmann et al., 2016, for an overview). Scientific discovery switches back and forth in a nonlinear process (National Research Council, 2012). This process entails forming hypotheses (i.e., the generation of hypotheses), testing hypotheses (i.e., determining how data has to be collected), and analyzing data (i.e., evaluating the evidence from the collected data). These steps in the process require skill and are delineated in the model of Scientific Discovery as Dual Search (Klahr & Dunbar, 1988) and in more recent conceptualizations of the respective scientific reasoning skills (Opitz et al., 2017). This scientific problem-solving process represents the hypothetico-deductive approach that constitutes one of several styles of scientific reasoning (Kind & Osborne, 2017). In terms of the hypothetico-deductive approach, refutable hypotheses about a scientific problem are derived from theoretical considerations and tested by an appropriate investigation (Krüger et al., 2020). The research presented here focuses on three scientific reasoning skills that are needed for scientific problem-solving (i.e., forming hypotheses, testing hypotheses, and analyzing data; Bruckermann, Straka, et al., 2021), as they have to date received little attention in the evaluation of CS projects' learning outcomes (Phillips et al., 2018; Stylinski et al., 2020).

Understanding concepts and facts of science is referred to as topic-specific knowledge. In the domain of wildlife ecology, topic-specific knowledge includes an understanding of ecological connectivity, such as interactions and relationships between species and the environment (Bruckermann, Stillfried, et al., 2022; Jordan et al., 2009). Such topic-specific knowledge about a specific domain is an individual learning outcome in CS projects that is frequently evaluated (see Aristeidou & Herodotou, 2020, for an overview). As a consequence, this type of knowledge is expected to translate into changes in behavioral intentions and actions (e.g., for invasive species; Jordan et al., 2011; attitudes toward science; Bruckermann, Greving, et al., 2021). This means that knowing more about wildlife may motivate individuals to intend to as well as actually conserve and protect wildlife species.

Epistemological beliefs represent individuals' evaluations of the status of knowledge and the process of knowledge generation (Hofer & Pintrich, 1997; Stahl & Bromme, 2007). Therefore, from a theoretical perspective, they are relevant for inquiry-based learning (Kremer et al., 2014; Reith & Nehring, 2020). Like scientific reasoning skills, epistemological beliefs represent individuals' thinking about how scientific knowledge is generated and thus are related to scientific reasoning skills (Kremer et al., 2014; Osterhaus et al., 2017). That is why the research presented here explores how epistemological beliefs contribute to inquiry-based learning, in addition to scientific reasoning skills, in informal learning contexts such as CS projects.

3 | THE DOUBLE ROLE OF SCIENTIFIC REASONING IN CS

Turning back to CS projects, previous research on inquiry-based learning has so far mostly investigated the development of topic-specific knowledge, scientific reasoning skills, and epistemological beliefs separately (for an overview, see Aristeidou & Herodotou, 2020; Crain et al., 2014). One study found, for example, that a CS project increased both participants' topic-specific knowledge and epistemological beliefs (Price & Lee, 2013). Other studies found, however, that participants' topic-specific knowledge increased after participation in a CS project, but their scientific reasoning skills did not (Jordan et al., 2011; Rögele et al., 2022). Results concerning the effects of involvement in a CS project on participants' scientific reasoning skills, epistemological beliefs, and topic-specific knowledge were inconsistent and inconclusive, if investigated separately (e.g., Jordan et al., 2011; Price & Lee, 2013). More importantly, with regard to the role of scientific reasoning skills in the inquiry-based learning approach, they can be both a prerequisite for the acquisition of topic-specific knowledge as well as an outcome of it (Edwards et al., 2017; Phillips et al., 2018). Thus, scientific reasoning skills might play a double role for inquiry-based learning in CS projects.

Scientific reasoning skills are considered to be a learning outcome in CS projects (Phillips et al., 2018; Stylinski et al., 2020). This is the case, as CS projects can provide opportunities for participants to engage in scientific reasoning by using scientific tools and methods (Mitchell et al., 2017; National Academies of Sciences, Engineering, and Medicine [NASEM], 2018; Phillips et al., 2018). Some research has demonstrated that participants developed scientific reasoning skills during a CS project, such as formulating valid research questions and providing valid research designs (Crall et al., 2013; Fernandez-Gimenez et al., 2008; Kountoupes & Oberhauser, 2008). In contrast, other research has not found enhanced scientific reasoning skills to be a learning outcome of CS projects (Brossard et al., 2005; Jordan et al., 2011; Trumbull et al., 2000). In CS projects, participants' scientific reasoning skills are seldom assessed by formal tests that capture their performance on a task, but instead by surveys that capture self-reported confidence in performing a task (e.g., Trumbull et al., 2000; see Stylinski et al., 2020, for an overview). Moreover, within the broad range of skills as a learning outcome, assessments have mostly focused on a narrow range of skills in the inquiry process, for example, recording reliable data, instead of on more complex scientific reasoning skills, for example, forming hypotheses (Stylinski et al., 2020).

Scientific reasoning skills are also a prerequisite for participants to master scientific activities and to profit from inquiry-based learning in a CS project (Edwards et al., 2017; Stylinski et al., 2020; Trumbull et al., 2000). A lack of proficiency in scientific reasoning skills not only jeopardizes participants' participation in the inquiry process (Burgess et al., 2017), but also might compromise the achievement of learning outcomes such as topic-specific knowledge from inquiry-based learning in CS projects (Edwards et al., 2017; Stylinski et al., 2020). Participants' achievement of learning outcomes improves when they get more deeply involved in scientific activities during inquiry-based learning (Gray et al., 2017; Phillips et al., 2018; Shirk et al., 2012). Masters et al. (2016) found that the more actively participants got involved in scientific activities, the more topic-specific knowledge they held at the end of online CS projects. Participants, however, need proficiency in scientific reasoning skills to get involved in scientific activities and, ultimately, to increase their individual learning outcomes from inquiry-based learning. Low proficiency in scientific reasoning as well as a mismatch between individual proficiency and the requirements of scientific activities might explain why only a few participants get involved in the more complex activities of the scientific inquiry process (Golumbic et al., 2017; Phillips et al., 2019). Hence, in terms of their learning outcomes, less proficient participants might not have profited equally from engaging with the scientific inquiry of the project (Trumbull et al., 2000). While scientific reasoning skills enable participants to become involved in scientific activities, epistemological beliefs represent their reflections on the processes of knowledge generation on a meta-level (Reith & Nehring, 2020). Hence, whether participants increase their topic-specific knowledge from their involvement in the scientific activities of a CS project also depends on their beliefs about how knowledge is generated. Previous research highlights that the revision of an individual's topic-specific knowledge in the natural sciences depends on their epistemological beliefs (Baytelman et al., 2020; Trevors, Kendeou, et al., 2017).

In research beyond research on CS projects, the role of scientific reasoning skills has differed depending on the kind of inquiry-based learning (i.e., confirmation or other kinds of inquiry). This has resulted in contradictory findings for the direction of the relationship between scientific reasoning skills and topic-specific knowledge (e.g., Schwichow et al., 2020). While school students' scientific reasoning skills have been shown to be a positive predictor variable of topic-specific knowledge in inquiry-based learning (Edelsbrunner et al., 2018; Stender et al., 2018), other studies found that topic-specific knowledge was a predictor of students' scientific reasoning skills (e.g., Schwichow et al., 2020). These differences in the direction of the relationship might depend on whether students utilized their scientific reasoning skills for developing topic-specific knowledge from the inquiry process. Students' scientific reasoning skills are a prerequisite when the inquiry process facilitates the application of skills for building new knowledge (Stender et al., 2018), which is not the case in more straightforward confirmation inquiry (Schwichow et al., 2020). Furthermore, students' epistemological beliefs could influence the acquisition of topic-specific knowledge and scientific reasoning skills when they represent beliefs about scientific knowledge and how it develops (Osterhaus et al., 2017). Beyond these previous findings in formal education, there is little evidence of the relationship in inquiry-based learning that occurs outside of that context, such as in CS projects. In CS projects, it is unclear whether participants' scientific reasoning skills are a prerequisite for acquiring topic-specific knowledge or whether their knowledge of the topic fosters participants' scientific reasoning skills through inquiry-based learning. We therefore investigated the double role of scientific reasoning skills with a rigorous and standardized measure to unravel whether scientific reasoning skills are a prerequisite or a learning outcome of CS projects.

4 | THE CURRENT RESEARCH

The research presented here aimed to examine the double role of scientific reasoning skills in the CS context and to disentangle the relationship between scientific reasoning and topic-specific knowledge. The rationale was that citizens in CS projects might need scientific reasoning skills to participate in scientific activities of the projects and acquire topic-specific knowledge. Scientific reasoning skills, however, might also be a learning outcome that depends on citizens' topic-specific knowledge of the research topic in the CS project. Therefore, we investigated the following research question:

1. Do scientific reasoning skills predict participants' level of topic-specific knowledge after participation in inquiry-based learning during a CS project, or vice versa?

Furthermore, we explored whether epistemological beliefs have a similar role like that of scientific reasoning skills in inquiry-based learning in CS projects. We also intended to disentangle its relationship with topic-specific knowledge and scientific reasoning skills. We, therefore, investigated the following exploratory research question:

2 Do epistemological beliefs, in addition to scientific reasoning skills, predict participants' level of topic-specific knowledge after participation in inquiry-based learning during a CS project, or vice versa?

We investigated these research questions in the context of a CS project on urban wildlife ecology by conducting longitudinal field studies that were each two-months long. We applied a cross-lagged panel design that allowed us to test for cause-effect relationships between scientific reasoning, topic-specific knowledge, and epistemological beliefs.

5 | METHOD

5.1 | Measures

In this study, the measures we assessed were scientific reasoning skills, epistemological beliefs, and topic-specific knowledge. The number of items, example items of each measure, Cronbach's alpha values for T1 and T2 as well as sources of validity evidence are presented in Table 1. Appropriate validity and reliability were pre-tested beforehand.

5.1.1 | Scientific reasoning skills

We assessed participants' scientific reasoning skills with an 18-item questionnaire that we adapted to the context of research on urban wildlife ecology on the basis of an established questionnaire (Krell, 2018). In the questionnaire, participants answered questions, for example, on how to formulate a hypothesis, and their answers were either true or false. Thus, the questionnaire was a formal test that was different from questionnaires that ask for participants' subjective experience on rating scales (Stylinski et al., 2020). All 18 items (see Supplementary Material S1; see Table 1 for Cronbach's alpha values) were single-choice questions and concerned with scientific reasoning in the context of research on urban ecology, which was the focus of the current Wildlife Researchers project (Bruckermann, Straka, et al., 2021). Six items each were related to the scientific reasoning skills of forming hypotheses, testing hypotheses, and analyzing data (Bruckermann, Straka, et al., 2021). We aggregated participants' answers on this scientific reasoning scale by dividing the number of correct answers by the total number of questions. The percentage of correct answers represented participants' scientific reasoning skills.

5.1.2 | Epistemological beliefs

We assessed participants' epistemological beliefs about scientific knowledge by asking them about Connotative Aspects of Epistemological Beliefs (Stahl & Bromme, 2007). This measure assessed how participants evaluated scientific knowledge. The original measure distinguished between two dimensions, texture of knowledge and variability of knowledge (Stahl & Bromme, 2007). The texture dimension had nine items and referred to beliefs about how structured and accurate scientific knowledge is. The variability dimension had seven items and referred to beliefs about how stable and dynamically changing scientific knowledge is. Yet, also a combination of these two dimensions provided valid results in previous research (Feinkohl et al., 2016; Kienhues et al., 2008; Kimmerle et al., 2015). We combined the two dimensions in our analyses because they represented epistemological beliefs on the same scale. On this scale, higher values represented more multiplistic beliefs whereas lower values represented more absolute beliefs (Rosman et al., 2017). Furthermore, we combined the two dimensions because we had no prior theoretical assumptions about different effects of each of the two dimensions.

TABLE 1 Item numbers, item examples, Cronbach's α and sources of validity evidence for scientific reasoning skills (1), epistemological beliefs (2), and topic-specific knowledge (3)

Measure	*N* items	Item examples	α_{T1}	α_{T2}	Sources
(1) Scientific reasoning skills	18 (SC)	*Item 1 (Forming hypotheses with one independent variable on urban wildlife ecology)* Scientists conduct research on the movement behavior of hedgehogs (*Erinaceus europaeus*) by tagging them with tracking devices and determining where they reside. For this purpose, scientists choose a city park in which a large-scale public event takes place over the course of the observation period. They ensure that they always observe the hedgehogs at the exact same time (see figure). Which hypothesis can the scientists test with this research? ○ They can test whether the hedgehogs are nocturnal. ○ They can test whether the hedgehogs are nocturnal and reside in city parks. ○ They can test whether hedgehogs reside in city parks despite the disturbance. ○ They can test whether hedgehogs reside in city parks.	0.73	0.97	Internal structure of the test content (Bruckermann, Straka, et al., 2021)
(2) Epistemological beliefs	16 (RS)	Knowledge about wildlife in biology is ... *Item 1*: stable ○ ○ ○ ○ ○ unstable *Item 2*: objective ○ ○ ○ ○ ○ subjective *Item 3*: confirmable ○ ○ ○ ○ ○ unconfirmable	0.80	0.84	—

TABLE 1 (Continued)

Measure	*N* items	Item examples	α_{T1}	α_{T2}	Sources
(3) Topic-specific knowledge	25 (SC/MC)	*Item 1* What do omnivorous animals, such as the fox and raccoon, feed on in the city (one answer option is correct) ? The fox and raccoon mostly feed on ... in the city. ○ Food reserves of their forays that they store away in rural areas ○ Mice and rats that have extraordinarily high populations in these areas ○ Food that is left behind by humans ○ Plant food, fruits and vegetables, which they find in allotment gardens ○ Bird eggs and fledglings	0.42	0.35	Expert ratings of the test content (Bruckermann, Stillfried, et al., 2022)

Abbreviations: MC, multiple-choice; RS, rating scale; SC, single-choice.

The measure consisted of 16 semantic differentials (e.g., static–dynamic, objective–subjective). All items (see Supplementary Material S1) were assessed on a bipolar 5-point scale with each word pair of the semantic differentials as anchors on each side of the 5-point scale (see Table 1 for Cronbach's alpha values). There were no further anchors in between. We later reversed some items so that all items had the softer word on the higher end of the scale and then averaged the scores for all items for each participant. Thus, higher scores indicated that participants believed that scientific knowledge is softer (i.e., more dynamic and more subjective; Stahl & Bromme, 2007).

5.1.3 | Topic-specific knowledge of urban wildlife ecology

For the assessment of topic-specific knowledge of urban wildlife ecology, we created single-choice items and multiple-choice items. To do so, we identified the most relevant topics of urban wildlife ecology from citizens' and scientists' perspectives beforehand (Bruckermann, Stillfried, et al., 2022), based on a Delphi approach (e.g., Blanco-López et al., 2015). We did so because, in CS projects, the focus is on local knowledge, that is, topic-specific knowledge with a close relation to regional issues and topics (Haywood et al., 2016). Exemplary topics concerned the nutrition of wildlife animals in cities, diseases of wildlife animals, urban habitats of wildlife animals, and the protection of biodiversity in cities (see Bruckermann, Stillfried, et al., 2022, for an overview). Within the topic of nutrition, for example, participants had to know on which food omnivorous animals feed in the city. Following these topics, we developed 25 single- and multiple-choice questions that the measure consisted of (see Supplementary Material S1 for all items; see Table 1 for Cronbach's alpha values). Participants' correct answers to these questions were divided by the total number of questions. Hence, topic-specific knowledge was assessed as the percentage of correct answers. The Cronbach's alpha values for the measure of topic-specific knowledge were low. Topic-specific knowledge of a particular field often covers a variety of unrelated aspects (Stadler et al., 2021). Rather than aiming for high interitem correlations, we aimed to create each item of the topic-specific knowledge measure for a specific content element so that the items covered the theoretical breadth of topic-specific knowledge and were not redundant (Stadler et al., 2021). Therefore, a rather high internal consistency could not be expected for this measure (Taber, 2018).

5.2 | Procedure

Participants answered an online questionnaire at the beginning of the project (T1) and 2 months later at the end of the project (T2). Both questionnaires were identical, except for demographical data that was only assessed at T1. Participants were informed beforehand via mail about each of the questionnaires and, the next time they logged in, they were automatically confronted with each of the questionnaires. Both questionnaires assessed participants' topic-specific knowledge, scientific reasoning skills, and epistemological beliefs along with other measures not reported here (i.e., attitudes and emotions toward wildlife, attitudes toward engagement in science and CS, motivation, pride, and psychological ownership). A local ethics committee had approved both questionnaires.

5.3 | Overview of the project

In this research, citizens of a metropolitan city in Germany participated in an urban ecology CS project on terrestrial mammals, which was called "Wildlife Researchers." The Wildlife Researchers project provided participants with the resources to inquire into the urban ecology of terrestrial mammals in the metropolitan city. Participants inquired into the urban ecology by collaborating with other participants and academic scientists on an online platform. Participants were involved with the collection and analysis of data as well as with the discussion of their results in an online forum. We report on data from two similar two-month long field studies of the Wildlife Researchers project that were conducted in October/November 2018 and April/May 2019. Participants could only participate once and thus engaged in either the first or the second field study. Although the field studies fell at different seasons of the year, there was little difference in the activity of the participants.

During the field studies, participants had access to an online platform on which they could perform several scientific activities, such as forming hypotheses, testing hypotheses, and analyzing data (see Figure 1; see Aristeidou et al., 2020, for a similar approach). Participants were provided with an introduction and tutorial on the research approach and its limitations, resources for data collection, and online tools for data analyses and discussions. To test their hypotheses, for example, participants in the project were responsible for collecting data on terrestrial mammals. Regarding the research approach, participants had to reflect upon fair design and biases that may occur when they decided on how to position a camera trap in their garden.

For inquiry-based learning, the platform followed certain design principles to support participants in scientific activities (Quintana et al., 2004). One principle was that participants needed guidance from experts who explained the specifics of a task. After uploading camera trap pictures, participants could identify animal species in the pictures, and validate pictures of

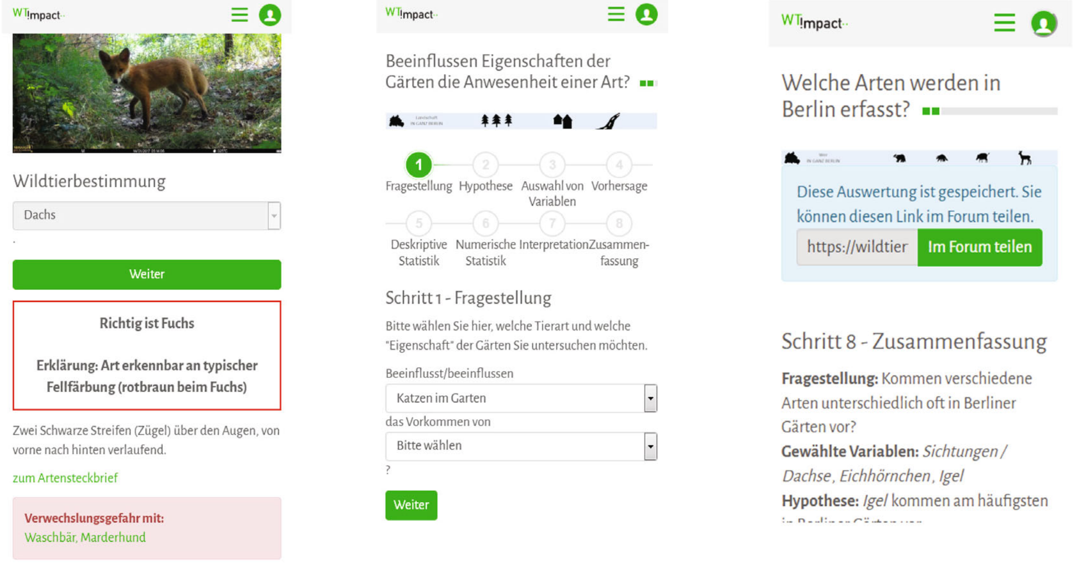

FIGURE 1 Screenshots of the internet platform (Mobile version). See the tutorial for species identification (left), the internet-based editor for hypothesis-driven analysis of selected questions (middle), and the export function of analysis results to the discussion forum (right). The screenshots have been cropped.

other participants. Therefore, in the data collection, participants completed a tutorial on species identification with expert feedback on each step of the activity so that they could then independently identify or validate the species (see Figure 1, on the left).

To support participants in forming their own hypotheses, we followed the design principle that complex activities should be structured and constrained to a meaningful degree. For selected questions, participants were able to specify their own hypotheses about relationships and differences for the species. On the platform, an internet-based editor allowed setting up relationships and testing differences for various animal species and environmental variables, for example, which environmental variables (e.g., characteristics of the gardens) might influence the presence of a species (e.g., red foxes; see Figure 1, in the middle).

Following data collection, participants had the opportunity to analyze their own data set and an aggregated data set of all participants' data, and to investigate relationships between species occurrence and landscape variables or other such parameters. To support participants' data analyses, we followed the principle that participants should be able to inspect data in different ways. Therefore, in the data analysis, relationships between sighting frequency and environmental variables could be viewed using both a plot and a map with color gradients. The results obtained could subsequently be transferred to an online forum for discussion with other participants (see Figure 1, on the right).

Participants could visit the online platform and perform activities at any time during the field studies, although data analyses were only possible after data collection had been finished. During the two-month field study, participants visited the internet platform on average 79% of the days ($M = 0.79$, $SD = 0.19$, range = 0.02–1.00). When participants visited the online platform, they performed at least one activity on average 18% of the days ($M = 0.18$, $SD = 0.15$, range = 0.02–1.00), such as analyzing data or discussing with other participants. When participants performed activities on the platform, they spent on average nearly 46 minutes per day ($M = 0.76$, $SD = 0.53$, range = 0.10–3.39).

5.4 | Participants

To recruit participants, we advertised the Wildlife Researchers project through public relation campaigns addressed to the general public. At the beginning of the project (T1), 375 participants answered the first questionnaire and, at the end of the project (T2), 185 of those also answered the second questionnaire. Both questionnaires were identical. Thus, 190 participants dropped out from the questionnaires over time, which is a dropout rate of 50.67%. In terms of the demographic composition of the sample, the dropout did not lead to any bias. Participants who completed only the first questionnaire did not differ from those participants who answered both questionnaires regarding their gender, $\chi^2(2) = 1.32$, $p = 0.518$, age, or education (by International Standard Classification of Education [ISCED] classification as described below), all ts < |0.5|, all ps >0.6.

From the 185 participants who also answered the questionnaire at T2, we excluded those who had missing values on the measures of scientific reasoning skills, epistemological beliefs, and topic-specific knowledge. Furthermore, we excluded participants who had only visited the online platform once because they were regarded as visitors as opposed to active members of the community that contributed to the inquiry process (Aristeidou et al., 2017). Of the final 144 participants in our analysis, 80 were female, 63 were male, and one indicated having a nonbinary gender. The mean age was $M = 53.58$ ($SD = 12.04$, range: 25–78). In terms of participants' highest educational qualification according to the ISCED, 3.5% had a general qualification for university entrance (ISCED 3), 12.5% had completed an apprenticeship (ISCED 4; German: "Lehre"), 12.5% had an advanced technical college entrance certification or a vocational school degree (ISCED 4), 55.5% had a college of higher education or university degree (ISCED 6 or 7), 11.1% had a doctoral degree or postdoctoral lecture qualification (ISCED 8), and 4.9% had a different degree.

5.5 | Data analysis

We tested the research questions using a cross-lagged panel design that facilitates the analysis of repeatedly measured data in path models. The purpose of cross-lagged panel designs is to investigate whether one variable influences another variable over time. The logic behind is as follows: If we assume that two variables are just related to each other over time, then they should always be related, independent from whether the first variable at the first time point is related to the second one at the second time point or vice versa (which are the so-called cross-lagged paths). Yet, if we assume that one variable influences the other variable over time, then they should be only related for one cross-lagged path but not for the other. Therefore, these two possible relations (i.e., cross-lagged paths) are calculated and compared to each other. Still, to account for the relation of one variable with itself over time (which are the so-called autoregressive paths or stabilities), these relations are also added to the model. Thus, the cross-lagged paths represent the relations between the two variables beyond the strong relations of each variable with itself over time. In order to be able to test such models in a cross-lagged panel design, each variable has to be assessed in the exact same way at each time point.

Following this logic, we used a cross-lagged panel design over two time points (T1 and T2) with a time-lag of 2 months in between. We also assessed the variables in the same way at each time point (see Measures, Section 5.1). Therefore, as explained, each variable should be stable across time. Stability means that the pretest value of each variable should be highly related to its own posttest value (Cole & Maxwell, 2003). To estimate the stability of the included variables, all cross-lagged panel designs add autoregressive paths to the model. For the sake of clarity, the intention for adding these paths is not to test for differences across time, which is not the focus of cross-lagged panel designs, but rather to account for the relation between pretest and posttest values. With these autoregressive paths set, the cross-lagged paths can then be added to explain the remaining variance of the variables at the second time point. Thus, the cross-lagged panel design allowed us to test for causal relations (normal and reversed causation) between our different variables while simultaneously controlling for their stability (Reinders, 2006).

Path analyses require at least five cases per estimated parameter (Bentler & Chou, 1987) or at least 10 cases per variable (Nunnally, 1967). These requirements are rules-of-thumb that have previously been used to estimate the sample size for two-wave cross-lagged panel models in science education research (e.g., Kulgemeyer et al., 2020). The models we estimated had either 6 parameters and 4 variables, or 11 parameters and 6 variables and thus required at least 40 cases for the model with 6 parameters and 4 variables, or at least 60 cases for the model with 11 parameters and 6 variables. Our sample size of 144 cases was, therefore, sufficient to test the models according to these rules-of-thumb.

The assessment of model fit was based on comparative fit indices instead of absolute fit indices such as the root mean square error of approximation (RMSEA). For path models with small degrees of freedom (df), such as the cross-lagged panel models that we aimed to test, the RMSEA is not a suitable indicator of model fit (Kenny et al., 2015). This circumstance had consequences both for the a priori estimation of power and for the assessment of the model fit. In structural equation modeling, power analyses are based on the RMSEA (e.g., Preacher & Coffman, 2006). Therefore, we did not estimate the power of our analyses in advance, also because small df models require unrealistic large sample sizes (MacCallum et al., 1996). For small df models, Kenny et al. (2015) suggest estimating parameters that were at first not specified in order to create a saturated model against which the nested model could then be compared. The nested model has less estimated parameters and it can principally be derived from a saturated model with more estimated parameters (Schermelleh-Engel et al., 2003). We compared a more parsimonious model with less estimated parameters that was nested in a more complex, hypothesized model with more estimated parameters. We used the Akaike information criterion (AIC) to compare the different model fits as this fit index is also computed for saturated models and accounts for model parsimony as well as fit (Schermelleh-Engel et al., 2003). Then, we compared the nested models using the χ^2 difference test because the difference between the test statistics of two nested models ($\Delta\chi^2$) follows a χ^2 distribution (Schermelleh-Engel et al., 2003).

In a first model, we tested the interrelations between scientific reasoning skills and topic-specific knowledge while accounting for the stability of both, scientific reasoning skills and topic-specific knowledge, that is, the relationship between their pretest and the posttest values (Model 1a). For the comparison with a more parsimonious model, we also tested only the stabilities of scientific reasoning skills and topic-specific knowledge each in a second model (Model 1b) that was nested within Model 1a.

In a third model (Model 2a), we further refined the initial path model (Model 1a) by adding epistemological beliefs at T1 and T2 and its interrelations with scientific reasoning skills and topic-specific knowledge as well as its stability. Again, for the comparison with a more parsimonious model, we also tested only the stabilities of scientific reasoning skills, topic-specific knowledge, and epistemological beliefs each in a fourth model (Model 2b) that was nested within Model 2a. All variables in the path models were entered as manifest variables (for further details, see Deng et al., 2018; Jackson, 2003; for limitations of this approach, see Discussion, Section 7.2). All path analyses were performed in Amos v22.0 (Arbuckle, 2013).

6 | RESULTS

For all variables at T1 and T2, means and standard deviations are presented in Table 2 and correlations in Table 3. All test statistics for the cross-lagged paths are presented in Table 4. The first path model tested two autoregressive paths and two cross-lagged paths (see Model 1a, Figure 2, top) and was a saturated model with $\chi^2(0) = 0.00$, RMSEA $= 0.00$, comparative fit index (CFI) $= 1.00$, and AIC $= 28.00$. The second, more parsimonious model, with the two autoregressive paths only, had a worse fit than the first, more complex model that we tested, with $\chi^2(4) = 13.41$, $p = 0.009$, RMSEA $= 0.13$, CFI $= 0.92$, and AIC $= 33.41$ (see Model 1b, Figure 2, bottom). This is a worse fit because the χ^2 test indicated a significant deviation between observed and expected data ($p < 0.01$) and the AIC was bigger in comparison to the more complex model. The χ^2 difference test also indicated a significant better fit of the complex model (Model 1a) compared to the more parsimonious model (Model 1b), $\chi^2_{\text{Diff}}(4) = 13.41$, $p < 0.01$ (see Table 5).

TABLE 2 Means (M) and standard deviations (SDs) for scientific reasoning skills (1), epistemological beliefs (2), and topic-specific knowledge (3)

Measure	N participants	M_{T1} (SD_{T1})	Range$_{T1}$	M_{T2} (SD_{T2})	Range$_{T2}$
(1) Scientific reasoning skills	144	0.67 (0.18)	0.22–1.00	0.67 (0.21)	0.00–1.00
(2) Epistemological beliefs	144	2.82 (0.45)	1.81–4.44	2.84 (0.48)	1.44–4.38
(3) Topic-specific knowledge	144	0.57 (0.11)	0.32–0.84	0.58 (0.10)	0.28–0.84

TABLE 3 Correlation table for scientific reasoning skills, epistemological beliefs, and topic-specific knowledge at T1 and T2

	(2)	(3)	(4)	(5)	(6)
(1) Scientific reasoning skills T1	−0.02	0.19*	0.58***	0.03	0.29***
(2) Epistemological beliefs T1	–	−0.002	−0.03	0.64***	0.12
(3) Topic-specific knowledge T1		–	0.13	−0.01	0.54***
(4) Scientific reasoning skills T2			–	0.02	0.20*
(5) Epistemological beliefs T2				–	−0.003
(6) Topic-specific knowledge T2					–

*$p < 0.05$. ***$p < 0.001$.

Besides the model fit, we also tested the paths of these two models. Autoregressive analyses for both, Model 1a and 1b, indicated temporal stability of topic-specific knowledge and scientific reasoning skills between T1 and T2 (all ps <0.001). Results for the test of cross-lagged paths for Model 1a indicated a positive relation between scientific reasoning skills at T1 and topic-specific knowledge at T2, but no relation between topic-specific knowledge at T1 and scientific reasoning skills at T2 (see Table 5). These results indicated that scientific reasoning skills positively influenced the acquisition of topic-specific knowledge.

To further explore the effects of epistemological beliefs about scientific knowledge, we tested a third path model with three autoregressive paths and six cross-lagged paths (see Model 2a, Figure 3, top). This model was a saturated model, with $\chi^2(4) = 2.93$, $p = 0.570$, RMSEA $= 0.00$, CFI $= 1.00$, and AIC $= 48.93$. In this case, the degrees of freedom were greater than the χ^2-value because χ^2-values tend to decrease for models with lower degrees of freedom. Therefore, the RMSEA and CFI cannot be meaningfully interpreted as absolute fit indices. The fourth, more parsimonious model, with the three autoregressive paths only (see Model 2b, Figure 3, bottom), had a less satisfactory fit than the third, more complex model that we tested, with $\chi^2(12) = 20.40$, $p = 0.060$, RMSEA $= 0.07$, CFI $= 0.96$, and AIC $= 50.40$. The fit was less satisfactory because, even though the χ^2 test failed to reach the level of significance ($p = 0.060$), the AIC was slightly bigger for this more parsimonious model than for the more complex model. Furthermore, the χ^2 difference test indicated a significant better fit of the complex model (Model 2a) compared to the more parsimonious model (Model 2b), $\chi^2_{\text{Diff}}(8) = 17.47$, $p < 0.05$ (see Table 5).

Besides the model fit, we also tested the paths of these two models. Autoregressive analyses for both, models 2a and 2b, indicated temporal stability of topic-specific knowledge, scientific reasoning skills, and epistemological beliefs between T1 and T2 (all ps <0.001). Again, results

TABLE 4 Test statistics for all cross-lagged paths of models 1a and 2a.

Model	Cross-lagged path	Test statistics
Model 1a[a]	Scientific reasoning skills T1 – Topic-specific knowledge T2	$\beta = 0.20$, $B = 0.12$, $SE_B = 0.04$, 95% CI_B [0.041; 0.199], $p = 0.005$
	Topic-specific knowledge T1 – Scientific reasoning skills T2	$\beta = 0.02$, $B = 0.04$, $SE_B = 0.13$, 95% CI_B [−0.217; 0.297], $p = 0.756$
Model 2a[b]	Scientific reasoning skills T1 – Topic-specific knowledge T2	$\beta = 0.20$, $B = 0.12$, $SE_B = 0.04$, 95% CI_B [0.037; 0.195], $p = 0.004$
	Topic-specific knowledge T1 – Scientific reasoning skills T2	$\beta = 0.02$, $B = 0.04$, $SE_B = 0.13$, 95% CI_B [−0.220; 0.302], $p = 0.756$
	Epistemological beliefs T1 – Topic-specific knowledge T2	$\beta = 0.13$, $B = 0.03$, $SE_B = 0.02$, 95% CI_B [−0.002; 0.062], $p = 0.060$
	Topic-specific knowledge T1 – Epistemological beliefs T2	$\beta = -0.01$, $B = -0.06$, $SE_B = 0.29$, 95% CI_B [−0.621; 0.509], $p = 0.844$
	Epistemological beliefs T1 – Scientific reasoning skills T2	$\beta = -0.02$, $B = -0.01$, $SE_B = 0.03$, 95% CI_B [−0.070; 0.056], $p = 0.826$
	Scientific reasoning skills T1 – Epistemological beliefs T2	$\beta = 0.05$, $B = 0.12$, $SE_B = 0.18$, 95% CI_B [−0.227; 0.469], $p = 0.493$

Abbreviations: AIC, Akaike information criterion; CFI, comparative fit index; RMSEA, root mean square error of approximation.

[a]Model fit of Model 1a: $\chi^2(0) = 0.00$, RMSEA = 0.00, CFI = 1.00, AIC = 28.00.

[b]Model fit of Model 2a: $\chi^2(4) = 2.93$, $p = 0.570$, RMSEA = 0.00, CFI = 1.00, AIC = 48.93.

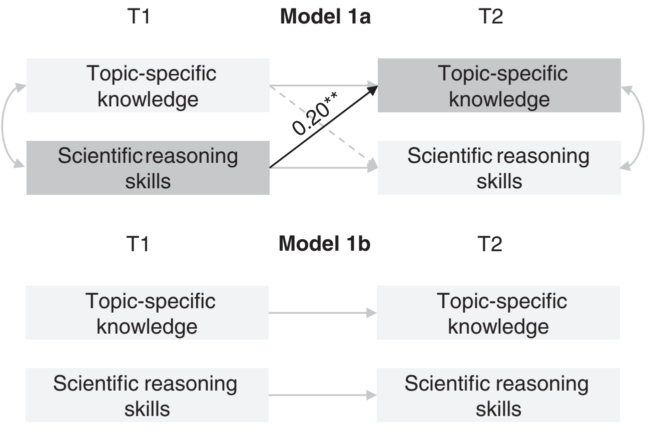

FIGURE 2 Two-wave cross-lagged path models for time-lagged effects between topic-specific knowledge and scientific reasoning skills. Model 1a (top) represents the causation model, Model 1b represents the autoregressive model. Standardized regression coefficients (β) of significant cross-lagged paths are reported (continuous lines), with all autoregressions, all *ps* < 0.001. Other paths (dashed lines) are not significant. $^{**}p < 0.01$

TABLE 5 Fit indices and model comparisons for models 1a–1b with the variables scientific reasoning skills and topic-specific knowledge and for models 2a–2b with the variables scientific reasoning skills, topic-specific knowledge, and epistemological beliefs.

Model	χ^2	df	*p*	RMSEA[a]	CFI	AIC	Comparison	$\Delta\chi^2$	Δdf
1a	0.00	0	——	0.00	1.00	28.00	M1b–M1a	13.41**	4
1b	13.41	4	0.009	0.13	0.92	33.41			
2a	2.93	4	0.570	0.00	1.00	48.93	M2b–M2a	17.47*	8
2b	20.40	12	0.060	0.07	0.96	50.40			

Abbreviations: AIC, Akaike information criterion; CFI, comparative fit index; RMSEA, root mean square error of approximation.

[a]In small *df* models, the RMSEA is not a suitable indicator in order to draw valid conclusions about the model fit (Kenny et al., 2015).

$^{*}p < 0.05$. $^{**}p < 0.01$.

for the test of cross-lagged paths for Model 2a indicated a positive relation between scientific reasoning skills at T1 and topic-specific knowledge at T2, but no relation between topic-specific knowledge at T1 and scientific reasoning skills at T2. Furthermore, there was a marginal positive relation between epistemological beliefs at T1 and topic-specific knowledge at T2, but no relation between topic-specific knowledge at T1 and epistemological beliefs at T2. There were no further significant relations. Thus, epistemological beliefs had a weak, positive influence on topic-specific knowledge that was statistically not significant, while scientific reasoning skills still positively influenced topic-specific knowledge.

7 | DISCUSSION

In this research, we investigated the relationship between topic-specific knowledge and scientific reasoning skills as well as epistemological beliefs in two longitudinal field studies of a CS

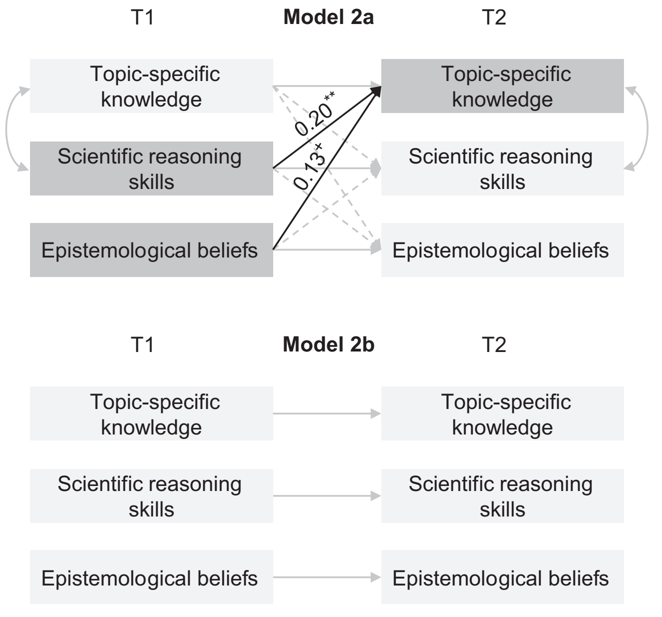

FIGURE 3 Two-wave cross-lagged path models for time-lagged effects between topic-specific knowledge and scientific reasoning skills, and epistemological beliefs. Model 2a (top) represents the causation model, Model 2b represents the autoregressive model. Standardized regression coefficients (β) of significant cross-lagged paths are reported (continuous lines), with all autoregressions, all ps < 0.001. Other paths (dashed lines) are not significant. $^{**}p < 0.01$, $^{+}p < 0.1$

project on urban wildlife ecology. This was done by using a cross-lagged panel design that allowed us to test cause-effect relationships. We examined whether the participants' scientific reasoning skills at the beginning of the project had a positive influence on their topic-specific knowledge at the end of the project, or vice versa. Furthermore, we exploratorily tested the role of epistemic beliefs for the relationship between topic-specific knowledge and scientific reasoning skills. We, thus, aimed to investigate the double role of scientific reasoning skills, a double role that has not yet been tested for in its relationship with topic-specific knowledge and epistemological beliefs in CS projects (e.g., Jordan et al., 2011; Price & Lee, 2013; Trumbull et al., 2000). Previous research has mostly used self-report questionnaires for assessing scientific reasoning skills instead of tests (Stylinski et al., 2020). In contrast, we implemented an assessment that was not based on self-report but tested participants' scientific reasoning skills. The scientific reasoning skills for forming hypotheses, testing hypotheses, and analyzing data have received little attention so far in evaluations of the learning outcomes in CS projects (Edwards et al., 2017; Stylinski et al., 2020). Our findings revealed that both scientific reasoning skills and epistemological beliefs at the beginning of the project positively predicted participants' topic-specific knowledge at the end of the CS project. The effect of epistemological beliefs, however, was only weak. Furthermore, the effect of scientific reasoning skills on topic-specific knowledge did not substantially differ between the model that included epistemological beliefs (Model 2a) and the model that did not include epistemological beliefs (Model 1a). The participants' topic-specific knowledge at the beginning of the CS project, however, predicted neither their scientific reasoning skills nor their epistemological beliefs at the end of the project. This means that the project participants' proficiency in scientific reasoning had a positive influence on their acquisition of topic-specific knowledge.

For our focus on the double role of scientific reasoning skills in CS projects, participants' skills were an important prerequisite for inquiry-based learning (Edwards et al., 2017; Stylinski et al., 2020). In our study, we assume that the higher participants' scientific reasoning skills were at the beginning of the CS project, the more frequently and deeply they possibly engaged with the scientific activities during the project. This assumption would be in line with previous research that has suggested that participants need scientific reasoning skills to engage in the different activities during a CS project (Burgess et al., 2017; Stylinski et al., 2020; Trumbull et al., 2000). Furthermore, we assume that when participants engaged in more activities that stimulate cognitive processes of scientific reasoning, their topic-specific knowledge probably increased toward the end of the CS project. However, our assumptions about participants' engagement and its effect on topic-specific knowledge need to be tested in further research.

Our findings in a CS context are in line with findings from previous research in the formal education context showing that scientific reasoning skills promote the acquisition of topic-specific knowledge (Kalinowski & Willoughby, 2019; Schwichow et al., 2020). More precisely, scientific reasoning skills need to be applied during inquiry-based learning to foster knowledge acquisition (Stender et al., 2018). Our results extend previous findings from the formal education context to a broader adult sample of different age groups in a CS project in the informal education context. They, therefore, highlight the relevance of scientific reasoning skills as a prerequisite for increasing participants' topic-specific knowledge as a learning outcome in CS projects.

Regarding scientific reasoning skills as a learning outcome, topic-specific knowledge had no significant effect on the acquisition of scientific reasoning skills from inquiry-based learning in our CS project. We tentatively assume that participants did not equally engage in the different scientific activities: From these different activities, some are regarded as more familiar in participants' experience (e.g., making observations, collecting data) whereas others are more unfamiliar (e.g., designing investigations, analyzing data; NASEM, 2018). Probably, participants' topic-specific knowledge was not sufficient for engaging in more distal scientific activities such as analyzing data. Behavioral data from another, earlier study on a similar sample of participants in the CS project presented here supports this tentative assumption: Participants in that study engaged less frequently in scientific activities of analyzing data and more frequently in collecting data and making observations (Bruckermann, Greving, et al., 2022). Engaging in more complex activities in CS projects, such as forming hypotheses and analyzing data, has been suggested to be more beneficial for learning (Gray et al., 2017; Phillips et al., 2018; Shirk et al., 2012). Similarly, in science education, research on inquiry-based learning suggests that more complex inquiry tasks stimulate reasoning processes on higher cognitive levels (Chinn & Brewer, 1993; Chinn & Malhotra, 2002). As participants engaged less in more unfamiliar activities, their scientific reasoning probably increased less and did not appear to be a learning outcome in our CS project. Participants' topic-specific knowledge, however, was correlated to scientific reasoning skills within the same time point. Hence, participants with higher topic-specific knowledge also had better scientific reasoning skills.

Besides scientific reasoning skills, epistemological beliefs also marginally and positively predicted topic-specific knowledge at the end of our CS project. This means that the more strongly participants believed in knowledge as being dynamic and changing (i.e., *softer* epistemic beliefs; Stahl & Bromme, 2007) at the beginning of the project, the more topic-specific knowledge on urban wildlife ecology they had at the end of the project. While findings in the formal education context have supported the relation between epistemological beliefs and higher topic-specific knowledge (Baytelman et al., 2020; Stathopoulou & Vosniadou, 2007; Trevors, Kendeou, et al., 2017; Trevors, Muis, et al., 2017), studies on informal learning in CS projects have been inconclusive (e.g., Price & Lee, 2013). Our findings, therefore, transfer previous research findings to CS projects by showing that epistemological beliefs also affect topic-specific knowledge. Still, scientific reasoning skills may be a stronger predictor than epistemological beliefs.

7.1 | Implications

Our findings on the effect of scientific reasoning skills on topic-specific knowledge have theoretical implications for researchers as well as practical implications for CS project managers. With regard to the theoretical implications, several typologies of CS projects suggest that engaging in more complex scientific activities during the inquiry process requires scientific reasoning skills in order to promote individual learning outcomes (Phillips et al., 2018; Shirk et al., 2012; Stylinski et al., 2020). Taking participants' scientific reasoning skills into account helps explain their learning of topic-specific knowledge. In our study, those skills that were more complex in participants' experience (i.e., forming hypotheses, testing hypotheses, and analyzing data: Stylinski et al., 2020) were strongly related to individual learning outcomes (i.e., topic-specific knowledge), probably because they stimulate cognitive processes (Chinn & Malhotra, 2002). However, we did not find an effect of topic-specific knowledge on the more complex scientific reasoning skills. For future research, we therefore suggest to compare participants' scientific reasoning skills in CS projects in which they are contributorily involved (i.e., collect and process data) with participants' scientific reasoning skills in CS projects in which they are collaboratively involved (i.e., form and test hypotheses, analyze and discuss data). Such a comparison could yield important insights for the predictive value of scientific reasoning for individual learning outcomes.

Our findings also have practical implications for CS project managers. To increase the potential of inquiry-based learning in CS projects, participants may need learning opportunities to increase their scientific reasoning skills right at the start. Especially participants with lower scientific reasoning skills may benefit from those learning opportunities because they may not profit from the learning opportunities in a CS project to the same extent as participants with higher scientific reasoning skills. For example, Gray et al. (2017) provided training on scientific reasoning before participants started the field data collection and found that participants' knowledge ultimately increased. The majority of CS projects so far have mostly trained and evaluated participants in a narrow set of skills having to do with data collection, for example, with species identification (e.g., Starr et al., 2014; van der Wal et al., 2016; see Stylinski et al., 2020, for an overview). Other researchers from the formal education context have already suggested training for promoting more complex scientific reasoning skills (Lazonder & Harmsen, 2016; Schwichow et al., 2016). We therefore suggest that initial training of scientific reasoning skills may help increase learning in CS projects.

7.2 | Strength, limitations, and future research

Our study draws its strength from investigating the relationship between scientific reasoning skills and the acquisition of topic-specific knowledge with a longitudinal, cross-lagged panel design. Furthermore, the assessment of participants' scientific reasoning skills was based on a standardized test that added to results from the currently prevalent self-report questionnaires in

CS projects (Stylinski et al., 2020). Our design allowed us to test scientific reasoning skills for their predictive value regarding topic-specific knowledge. Due to the cross-lagged panel design, we could test cause-effect relationships among these variables that had previously only been considered either in correlational analyses (e.g., Masters et al., 2016) or descriptive analyses (e.g., Jordan et al., 2011).

Yet, at the same time, our findings have to be interpreted with caution. Conclusions on cause-effect relationships from cross-lagged panel analyses of field studies are limited by the fact that other variables beyond those included in the model could also have explanatory power on an individual level. That is why we included epistemological beliefs as another variable that, however, did not significantly influence topic-specific knowledge in Model 2a. Furthermore, the relationship between scientific reasoning skills and topic-specific knowledge did not change when we included epistemological beliefs. We suggest testing this relationship in experimental studies, that are yet uncommon in research on CS projects (cf. Greving et al., 2022), because such experiments could rule out influences of third variables by randomly assigning participants to the conditions. These studies should try to promote scientific reasoning skills in the experimental condition in order to investigate whether participants gain topic-specific knowledge from the following inquiry learning in the CS project.

Our findings have extended previous research on the relationship between scientific reasoning and topic-specific knowledge (e.g., Schwichow et al., 2020; Stender et al., 2018) by studying adults of a much broader age range in informal learning. However, the sample was well-educated and it might, therefore, have been easier for them to engage in scientific reasoning for inquiry-based learning. Engaging in scientific reasoning might be more challenging to individuals who have few connections to science (Pandya, 2012). Future research should also test this relationship for individuals who have infrequent contact with science and a lower level of education.

Furthermore, even though our sample size was sufficiently large enough, we relied on rules-of-thumb when we estimated our sample size. We did so because power analyses for path models use the RMSEA fit index that is not a suitable index for cross-lagged panel models with small df (Kenny et al., 2015) which was the case for our models. Therefore, future research should use a larger sample that might increase the generalizability of the findings beyond our typical CS participants.

A strength of our study is that we assessed topic-specific knowledge with a test instrument instead of with self-reports as in most CS projects (see Peter et al., 2019, for an overview). Still, we need to discuss the internal consistency of our test instrument. We measured participants' topic-specific knowledge with a set of 25 questions, each created to assess a distinct knowledge element. While this approach allowed us to cover the knowledge construct in its theoretical breadth (Bruckermann, Stillfried, et al., 2022), our analyses revealed low correlations among the questions resulting in a somewhat low Cronbach's alpha value. However, according to a previous discussion in the literature (Stadler et al., 2021; Taber, 2018), this value does not indicate a misrepresentation of the construct, but rather that the questions are not redundant and represent the theoretical breadth of the knowledge construct. A further step in modeling topic-specific knowledge would be to consider such knowledge not as a reflective construct but rather as a formative construct (Stadler et al., 2021). In CS projects, participants' local knowledge might be a fruitful avenue to empirically compare the two approaches of modeling knowledge as a construct because such local knowledge is less curricular structured than in formal learning (Stocklmayer & Bryant, 2012).

Our findings showed that scientific reasoning skills in inquiry-based learning promote knowledge acquisition. We conclude that participants in our study acquired topic-specific knowledge beyond the knowledge that they already had through the use of their scientific reasoning skills in inquiry-based learning. Although our explanation is in line with previous research (e.g., Stender et al., 2018), it would be useful to gather further (behavioral) data on the frequency with which participants formed hypotheses, tested them, and analyzed the data. Online CS platforms may be a particularly useful tool to investigate such data, as they provide participants with the resources for scientific reasoning (e.g., a modeling software tool; Gray et al., 2017; see Aristeidou & Herodotou, 2020, for an overview). Online CS platforms also record data on participants' behavior in log-files (e.g., Aristeidou et al., 2017). Previous research has not been able to establish a link between participants' knowledge at the beginning of a project and their engagement in scientific activities during the project (Masters et al., 2016). Future research should, therefore, test whether participants' scientific reasoning skills increase their actual engagement in scientific activities that require reasoning on the online CS platform, which in turn may promote their acquisition of topic-specific knowledge.

8 | CONCLUSION

Our research provides evidence that scientific reasoning skills at the beginning of a CS project affect participants' acquisition of topic-specific knowledge at the end of a CS project. We suggest that CS participants need developed scientific reasoning skills to engage in inquiry-based learning for acquiring knowledge on the specific topic they are working with (e.g., urban wildlife ecology). Participants' belief that knowledge is subject to change (i.e., softer epistemological beliefs) also marginally contributed to their greater topic-specific knowledge after participating in a CS project. Thus, taking the prerequisites with which participants enter and join a project into account may explain individual learning outcomes of CS projects. The provision of training in scientific reasoning may help increase individual learning outcomes for adult and more heterogeneous participant groups in CS projects.

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