

Intuitive visual representations of electromagnetic radiation and molecules

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Understanding how learners interpret visual representations of invisible scientific phenomena is crucial for teaching and designing effective instructional materials. This study investigated which visualizations of infrared radiation, radiation absorption, and molecules are perceived as most intuitively comprehensible by students and adults. Grounded in dual process theories of cognition and cognitive load theory, we hypothesized that intuitive visualizations increase cognitive fluency, thereby reducing extraneous cognitive load. A total of $n = 377$ students aged 14–15 and $n = 100$ adults participated in an online survey, selecting the visualization they found most convincing for each of the scientific concepts. The visualizations were developed based on prior physics education research, and participants' preferences were analyzed using Bayesian model comparison. Across all topics, certain visualizations—especially those developed in prior domain-specific research—were strongly preferred, suggesting that intuitive comprehensibility can be systematically supported through thoughtful visual design. Differences between student and adult preferences highlighted the role of prior knowledge and visual familiarity, as adults were clearer in their choices. The findings contribute to a systematic investigation of visual representations used in science education and science communication and offer practical guidance for developing intuitive visualizations in instructional contexts.

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I. INTRODUCTION

Visual representations play a crucial role in communicating science concepts by illustrating invisible or abstract phenomena, visualizing phenomena that are too small, large, fast, or slow to observe, such as the greenhouse effect, and organizing complex information and displaying data [1]—in other words, by visualizing the invisible. From a communication perspective, the visual representations are not the information itself but are supposed to convey information [2]. In instructional materials, visual and verbal representations—or more broadly, text and graphics or visualizations—are therefore combined to convey some kind of information. For example, arrows may, among others, be used to illustrate forces, labels, changes, or radiation, for example, in typical illustrations explaining

the greenhouse effect [3]. In these illustrations, visible light might be depicted as wavy arrows with shorter wavelengths, while infrared radiation is represented as wavy arrows with longer wavelengths. Although the wavelengths in the visualizations do not correspond with the actual wavelengths of these types of radiation, this visual difference is intended to represent that the two types of radiation differ in their wavelengths—a key characteristic of each.

In science education, it has been argued that the use of multiple external representations, i.e., texts, graphs, or pictures, is beneficial for learning processes (for biology education, see Ref. [4]; for chemistry education, see Ref. [5], and for physics education see Ref. [6]). Multiple external representations address different sensory and working memory channels, i.e., verbal/auditory or visual/pictorial channels [7], and can therefore support meaningful learning and deep level comprehension [8]. This approach has been applied in various scientific contexts, including ray optics and experimental physics, where combining multiple representations has shown positive effects on students' conceptual understanding [9,10].

For designing effective visual representations, it is important to consider that students do not automatically

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unpack the information conveyed by visual and verbal representations; rather, they have to cognitively process and interpret what they see. One way to support learners in interpreting visualizations is to recognize the constraints of human working memory, as described in cognitive load theory [11,12]. Recognizing these constraints has been shown to be an effective approach to instructional design in various contexts [1]. Cognitive load theory identifies three types of load that working memory processes during learning: extraneous cognitive load, intrinsic cognitive load, and germane cognitive load. Extraneous cognitive load is the learners' additional cognitive effort in learning new content caused by poor instructional design that diverts mental resources from learning. Intrinsic cognitive load is the learner's mental effort due to the inherent complexity of the content and is influenced by prior knowledge. Germane cognitive load is the learners' mental effort devoted to the actual learning of new content. Aligned with research about cognitive load, Mayer and Moreno [13] proposed criteria to reduce incidental processing, i.e., extraneous cognitive load [11], to facilitate learning processes by freeing cognitive resources for essential processing, i.e., germane cognitive load, and thus for meaningful learning [12]. However, even when considering these criteria in the design of cognitively useful visualizations, they can still be functionally ineffective if the learners do not interpret them as intended [1]. Interpretation of visualizations is influenced by prior knowledge and intuitive understanding, which varies among individuals [1,14,15] and is shaped by cultural backgrounds, for example, in how colors are perceived [3]. For instance, red is commonly associated with hot water, while blue represents cold water [3,16]. Therefore, we argue that for designing effective visual representations, at least two key goals should be pursued: (i) minimizing extraneous cognitive load on learners' working memory and (ii) aligning with and building on learners' prior knowledge to support interpretation and comprehension.

One abstract and complex phenomenon we cannot observe directly is the enhanced greenhouse effect. To understand the greenhouse effect, several science concepts are necessary, such as the conversion of electromagnetic radiation and the absorption and re-emission of infrared radiation when interacting with greenhouse gases. To facilitate learning about the greenhouse effect, learning environments often use visualizations that represent these underlying scientific phenomena. However, research shows that students do not necessarily interpret these visualizations as intended and, for example, struggle with interpreting wavy arrows that represent infrared radiation [3]. When learning about the greenhouse effect, learners' intrinsic cognitive load can be expected to be high due to the inherent complexity of the phenomenon [11], as various science concepts must be combined and held in working memory. Therefore, reducing extraneous cognitive load is

especially important so that learners can allocate resources to actual learning or germane cognitive load.

Hence, in line with the goal of minimizing cognitive load on learners' working memory [1], we aimed to design visualizations of the underlying science concepts that are intuitively comprehensible—that is, representations whose information is easy to process. Guided by dual-process theories of cognition [17,18], we assume that intuitively understandable visualizations enhance cognitive fluency. Increased fluency, in turn, is expected to reduce the need for incidental processing—what cognitive load theory refers to as extraneous cognitive load [11,13]. By making visual information more immediately accessible, learners can allocate more mental effort to essential processing, thus increasing germane cognitive load and supporting learning [12,13].

We argue that designing intuitively understandable visualizations is, in general, of great importance for instructional materials about complex phenomena in physics and other science disciplines, where students need to handle several physics concepts in their working memory, and intrinsic cognitive load is thus high. Intuitively understandable visualizations of concepts underlying the greenhouse effect, like infrared radiation or molecules, can be used in instructional materials to free resources for germane cognitive load. Hence, designing intuitively understandable visualizations of infrared radiation, absorption, and molecules is an important building block for creating effective learning materials not only about the greenhouse effect but also about other phenomena in which electromagnetic radiation or particles play a central role.

To pursue the second goal, aligning with and building on learners' prior knowledge to support interpretation and comprehension, we based our visualizations on previous design studies in physics education research as well as commonly used visualizations. Particularly, insights from design studies focusing on learning about optics, electromagnetic radiation, and the particulate nature of matter in lower secondary education inform the design of our visualizations.

Based on the works of Herdt [19] and Wiesner *et al.* [20], Haagen-Schützenhöfer [21,22] developed a visual representation for visible light in the form of white, diverging arrows, and for the absorption of light in the form of broad, wavy arrows with a missing tip. This representation was used and adapted for teaching about electromagnetic radiation in general, adding the name of the radiation type as text inside the arrows, by Zloklikovits and Hopf [23]. Concerning the representation of submicroscopic particles, Wiener *et al.* [24] developed a typographic visual representation which proved effective in their study investigating a learning environment on the subatomic structure of matter. This approach was further developed by Budimaier and Hopf [25], who used typographic visual representations in a learning environment on the particulate

nature of matter. They also found positive effects of their learning environment on student understanding [26]. These previous projects investigated the described visual representations regarding their suitability to illustrate the model character of representations about the phenomenon. Additionally, their aim was to avoid evoking alternative student conceptions, for example, that sunlight is yellow and infrared radiation is red, or that the particles forming an object are the same color as the object. Based on acceptance probing interviews [27], these studies found that students accepted these visualizations in the proposed learning materials, and they found positive effects on student learning [21–25].

Hence, we developed potential visual representations of infrared radiation and greenhouse gas molecules for visualizations of the greenhouse effect, drawing on both previous domain-specific research on student conceptions and visualizations, as well as cognitive load theory. Thereby, our aim was to address both goals as outlined above.

To explore the intuitive comprehensibility of these visual representations, participants were presented with different visualizations of a given phenomenon based on the previous design studies discussed above [21–25] and on commonly used representations [3]. Participants were asked to select the illustration that they thought represented or most clearly represented the given phenomenon. This approach was intended to encourage intuitive judgments based on perceived clarity and comprehensibility. In line with dual-process theories, we assumed that the image selected most frequently would be the one most intuitively understood—and thus likely to enhance cognitive fluency when integrated into more complex visualizations of the greenhouse effect.

The following research questions guided the investigation:

RQ1: Among a set of visualizations depicting invisible scientific phenomena (such as electromagnetic radiation and molecules), which are perceived as the most convincing by participants?

RQ2: Do preferences for visualizations differ between students and adults, and if so, where do these differences occur?

II. METHODS

A. Study design and data collection

1. Participants

To investigate which visual representations can be useful for teaching the greenhouse effect at the end of lower secondary education, 14- to 15-year-olds were chosen as the target group. The students participated voluntarily in the study as part of a workshop conducted by the physics education research groups at the Universities of Innsbruck and Graz. It is important to note that these workshops do not include any instruction on the survey topic—neither on

visual representations and electromagnetic radiation nor on absorption or molecules.

Additionally, to cross-check our results, we conducted an online survey via *SurveyCircle*, a participant recruitment platform for online surveys used in research [28], to obtain a comparative sample of adults. In total, $n = 377$ students (aged 14–15) and $n = 100$ adults (aged 20–57, median 25) voluntarily participated in our study—both being convenience samples. Of the adults, 76 identified as female and 24 identified as male. Of the students, 154 identified as male, 207 identified as female, 7 identified as diverse, and 9 did not state any gender. The students were from both lower and higher track Austrian schools (“Mittelschule” and “Gymnasium”). Adult participants were from Germany ($n = 79$), Austria ($n = 14$), and Switzerland ($n = 7$) and varied in their formal education level, with their highest degree earned ranging from no school qualification to a completed doctorate, but most participants had either finished a university degree ($n = 63$) or a high school diploma ($n = 35$).

All $n = 100$ adults completed an online questionnaire comprising all items on *SurveyCircle* and were randomly assigned to either group 1 or group 2 for items 4–7. The student participants completed different sets of three to four questions that were added to existing evaluation questionnaires for unrelated workshops they attended at the Universities of Innsbruck and Graz. This approach allowed us to obtain a convenience sample that was more diverse and less self-selected than if we had distributed the survey independently. However, due to time constraints, it was not feasible to include all ten items in the workshop questionnaires. Instead, students responded to subsets of questions based on the topic: the representation of infrared radiation ($n = 147$, items 1–3), the representation of absorption ($n = 230$, items 4–6, divided into two groups), and the representation of molecules ($n = 176$, items 7–10).

2. Development of visualizations

Building on the findings of design-based research (DBR) projects focused on developing learning environments for optics [21] and electromagnetic radiation [23,29], we created four potential visual representations of infrared radiation (Tables I and II) and eight for the absorption of light and radiation (Table III). Additionally, we developed four wavelike potential visual representations of infrared radiation, like the one investigated by Nelson and Olander [3], which we assume to be similar to representations used in various instructional materials. However, a study by Neumann and Hopf [30] found that while most students intuitively associated infrared radiation and UV radiation with being invisible, some were confused about their visibility and potential red or blue color. Therefore, we intentionally avoided the use of color to prevent reinforcing alternative conceptions. Instead, we varied the wavelengths and employed solid and dashed lines (Tables IV and V).

TABLE I. Items 1 and 2 asked participants to select the image representing long-wave, invisible infrared radiation. Visualizations offered for selection are depicted for each item.

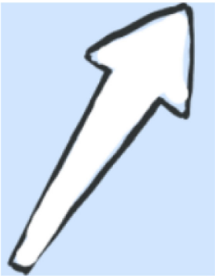
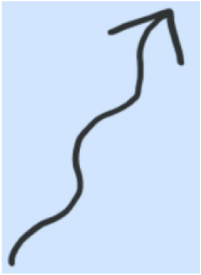
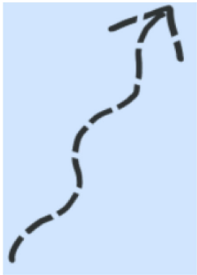
Item text	In the images below, different types of radiation are represented by arrows.			
	Choose the image that you think represents long-wave, invisible infrared radiation.			
Visualizations item 1				
Visualizations item 2				

TABLE II. Item 3 asked participants to select the image representing invisible infrared radiation. Visualizations offered for selection are depicted.

Item text	INVISIBLE radiation is represented in different ways.			
	Which representation do you think is most suitable for depicting INVISIBLE radiation?			
Visualizations				

Visual cues like dashed lines and transparency were employed to support conveying the information. For example, dashed lines are used in geometry to show invisible objects.

While Haagen-Schützenhöfer’s [21] visual representations—centered on light phenomena—primarily emphasized color to depict absorption and scattering, our focus in the context of the greenhouse effect lies in energy transfer and temperature change resulting from the absorption of light and infrared radiation. To represent this, our absorption visuals incorporate a thermometer and red shading of the ground to illustrate the associated increase in energy and temperature.

Similarly, the typographic representations of CO₂ and O₂ molecules used in our survey (Tables IV and V) are grounded in previous DBR projects aimed at supporting learning in physics education, particularly regarding the particulate nature of matter [25,26] and the subatomic structure of matter [24,31]. As an alternative to the typographic models suggested by these research projects, we also offered space-filling models in both black-and-white and colored variants. Both types of representation were provided in two versions: a smaller one maintaining approximately accurate intermolecular distances [25] and a larger version with reduced spacing for visual clarity.

TABLE III. Items 4–6 asked participants to select the image representing the absorption of visible light or radiation. Participants were randomly assigned to one version of the items (group 1 or group 2), either visible light or radiation. In the table, the difference is marked in bold; this was not done in the survey. Visualizations offered for selection in items 4 and 5 are depicted. In item 6, participants were presented with their two previous answers from items 4 and 5 and asked to select one. An example is given in the table.

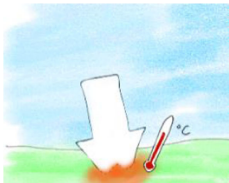
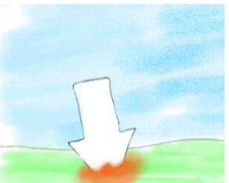
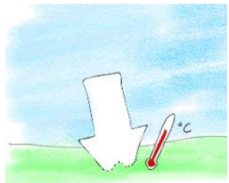
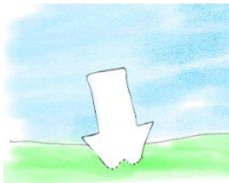
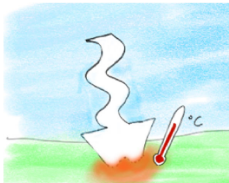
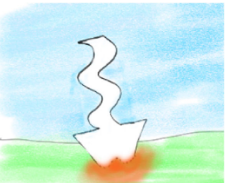
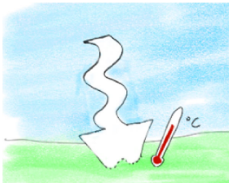
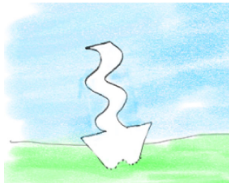
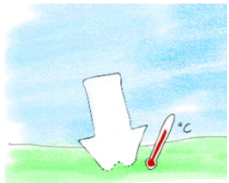
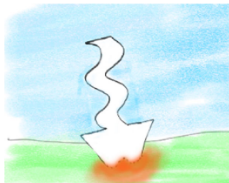
	Group 1	Group 2
	In the images below, you can see how visible light is absorbed by the Earth's surface. This means that the light is taken in by the ground, causing it to warm up.	In the images below, you can see how radiation is absorbed by the Earth's surface. This means that the radiation is taken in by the ground, causing it to warm up.
Item text	Choose the image that you think represents this process.	
Visualizations item 4		
Visualizations item 5		
Example visualizations item 6	Option 1: Selection from item 4, e.g.: 	Option 2: Selection from item 5, e.g.: 

TABLE IV. Item 7 asked participants to select the image representing CO₂ molecules most clearly. In item 10, participants were then presented with their chosen model (typographic, space-filling black, space-filling colored) in two variations, a smaller version and an enlarged one. An example is given in the table.

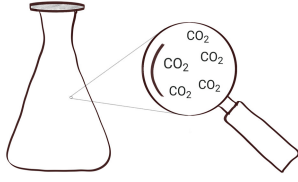
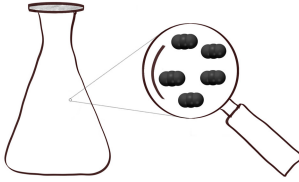
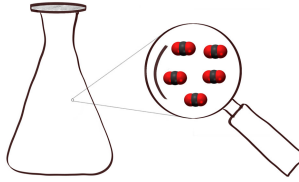
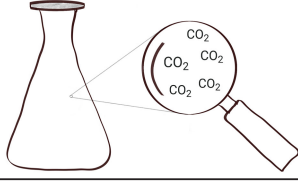
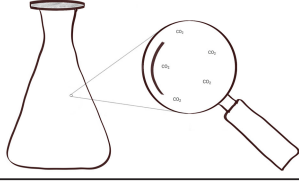
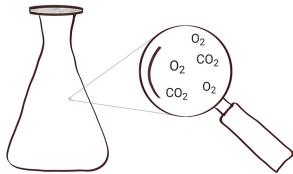
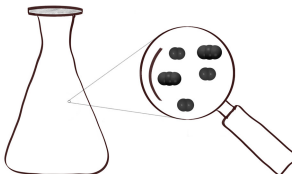
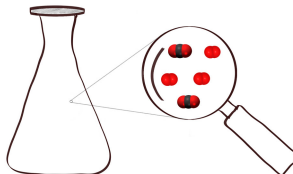
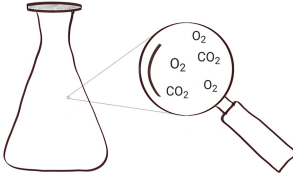
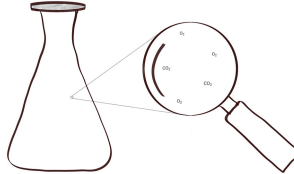
Item text	In the images below, each vessel is filled with the invisible gases oxygen (O ₂) and carbon dioxide (CO ₂). In the magnifying glass, individual molecules within the vessel are depicted.		
	Choose the image that you think represents the molecules most clearly.		
Visualizations item 7			
Example Visualizations item 8, based on selection from item 7			

TABLE V. Item 9 asked participants to select the image representing O_2 and CO_2 molecules most clearly. In item 10, participants were then presented with their chosen model (typographic, space-filling black, space-filling colored) in two variations, a smaller version and an enlarged one. An example is given in the table.

Item text	In the images below, each vessel is filled with the invisible gases oxygen (O_2) and carbon dioxide (CO_2). In the magnifying glass, individual molecules within the vessel are depicted.		
	Choose the image that you think represents the molecules most clearly.		
Visualizations item 9			
Example visualizations item 10, based on selection from item 9			

3. Items

Based on the visual representations described in Sec. II A 2, we developed ten items for the survey. These items asked participants to identify which image, in their opinion, best represented the respective phenomenon in the case of infrared radiation and absorption, and which image most clearly depicted the molecules in the case of molecular representations. The answer options for each item were randomized to control for order effects. The survey was administered in German as an online survey via Qualtrics. An English translation of all items is provided in Tables I–V.

Items concerning the visual representation of infrared radiation are presented in Tables I and II. In the survey, items 1 and 2 were shown in randomized order, with item 3 always following immediately after.

To investigate the perception of absorption visualizations, participants were randomly assigned—via automatic randomization—to one of two groups of approximately equal size. One group was presented with items asking about absorption of visual light, the other group was presented with items asking about absorption of radiation; therefore, only varying terminology. The two versions of the items were identical otherwise. Items 4 and 5 were presented in randomized order, and Item 6 was always shown directly afterward. These items are presented in Table III.

Items 7–10 focused on the representation of molecules. Participants were shown three different visualization formats: a typographic model, a black-and-white space-filling model, and a colored space-filling model. In item 7, participants were asked to select the image that best represented CO_2 molecules; in item 9, the same question was posed for a mixture of O_2 and CO_2 . Items 8 and 10 then

displayed the selected representation from the previous item in two versions: one smaller, with approximately accurate intermolecular spacing [25] and one enlarged version with reduced spacing. Participants were again asked to choose between them. The pairs of Items 7 and 8 and Items 9 and 10 were each presented in randomized order, but the related items were always shown consecutively. Items 7 and 8 are displayed in Table IV, and items 9 and 10 in Table V.

B. Analytical approach in a Bayesian framework

While a classical statistical or frequentist approach, such as a chi-squared test, could be used to assess whether the observed frequencies deviate from a uniform distribution, it does not provide detailed insight into the structure of participants' preferences. In particular, it offers no direct estimation of the underlying choice probabilities, nor does it quantify how strongly the data support one explanation over another. Moreover, frequentist methods rely heavily on values and null hypothesis significance testing, which have been widely criticized for their limitations in interpretability and informativeness [32]. A Bayesian framework, however, allows for direct comparison of hypotheses, probabilistic statements about hypotheses and model parameters, in our case, providing richer and more intuitive insights into participants' preferences.

We therefore adopted a Bayesian approach [33]. The core of Bayesian inference lies in Bayes' theorem, which provides a formal mechanism for updating beliefs in light of new evidence. Bayesian inference begins with specifying a *prior distribution*, which represents our initial beliefs (priors) about possible values of the parameters before seeing the data. This prior probability distribution can be uninformative (i.e., assuming equal plausibility to a wide

range of parameter values) or informed by theory or previous empirical results [34].

After collecting the data, the prior is updated using Bayes' theorem to produce the *posterior distribution*, which reflects our updated beliefs about the parameters in light of the evidence. A *posterior distribution* combines the prior and the likelihood of the observed data to give a complete picture of the parameter's probable values. Unlike point estimates or binary decisions derived from classical statistics, the Bayesian approach yields a full distribution over possible parameter values. One key advantage of this approach is the interpretability of *credible intervals* derived from the posterior. A 95% credible interval, for example, can be directly interpreted as: "there is a 95% probability that the true parameter value lies within this range." This contrasts with frequentist *confidence intervals*, which refer to hypothetical repeated sampling and do not allow direct probabilistic statements about the parameter itself [35].

This approach offers several advantages over traditional frequentist methods, especially in our context. First, it enables the estimation of the actual choice probabilities for each visualization, rather than merely testing whether the observed frequencies deviate from a uniform distribution. Second, Bayesian methods provide a natural way to express uncertainty through posterior distributions and credible intervals, allowing us to quantify how confident we are in those estimated preferences [36]. Third, Bayesian analysis allows for the direct comparison of competing models, such as a model assuming equal preference versus one that allows for skewed distributions. Finally, the framework allows for the explicit inclusion of prior assumptions, whether uninformative or informed by theoretical or empirical considerations, making the reasoning process transparent and reproducible [37].

Importantly, Bayesian methods yield interpretable probabilistic statements about the parameters of interest. For example, instead of reporting whether the frequency of a certain choice is significantly higher, we can report the probability that a given visualization is preferred by more than 50% of participants—or quantify how strongly the data support this conclusion via a Bayes factor [32]. This approach also allowed us to go beyond simple hypothesis testing and instead make probabilistic inferences about the relative convincingness of the visualizations.

C. Bayesian categorical analysis

All items used in our study resulted in categorical responses, in which participants selected one option from a certain number (two, three, or four) of possible visualizations for each item. Such data are naturally modeled using a multinomial distribution, which describes the probability of observing a particular set of category counts given a set of underlying choice probabilities $\Theta = (\Theta_1, \Theta_2, \dots, \Theta_k)$, where $\sum \Theta_i = 1$.

In a Bayesian framework, we treat these probabilities not as fixed unknown quantities but as random variables, expressing our uncertainty about their true values. Therefore, we do not estimate directly from the data alone; instead, we begin by assigning a prior distribution over the space of possible vectors. For multinomial data, a natural and mathematically convenient choice is the Dirichlet distribution, which is a distribution over probability vectors (i.e., vectors of positive numbers that sum to one). The Dirichlet prior is parameterized by a vector α_i , where each i represents a (pseudo-)count or prior belief in the frequency of category i . This means the prior is not a single fixed value, function, or matrix, but a distribution over vectors. After collecting the data, we then update this prior using Bayes' theorem, i.e., calculating the posterior distribution. The Dirichlet distribution is the conjugate prior of the multinomial distribution, meaning that the posterior distribution over the probabilities also follows a Dirichlet form. This mathematical convenience enables us to update our beliefs in a closed-form manner upon observing new data [34,37].

A symmetric Dirichlet prior [e.g., $\text{Dirichlet}(1, 1, \dots, 1)$] reflects complete initial uncertainty, assigning equal prior probability to all possible distributions of preferences. After observing the data, we obtain a posterior distribution that combines prior beliefs with empirical evidence. This posterior tells how likely different configurations of category probabilities are, given the observation. It allows for interpretation beyond point estimates—for example, we can compute credible intervals for each category or make probabilistic statements like "there is a 95% probability that category 4 is preferred by more than half the participants" [36].

In addition to parameter estimation, the Bayesian framework enables model comparison. Using Bayes factors, we can compare the likelihood of the observed data under two competing models—such as a uniform preference model (i.e., all visualizations equally convincing) and a data-driven model with unknown, potentially skewed preferences. The Bayes factor provides a continuous measure of evidence, which overcomes many of the limitations of binary decision rules in null hypothesis significance testing [32,38]. As a rule of thumb, a Bayes factor (BF) greater than 3 is typically interpreted as moderate evidence, greater than 10 as strong evidence, and above 100 as decisive evidence in favor of one model over the other; conversely, a BF less than 1/3 indicates moderate evidence, less than 1/10 strong evidence, and less than 1/100 decisive evidence in favor of the competing (often null) model [38].

D. Analysis procedure

For each survey item, participants selected the visualization they found most convincing among a fixed set of alternatives. The resulting data consisted of observed frequencies across the available categories. To analyze

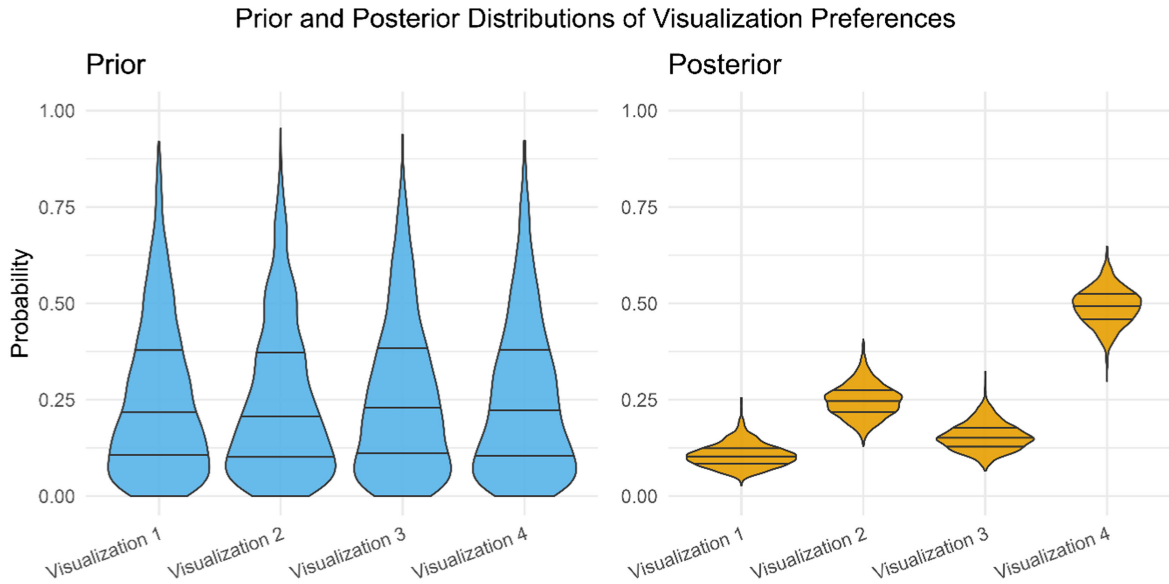


FIG. 1. Prior and posterior distributions of visualization preferences for an exemplary item.

these response distributions, we applied a Bayesian model comparison approach using the software R [39], evaluating whether the observed choices were likely to result from random selection (i.e., uniform preference) or from systematic preferences for specific visualizations. Analysis code can be obtained from the authors.

1. Model specification

We compared two models for each item:

- Model M_0 assumed that all visualizations were equally likely to be chosen. This corresponds to a multinomial distribution with fixed parameters $\Theta_i = \frac{1}{k}$, where k is the number of visualizations in the item.
- Model M_1 allowed for unequal response probabilities and modeled the category preferences using a Dirichlet-multinomial distribution with unknown parameters $\Theta \sim \text{Dirichlet}(\alpha)$.

For the prior distribution in Model M_1 , we used a symmetric Dirichlet prior with $\alpha = (1, 1, \dots, 1)$. This reflects complete prior uncertainty, assigning equal plausibility to all possible response distributions while remaining mathematically convenient for analytical computation [37].

2. Inference and interpretation

For each survey item, we computed the posterior distribution over the category probabilities. These posterior distributions provide a detailed and interpretable summary of participants' choices. From them, we extracted posterior means and 95% credible intervals for each visualization, offering estimates of the likelihood that a randomly selected participant would choose a given representation, along with the uncertainty surrounding those estimates.

To aid interpretation, we visualized the posterior distributions using violin plots, making it possible to compare

the estimated probabilities and their distributions across categories. An example is shown in Fig. 1, which displays both the prior and posterior distributions for one of the survey items. The comparison illustrates how the empirical data substantially shift the distribution away from uniform uncertainty, indicating a clear preference for specific categories, in this case, visualization 4.

3. Bayes factor model comparison

To quantify the strength of evidence for systematic preferences, we computed the Bayes factor (BF) comparing model M_1 (free preferences) against model M_0 (uniform distribution). The BF is defined as $\text{BF} = \frac{P(\text{data}|M_1)}{P(\text{data}|M_0)}$ where $P(\text{data}|M_i)$ denotes the marginal likelihood of the data under model M_i [38].

4. Group comparisons

To examine potential differences between students and adults, we conducted the Bayesian analysis separately for each group. This yielded posterior distributions over the category probabilities for each visualization within each population. We then compared these distributions in two complementary ways. First, we performed a qualitative comparison by visualizing the posterior distributions from both groups in side-by-side violin plots, allowing for a direct visual inspection of group-level similarities and differences. Second, we conducted a quantitative comparison by computing the posterior distribution of the difference in probabilities between groups for each visualization. This enabled us to estimate, for example, the probability that adults were more likely than students to prefer a particular representation. Additionally, we computed Bayes factors to formally test whether the group-level distributions were more likely to have been drawn from a

single shared population or from two distinct populations. Together, these comparisons allowed us to assess whether the two groups exhibited similar patterns of preference and to explore possible age- or experience-related differences in how visualizations were interpreted.

III. RESULTS

A. Representation of IR radiation

1. Diverging arrows

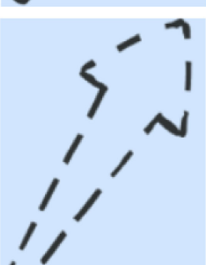
First, we investigated which visualization of infrared radiation was preferred. To obtain an estimate of overall visualization preferences, we pooled responses from both

students and adults ($n = 247$) and calculated the posterior distribution over the four available visualizations using a symmetric Dirichlet(1, 1, 1, 1) prior.

Visual representation of infrared radiation was addressed by Items 1–3, with Item 1 presenting four potential visualizations based on previous DBR projects by Haagen-Schützenhöfer [21] and Zloklikovits and Hopf [23]. The resulting posterior means and credible intervals for Item 1 are shown in Table VI.

The analysis reveals that visualization IR4 was by far the most preferred representation, with an estimated posterior mean of 52.5% and a 95% credible interval ranging from 46.5% to 58.5%. Visualization IR2

TABLE VI. Posterior mean probabilities and 95% credible intervals for each visualization option, based on pooled responses from students and adults ($n = 247$). The estimates are derived from a Bayesian Dirichlet-multinomial model with a uniform Dirichlet(1, 1, 1, 1).

Visualization	Image of visualization	n	Posterior mean (%)	95% credible interval
IR1		23	9.6	[6.2%, 13.4%]
IR2		58	23.5	[18.5%, 29.1%]
IR3		35	14.4	[10.4%, 18.8%]
IR4		131	52.5	[46.5%, 58.8%]

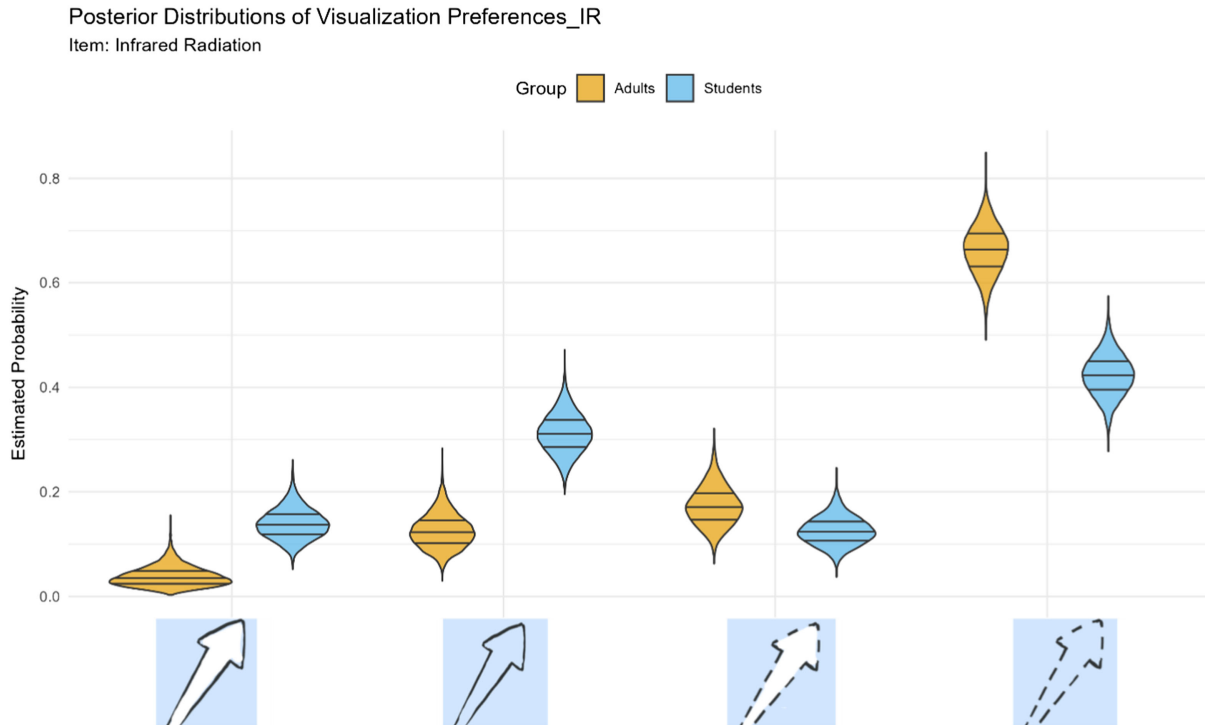


FIG. 2. Posterior distributions over choice probabilities for each visualization, by group (students or adults). Violin plots show the full posterior density with inner quartile markers.

followed at a distance, with a posterior mean of 23.5% (95% CI: [18.5%, 29.1%]), while visualizations IR3 and IR1 were chosen less frequently, with posterior means of 14.4% (95% CI: [10.4%, 18.8%]) and 9.6% (95% CI: [6.2%, 13.4%]), respectively. We also calculated the Bayes factor $BF = 5.05 \times 10^{19}$, providing overwhelming evidence for differences in visualization preferences among the participants. These results indicate a strong consensus across participant groups in favor of visualization IR4 as the most convincing representation of infrared radiation in this context.

A separate analysis of students' and adults' answers shows that both groups clearly preferred visualization IR4. In the student group, the posterior mean for visualization IR4 was 42.3% (95% CI: [34.4%, 50.2%]), and in the adult group, it was even 66.3% (95% CI: [57.0%, 74.9%]). This indicates a much stronger preference for visualization IR4 among adults. The posterior distributions for both groups are presented in Fig. 2.

2. Commonly used “wavy” arrows

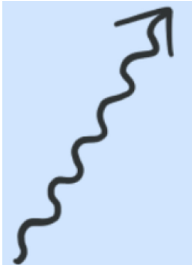
In the second item addressing the visual representation of infrared radiation, we used representations similar to the one investigated by Nelson and Olander [3] in variations of wavelengths as well as dashed and solid lines. The resulting posterior means and credible intervals for the pooled responses are shown in Table VII.

The analysis reveals that visualization IR6 was the most preferred representation, with an estimated posterior mean of 37.6% and a 95% credible interval ranging from 31.7% to 43.8%. However, visualization IR5 followed with overlapping 95% credible intervals, the posterior mean being 28.8%, and the 95% CI ranging from 23.4% to 34.5%. Visualization IR8 was chosen a little less frequently, with a posterior mean of 20.8% (95% CI: [16.0%, 26.0%]), while visualizations IR7 was chosen by fewer participants (posterior mean: 12.8%, 95% CI: [9.0%, 17.2%]). However, the Bayes factor $BF = 7.44 \times 10^6$ indicates that the distribution is not uniform.

A separate analysis of students' and adults' answers shows that the groups differ concerning their preferences. In the student group, a majority chose visualization IR 5, with a posterior mean of 33.3% (95% CI: [26.1%, 41.1%]). Conversely, most adults chose visualization IR6, with a posterior mean of 49.1% (95% CI: [39.6%, 58.6%]). Posterior distributions for both groups are presented in Fig. 3.

A further comparison of the results for both groups is presented in Table VIII. Results show that for adults, the difference in posterior means between the most popular option, visualization IR 6, and the other options is much bigger than for students. Moreover, students even chose a different option most frequently, visualization IR 5.

TABLE VII. Posterior mean probabilities and 95% credible intervals for each visualization option, based on pooled responses from students and adults ($n = 246$). The estimates are derived from a Bayesian Dirichlet-multinomial model with a uniform Dirichlet(1, 1, 1, 1).

Visualization	Image of visualization	n	Posterior mean (%)	95% credible interval
IR5		71	28.8	[23.4%, 34.5%]
IR6		93	37.6	[31.7%, 43.8%]
IR7		31	12.8	[9.0%, 17.2%]
IR8		51	20.8	[16.0%, 26.0%]

3. Overall preference

In item 3, we presented participants with a mix of the options of items 1 and 2, visualizations IR2, IR4, IR5, and IR6 (Table II). The resulting posterior means and credible intervals for the pooled responses are shown in Table IX. The analysis reveals that visualization IR4 was clearly the most preferred representation, with an estimated posterior mean of 44.6% and a 95% credible interval ranging from 38.5% to 50.8%. Interestingly, visualization IR6 followed with a posterior mean of 29.9% (95% CI: [24.4%, 35.7%]), while visualizations IR5 and IR2 were chosen less frequently, with posterior means of 15.1% (95% CI: [10.4%, 18.8%]) and 10.4% (95% CI: [11.0%,

19.8%]), respectively. We also calculated the Bayes factor $BF = 1.18 \times 10^{13}$, providing overwhelming evidence for differences in visualization preferences among the participants. These results indicate a strong consensus across participant groups in favor of visualization IR4 as the most convincing representation of infrared radiation in this context. A separate analysis of students' and adults' answers shows that both groups preferred visualization IR4. The posterior distributions for both groups are presented in Fig. 4. In the student group, the posterior mean for visualization IR4 was 40.4% (95% CI: [32.7%, 48.4%]), in the adult group, it was 50.1% (95% CI: [40.5%, 59.8%]).

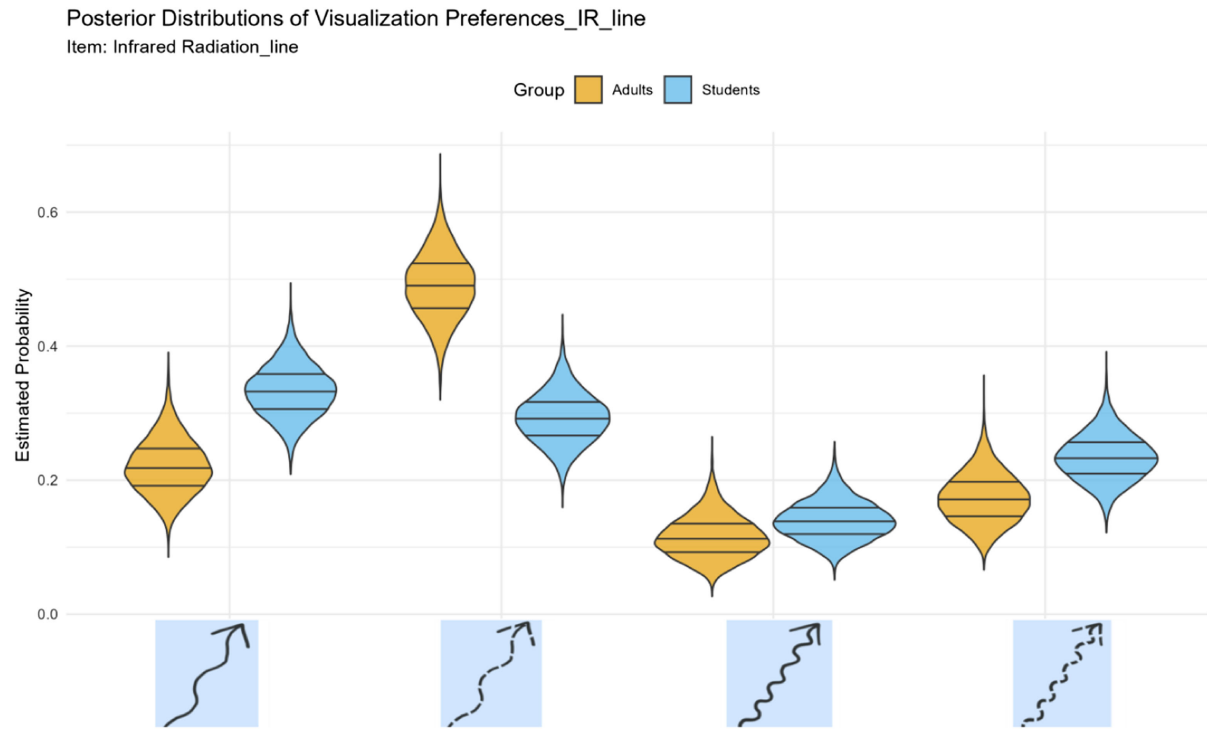


FIG. 3. Posterior distributions over choice probabilities for each visualization, by group (students or adults). Violin plots show the full posterior density with inner quartile markers.

TABLE VIII. Posterior mean probabilities and 95% credible intervals for each visualization option, based on students’ responses ($n = 146$), $\text{BF} = 3.31$ and adults’ responses ($n = 100$), $\text{BF} = 4.73 \times 10^5$ separately.

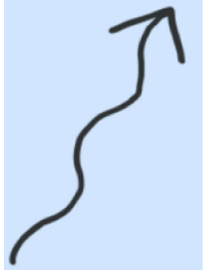
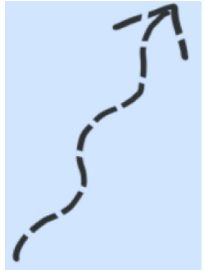
Visualization	Students			Adults		
	n	Posterior mean (%)	95% credible interval	n	Posterior mean (%)	95% credible interval
IR5	49	33.3	[26.1%, 41.1%]	22	22.1	[14.8%, 30.5%]
IR6	43	29.3	[22.1%, 36.9%]	50	49.1	[39.6%, 58.6%]
IR7	20	14.0	[8.9%, 20.1%]	11	11.5	[6.2%, 18.4%]
IR8	34	23.4	[16.9%, 30.5%]	17	17.3	[10.7%, 25.0%]

TABLE IX. Posterior mean probabilities and 95% credible intervals for each visualization option, based on pooled responses from students and adults ($n = 247$). The estimates are derived from a Bayesian Dirichlet-multinomial model with a uniform Dirichlet(1, 1, 1, 1).

Visualization	Image of visualization	n	Posterior mean (%)	95% credible interval
IR2		25	10.4	[6.9%, 14.5%]

(Table continued)

TABLE IX. (Continued)

Visualization	Image of visualization	n	Posterior mean (%)	95% credible interval
IR4		111	44.6	[38.5%, 50.8%]
IR5		37	15.1	[11.0%, 19.8%]
IR6		74	29.9	[24.4%, 35.7%]

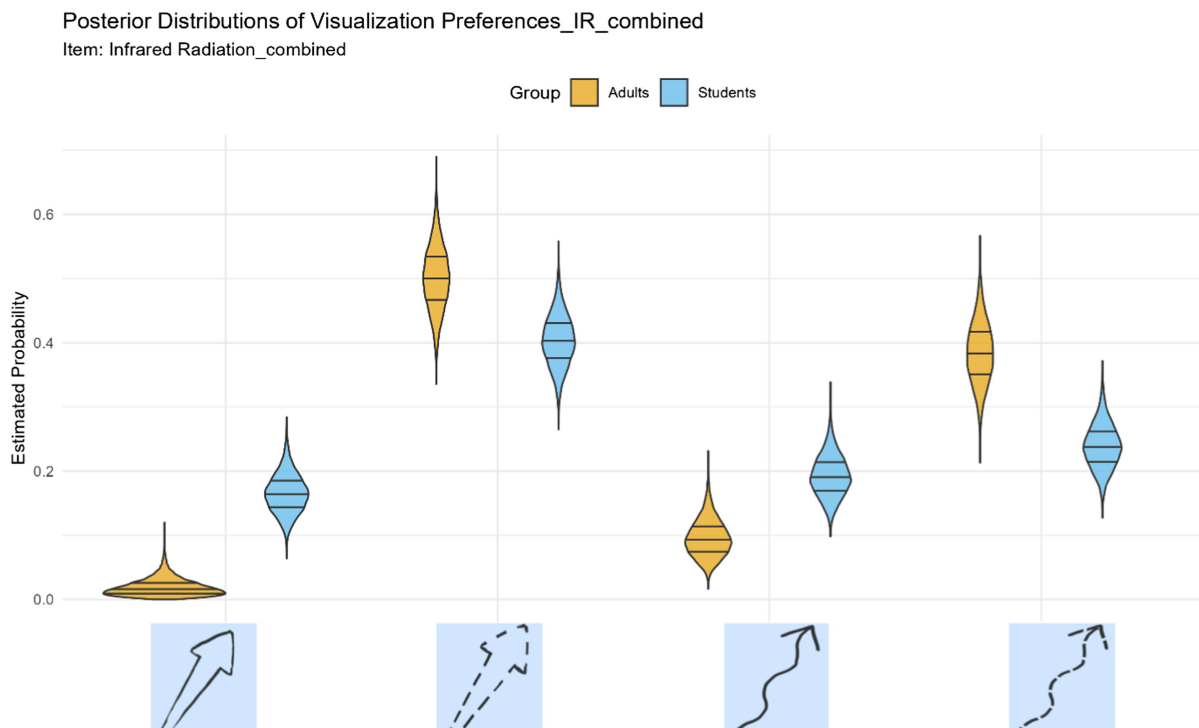
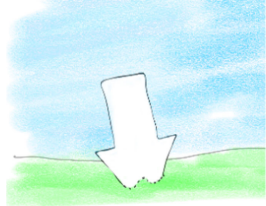
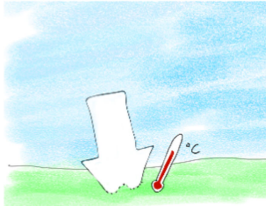
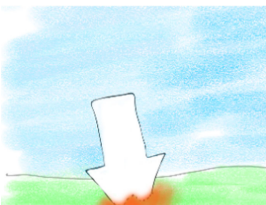
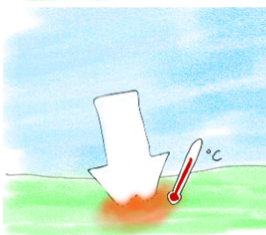


FIG. 4. Posterior distributions over choice probabilities for each visualization, by group (students or adults). Violin plots show the full posterior density with inner quartile markers.

TABLE X. Posterior mean probabilities and 95% credible intervals for each visualization option, based on pooled responses from students and adults in both groups ($n = 330$) addressing Items 4 and 5 (straight and wavy arrows). The estimates are derived from a Bayesian Dirichlet-multinomial model with a uniform Dirichlet(1, 1, 1, 1).

Visualization	Image of Visualization	Count	Posterior mean (%)	95% credible Interval
V1		25	4.0	[2.6%, 5.6%]
V2		108	16.6	[13.9%, 19.6%]
V3		99	15.2	[12.6%, 18.0%]
V4		420	64.2	[60.5%, 67.8%]

However, for adults, the 95% credible interval for visualization IR4 overlapped with the one for visualization IR6 (posterior mean: 38.4%, 95% CI: [29.3%, 48.0%]).

We therefore conducted a separate analysis of the pooled responses concerning visualizations IR4 and IR6, calculating the Bayes factor. The resulting $BF = 6.56$ provides moderate evidence against a uniform distribution.

B. Representation of absorption

1. Overall visualization preference

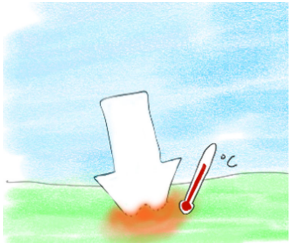
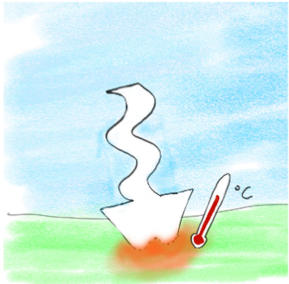
Items 4–6 investigated which visualization of absorption was preferred. To obtain an estimate of overall visualization preferences, we pooled responses to Items 4 and 5 (straight arrows and wavy arrows) from both students and adults in both groups ($n = 330$), i.e., presented with items asking about the absorption of light and the absorption of radiation. We calculated the posterior distribution over the four available visualizations using a symmetric Dirichlet(1, 1, 1, 1) prior.

The resulting posterior means and credible intervals are shown in Table X.

The analysis reveals that visualization 4 was by far the most preferred representation, with an estimated posterior mean of 64.2% and a 95% credible interval ranging from 60.5% to 67.8%. Visualizations 2 and 3 followed at a distance, with posterior means of 16.6% (95% CI: [13.9%, 19.6%]) and 15.2% (95% CI: [12.6%, 18.0%]), respectively. Visualization 1 was the least preferred, with a posterior mean of only 4.0% and a 95% credible interval from 2.6% to 5.6%. These results indicate a strong consensus across participant groups in favor of visualization 4 as the most convincing representation of the absorption of light or radiation in this context.

Regarding the final choice between a straight and wavy arrow, we analyzed the response distribution using a Bayesian model comparison. Participants selected one of the two options (straight or wavy), resulting in 133 choices of the straight arrow and 187 choices of the wavy arrow. We compared two models: a null model (M_0), assuming equal preference for both options (i.e., a fixed binomial probability of 0.5), and an alternative model (M_1), which allowed for unknown preference probabilities estimated via a

TABLE XI. Posterior mean probabilities and 95% credible intervals for each visualization option of arrows, based on pooled responses from students and adults ($n = 330$). The estimates are derived from a Bayesian Dirichlet-multinomial model with a uniform distribution.

Visualization	Image of visualization	Count	Posterior mean (%)	95% credible interval
Straight arrow		133	41.6	[36.4%, 47.1%]
Wavy arrow		187	58.4	[52.9%, 63.6%]

Dirichlet-multinomial distribution with a uniform prior [Dirichlet(1,1)]. The resulting Bayes factor was $BF_{10} \approx 12.24$, indicating strong evidence in favor of unequal preferences. However, for the students only, there

is strong evidence that there is no preference for straight or wavy arrows ($BF_{10} \approx 0.09$). Table XI as well as Fig. 5, provide an overview of the corresponding posterior means as well as 95% credible Intervals.

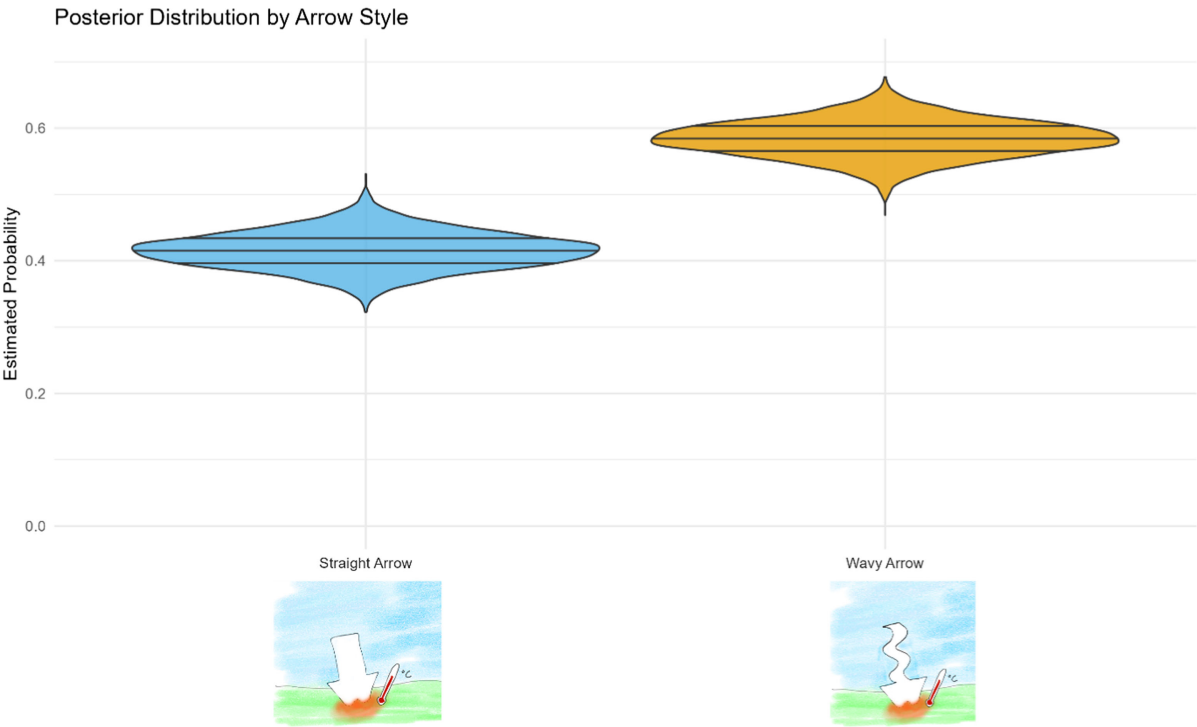


FIG. 5. Posterior distributions of the estimated probability that each arrow style was selected as the most convincing visualization. The violin plots show Bayesian posterior densities for the “straight arrow” and “wavy arrow” conditions, based on a Dirichlet-multinomial model with a uniform prior. Inner dashed lines represent the interquartile range and median of the posterior distribution. The results suggest a higher preference for the wavy representation.

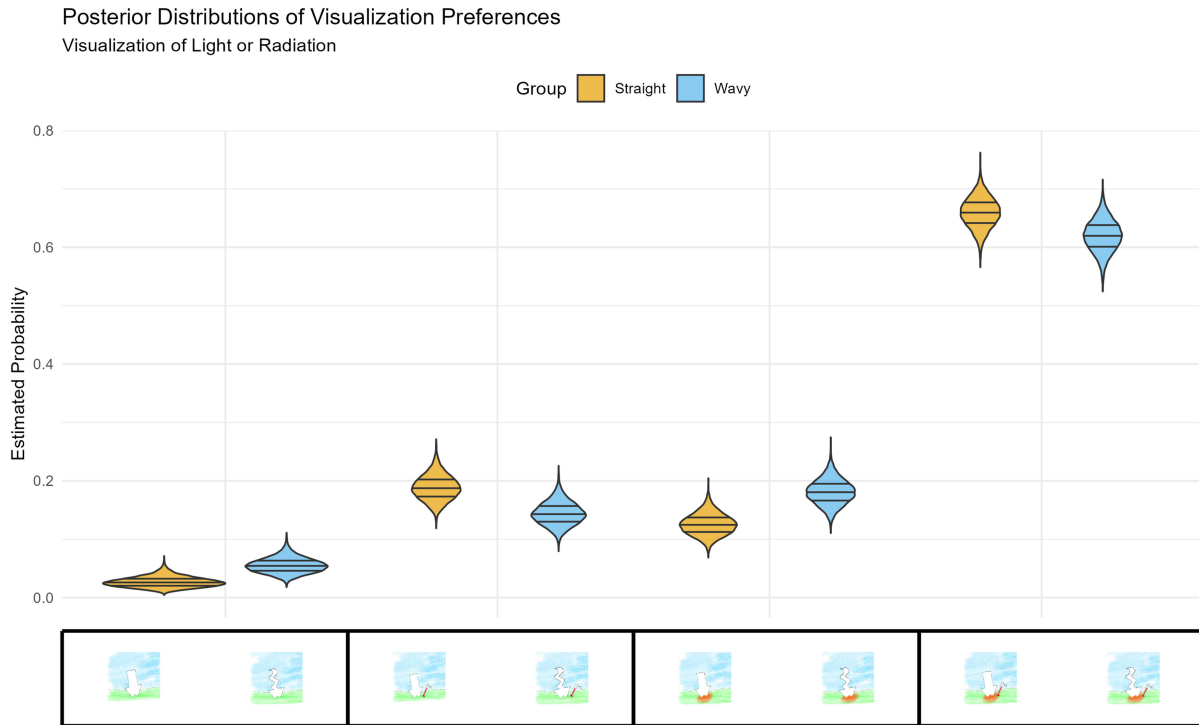


FIG. 6. Posterior distributions over choice probabilities for each visualization, by arrow style. Violin plots show the full posterior density with inner quartile markers.

2. Effects of terminology and representational style

This item was designed to explore whether participants' preferences for visualizations of electromagnetic phenomena are influenced by the terminology used ("visible light" vs "radiation") and the representational style (straight vs wavy arrows). To this end, we implemented a 2×2 between-subjects factorial design, yielding four conditions:

- Light + straight arrows.
- Light + wavy arrows.
- Radiation + straight arrows.
- Radiation + wavy arrows.

Each participant saw two versions of the item, light + straight arrows and light + wavy arrows (in randomized order) or radiation + straight arrows and radiation + wavy arrows (in randomized order). They selected the visualization they found most convincing out of four alternatives in each item. This design allowed us to independently assess the effects of scientific terminology and representational style on participants' interpretive preferences.

To evaluate differences in response distributions across the four conditions, we conducted a Bayesian model comparison based on Dirichlet-multinomial likelihoods. We compared the marginal likelihoods of four models:

- H0 (null model): All groups share the same distribution of preferences.
- H1 (terminology effect): Distinct distributions for "light" vs "radiation."
- H2 (representational style effect): Distinct distributions for straight vs wavy arrows.

- H3 (full model): Each condition has its own distribution (full interaction).

Using a Bayesian approach based on Dirichlet-multinomial marginal likelihoods with a symmetric Dirichlet(1, 1, 1, 1) prior, we computed Bayes factors for each model relative to the null. The results were as follows:

- BF_{10} (terminology effect): 0.04—strong evidence against a terminology effect.
- BF_{20} (representational style effect): 0.04—strong evidence against a style effect.
- BF_{30} (full model): 0.00—decisive evidence against an interaction between terminology and style.

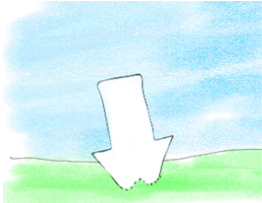
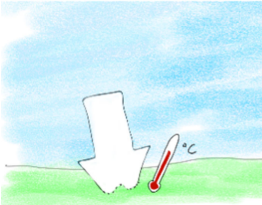
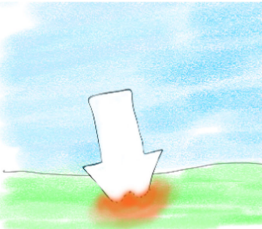
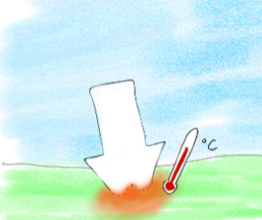
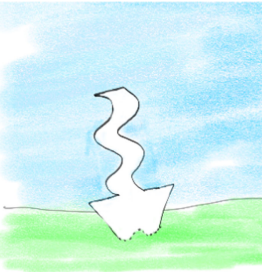
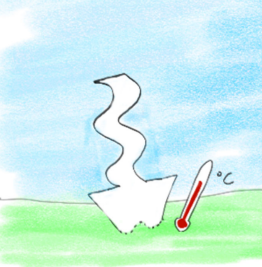
These results indicate that participants' preferences did not differ substantially depending on whether visualizations used straight or wavy arrows or which terminology ("light" vs "radiation") was used.

Importantly, Visualization 4 remained the dominant choice across both conditions (Fig. 6 and Table XII), with posterior means of 65.9% (CI [60.7%, 70.8%]) in the straight condition and 61.9% (CI [56.6%, 67.2%]) in the wavy condition, suggesting a consistent overall preference for this representation regardless of visual style.

3. Group differences

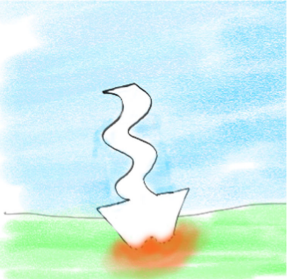
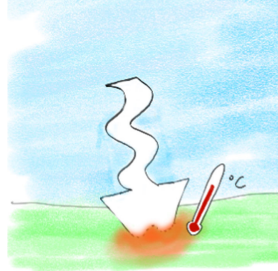
To evaluate whether students and adults differed in their overall preferences for visualizations, we compared a Bayesian model assuming a shared response distribution (null model) to a model allowing for separate distributions for each group. This comparison, based

TABLE XII. Posterior mean probabilities and 95% credible intervals for each visualization option of arrows, based on pooled responses from students and adults ($n = 330$). The estimates are derived from a Bayesian Dirichlet-multinomial model with a uniform distribution.

Visualization	Image of visualization	Count	Posterior mean (%)	95% credible interval	Condition
V1		8	2.7	[1.2%, 4.7%]	Straight arrow
V2		62	18.8	[14.9%, 23.4%]	Straight arrow
V3		41	12.6	[9.3%, 16.3%]	Straight arrow
V4		219	65.9%	[60.7%, 70.8%]	Straight arrow
V1		17	5.5%	[3.3%, 8.3%]	Wavy arrow
V2		46	14.4%	[10.9%, 18.5%]	Wavy arrow

(Table continued)

TABLE XII. (Continued)

Visualization	Image of visualization	Count	Posterior mean (%)	95% credible interval	Condition
V3		58	18.1%	[14.2%, 22.4%]	Wavy arrow
V4		201	61.9%	[56.6%, 67.2%]	Wavy arrow

on Dirichlet-multinomial marginal likelihoods and a uniform Dirichlet(1, 1, 1, 1) prior, yielded a Bayes factor of $BF_{10} \approx 56,737$, providing overwhelming evidence in favor of the model with distinct preference distributions across groups.

To examine the specific visualizations contributing to the overall group difference, we computed the posterior distributions of differences in response probabilities between adults and students for each visualization (Fig. 7). Visualization 4 emerged as the most distinctively

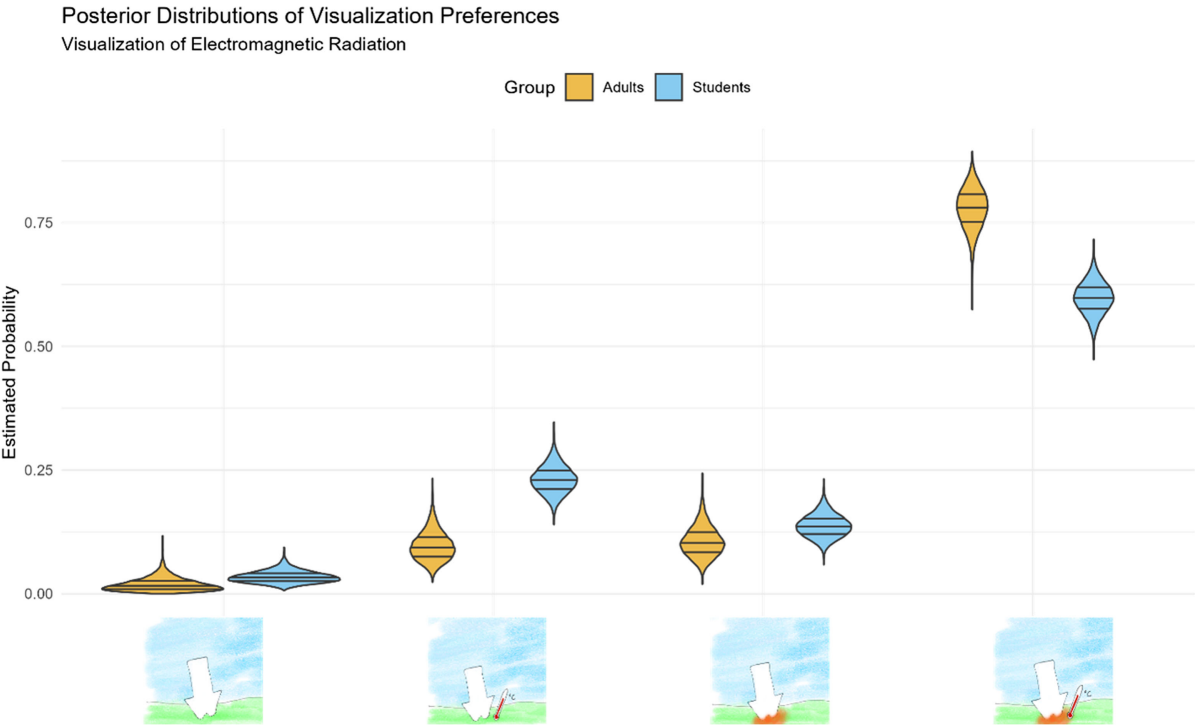


FIG. 7. Posterior distributions of visualization preferences for the item “radiation + straight light rays,” shown separately for students and adults.

preferred option among adults, with a posterior mean difference of 22.3 percentage points (95% credible interval: [14.8%, 29.4%]). In contrast, visualizations 1–3 were all selected less frequently by adults. The differences were most pronounced for visualization 2 (mean difference: −10.6%, 95% CI: [−15.9%, −4.9%]), followed by visualization 3 (−8.0%, 95% CI: [−13.1%, −2.5%]) and visualization 1 (−3.8%, 95% CI: [−6.4%, −1.1%]).

C. Representation of molecules

Next, we investigated which visualization of molecules was preferred. To obtain an estimate of overall visualization preferences, we pooled responses from both students and adults ($n = 276$) to items 7 and 9 (CO_2 and mixed $\text{O}_2 + \text{CO}_2$) and calculated the posterior distribution over the four available visualizations using a symmetric Dirichlet(1, 1, 1) prior.

The resulting posterior means and credible intervals are shown in Table XIII as well as Fig. 8.

The analysis reveals that the typographic visualization was by far the most preferred representation, with an estimated posterior mean of 75.9% and a 95% credible interval ranging from 72.1% to 79.4%. The colored space-filling model visualization followed, with a posterior mean of 19.8% (95% CI: [16.6%, 23.2%]). The black space-filling model visualization was the least preferred, with a posterior mean of only 4.3% and a 95% credible interval from 2.8% to 6.1%. These results

indicate a strong consensus across participant groups in favor of the typographic representation as the most convincing representation of greenhouse gas molecules in this context.

1. Difference in visualization size

Next, we investigated which size of visualization of molecules was preferred. To obtain an estimate of overall visualization preferences, we pooled responses from both students and adults ($n = 330$) to Items 8 and 10 (CO_2 and mixed $\text{O}_2 + \text{CO}_2$) and calculated the posterior distribution over the four available visualizations using a symmetric Dirichlet(1, 1) prior.

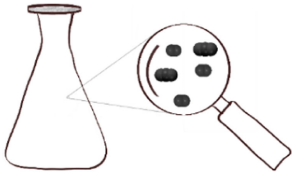
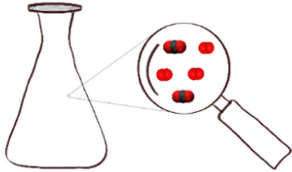
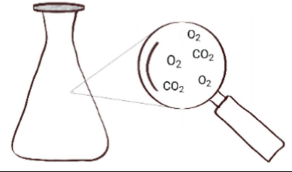
The resulting posterior means and credible intervals are shown in Table XIV.

The analysis reveals that the large visualization was the preferred representation, with an estimated posterior mean of 76.8% and a 95% credible interval ranging from 73.3% to 80.1%. These results indicate a strong consensus across participant groups in favor of the large molecule representation.

2. Difference for a mixture of molecules

To evaluate whether the preference of visualization depended on whether CO_2 or a mixture between CO_2 and O_2 was displayed, we compared a Bayesian model assuming a shared response distribution (null model) to a model allowing for separate distributions for each group. This comparison, based on Dirichlet-multinomial marginal

TABLE XIII. Posterior mean probabilities and 95% credible intervals for each visualization option of molecules, based on pooled responses from students and adults ($n = 276$, 2 items) to Items 7 and 9 (CO_2 and mixed $\text{O}_2 + \text{CO}_2$). The estimates are derived from a Bayesian Dirichlet-multinomial model with a uniform Dirichlet(1, 1, 1).

Visualization	Image of visualization	Count (CO_2 and mixed combined)	Posterior mean (%)	95% credible interval
V1		23	4.3	[2.8%, 6.1%]
V2		109	19.8	[16.6%, 23.2%]
V3		420	75.9	[72.1%, 79.4%]

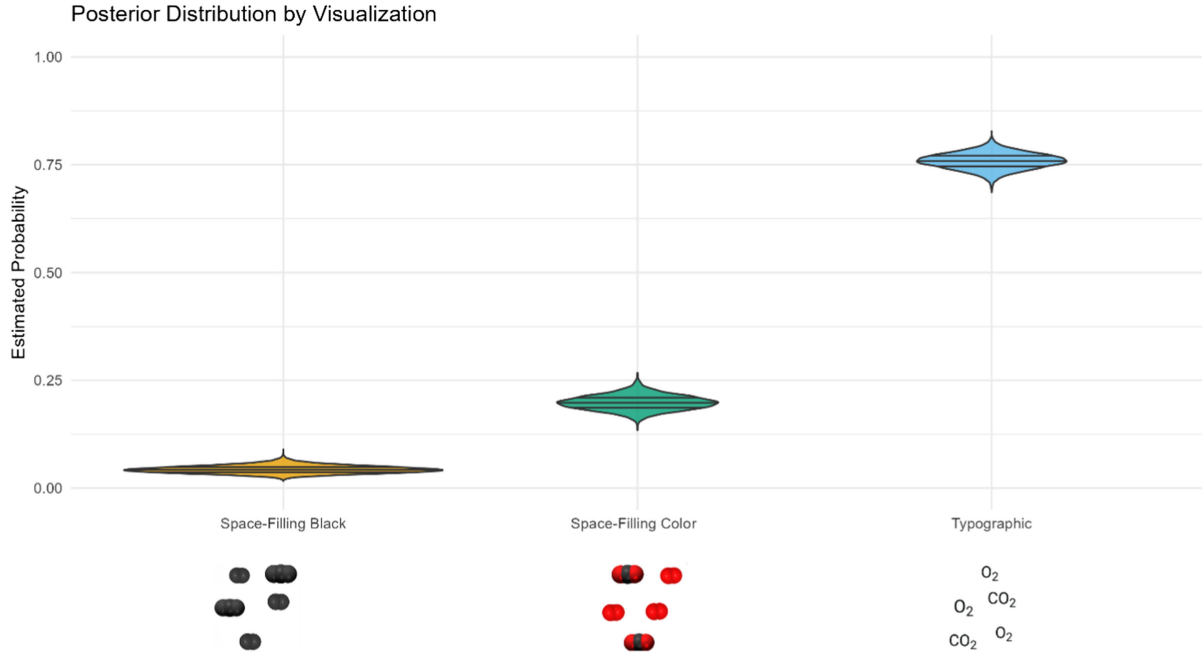


FIG. 8. Posterior distributions of the estimated probability that each visualization was selected as the most convincing representation. The plot shows results for three visualizations: typographic, black space-filling model, and colored space-filling model. Violin plots depict the full posterior density based on a Bayesian analysis using a Dirichlet-multinomial model with a uniform prior. Inner lines indicate the interquartile range and median of the posterior distributions.

likelihoods and a uniform Dirichlet(1, 1, 1) prior, yielded a Bayes factor of $BF_{10} \approx 0.025$, providing strong evidence in favor of the model with a shared preference distribution.

3. Difference between students and adults

To evaluate whether the preference for visualization differed between students and adults, we compared a Bayesian model assuming a shared response distribution (null model) to a model allowing for separate distributions for each group. This comparison, based on Dirichlet-multinomial marginal likelihoods and a uniform Dirichlet(1, 1, 1) prior, yielded a Bayes factor of $BF_{10} \approx 2.17$, providing only anecdotal evidence in favor of the model with a separate preference distribution.

TABLE XIV. Posterior mean probabilities and 95% credible intervals for visualization size of molecules, based on pooled responses from students and adults ($n = 276$) to items 8 and 10 (CO_2 and mixed $O_2 + CO_2$). The estimates are derived from a Bayesian Dirichlet-multinomial model with a uniform Dirichlet(1, 1).

Visualization	Count	Posterior mean (%)	95% credible interval
Large molecules	450	76.8	[73.3%, 80.1%]
Small molecules	135	23.2	[19.9%, 26.7%]

IV. DISCUSSION

This study investigated how different visualizations of invisible scientific phenomena—specifically electromagnetic radiation and gas molecules—are perceived by learners and adults in terms of intuitive comprehensibility. Guided by cognitive load theory and dual-process theories of cognition, we examined which representations participants found most convincing and whether preferences varied between students and adults. We addressed two central research questions:

RQ1: Among a set of visualizations depicting invisible scientific phenomena, such as electromagnetic radiation and molecules, which are perceived as the most convincing by participants?

RQ2: Do preferences for visualizations differ between students and adults, and if so, where do these differences occur?

In the following sections, we discuss the findings for each question in turn, interpret them in light of our theoretical assumptions, and explore their implications for instructional design in science education.

A. Preferred visualizations of invisible scientific phenomena (RQ1)

Overall, the analysis of participants' responses shows a clear preference for visual representations based on previous research by Haagen-Schützenhöfer [21], Zloklikovits

and Hopf [23], Wiener *et al.* [24], and Budimaier and Hopf [25] over other, commonly used visualizations. In the survey, respondents were asked to choose the visualization they felt most clearly conveyed a given scientific concept (Sec. II A 3). This approach was intended to elicit which representations appeared most intuitive to them, thereby providing insights into the perceived comprehensibility of different visualizations.

Regarding infrared radiation, most participants favored visualization IR4, a diverging, transparent arrow with dashed lines (Table IX). This visual representation aligns with the arrow shape proposed by Haagen-Schützenhöfer [21], but incorporates modifications reflecting the properties of infrared radiation described in the item text, specifically its invisibility. In contrast, preferences concerning the wavy visualization were less pronounced in the student group (Fig. 3). This finding is consistent with Nelson and Olander's [3] study, where eighth-grade students struggled to interpret waviness as a defining characteristic of arrows. Considering both our results and those from Nelson and Olander [3], we argue that this kind of wavy representation may not be suitable for instructional materials in school science education.

For absorption, participants preferred visualizations featuring a thermometer and a red-shaded ground, marking areas where radiation or light was absorbed (Table X). Prior research suggests that red is commonly associated with warming or warm [3]. However, a closer analysis of student responses reveals that this group did not favor the wavy arrow in our survey. This suggests that “waviness” and a broken tip alone are insufficient to signify absorption in infrared radiation visualizations. While these features may be effective in optics instruction when combined with color cues [21], our results indicate that this representation of absorption is not universally applicable to all types of radiation, particularly when illustrating energy transfer. Based on our findings, we recommend incorporating additional visual cues, such as thermometers and the red shading. However, we do not know how students actually interpreted these cues and what led them to select one version over another (see Sec. IV D).

The 2×2 design varying terminology (“visible light” vs “radiation”) and representational style (straight vs wavy arrows) revealed insights regarding students’ and adults’ preferences for visualizations of radiation absorption. Bayesian model comparison showed strong evidence against an effect of terminology, and strong evidence against an effect of representational style. This suggests that the specific wording used to describe the phenomenon (light vs radiation) or the visual form (straight vs wavy) had little impact on how participants interpreted the visualizations. A closer look at the response patterns showed that the most convincing visualization was clearly and consistently favored across all conditions.

Therefore, introducing additional visual cues (thermometer and red shading) was effective in increasing intuitiveness of visualizations of absorption, independent of representational style and verbal representation. This consistent preference for visualization V4 aligns with dual-process theories of cognition [17,18], which suggest that intuitive processing is guided by perceptual features.

Interestingly, the preferences regarding the visual representation of the molecules were the most conclusive. Both students and adults overwhelmingly favored the typographic representation based on prior research by Wiener *et al.* [24] and Budimaier and Hopf [25] over the space-filling model (Table XIII). This preference may stem from the typographic representation’s clarity, as it explicitly conveys the substance’s chemical formula, eliminating the need to interpret the space-filling model. Furthermore, the clear preference for larger molecule depictions—despite their deviation from accurate atomic spacing—suggests that ease of recognition is a key factor. However, as argued by Budimaier and Hopf [25], visualizing the actual spacing may support learning about the structure of matter. Thus, the choice of representation should align with the intended learning objective: while the larger representation may reduce extraneous cognitive load, the smaller one could more effectively foster an understanding of molecular structure.

B. Differences in visualization preferences between groups (RQ2)

Across all visualizations, the preferences of adult participants were clearer and more decisive than those of students. This suggests that age or prior familiarity with conventional scientific representations may influence preferences, consistent with earlier research on representational competence [40,41]. For example, adults exhibited stronger preferences regarding the use of wavy arrows, which aligns with findings that familiarity with disciplinary conventions facilitates interpretation [42]. Similarly, chemical formulas in typographic representations were favored across groups, but appeared especially familiar to adults, likely due to prior exposure to chemical notation.

These results can be interpreted in light of cognitive load theory, as novices are more easily overloaded when encountering unfamiliar representations, whereas learners with more prior knowledge can process such forms with lower extraneous cognitive load [43]. Our findings, therefore, suggest that students may require additional scaffolding for the interpretation of representational elements that are commonly used in science education but not yet part of their representational repertoire. Differences in familiarity should thus be considered when designing instructional materials, ensuring that the chosen visualizations do not impose unnecessary cognitive load on learners who lack prior exposure.

C. Implications and future research

Based on these findings, we argue that the visualizations proposed by Haagen-Schützenhöfer [21], Zloklikovits and Hopf [23], Wiener *et al.* [24], and Budimaier and Hopf [25] are not only suitable to support interpretation and comprehension by aligning with and building on learners' prior knowledge but also to reduce extraneous cognitive load. However, adaptations may be necessary depending on the context and the phenomenon being taught or communicated. As described in the Introduction, one goal that should be pursued when designing effective visual representations is to minimize extraneous cognitive load, thereby freeing up working memory resources for germane cognitive load and actual learning [11,12]. Our study provides an example of how intuitively understandable visualizations can be developed to facilitate learning about complex and/or invisible phenomena. Beyond the context of the greenhouse effect, a similar study design could be used when developing visual representations in other areas of physics where learners need to understand nonvisible processes, such as electromagnetism, energy transfer, or quantum phenomena. The findings further suggest that visualizations of visible light, infrared radiation, absorption, and molecules can be incorporated not only into learning materials about the greenhouse effect, but also into broader contexts where electromagnetic radiation or molecules play a crucial role. In this way, our study offers insights that can inform general design principles for intuitive representations across science domains.

Our findings contribute to the growing body of evidence supporting these visual representations' effectiveness in fostering learning. However, two critical questions remain: (i) Do these representations actually minimize cognitive load in specific learning contexts?, and (ii) Are they more effective than alternative visualizations in fostering student learning? Future research should address these questions by examining learning environments that employ these visual representations, with a particular focus on cognitive load measurement. Qualitative studies, for example, using interviews or think-aloud methods, could provide insight into why students perceive certain visualizations as more intuitive and which specific features they find helpful or confusing. Additionally, comparative (quasi-)experimental studies—in which only the representation varies between groups while learning progress is monitored—would provide valuable insights into their effectiveness. From previous design studies [21,23–25], there is evidence that these visualizations are helpful in facilitating student learning, but a (quasi-)experimental design has not been investigated yet.

Beyond the questions of cognitive load and learning effectiveness, future research could explore the generalizability and adaptability of these visualizations. For instance, it would be valuable to investigate whether similar design features support learning about other abstract

scientific concepts (e.g., sound waves, fields, or quantum phenomena).

Finally, studies involving teachers could investigate how these representations are interpreted and used in teaching practice.

D. Limitations

This study aimed to identify which representations, from a selection informed by prior research, were most intuitively understandable for students and adults. However, a key limitation is that we cannot infer participants' actual reasoning behind their choices based on their responses alone. Gaining deeper insight into why certain representations were preferred would require additional qualitative methods, such as interviews or think-aloud protocols. Acceptance-probing interviews conducted in earlier studies on the representation of electromagnetic radiation [21,22,44] as well as on typographic representations [24,25] have provided valuable insights into how students interpret visualizations within specific instructional contexts. Building on these findings, future research could aim to generalize across contexts by identifying representational features that consistently support intuitive understanding. This would allow for the development of design principles for visualizations that are as broadly applicable as possible across topics, science disciplines, and learner populations. To date, a systematic investigation of the advantages and disadvantages of different visualizations remains lacking. This study represents an initial step toward addressing this research gap by providing empirical insights into the intuitive comprehensibility of selected visual representations.

Another limitation is that we did not directly measure cognitive load. Instead, we inferred from dual-process theories of cognition [17,18] that the most frequently chosen image would be the most intuitively understandable, thereby enhancing cognitive fluency and potentially reducing cognitive load. However, this assumption remains untested, and future research should include empirical cognitive load measurements, such as self-reports or physiological indicators, to validate this claim.

Furthermore, preference and intuitive comprehensibility do not necessarily equate to learning effectiveness. While our results suggest that these visual representations have the potential to support learning processes, their actual impact on knowledge acquisition and retention remains unexamined. A more comprehensive investigation, such as controlled experimental studies assessing learning outcomes, is needed to determine their educational effectiveness.

Regarding our sample, the study included 14- to 15-year-old students and, for comparison, adults. The observed preference differences between these groups suggest that familiarity with certain visualizations may develop with age or experience. Consequently, our findings cannot be

generalized to students of all age groups. Moreover, as discussed in the Introduction, prior knowledge is influenced by cultural background, meaning that students from different educational contexts or regions may interpret these representations differently. Future studies should explore broader and more diverse samples to assess how cultural and educational backgrounds influence visualization preferences.

V. CONCLUSIONS

In this study, we aimed to examine which visualizations of invisible scientific phenomena—specifically electromagnetic radiation and molecules—are perceived as most intuitively understandable by students and adults. Drawing on cognitive load theory [11,12] and dual-process theories of cognition [17,18], we explored which visualizations of these phenomena participants found most convincing and whether preferences differed between students and adults. Our findings indicate that visualizations developed in prior domain-specific research, such as the diverging arrow for infrared radiation [21,44] and the typographic representation [24,25] for molecules, were consistently preferred across age groups compared to more traditional visualizations. These representations appear to align well with learners' intuitive understanding, suggesting they may support cognitive fluency and reduce extraneous cognitive load.

Importantly, our results also highlight that students' preferences were less consistent than those of adults, pointing to the role of familiarity and prior exposure in the interpretation of visual elements. This underscores the need to consider learners' representational competence when designing visualizations for instructional use. Moreover, preferences for certain visual features—such as straight over wavy arrows—were more influential than changes in terminology, supporting the idea that perceptual features play a key role in intuitive processing.

Furthermore, this study demonstrates the potential of Bayesian data analysis to enrich physics education research. The use of posterior distributions and Bayes

factors allowed for intuitive, probabilistic interpretations of students' and adults' preferences for visualizations that go beyond dichotomous significance testing. Especially in exploratory or design-oriented studies, Bayesian methods can provide a flexible framework for evaluating the effectiveness of instructional materials under uncertainty. Future work could use Bayesian hierarchical models to investigate how individual differences (e.g., prior knowledge or representational competence) influence interpretation patterns and to inform the iterative refinement of visualizations in research cycles.

While our findings provide initial insights into the intuitive comprehensibility of selected visual representations, further research is needed to assess their actual impact on learning. In particular, future studies should measure cognitive load more directly and investigate the long-term effects of these visualizations on knowledge acquisition and retention. Additionally, qualitative methods could help uncover the reasoning behind learners' preferences and reveal how representations are interpreted in authentic learning settings. By integrating findings from different methodologies, future research can contribute to the development of broadly applicable design principles for visualizations in science education.

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DATA AVAILABILITY

The data are not publicly available. The data are available from the authors upon reasonable request.

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