Effects of explanation support on learning genetics

William A. Sandoval[1], Valerie Crawford[2], Marie Bienkowski[2], Karen Hurst[2], Kelli Millwood[1]

ABSTRACT

This study examined the effects that different kinds of technology-based representational tools have on students' genetics learning. One form of tool represented *phenomenological* features of genetics – genes, pedigrees, and so on – and were embedded in a simulations-based software program. and another tool provided *discursive* representation to support students' construction of explanations. In a quasi-experimental study, students completed a 3-week unit on genetics. Students in one condition learned genetics using only the phenomenological tool and exploring simulations of population level genetic phenomena; students in a second condition used this same tool for the same activities and used a word processor to write explanations of events that occurred in the simulations; and students in a third condition used the phenomenological tool to complete the same activities, and wrote explanations of the simulations using the discursive tool. Pre- and post-assessments of students' understanding of basic genetics concepts showed no differences among conditions. A post-test explanation task, however, showed that students who had learned genetics with explicit, discursive support for explanation construction were significantly more likely to correctly apply genetics concepts to explain a specific problem than students who learned genetics without explanation construction supports. We argue that students' efforts to explain provided a context for organizing genetics ideas into a coherent conceptual framework, and that the discursive representations provided key features of that framework.

KEYWORDS

explanation, genetics, argumentation

Forms of representation play a central role in the construction of scientific knowledge, and research on computer-based learning technologies has shown the efficacy that representations can have for students' science learning (e.g., Kozma, Russell, Jones, Marx, & Davis, 1996; Linn, Bell, & Hsi, 1998; White, 1993b). This study explored the relative effects of different forms of representational scaffolds on students' learning of genetics. One form of representation was phenomenological, representing various genetics phenomena directly, including meiosis and mitosis, pedigrees, and genetic effects in populations, embedded in a software application called GenScope (Horwitz & Christie, 2000). The other form of representation was discursive, embedded in a journaling tool called ExplanationConstructor (Sandoval, 2003), designed to support students' written explanations of particular genetics problems. This program was specifically designed to work with other computer-based environments that allow students to generate data to incorporate into their explanations, and has been effective in helping students learn about evolution (Reiser et al., 2001). This study investigated two questions. First, would combined phenomenological and discursive supports help students to learn genetics concepts better than phenomenological supports alone? Second, would combined supports help students to construct better explanations for genetics problems than phenomenological supports alone? Our hypothesis was that the effort to explain complex problems would encourage students' application and integration of key genetics concepts, and that specific supports for explanation would be better than no support.

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[1] Graduate School of Education & Information Studies, University of California, Los Angeles

[2] Center for Teaching and Learning, SRI, International, Menlo Park, CA

THEORETICAL FRAMEWORK

Our perspective on science learning is grounded in situated, apprenticeship models of learning (Collins, Brown, & Newman, 1989; Lave & Wenger, 1991; Rogoff, 1990). We see science education as an apprenticeship into the reasoning and discursive practices of scientific disciplines. This entails more than just the acquisition of conceptual knowledge to include learning how to apply such knowledge to explaining particular problems within the discipline. Such explanations and arguments themselves rest on discursive practices generated within disciplines (Latour, 1987; Latour & Woolgar, 1986; Toulmin, 1958). Part of what it means to learn science, then, is learning how to organize and interpret data to construct persuasive explanations for particular problems.

Learning to explain problems successfully entails more than mastering particular concepts. First, it is quite possible that students can learn specific concepts without putting them together into an explanatory framework that can be applied to specific problems. For example, there is a robust finding that students with even multiple years of biology education remain unable to use the theory of natural selection to explain particular problems (see Wood-Robinson, 1995). Adequately explaining problems requires that specific domain concepts be integrated into explanatory frameworks. Second, explanation is a rhetorical task, and scientific explanations in particular must conform to particular epistemic criteria such as maintaining causal coherence, warranting claims, ruling out alternatives, and so forth (Gitomer & Duschl, 1995).

For genetics learning, explaining phenomena means being able to interpret observed patterns of trait inheritance to infer genetic rules governing inheritance. It also includes being able to apply rules of genetic inheritance to explain observed phenotypes within family pedigrees and populations. Reasoning from genotypes to phenotypes (cause-to-effect) is generally easier than reasoning from observed phenotypes to genotypes (effect-to-cause) (Stewart, Hafner, Johnson, & Finkel, 1992). Students have other conceptions of inheritance counter to Mendelian models, such as “blending” models in which parents’ traits are somehow mixed, and others (Wood-Robinson, 1995). Explaining problems is both a way to elicit students’ understanding and provide a context in which normative concepts can be explored.

Phenomenological representations

We label as *phenomenological* software tools that are designed to represent natural phenomena in pedagogically relevant ways. Many such tools have been designed for science education and have been successful in supporting students’ learning (e.g., Schank & Kozma, in press; White, 1993b). The central idea behind these tools is that software can represent features of the world that are otherwise hard to see or experience, in ways that allow students to focus on important scientific ideas. Such representations can provide students with intermediate causal models that can link students’ intuitive ideas to more formal theoretical principles (White, 1993a).

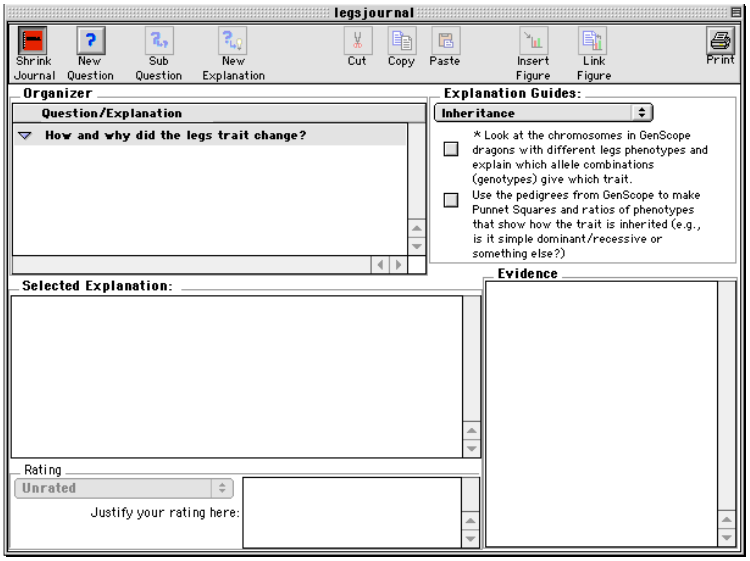
GenScope was originally developed to address well-known conceptual difficulties that students have in understanding genetics. One problem is that genes themselves and the processes by which they operate are microscopic and thus beyond students’ everyday experience. A deeper conceptual problem is that understanding genetics means synthesizing various constructs and ideas across several levels, including chromosomes, DNA, cells, individual organisms, and populations (Kindfield, 1993). For example, a single gene could have two alleles that combine to produce two or even three phenotypic variations of a trait. Within a population, individuals have different allele combinations that lead to various possibilities for their combination. To complicate matters further, allele combinations are probabilistic. For instance, although there might be a one in four chance of getting ingrown toenails, any given four offspring may not inherit that trait.

The simulations in GenScope allow students to explore questions of allele combination and trait inheritance and distribution by providing various tools that represent different levels (Horwitz & Christie, 2000). Students can create organisms (the default creatures are dragons) and look directly at their chromosomes and even manipulate them to see what they do. Individuals can be mated to generate family pedigrees, again where individuals' chromosomes can be inspected and changed. GenScope can also be programmed to simulate populations to explore how traits can be distributed over time and among large numbers of individuals. Studies with GenScope show it to be effective as part of a carefully sequenced genetics curriculum (Hickey, Kindfield, Horwitz, & Christie, 2000).

Discursive representations

ExplanationConstructor is an example of what we call *discursive* representations. The purpose of the tool is not to represent a particular type of phenomena, but to represent the components of a scientific explanation, and to help students organize data to support claims made in an explanation. Such tools have become increasingly common in recent years, as means to help students articulate their thinking in terms of important epistemological categories, like theories, evidence, and so on (Bell & Linn, 2000; O'Neill & Gomez, 1994; Scardamalia & Bereiter, 1993; Toth, Suthers, & Lesgold, 2002). One of the key rationales behind such tools is that by differentiating their ideas from the evidence they use to support those ideas, students will be better able to examine how well their ideas fit data and how they relate to broader theoretical frameworks.

ExplanationConstructor is designed specifically to link explanations that students write to questions they are trying to answer, and to encourage students to integrate data to support specific explanatory claims. The software provides explanation guides, in the form of sets of prompts, that give students hints about the major components of explanatory frameworks within a domain. Figure 1 shows the basic structure of the software, with the question and guide prompts available in one of the problems students explored during the present study. The prompts together constitute an explanatory framework that integrates multiple levels of genetic phenomena (e.g., genes, chromosomes, genetic inheritance, crosses of individuals, and population-level dynamics) to adequately explain the outcomes of simulations. We hypothesized that this scaffolding would help students' to appropriate key genetics frameworks as they practiced explaining specific problems augmenting the most recent version of the GenScope curriculum. We reasoned that this structured support would be more helpful than mere practice with explaining problems that required students to construct their own explanatory frameworks without guidance. We hypothesized that the structured guidance provided by ExplanationConstructor's discursive representations would help students to learn the underlying genetics concepts better than students learning with phenomenological representations only, even when they had explanation practice.



How and why did the legs trait change?

☐ * Look at the chromosomes in GenScope dragons with different legs phenotypes and explain which allele combinations (genotypes) give which trait.

☐ Use the pedigrees from GenScope to make Punnet Squares and ratios of phenotypes that show how the trait is inherited (e.g., is it simple dominant/recessive or something else?)

Figure 1: View of ExplanationConstructor journal used in one of the problems of this study. Explanations are created to answer specific questions, recorded at upper left. Explanation guides, at upper right, prompt students for pieces of the explanation. GenScope data could be pasted into Evidence box at right.

STUDY DESIGN AND PROCEDURES

Study Setting, Design, and Materials

This study was conducted in a socioeconomically diverse high school in a major metropolitan area in California. Two teachers collaborated with the research team to implement a three week genetics unit in four classes each. A quasi-experimental design was used to compare the hypotheses stated above, summarized in Table 1 (teachers' names are pseudonyms). For each condition, students completed a curriculum adapted from the developers of GenScope (Horwitz & Christie, 2000; Kindfield & Hickey, 1999). In the two explanation conditions, this curriculum was augmented with three explanation tasks completed at the end of each week of the curriculum. In these tasks, students were asked to explain inheritance patterns in a GenScope simulation related to the conceptual topics they had covered that week, and to use GenScope to generate data for inclusion in their explanations. Students in the Unstructured Explanation condition used a word processor to write their explanations, and those in the Structured Explanation condition used ExplanationConstructor. Students in the Structured Explanation condition also took part in a class discussion about the criteria for good explanations. We expected that the Structured Explanation group would learn more genetics than the Unstructured Explanation group, which would learn more than the No Explanation group.

Table 1: Summary of study design, showing number of students in each condition.

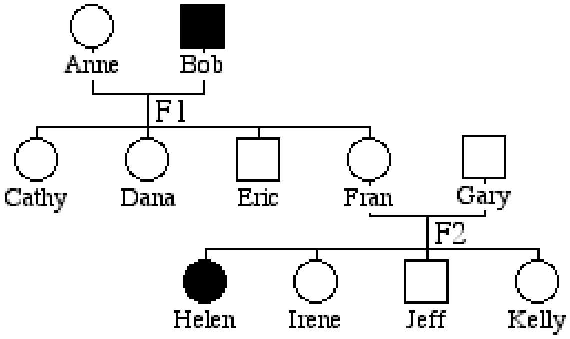
Condition	Teacher		Total
	Janet	Bill	
No Explanation (NE)	26	36	62
Unstructured Explanation (UE)	24	32	56
Structured Explanation (SE)	58	51	109

Measures and procedures

For this paper, we examine two sets of data collected during this study. Students' conceptual understanding of genetics was measured before and after the genetics unit, using paired versions of an assessment developed for the GenScope curriculum (Kindfield & Hickey, 1999). This assessment is comprised of multiple choice and short answer items designed to assess students' understanding of specific mechanisms of inheritance, such as dominant and recessive traits, sex linkage, and so on. Within each condition, two versions of the assessment were counter-balanced across the pre and post tests.

We designed a post-test task to specifically assess students' ability to explain genetics problems. This task asked students to explain the transmission of a recessive trait from grandfather to granddaughter. The task scenario included a representation of a pedigree (family tree) showing the phenotypic pattern of the trait in three generations of the family (Figure 2). This problem required students to use effect-to-cause reasoning to explain how the given phenotypes arise from an underlying inheritance mechanism. In order to explain this problem successfully, students have to interpret the pattern of inheritance represented by the pedigree, understand recessive and dominant traits, infer genotypes for the relevant members of the family, and demonstrate how these lead to the observed data. In other words, students must understand not just the definition of dominant and recessive traits, but understand the predicted inheritance patterns implied by the dominance relations and how such a pattern could be produced across generations.

The family tree below shows the pattern of inheritance of the ingrown toenails trait. Anne and Bob have four children: Cathy, Dana, Eric, and Fran. Fran and Gary also have four children: Helen, Irene, Jeff, and Kelly. Bob has ingrown toenails, and his granddaughter Helen does also (shown by the filled symbols), but none of the other family members has this trait (shown by the open symbols).



Please give a detailed explanation of how Helen inherited the ingrown toenails trait from her grandfather. Use specific examples from the pedigree for your evidence.

Figure 2: Post-test explanation task. Students in all conditions had seen similar pedigrees in GenScope.

Students' explanations for this problem were scored on four separate dimensions: Content, Evidence, Reasoning, and Terminology. Use of Evidence was scored on a 4-point ordinal scale, from 0 to 3; each other dimension was scored on an a scale of 0 to 4, where 0 was completely incorrect or inappropriate, and 4 was entirely correct or appropriate. The Content dimension measured the extent to which students articulated the correct inheritance mechanism. The Evidence dimension measured the extent to which students appealed to appropriate evidence given in the problem to support their claims. The Reasoning dimension assessed the degree to which students exploited domain-relevant reasoning strategies (i.e., effect-to-cause) to explain the problem. Finally, the Terminology dimension assessed students' use of appropriate genetics terms in their explanations. Scorers were graduate students in education at a large, private university. All scorers were blind to the condition with which tests were associated, and to student identity. Reliability of scoring on the explanation task was established by independent scoring of 20% of all explanations by two raters. Inter-rater agreement on the Content dimension was .71 (Kappa .641, indicating a good level of agreement beyond chance alone), and .85 or higher on the other three dimensions.

FINDINGS

Conceptual understanding

Analysis of variance for repeated measures was conducted to examine students' learning of genetics concepts. The pre- and post-test measures of students' understanding of genetics, using the test developed for use with the GenScope software and curriculum (Kindfield & Hickey, 1999) were used as the dependent variables. Students in all conditions demonstrated statistically significant gains from the pre-test to the post-test (Table 2). As in previous studies (Hickey et al., 2000), the GenScope curriculum was effective.

Table 2: Genetics concept learning for each condition.

	Pretest		Posttest				
	Mean	SD	Mean	SD	N	F	Sig
No Explanation	10.28	3.35	20.93	5.45	49	179.342	.000
Unstructured Explanation	10.70	5.42	20.97	6.99	52	401.336	.000
Structured Explanation	10.90	4.74	21.30	6.35	90	278.093	.000

To examine whether condition had an effect on students' learning of genetics concepts, analysis of variance was conducted using the post-test score as a dependent variable, pre-test score as a covariate to control for differences among students, and Teacher and Condition as factors. Contrary to our expectations, ANCOVA detected no differences in genetics learning among conditions. There was, however, a main effect of teacher, with Bill's students performing better than Janet's, $F(2,192) = 8.50$, $p < .05$.

Given that students in all conditions demonstrated statistically significant learning of core genetics concepts, if conceptual learning in genetics suffices for students to be able to explain a relatively simple, paradigmatic genetics problem, then we would expect students in all conditions to show similar levels of proficiency on the explanation task. This was not the case.

Explanation construction proficiency

On the measure of explanation construction proficiency, there was a main effect of condition on the Content dimension, $F(2, 192) = 6.27$, $p < .05$, and the Evidence dimension, $F(2, 192) = 5.46$, $p < .01$. Scheffe post-hoc comparisons showed that on both dimensions the Structured Explanation condition significantly outperformed the No Explanation condition (Table 3). Also, on the Content dimension, there was a trend toward better performance for the Structured Explanation over the Unstructured Explanation condition. There were no significant effects of the teacher. These results suggest that explanation support helped students to integrate their conceptual understanding into an explanatory framework, and that specific support for explanation may be more effective than unstructured practice. Students who had structured practice explaining problems were better able to apply the appropriate rules of genetic inheritance to this problem, and to more effectively use the evidence available in the problem to justify their reasoning.

Table 3: Scheffe post-hoc comparisons of Content and Evidence dimensions of explanation task.

Dimension	Condition		Mean Difference	Std. Error	Sig.
Content	NE	UE	-.1672	.28509	.842
		SE	-.7316	.24702	.014*
	UE	SE	-.5644	.25206	.084
Evidence	NE	UE	-.4196	.21842	.161
		SE	-.6391	.18925	.004*
	UE	SE	-.2195	.19311	.525

CONCLUSIONS

This study sought to explore the relative effects that different kinds of technology-based representations have on high school students' learning of genetics. We hypothesized that students given discursive representations of explanation components and phenomenological representations for exploring genetics phenomena would learn more genetics than students who learned using phenomenological representations alone, even if they had practice explaining problems. Our results partially confirmed this hypothesis, and help to refine our understanding of the effects of explanation support on scientific reasoning. On the typical, multiple choice and short answer conceptual assessment, explanation practice did not have any effect on student performance – students in all conditions showed significant improvement in their understanding of core genetics concepts. Instead, performance differences were detected when students were asked to apply genetics concepts to the explanation of a particular problem. Students who had structured practice explaining problems were better able to explain the underlying mechanism of an observed inheritance pattern, and used more appropriate evidence to justify their claims.

One possible explanation for this difference is that the students who received structured explanation support developed better conceptual frameworks in which to organize specific genetics concepts. Such a framework includes knowledge about how to interpret patterns of data to infer which genetic inheritance rules might apply, and how to discriminate among them. In our post-test task, students had to recognize that the family tree they were given showed a recessive pattern, and use their understanding of inheritance rules and allele combination to explain the inheritance across generations. Although the GenScope assessments used in the study asked students to interpret allele combinations in both genotype-to-phenotype and phenotype-to-genotype problems, these questions were posed in connection to particular individuals and not across generations. Thus, it is possible that students did not recognize how those rules applied in the explanation post-test task. The additional problems students explored in both explanation conditions posed these sorts of cross-generational questions, and ExplanationConstructor's prompts may have provided needed scaffolding to help students build their own explanatory frameworks from the basic genetics rules they were learning.

Another explanation is that structured explanation representations gave students a better understanding of the form of a good explanation – what the key components of an adequate genetics explanation are and how to use data to support claims in an explanation. Besides using ExplanationConstructor, these students had some explicit instruction regarding the elements of a good scientific explanation. The students in the Unstructured Explanation condition had the same practice explaining problems, but with neither software support nor explicit instruction about explanations. This account is more in line with our theoretical view that explanation support provides epistemic guidance about the nature of scientific explanation. Yet, these data do not allow us to rule out either explanation for the performance differences we observed. A methodological issue is that the explanation task given here may not have been able to discriminate conceptual integration and epistemic aspects of explanation. It was a relatively simple problem, and very similar to what students had covered in the curriculum. Ongoing analyses of the explanations that students wrote during the curriculum in both the Unstructured and Structured Explanation conditions may help us to discriminate more clearly epistemic aspects of explanation, such as the use of evidence, from genetics-specific aspects.

Our findings also raise questions about the integration of technology into science instruction that these data are unable to discriminate. Clearly, the teachers here played an important role both in what students learned and how they approached explanation. At the same time, students' explanation performance was not significantly affected by their teachers, suggesting that the discursive supports provided by ExplanationConstructor had an important impact. Our content analyses of students' explanations during the unit can help to illuminate the role that software played in supporting explanation. A useful extension of this study would combine such analyses with discourse analyses of the classrooms, in order to help us explain the effects the teachers had on students performance on the genetics assessment but why possible differences in teaching did not extend to students' explanation performance.

This study demonstrates that different types of scaffolds have differential effects on what students learn. It demonstrates a need for further research on understanding how such effects unfold in the classroom, and how types of representations interact with each other, with teachers' practices, and with students' own practices. Mapping out such relationships will help software designers to build better tools, and teachers and students use such tools more effectively.

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