Student Note-Taking in Narrative-Centered Learning Environments: Individual Differences and Learning Effects

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Abstract. Note-taking has a long history in educational settings. Previous research has shown that note-taking leads to improved learning and performance on assessment. It was therefore hypothesized that note-taking could play an important role in narrative-centered learning. To investigate this question, a note-taking facility was introduced into a narrative-centered learning environment. Students were able to use the facility to take and review notes while solving a science mystery. In this paper we explore the individual differences of note-takers and the notes they take. Finally, we use machine learning techniques to model the content of student notes to support future pedagogical adaptation in narrative-centered learning environments.

1 Introduction

Narrative is central to human cognition. Because of the motivational and contextual properties of narrative, it has long been believed that story-based learning can be both engaging and effective. Research has begun to develop narrative-centered learning environments that combine story contexts and pedagogical support strategies to deliver compelling learning experiences. Contextualizing learning within narrative affords the use of artificial intelligence techniques that tailor narrative and educational content to students' actions, affective states, and abilities. Drawing on an interdisciplinary body of work including intelligent tutoring systems, embodied conversational agents, and serious games, these environments offer the promise of adaptive, motivating learning experiences. Narrative-centered learning environments are currently under investigation in a range of domains, including military soft-skills training [9, 20], anti-bullying education [2], health intervention education [11], and science learning in microbiology and genetics [13].

Note-taking has a long history in educational settings. It has repeatedly been found that student note-taking leads to 1) improved learning, regardless of whether the students had the opportunity to review their notes prior to evaluation [19], and 2) increases in test performance [4,10]. Note-taking is believed to simulate the generative process in which students encode connections between prior knowledge and learning content [15]. Students' must self-regulate note-taking during learning episodes to manage strategy use, prior knowledge, and attentional capacity [19, 22]. Thus, self-regulatory processes can be observed via student note-taking.

In this paper we investigate the merit of modeling student note-taking behavior. The approach adopted here draws on recent work in which linguistic features extracted from student writing have played important roles in modeling student learning in an intelligent tutoring system [8] and in analyzing student interactions in on-line discussions [12, 16]. ITSPOKE [8] predicts student learning using five sets of linguistic features automatically extracted from the essays written by students. These features include surface, semantic, pragmatic, discourse structure, and local dialogue context features, with the semantic features serving as the strongest predictor. ARGUNAUT [12] assists human tutors mediating student on-line discussions by analyzing student contributions in a discussion and recognizing important student actions. Student action classifiers are trained from features including manual analysis of individual and connected contributions of students, where preliminary results suggest the importance of the *critical-reasoning* feature. Another approach employs *speech acts* to investigate student interactions in on-line discussions [16]. Two speech act classifiers, a *question* classifier and an *answer* classifier, were constructed from *n*-gram features automatically computed from student postings.

Motivated by note-taking findings in the learning sciences literature and research in human language technologies, we analyze notes taken by middle school students in an experiment with the CRYSTAL ISLAND learning environment. The remainder of the paper is organized as follows: Section 2 describes CRYSTAL ISLAND, the narrative-centered learning environment that has been developed in our lab and its note-taking functionalities. Sections 3, 4, and 5 report on an empirical study using CRYSTAL ISLAND that examines individual differences in note-taking and preliminary models of note taking. Design implications and limitations are discussed in Sections 6 and 7, respectively. Conclusions and directions for future work follow in Section 8.

2 Crystal Island and Note-Taking

CRYSTAL ISLAND is a narrative-centered learning environment that features a science mystery set on a recently discovered volcanic island. The curriculum underlying CRYSTAL ISLAND's science mystery is derived from the state standard course of study for eighth-grade microbiology. Students play the role of the protagonist, Alyx, who is attempting to discover the identity and source of an unidentified infectious disease plaguing a newly established research station. The story opens by introducing the student to the island and members of the research team for which the protagonist's father serves as the lead scientist. Several of the team's members have fallen gravely ill, including Alyx's father. Tensions have run high on the island, and one of the team members suddenly accuses another of having poisoned the other researchers. It is the student's task to discover the outbreak's cause and source, and either acquit or incriminate the accused team member.

CRYSTAL ISLAND's expansive setting includes a beach area with docks, a large outdoor field laboratory, underground caves, and a research camp with an infirmary, lab, dining hall, and living quarters for each member of the team. Throughout the mystery, the student is free to explore the world and interact with other characters while forming questions, generating hypotheses, collecting data, and testing hypotheses. Students can pick up and manipulate objects, take notes, view posters, operate lab equipment, and talk with non-player characters to gather clues about the source of the disease. During the course of solving the mystery, students are minimally guided through a five-problem curriculum. The first two problems deal pathogens, including viruses, bacteria, fungi, and parasites. Students gather information by interacting with in-game pathogen "experts" and viewing books and posters in the environment. In the third problem, students are asked to compare and contrast their knowledge of four types of pathogens. The fourth problem guides the student through an inquiry-based hypothesis-test-and-retest problem. In this problem students must complete a "fact sheet" with information pertaining to the disease inflicting members of the CRYSTAL ISLAND research team. Once the "fact sheet" is completed and verified by the camp nurse, the student completes the final problem regarding the treatment of viruses, bacteria, fungi, and parasites, and selects the appropriate treatment plan for sickened CRYSTAL ISLAND researchers. The story and curriculum are interwoven throughout the student experience.

The virtual world of CRYSTAL ISLAND, the semi-autonomous characters inhabiting it, and the user interface were implemented with Valve Software's Source™ engine, the 3D game platform for Half-Life 2. The Source engine also provides much of the low-level (reactive) character behavior control. The character behaviors and artifacts in the storyworld are the subject of continued work. Note-taking functionalities were recently added to the CRYSTAL ISLAND environment. Students access their notes using the 'N' key, which launches an in-game dialog where students can review their notes and supply additional comments if they so choose. Below we report findings on the use of note-taking in a CRYSTAL ISLAND study and investigate the potential benefits of modeling student notes.

3 Experiment Method

3.1 Participants

There were 54 female and 62 male participants varying in age and race. Approximately 2% of the participants were American Indian or Alaska Native, 5% were Asian, 29% were Black or African American, 58% were Caucasian, 6% were Hispanic or Latino, and 6% were of other races. Participants were all eighth grade students ranging in age from 12 to 15 ($M = 13.27$, $SD = 0.51$). The students had recently completed the microbiology curriculum mandated by the North Carolina state standard course of study before receiving the instruments, tests, and interventions of this experiment.

3.2 Materials and Apparatus

The pre-experiment paper-and-pencil materials for each participant were completed one week prior to intervention. These materials consisted of a researcher-generated CRYSTAL ISLAND curriculum test, demographic survey, achievement goals questionnaire [5], Self-Efficacy for Self-Regulated Learning (SESRL) [3], Science Self-Efficacy, modified from [14], and immersion tendencies questionnaire [20]. The CRYSTAL ISLAND curriculum test consists of 23 questions created by an interdisciplinary team of researchers and was approved for language and content by the students' eighth-grade science teachers. Elliot and McGregor's achievement goals questionnaire is a validated instrument that measures four achievement goal constructs (mastery-approach, performance-approach, mastery-avoidance, and performance-avoidance goals) [6]. Bandura's Self-Efficacy for Self-Regulated Learning scale [3] consists of 11 items rated by participants on a 7-point Likert scale. Witmer and Singer developed and validated the Immersive Tendencies Questionnaire (ITQ) to measure individual predispositions towards presence experiences [20]. The ITQ consists of three subscales: activity involvement tendency, activity focus tendency, and video game playing tendency. Participants indicate their level of tendency for each item on a 7-point Likert scale. Witmer and Singer found individual tendencies, as recorded by the ITQ, to be predictive of presence [20].

Post-experiment materials were completed immediately following intervention. These materials consisted of the same CRYSTAL ISLAND curriculum test, achievement goals questionnaire [6], interest [18], science self-efficacy, and the presence questionnaire [20]. The interest scale was adapted from those used by Schraw to capture differences across groups and to examine within-subject relationships with learning outcomes [18]. Participants' presence experience was captured by the Presence Questionnaire (PQ) developed and validated by Witmer and Singer [20]. The PQ contains several subscales including involvement/control, naturalism of experience and quality of the interface scales. The PQ accounts for four categories of contributing factors of presence: control, sensory, distraction, and realism.

4 Design and Procedure

4.1 Design

The experiment randomly assigned students to a CRYSTAL ISLAND narrative condition or a minimal-narrative condition. The focus of the study was to investigate the role of note-taking in narrative-centered learning. Students received an intervention consisting of the CRYSTAL ISLAND microbiology curriculum through one of two deliveries. The CRYSTAL ISLAND narrative condition supplemented the curriculum with the full CRYSTAL ISLAND narrative, including the poisoning scenario, character backstories, and character personality. The CRYSTAL ISLAND minimal-narrative condition supplemented the curriculum with the minimal story required to support the curriculum. In this condition, the story consisted of research members falling ill and the request for the student to uncover the mysterious illness. The minimal-narrative condition did not include the poisoning storyline, character back stories or explicit character personality. Students were able to take notes in both conditions.

4.2 Participant Procedure

Participants entered the experiment room having completed the pre-test and instrumentation one prior to the intervention. Participants were first instructed to review CRYSTAL ISLAND instruction materials. These materials consisted of the CRYSTAL ISLAND backstory and task description, a character handout, a map of the island, and a control sheet. Participants were then further directed on the controls via a presentation explaining each control in detail. This included a brief remark that the ‘N’ key could be used to take notes. Five minutes were allotted for this instruction.

Participants in the CRYSTAL ISLAND conditions (narrative and minimal-narrative) were given 50 minutes to work on solving the mystery. Solving the mystery consisted of completing a number of goals including learning about pathogens, viruses, bacteria, fungi, and parasites, compiling the symptoms of the sickened researchers, recording features of hypothesized diseases causing the CRYSTAL ISLAND illness, testing a variety of possible sources, and reporting the solution (cause and source) back to the camp nurse to design a treatment plan.

Immediately after solving the science mystery of CRYSTAL ISLAND, or 50 minutes of interaction, participants completed the post-experiment questionnaires. First to be completed was the CRYSTAL ISLAND curriculum test, followed by the remaining post-experiment questionnaires. Completion of post-experiment materials took no longer than 35 minutes for participants. In total, experiment sessions lasted 90 minutes.

5 Results

5.1 Annotating the Notes Corpus

To analyze the type of notes taken by students, the corpus was annotated using a coding scheme consisting of six categories of tags that characterize the contents of student notes (Table 1). The four main categories were *Narrative (N), Curricular (C), Hypothesis (H),* and *Procedural (P)*. Notes containing facts from the narrative storyline, such as summaries of the unfolding plot, observations of particular objects located in specific area of the environment, and symptoms of ill-stricken characters were tagged with *N*. Similarly, notes pertaining to facts from the curriculum, such as definitions or characteristics of viruses and bacteria, were tagged with *C*. Student notes that explicitly expressed possible solutions regarding the source or cause of the outbreak or solution to the scientific mystery were tagged as *H*. A hypothesis could be either narrative (e.g., suspecting a character of poisoning others) or curricular (e.g., guessing the cause of the disease wreaking havoc on the island). Notes that were directed at maintaining a set of tasks to be completed were tagged as *P*. Two additional categories include Garbage (*G*) and Other (*O*). *G* is used to mark notes that do not contain any meaningful information while *O* covers the remaining notes that

Table 1. Tagging scheme for note-taking content.

Category(tag)	Description	Student Example	Freq.
Narrative (*N*)	Notes contain facts from the unfolding storyline	*Teresa - fever, pain, vomiting*	79
Curricular (*C*)	Notes contain facts from the learning content	*fungi is easily spread on its own from person to person*	156
Hypothesis (*H*)	Notes contain a possible solution to the source and / or cause of the mysterious illness	*I think that she might have something to do with Adola.*	16
Procedural (*P*)	Notes pertain to tracking tasks/goals to be completed	*Something is wrong with dad and i have to find what*	22
Garbage (*G*)	Notes do not contain any meaningful information	*BLAH BLAH BLAH*	4
Other (*O*)	Notes contain meaningful information, but do not belong to any other category	*Scientific method: 1. find method question/problem*	17

contain meaningful information but do not belong to any one of the categories in the current coding scheme.

Using the annotation scheme described above, four judges each tagged the corpus. Inter-rater reliability was determined using both Fleiss' kappa [7], which allows for more than two raters, and Cohen's kappa [5], for each pair of raters. There was full agreement between all four judges according to Fleiss's kappa (K = .70). There were six possible pairings of judges. The paired-judge kappas ranged from moderate agreement to full agreement: judge2-judge4 (.59), judge1-judge4 (.62), judge3-judge4 (.66), judge2-judge3 (.73), judge1-judge3 (.77), and judge1-judge2 (.82). From the tagged corpus, a voting scheme was used to select the tag with the highest frequency for each note. In instances of ties (n = 17) the scheme defaulted to Judge 1.

For purposes of analysis, we calculate the frequency of notes taken in each category for each student. These frequencies are the basis for the results reported below.

5.2 The Effects and Individual Differences of Note-Taking

Fifth-three percent of the students (n = 62, Total n = 116) took notes in CRYSTAL ISLAND. In general, post-test performance and learning gains were unaffected by student note-taking (i.e., no statistical significance found). However, students who took notes on hypotheses (n = 10) surrounding the solution to the mystery did perform significantly better on the curriculum post-test, $t(114) = 2.18$, $p = 0.03$. Hypothesis note-takers also performed significantly better on the curriculum pre-test, $t(114) = 2.16$, $p = 0.03$. This suggests that high achieving students are more likely to take hypothesis notes.

In reviewing the differences between the narrative and minimal-narrative conditions we find that students in the minimal-narrative condition took significantly more curriculum notes, $t(114) = 2.59$, $p = 0.01$. Meanwhile students in the narrative condition took significantly more procedural notes, $t(114) = -2.40$, $p = 0.01$. Perhaps surprisingly, there was no statistically significant difference the notes taken regarding the unfolding narrative between conditions.

Gender played a significant role in note-taking. Overall, females took significantly more notes than males, $t(114) = 2.19$, $p = 0.03$. Females also took significantly more curriculum notes ($t(114) = 2.08$, $p = 0.04$) and narrative notes ($t(114) = 1.83$, $p = 0.06$, marginal significance). While there were few garbage notes ($n = 4$, all composed by male students), a two-tailed t-test reveals marginal significance, $t(114) = -1.64$, $p = 0.10$. There were no significant differences between gender for hypothesis and procedural notes.

High mastery-approach students (students with goals of understanding content for the sake of its own value), as measured by Elliot and McGregor's Achievement Goals Questionnaire [6], took significantly more notes than low mastery-approach students, $t(114) = 2.06$, $p = 0.04$. This includes high mastery-approach students taking significantly more narrative notes ($t(114) = 2.44$, $p = 0.01$) and procedural notes ($t(114) = 2.01$, $p = 0.05$) than low mastery approach students. There were no significant differences for curriculum notes or hypothesis notes between low and high mastery-approach students. There were also no significant differences when considering other goal orientations (performance-approach, performance-avoidance, and mastery-avoidance).

Finally, there were significant correlations between note-taking and student efficacy for self-regulated learning (SRL) [3]. A positive correlation was found between hypothesis note-taking and self-efficacy for SRL, $r(114) = 0.185$, $p = 0.04$. There was also a significant positive correlation between narrative note-taking and self-efficacy for SRL, $r(114) = 0.29$, $p = 0.002$.

5.3 Modeling the Content of Student Note-Taking

We consider several machine learning techniques, namely, support vector machines (SVMs), naïve Bayes, nearest neighbor, and decision trees to induce models that predict note-taking categories characterizing the content of the notes. All models are induced using the Weka machine learning toolkit [21] using a tenfold cross validation scheme to produce the training and testing datasets. Tenfold cross-validation is widely used for obtaining the acceptable estimate of error [21].

We utilize Weka's StringToWordVector filter to transpose a string value to a feature vector consisting of unigram tokens. Each token represents an individual feature within the feature vector. The filter supports several additional parameters, such as binary versus word count, TF and IDF weighting, and several optional stemming algorithms. For our analysis, the unigram tokenizer was chosen over the *n*-gram tokenizer, in part because of the filter's inability to eliminate stopwords prior to tokenization. For instance, phrases such as *towards the door* would not eliminate the stopword *the* prior to tokenization. Instead of creating a single bigram *towards door*, the filter would create two bigrams *towards the* and *the door*. The default stoplist, as well as a stemming algorithm, were chosen to reduce the dimensions of the feature space and improve classifier performance [1].

For modeling purposes, notes were stripped of punctuation, contractions were tokenized (i.e., *hasn't* → *has not*), and typos and misspellings were corrected. Additionally, numbers and measurements, such as *15* and *nm/nanometer* were each aggregated into a special token [16].

The best performing induced model (SVM) correctly classified 86.4% of instances. The SVM model was followed by naïve Bayes (83.2%), nearest neighbor (81.0%), and decision tree (80.6%). The highest true positive rates (SVM model) were achieved with the *curriculum* and *narrative* class. These two classes also comprised 86% of all instances. While hypothesis and procedural classes performed worse on recall (37.5% and 50% respectively), it is worth noting that precision values were reasonable for both classes (54.5% and 73.3%). The kappa between the judge-annotated corpus and the SVM classification was .77. Using the tag occurring most frequently, *curriculum*, as a baseline measure (57.1%) we find the frequency with which the SVM model correctly classified instances significantly outperformed this baseline model, $\chi^2(5, N = 273) = 49.84$, $p < 0.0001$.

6 Discussion

Note-taking offers a view into the problem-solving processes undertaken by students. The study reveals that students who took hypothesis notes performed better on post-tests, confirming inquiry-based learning findings that it is critical that learning environments scaffold students' hypothesis generation activities. The individual differences suggest which students are likely to take notes, a finding that can inform the design of tutorial interventions that encourage note-taking for students who otherwise would be unlikely to take notes. The results identify several correlations between note-taking and self-efficacy for self-regulated learning (SRL), which can provide insight into student strategy use.

The results also suggest that we can accurately model the content of student note-taking. Because the note-taking classifiers can operate with a high level of accuracy, we may be able to incorporate them into learning environments to monitor strategy use. The key diagnostic information they can provide offers the opportunity for learning environments to scaffold note-taking strategies that are likely to lead to desirable learning outcomes.

7 Limitations

The experiment was designed to control for time on task, allowing 50 minutes for the intervention. As a result of this constraint, only 49 students of the 116 CRYSTAL ISLAND participants finished or were working on the final problem at the end of the 50 minute session. An alternative design might consider controlling for task completion. The time constraint may have had an adverse effect on students' strategies to make use of note-taking, resulting in fewer students' taking notes or a diminished quantity of their notes.

8 Conclusion

Given the role of note-taking in self-regulatory learning processes, the study has design implications for intelligent tutoring systems in general and narrative-centered learning environments in particular. The results indicate that students taking hypothesis notes regarding likely solutions to a narrative-centered science problem show better performance on post-test measures. Furthermore, the ability to induce models that accurately predict the content of student notes provides a view into student self-regulatory processes, which can be used by tutoring systems to monitor some forms of student strategy use.

The results suggest several directions for future work. First, it will be interesting to extend this analysis across a larger corpus of notes. The study reported here highlights the merits of note-taking within narrative-centered learning environments; future studies should consider conditions designed to motivate note-taking and specific note-taking formats (e.g., [10]). Another interesting direction for future work is considering alternative approaches to motivating students to take notes given individual differences. In particular, it is important to explore motivational techniques in the context of note-taking that target students with approach goals in contrast to those with avoidance goals. It is important to identify which motivational techniques for note-taking are most effective for students with a mastery orientation in contrast to those with a performance orientation.

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