Tracking Representational Flexibility Development through Speech Data Mining

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***Abstract*—In this work-in-progress research we exploited and investigated a virtual reality (VR) based, flexibility learning environment (FLE) in which adolescents with autism use, customize, and design an assortment of simulation games that represent and exemplify the application of forces and Newton's laws of motion. The simulation/game modeling and making tasks acted as the primers of practicing and assessing representational flexibility in solving the engineering design problems with computational thinking. The participants' participation behaviors and verbal utterances during the intervention sessions have been archived via screen and webcam recordings. The current study findings indicated that two approaches of speech or text data mining, multi-label classification and similarity index, can act as the in-situ performance assessment methods to evaluate the representational flexibility development for engineering design and computational thinking of a heterogeneous learner group.**

Keywords—educational data mining, representational flexibility, learning by making, virtual reality

I. Introduction

Representational flexibility—the ability to consider simultaneously multiple representations of a single object or event and to switch flexibly between them based on a changed condition—is a critical index for the practices of problem solving in engineering and computational education [1-6]. The development and enactment of representational flexibility in cognitive processes is dependent on the interaction of individuals' skills and cognitive styles, contextual cues, and tasks; hence, it is especially demanding for certain learner groups [7]. Prior research observed that learners with autism spectrum disorder (ASD) experienced difficulty in representational flexibility, due to a detail-focused cognitive style and a lack of holistic processing more than a deficit [4, 8]. Representational inflexibility can and should be dynamically fostered in a diverse student population to ensure their talent for computational science and engineering does not go untapped.

Empirical research on the construct of representational flexibility is lacking, despite the prevalence of studies investigating the role and process of flexible representations in STEM learning and problem solving. Also largely unexplored is the territory of evaluating representational flexibility in real time and a contextualized problem-solving setting. The literature indicates card sorting, flexible item selection, and insight problems, along with qualitative observation or interviewing are the major methods of flexibility evaluation [9]. But these domain-generic flexibility tasks may fail to capture the multifactorial complexity and ecological validity of representational flexibility that is faced in problem solving in a real-world environment [3, 10].

The development of representational flexibility is a result of context, task, and subject preferences and learning states, and hence should be dynamically tracked and adaptively supported [11-12]. The current research, as part of a longitudinal project examining the development of representational flexibility for learners with diverse and special needs, ***aims to*** explore the development and assessment of representational flexibility via real-time data mining and modeling of the speech data from learners who were involved in simulation-based engineering design and scientific problem solving. Specifically, it addresses the following research questions:

a) What is the applicability of using speech data mining as a performance assessment method of representational flexibility?
b) To what extent will learners with autism develop representational flexibility during simulation-based, design-oriented scientific problem solving based on speech data mining?

II. Learning Environment for Representational Flexibility Practice and Assessment

In a recent paper on cognitive flexibility, Ionescu [7] claimed that an environment that encourages and scaffolds active experimentation and evaluation of representations should promote the enactment of representational flexibility. Activities of inventing a representation, examining it in detail, and using it contribute to the practice of representational flexibility [3]. A sense of authenticity and real-world applicability are important for motivating participation in these representational practices [13].

Specifically, making digital simulations and games is a complex and creative task requiring the ability to model real-world situations and think at multiple levels of abstraction, and is considered one of the most meaningful and diverse mediums for supporting and studying computational representational practices [14]. Prior studies [15-19] have examined and supported the use and effectiveness of simulation and game design as an expressive medium activating representation experimentation and communication for adolescents, including those with special needs. Prior research also indicated that constructing representations in a design inquiry setting would motivate the externalization and bridging of multiple representations and hence facilitate the emergence of translation and abstraction in the representation generated [15-16,20].

intervention sessions among them based on the multiple baseline across-subject research design. Before the intervention, all participants were oriented to the FM-AR environment. The baseline data of the target participants were collected via a packet of representational flexibility tasks, including the Wisconsin Card Sorting Test, spatial and mathematical insight problems, and VR simulation-based artifact design problems. The intervention consists 12 sessions, taking place at each participant's home. During an intervention session, participants logged into the OpenSim-based virtual world to complete simulation and game design tasks. During their design inquiries, participants interacted with not only digital artifacts and simulated systems, but also a variety of task-related virtual agents and avatars. These

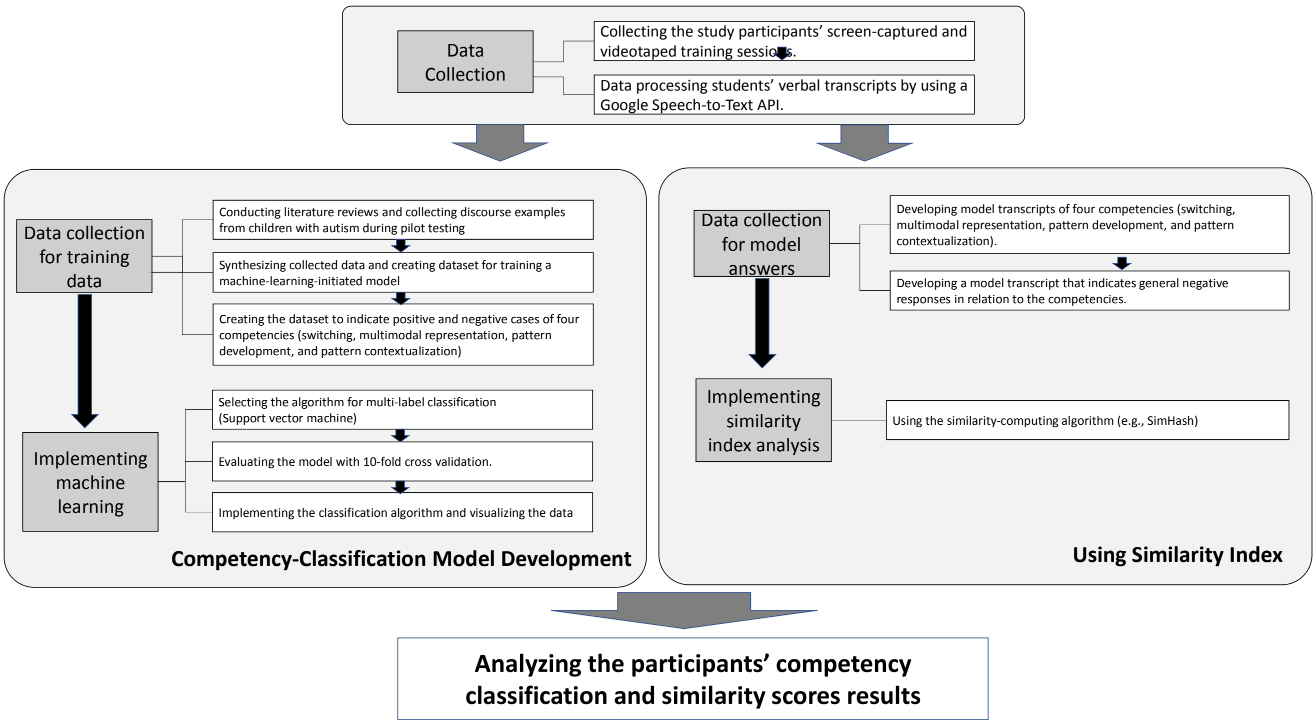

Fig 1. Overview of data processing and implementation.

Therefore, in the current research we exploited and investigated a virtual reality (VR) based, flexibility learning environment (FLE) in which adolescents with autism use, customize, and design an assortment of scientific simulation games (e.g., bridges design) that represent and exemplify the application of forces and Newton's laws of motion. The simulation/game modding and making tasks acted as the primers of practicing and assessing representational flexibility (e.g., holistic pattern recognition, rule or sets shifting, creative pattern contextualization) in solving the problems of forces and Newton's laws of motion. The multimodal interaction interface and innate construction kit of OpenSimulator (OpenSim), a server-side VR platform, helped to support the learners' interpretation, communication, and construction of multiple representations in a design inquiry setting.

III. METHODS

A. Participants and Data Collection

Seven adolescents with high-functioning autism (aged 14-19) participated in the FLE program, with a staggered start of the

interactive and context-sensitive agents, either puppeteered by trained facilitators using a voice-morphing app or preprogrammed by the computer, provided naturalistic prompting and personalized learner support.

The participants' participation behaviors and discourses have been archived via screen and webcam recordings. The data collection and analysis are still ongoing at this moment. In the current paper, we focus on reporting the educational data mining and current findings with the speech data—verbal utterances and responses from the participants during their design and problem-solving task performance. We used a Google speech-to-text API to automatically transcribe the study participants' verbal utterance/response data.

B. Speech Data Mining

We implemented two educational data mining approaches to assess the participants' representational flexibility competency states with the transcribed speech data: (1) developing a competency-classification model and (2) using the similarity index. Figure 1 is the flow chart depicting how we implemented both approaches in this study.

B.1 Competency-classification model

We aimed to build a preliminary machine-learning model to automatically classify students' verbal utterances into a set of predefined competency categories. Building on the literature on representational flexibility, we defined the componential facets or categories of the construct as: sets shifting or switching, multimodal representation, pattern development, and pattern contextualization. We employed a multi-label classification approach for supervised machine learning [21] along with LightSIDE—a text mining tool to process the participants' competence-related verbal utterances and responses.

Developing training data of the model. To build a model-training dataset, we sampled competence-relevant discourses from younger ASD children during their pilot-training sessions. This training dataset helped to define the nature or key features of the preset eight classifiers (i.e., positive/negative cases of the four competency categories). For each classifier, we also delineated a set of sample or model examples that capture key clues or features to be identified during the model training.

Model implementation. To implement the classification algorithm, we adopted a group of feature-extraction conditions (i.e., unigram, bigram, trigram, line length, word/POS pair, and contains non-stop words) to extract text features from the training dataset. To evaluate the model, we sampled the screen- and web-recorded verbal utterance data captured from 20 one-hour intervention sessions of the study participants. We then conducted the support vector machine (SVM) classifier, which sought maximum margins between latent groups of the textual data. To evaluate the model, we employed 10-fold cross-validations. For the multi-label classifications, the performance was acceptable on average (performance accuracy: .761, kappa coefficient: .604).

B.2 Similarity index measure

We also used the text similarity index as an alternative text mining method to assess the participants' flexibility competency states. We used the data-mining tool Orange [22] to calculate the text-similarity scores of the participants' verbal transcripts in comparison with the model/exemplary transcripts in relation to each competency classifier. We then employed the similarity measure to examine how the participants' verbal transcripts during the intervention sessions appeared to be close to the model transcripts for each competency classifier. Using the algorithm, *Simhash* [23], we computed the cosine similarity scores that indicated the participants' competency states captured by their verbal utterance/response data.

IV. Results

A. Competency Classification Finding

Using multi-label text classifications, we trained a total of eight classifiers (positive/negative classifiers of four competencies) and then classified the participants' verbal utterance datasets in each competency category. Figure 2 shows an exemplary time-series bar graph—demonstrating the competency development of the participants. According to Figure 2, the participants' competency proficiency increased after they proceeded through the intervention sessions. This finding is consistent with a preliminary behavior analysis with a sub-sample of the current performance data set, which indicated a total of 673 enactments and an average of 11.22 enactments of representational flexibility per intervention session and per autistic participant. On the other hand, the increasing negative enactments of the competencies during the intervention sessions indicated that the study participants tended to undergo cognitive challenges when tackling the flexibility training tasks.

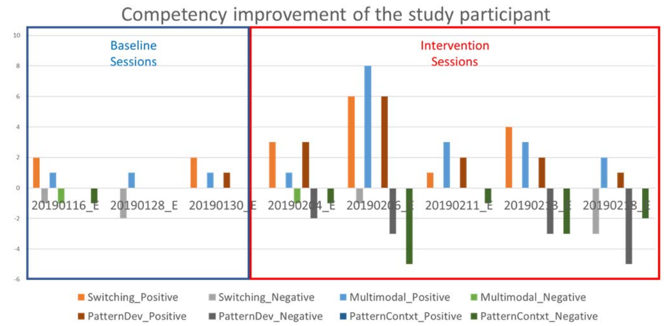

Fig 2. Time-series bar graph of the competency development.

B. Similarity Index Scores

The average cosine similarity scores increased steadily from 0.1 to 0.2 in the participants' first four intervention sessions, indicating an instant effect of the activities on participants' acquisition of the representational flexibility competencies. However, there was learner heterogeneity in competency development. For example, Figure 3 portrays the bar graphs of two exemplary participants' cosine-similarity scores computed from their verbal utterance/response data during part of the intervention sessions. As the bar graph illustrated, participant 1 tended to show a steady, increasing similarity scores across the sessions, suggesting gradually developed flexibility competencies. Differently, the graph showed that participant 2 had variations of the similarity scores across his intervention sessions. The qualitative behavior analysis with the recorded participation behaviors confirmed the similarity index finding. There was an increasing frequency of positive enactments of representational flexibility competencies by Participant 1 during the intervention sessions, whereas the representation-flexibility performance of Participant 2 tended to fluctuate with the assigned task types during the training.

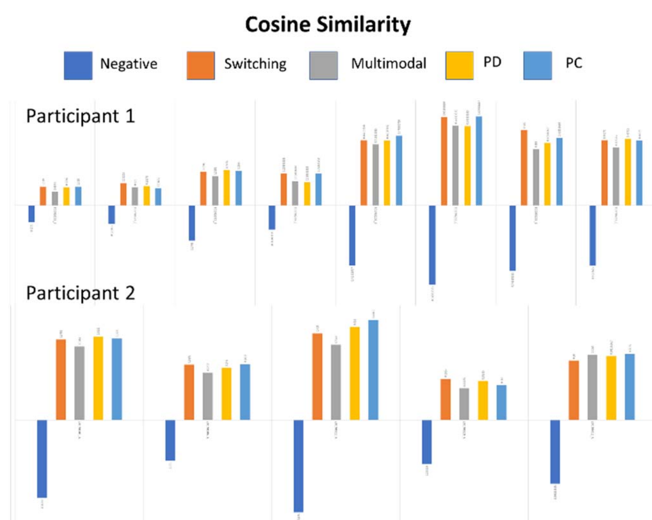

Fig 3. Similarity scores of the study participants.

V. Conclusions and Implications

The current study findings indicated that two approaches of speech or text data mining, multi-label classification and similarity index, can act as the in-situ performance assessment methods to evaluate the representational flexibility development of a heterogeneous learner group. These methods, used along with free and open speech-to-text and data mining tools, can afford a longitudinal and non-intrusive tracking of cognitive flexibility states, which can drive the future development of adaptive and dynamic flexibility performance support. The findings also suggest that VR-supported, design-oriented simulation and game design tasks can act as primers for representational flexibility acquisition and assessment. The study findings can inform on the selection and implementation of performance assessment methods that capture, analyze, and model the cognitive states of learners with special needs to provide evidence-based, individualized training of representational flexibility. The findings on the flexibility learning environment will help to advance the research and training of representational flexibility for problem solving in both STEM and special education.

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