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U of M

Improving Comprehension Strategies of Struggling Adult Readers through Conversational Trialogues with AutoTutor

Art Graesser

NSF

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DEPARTMENT OF THE NAVY ONR Science & Technology

ARL

ADL Advanced Distributed Learning

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Overview

- Conversational Agents in Learning Environments
- Dialogues, Trialogues, and N-alogs
- AutoTutor Trialogues to Help Struggling Adult Readers

Why focus on adults with low literacy?

- 1 out of 6 adults in the US do not read well enough for them to get a decent job (National Research Council, 2011; Programme for International Assessment of Adult Competencies, OECD, 2011).
- Attendance is a problem because work schedules, childcare issues, and transportation difficulties (Greenberg, Reder, Rosen).
- Comprehension training interventions for adult readers are few in number, with weak evidence they are helpful (Greenberg, Mellard, Sabatini).
- AI technology can come to the rescue by improving comprehension training and providing intelligent support, 24-7!

Graesser, A.C., Greenberg, D., Olney, A.M., & Lovett, M.W. (in press). Educational technologies that support reading comprehension for adults who have low literacy skills. In D. Perin (Ed). *Wiley adult literacy handbook* . New York: Wiley.

Organizations committed to improve adult literacy

Commission on Adult Basic Education: http://www.coabe.org/

Institute of Education Sciences: http://ies.ed.gov/

Literacy Information and Communication System: http://lincs.ed.gov/

Office of Career, Technical, and Adult Education:
http://www2.ed.gov/about/offices/list/ovae/index.html

ProLiteracy: http://www.proliteracy.org/

VALUEUSA: http://www.valueusa.org/

Daphne Greenberg
Jan Frijters
Art Graesser
Maureen Lovett
Lee Branum-Martin
Andrew Olney

csal
center for the study of adult literacy

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Georgia State University · University of Toronto · SickKids · The University of Memphis Institute for Intelligent Systems · Brock University

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Georgia State University. The opinions expressed are those of the authors and do not represent views of the Institute or the U.S. Department of Education.

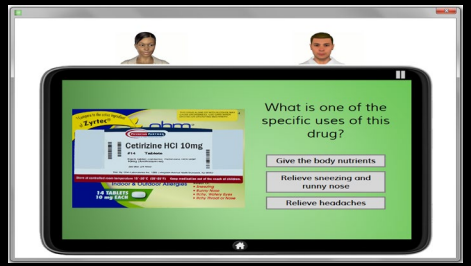
Conversational Agents in Learning Environments

Graesser, A.C., Rus, V., Hu, X. (2017). Instruction based on tutoring. In R.E. Mayer and P.A. Alexander (Eds.), *Handbook of Research on Learning and Instruction* (pp. 460-482). New York: Routledge Press.

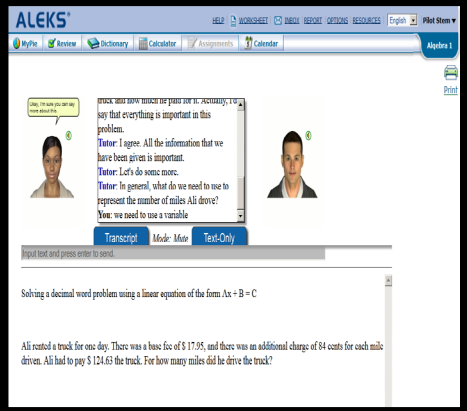
Nye, B.D., Graesser, A.C., & Hu, X. (2014). AutoTutor and family: A review of 17 years of natural language tutoring. *International Journal of Artificial Intelligence in Education, 24,* 427–469.

Adaptive Intelligent Conversational Agents

STEVE

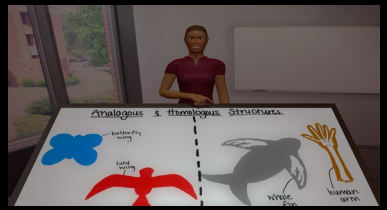


AutoTutor Trialogs

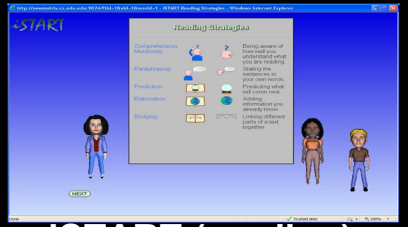


AutoTutor Trialogs with ALEKS algebra

Tactical Language and Culture System

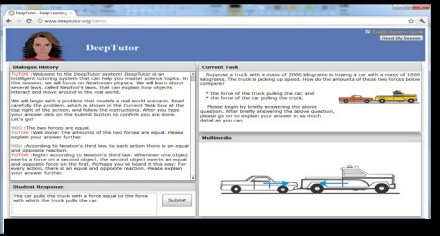


Guru (biology)

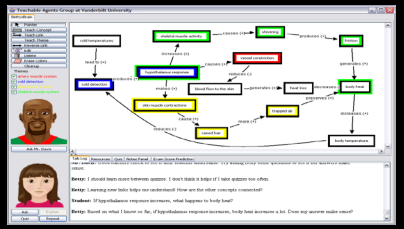


iSTART (reading)

Mission Rehearsal



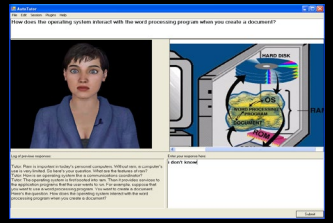
DeepTutor (physics)



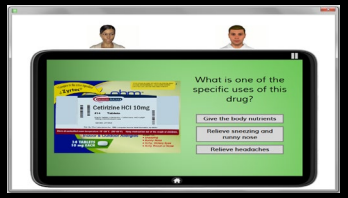
Betty's Brain

Herman-the-Bug

Memphis Intelligent Conversational Agents

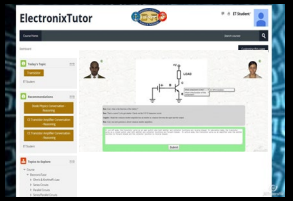


AutoTutor (computer literacy)

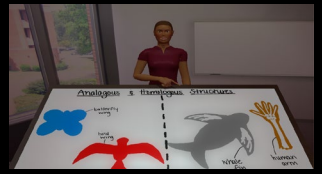


AutoTutor (reading comprehension)

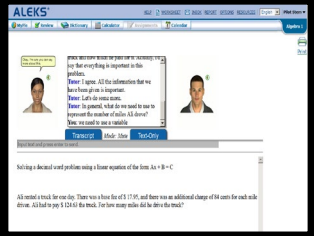
ARIES (scientific reasoning)



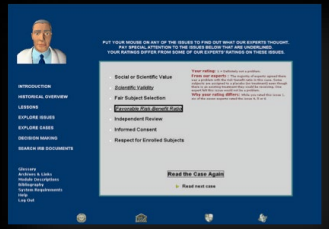
ElectronixTutor



Guru (biology)

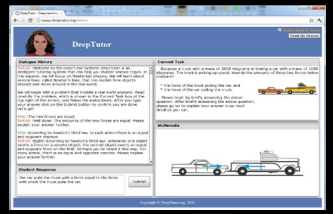


AutoTutor (with ALEKS algebra)



HURA Advisor (research ethics)

Personal Assistant for Lifelong Learning (PAL3)



DeepTutor (physics)

Functions of Conversational Agents

- Help when initiated by the user
- Navigational guide
- Modeling action, thought, and social interaction
- Adaptive intelligent conversational dialog
- Staging arguments to prompt deeper learning
- Staging scenarios for assessment
- Many roles: peers, tutor, mentor

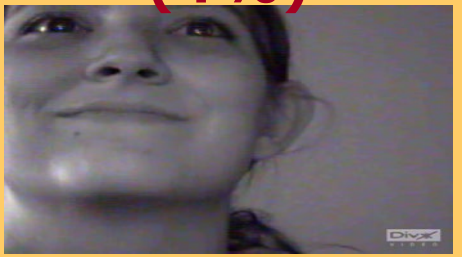
Emotions During Learning

(Graesser, Baker, Craig, D'Mello, Lehman, Rodrigo)

Boredom
(23%)

Confusion
(25%)

Delight
(4%)



Flow
(28%)

Frustration
(16%)

Surprise
(4%)

Measures collected at different grain sizes

1) **Lessons** attempted and completed
2) **Performance in each lesson**
3) **Selecting answers** to multiple choice questions
4) **Semantic matches** between natural language input and expectations or misconceptions
5) **Initiative** by asking questions, selecting tasks, and performing unprompted actions
6) **Fluency** of language and action
7) **Engagement** by response time patterns & coupling with item difficulty
8) **Emotions** (confusion, frustration, boredom, etc.)

Meta-analyses on Intelligent Tutoring Systems

		Effect Size
Kulik & Fletcher (2016)	50 comparisons	0.66
VanLehn (2011)	54 comparisons, STEM	0.58
Ma, Adesope, Nesbit, & Liu (2014)	107 comparisons	0.43
Steenbergen-Hu & Cooper (2014)	39 comparisons, college	0.35
Steenbergen-Hu & Cooper (2013)	26 comparisons, math, K12	0.05
Ritter, Kulikowich, Lei, et al. 2007)	Cognitive Tutor, math, WWCH	0.38
Fletcher & Morrison (2012)	Digital Tutor (1-study, N = 26)	3.17
Nye, Graesser, & Hu (2014), Graesser (2016)	AutoTutor (science, dozens of studies)	0.60 to 0.80

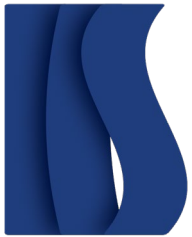
Generalized Intelligent Framework for Tutoring

Army Research Lab and University of Memphis

www.gifttutoring.org

Sottilare, R., Graesser, A., Hu, X., & XXXX (2013-2018). *Design Recommendations for Intelligent Tutoring Systems*.

- Learner modeling (2013)
- Instructional strategies (2014)
- Authoring tools (2015)
- Domain knowledge (2016)
- Assessment (2017)
- Teams (2018)
- Self-improving systems (2019)



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Dialogues and Trialogues

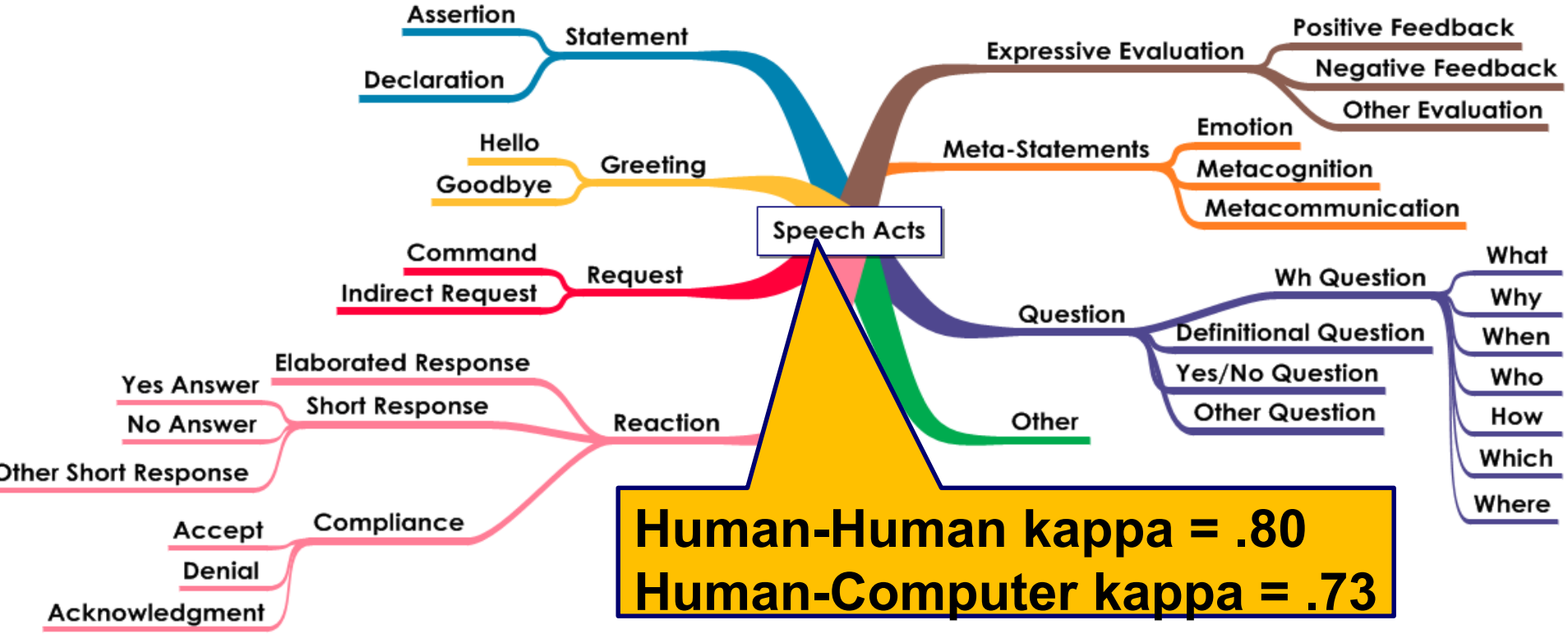
Graesser, A.C. (2016). Conversations with AutoTutor help students learn. *International Journal of Artificial Intelligence in Education, 26*.124-132.

Graesser, A.C., Forsyth, C., & Lehman, B. (2017). Two heads are better than one: Learning from agents in conversational trialogues. *Teachers College Record, 119*, 1-20.

Expectation & Misconception-Tailored Dialog

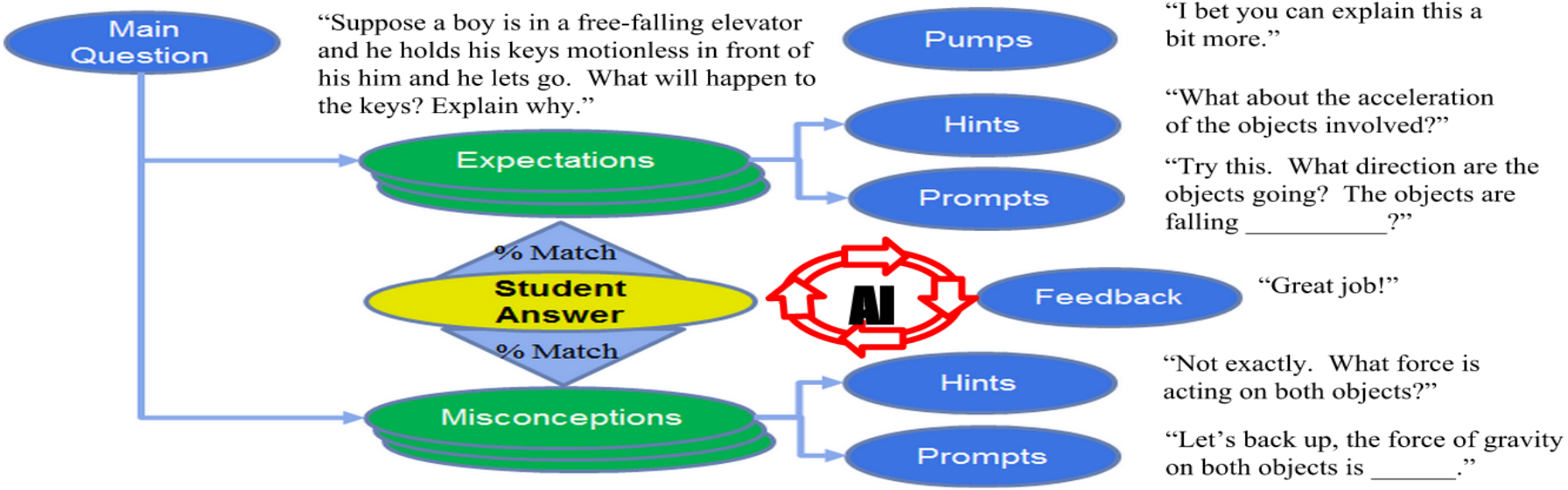
- **Tutor asks question that requires explanatory reasoning**
- **Student answers with fragments of information, distributed over multiple turns**
- **Tutor analyzes the fragments of the explanation**
  - ***Compares to a list of expected good idea units (via LSA and Regular expressions)***
  - ***Compares to a list of expected errors and misconceptions***
- **Tutor posts goals & performs dialog acts to improve explanation**
  - ***Fills in missing expected good idea units (one at a time)***
  - ***Corrects expected errors & misconceptions (immediately)***
- **Tutor handles periodic sub-dialogues**
  - ***Student questions***
  - ***Student meta-communicative acts (e.g., What did you say?)***

Speech Act Hierarchy



AutoTutor-Style (EMT) Dialog

Dialog with student
cover expectations & correct misconceptions



Managing One AutoTutor Turn

- **Short feedback on the student's previous turn**

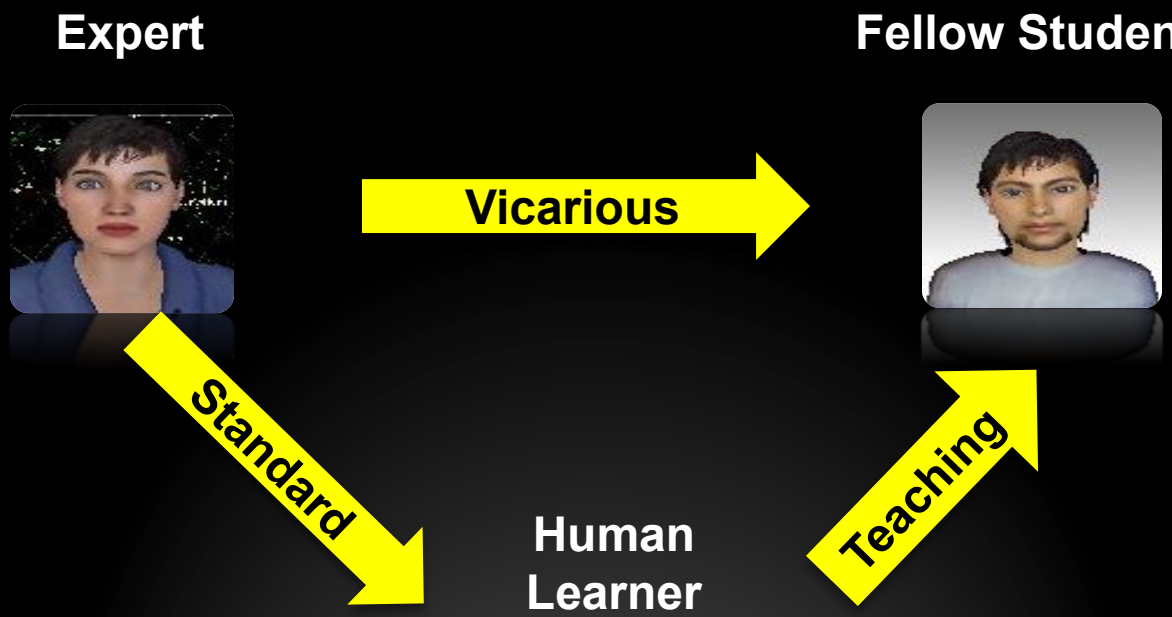
  Positive feedback: "Yeah" "Right!"
  Neutral feedback: "Okay" "Uh huh"
  Negative feedback: "No" "Not quite"

- **Advance the dialog by one or more dialog moves that are connected by discourse markers**
- **End turn with a signal that transfers the floor to the student**
  - **Question**
  - **Prompting hand gesture**
  - **Head/gaze signal**

Challenges

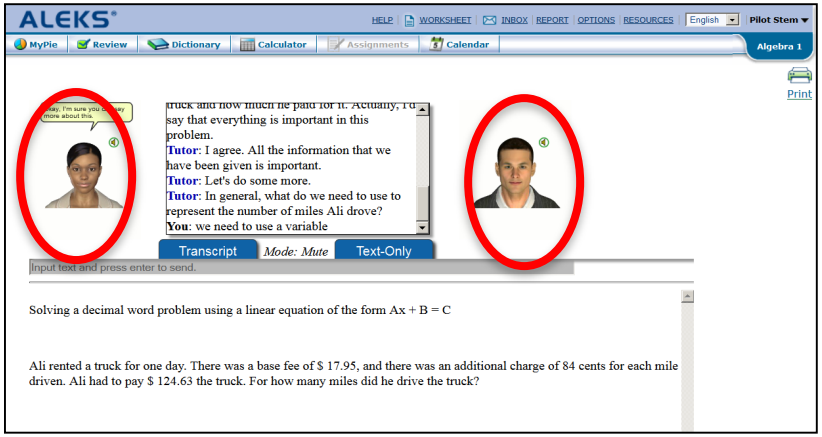
- **Semantic matches are pretty good but not perfect → Understanding is limited**
- **Semantic blur between expectations and misconceptions → Some errors in feedback**
- **Learners expect full credit when they express a couple of juicy words instead of a sufficiently articulated statement → The can be irritation or frustration**
- **High verbal or knowledgeable learners read printed conversation faster than listening to an agent**
- **Limited ability to handle student questions and requests**

Adaptive Trialogues



Trialogues in Literacy and Numeracy

Xiangen Hu, *University of Memphis*



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Advantages of Trialogues

- Two agents can model desired social interactions
- Two agents can disagree, stage an argument, and create cognitive disequilibrium
- A peer agent can echo a learner's contribution in a well articulated language, so:
  - Agent gets blame for a bad answer
  - Agent and learner gets credit for a good answer
  - Learner sees a well articulated response.
- Peer agent model good inquiry and receive good responses from the tutor agent


Annenberg Library
Library Hours: 8am - 6pm (Mon. - Fri.)
9am - 1pm (Sat.) Closed (Sun.)
Notice for library users:
1. Bring your student ID to the library.
2. No food or drink is allowed in the library.
3. Please keep quiet in the library.
4. Put books back where you find them when you are finished with the books.
5. You can check out up to two books.
6. You can keep the books for one week.
EXIT

Trialogue (English Language Skills)

Agent	Utterance
Lisa:	Hey, Ron, you need to leave your water outside. I'm going to go talk to my friends. I'll see you guys inside.
Ron:	Why did she tell me I have to leave my water outside, Tim?
Human (Tim):	I don’t know.
Ron:	Tim, why can't I drink water?
Human (Tim):	The books may get wet.
Lisa:	Why do you still have your water bottle, Ron? Look at rule number 2. We cannot get in the library with food or drink.

AutoTutor Trialogues to Help Struggling Adult Readers

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Georgia State University

University of Toronto

SickKids

The University of Memphis
Institute for Intelligent Systems

Brock University

The research reported here is supported by the Institute of Education Sciences, U.S. Department of Education, through Grant R305C120001
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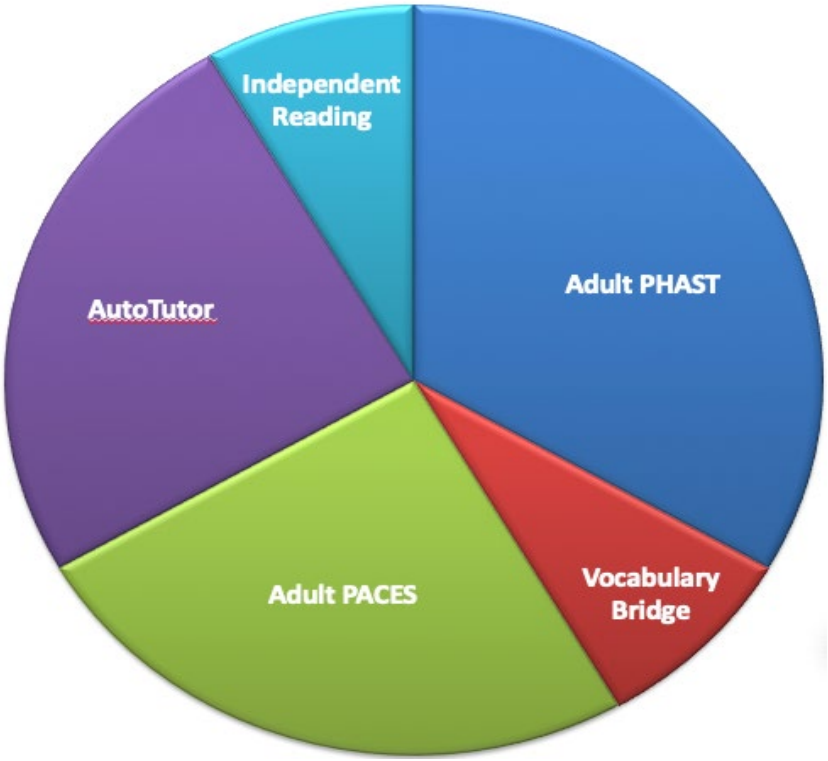
Intervention to Improve Reading for Adults



- Adults who read at grade levels 3-7.9
- 100 instructional hours
- 2 times weekly
- 2-3 hours per duration
- Atlanta and Toronto areas
- 253 in the intervention
- Comparison to business as usual

Adult PACES Comprehension Program

- **P = Predicting purpose with text signals and key information.**
- **A = Acquiring vocabulary with context clues.**
- **C = Clarifying common sources of confusion with clarifying questions.**
- **E = Evaluating and elaborating through questioning.**
- **S = Summarizing with text maps.**

Lovett, M.W., Lacerenza, L., De Palma, M., & Frijters, J.C. (2012). Evaluating the efficacy of remediation for struggling readers in high school. *Journal of Learning Disabilities*. 45, 151-169.

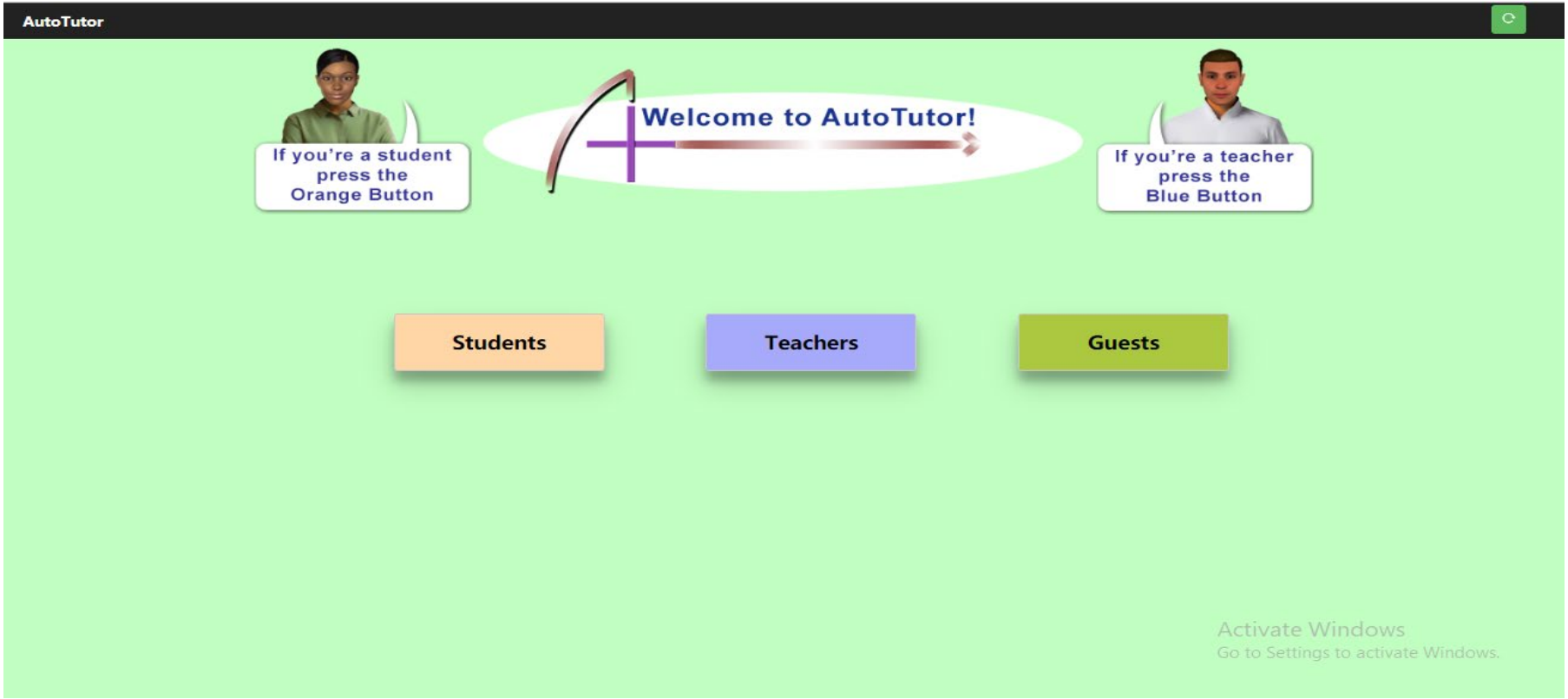
Multilevel theoretical framework of discourse comprehension

- **Words**
- **Syntax**
- **Textbase**
  - Explicit ideas (propositions)
  - Referential cohesion
- **Situation model**
  - Causal, intentional, temporal, spatial, logical relationships
  - Connectives, signaling words
- **Genre and rhetorical structure**
- **Pragmatic communication**

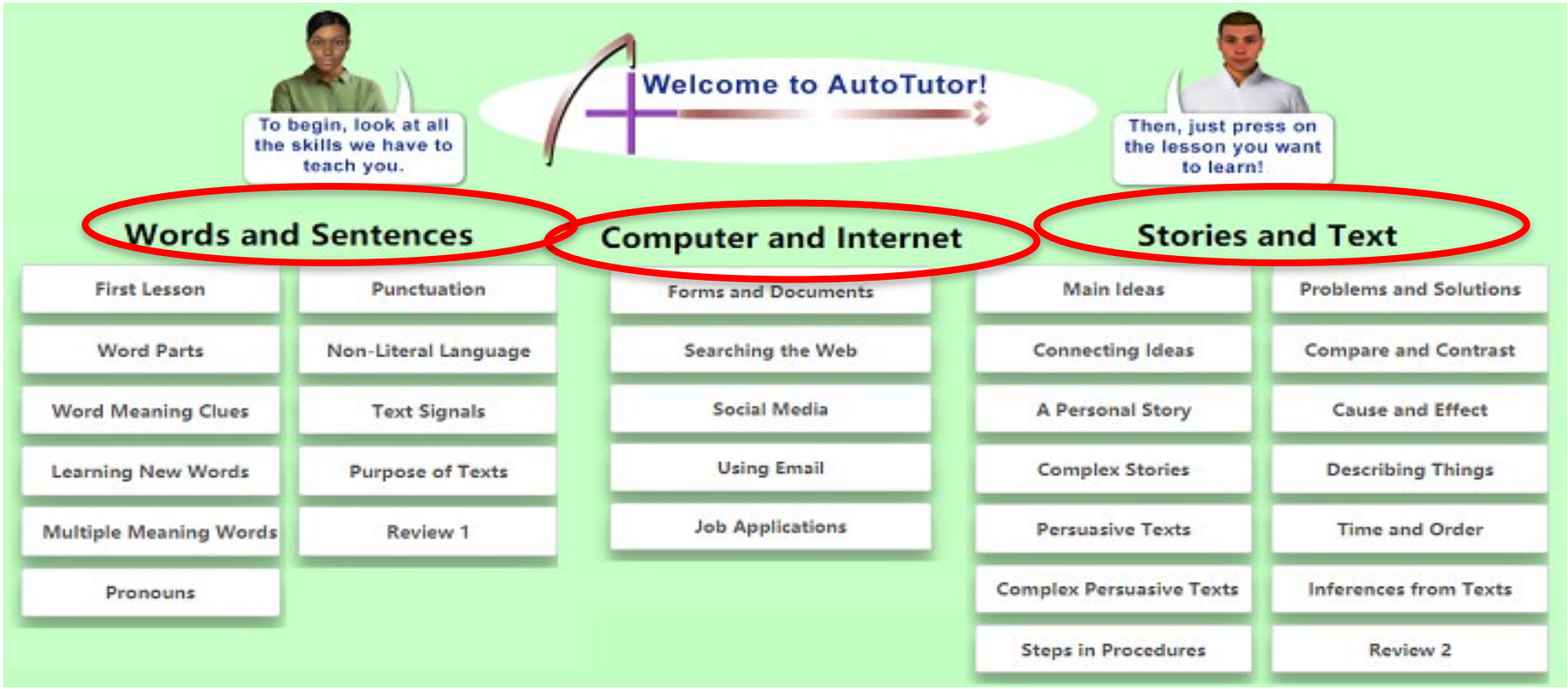
Graesser, A.C., & McNamara, D.S. (2011). Computational analyses of multilevel discourse comprehension. *Topics in Cognitive Science, 3*, 371-398.

Also Goldman, Kintsch, Perfetti…

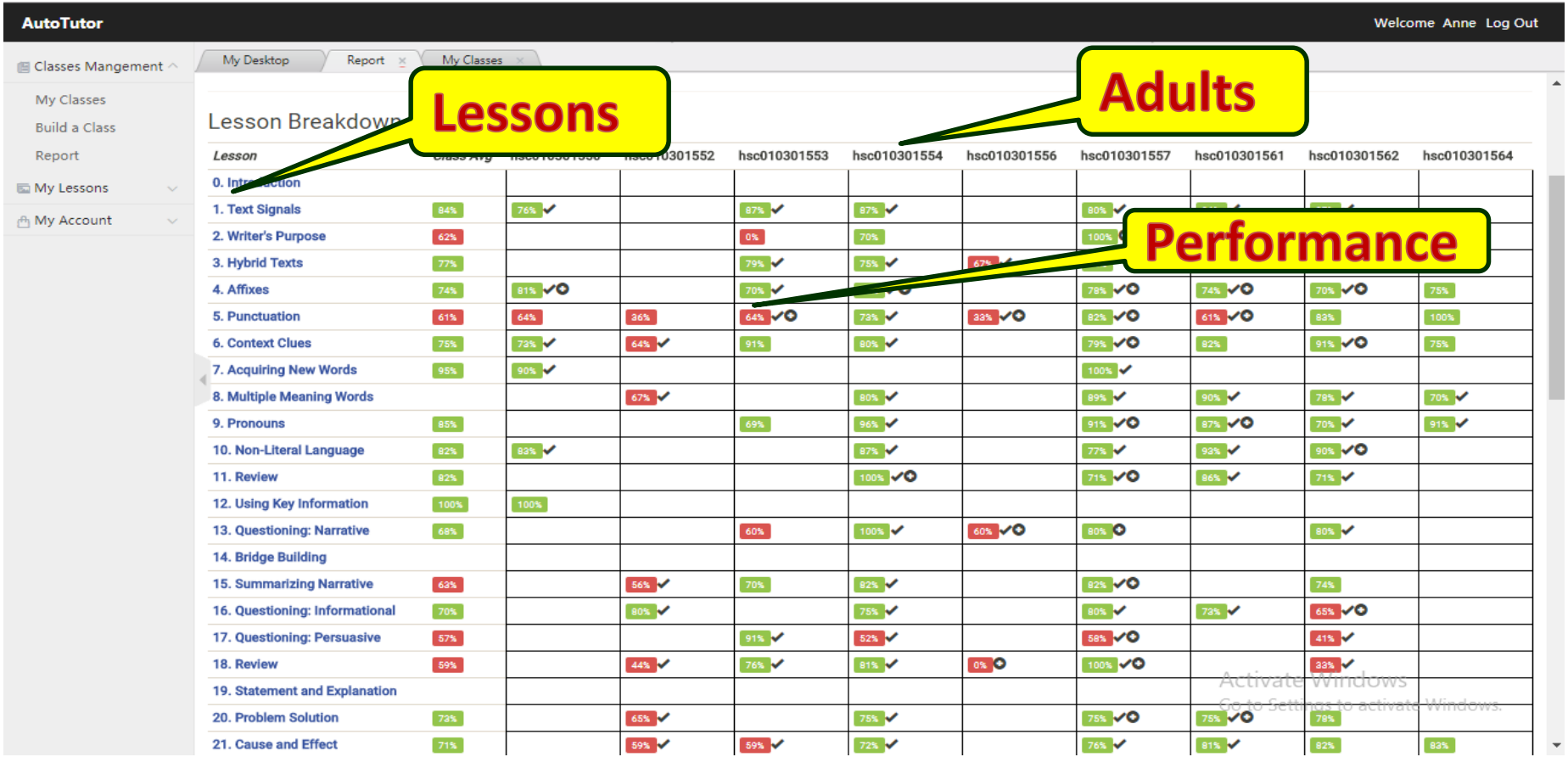
Home Web Page



Scope of Lessons



Database for Instructor



More Details about AutoTutor for CSAL

- **35 lessons on comprehension**

  20-60 minutes each
  Summary Nugget → Conversational Training
  Cover theoretical components and PACES curriculum

- **Conversation patterns**

  Agents in trialogues generate questions, hints, feedback, corrections, explanations, and guidance on using the system

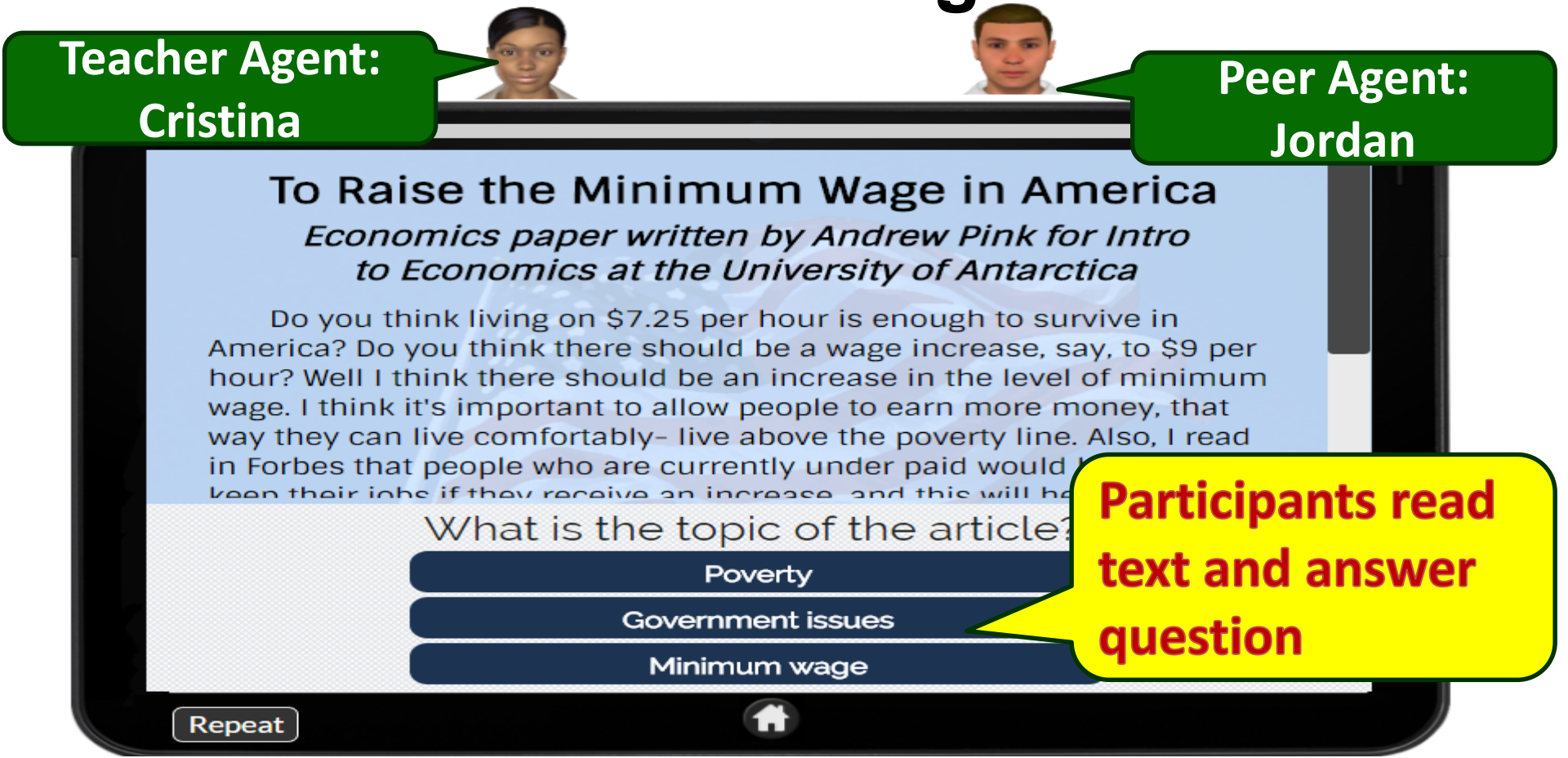
  Conversation modes: Testing, helping the peer, game competition

  Minimal natural language input from adult

- **Multiple media**

- **Practical texts and tasks for adults**

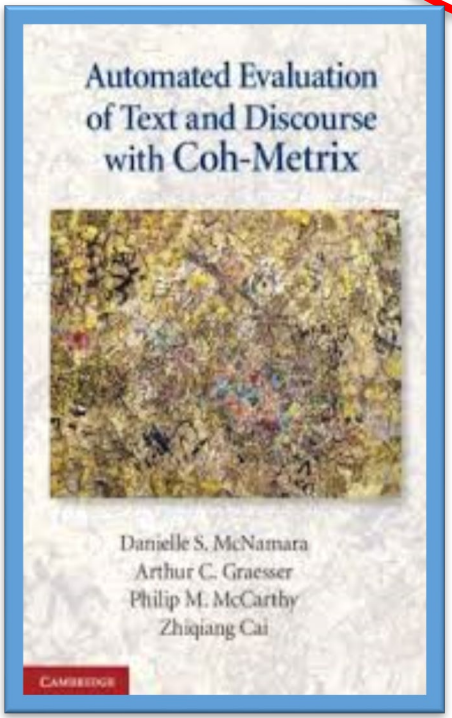
AutoTutor Trialogue



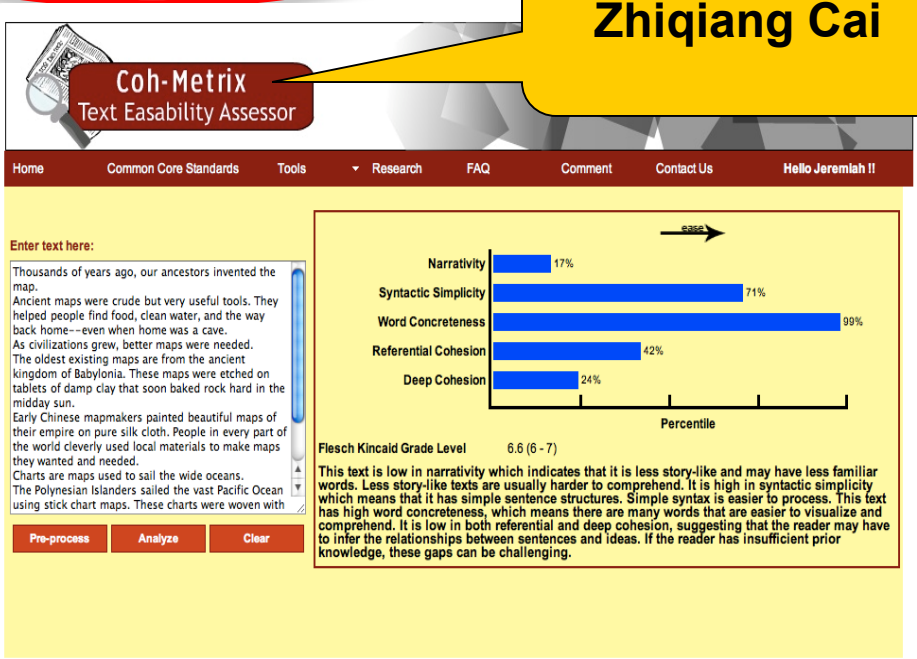
Tutorial On Digital Literacy

Discourse Formality

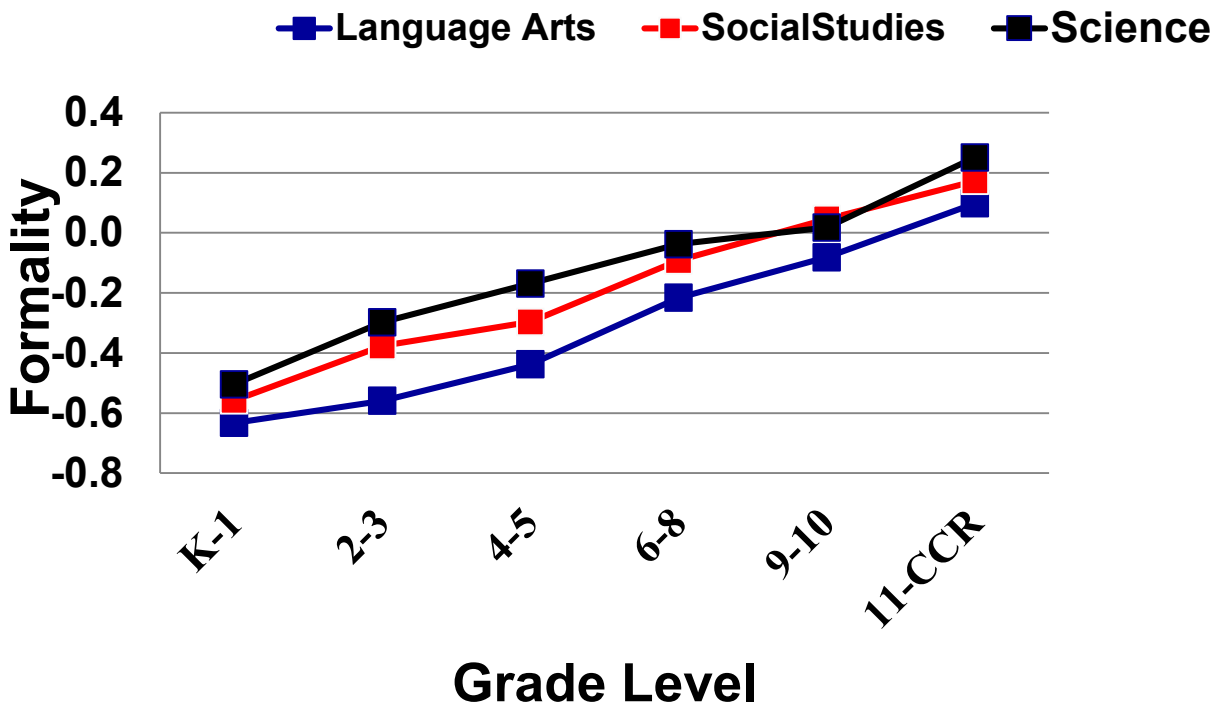
Informational Genre + High Cohesion + Complex Syntax + Abstract Words



Cohmetrix.com
Zhiqiang Cai



Coh-Metrix Formality Scores as a Function of Genres and Grade Levels

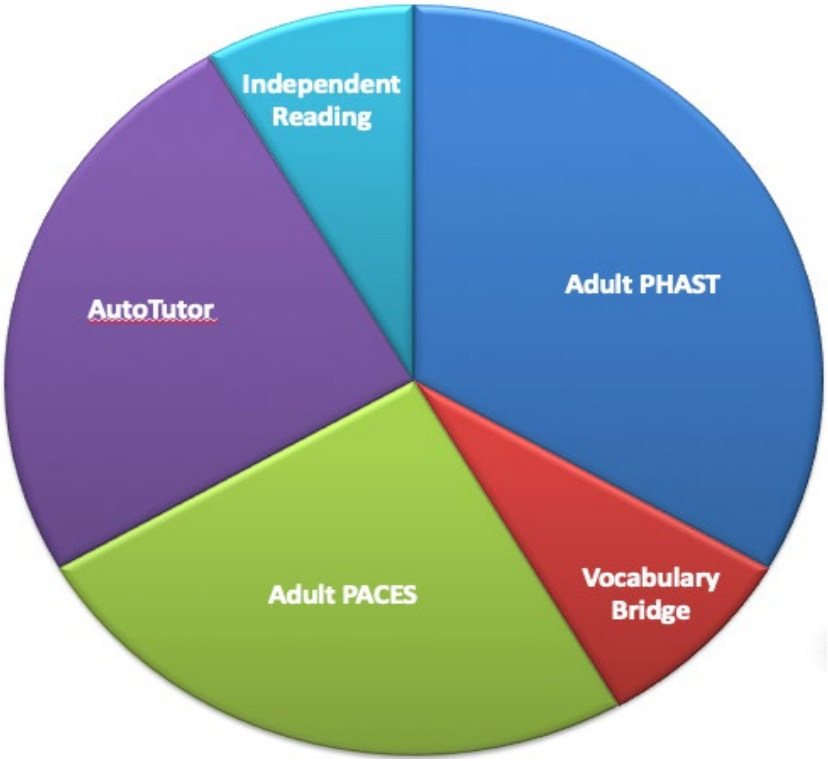


Graesser, A.C., McNamara, D.S., Cai, Z., Conley, M., Li, H., & Pennebaker, J. (2014). Coh-Metrix measures text characteristics at multiple levels of language and discourse. *Elementary School Journal. 115*, 210-229.

Types of Adaptivity

- **Lessons start out at a medium level of difficulty and branch to easy or hard depending on performance.**
- **In the inner loop (VanLehn, 2006), the conversational moves depend on the input of the adult learner.**
- **In the game competitions, the peer agent's actions always end up losing to the adult learner at the end.**

Intervention Design

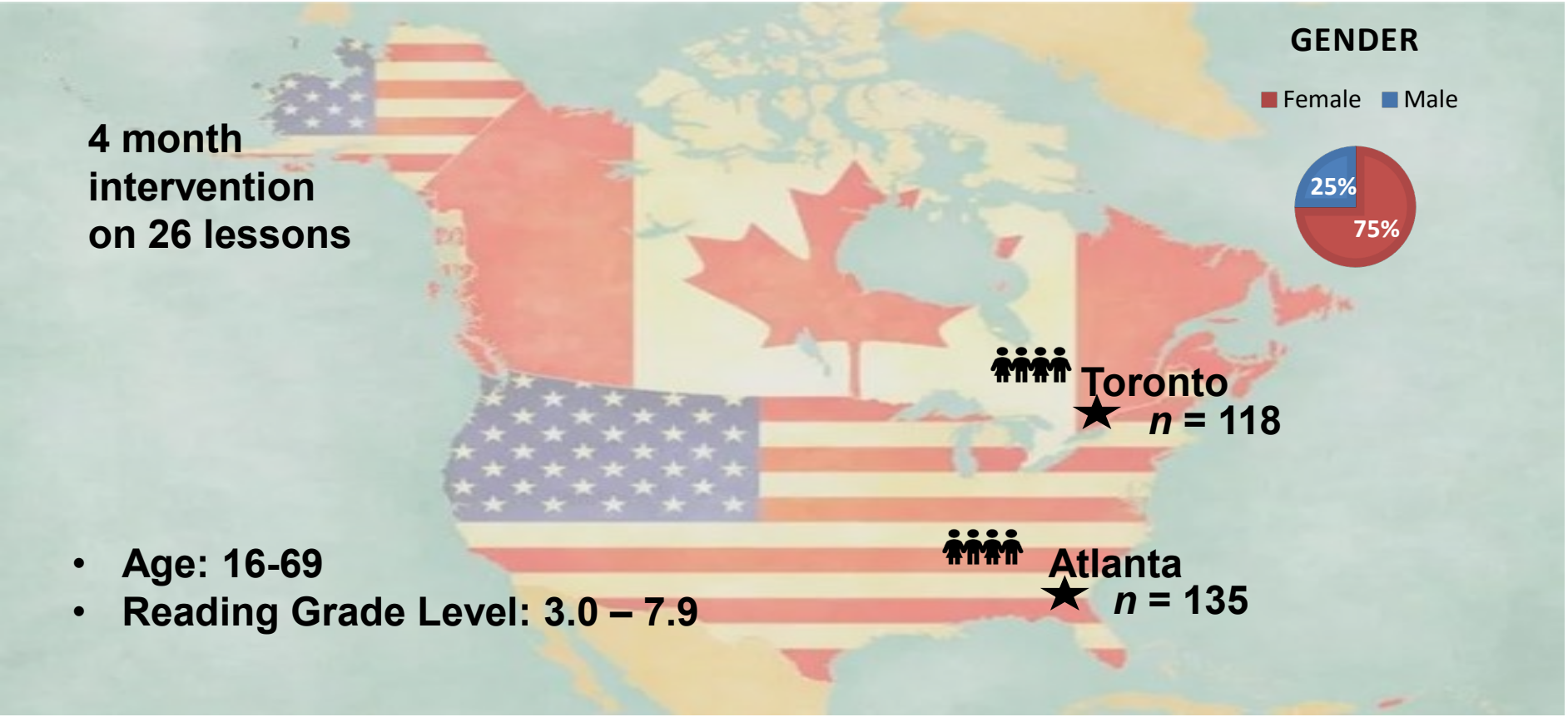


I. Pretest on dozens of measures
II. Intervention (100 hours)
III. Posttest with dozens of measures

Three comprehension measures

- Woodcock-Johnson
- Sara (Educational Testing Service)
- Lexia (formerly Rapid)

Study on Adult Readers (N=253)



Overall Results of AutoTutor

- **Completion of lessons**
  - 26 lessons were used in the analysis
  - 68.2% of lessons attempted
  - 55.3% of the lessons completed
- **Performance in answering questions**
  - 68% answered correctly on first attempt
  - 78% likelihood of branching to difficult texts rather than easy texts/items after performing on medium texts/items
  - 32.8 seconds per question

Cluster Analysis

Features

- Performance time & accuracy crossed with
  four levels of reading comprehension
  (Words, Textbase, Situation model, Rhetorical structure)

Method

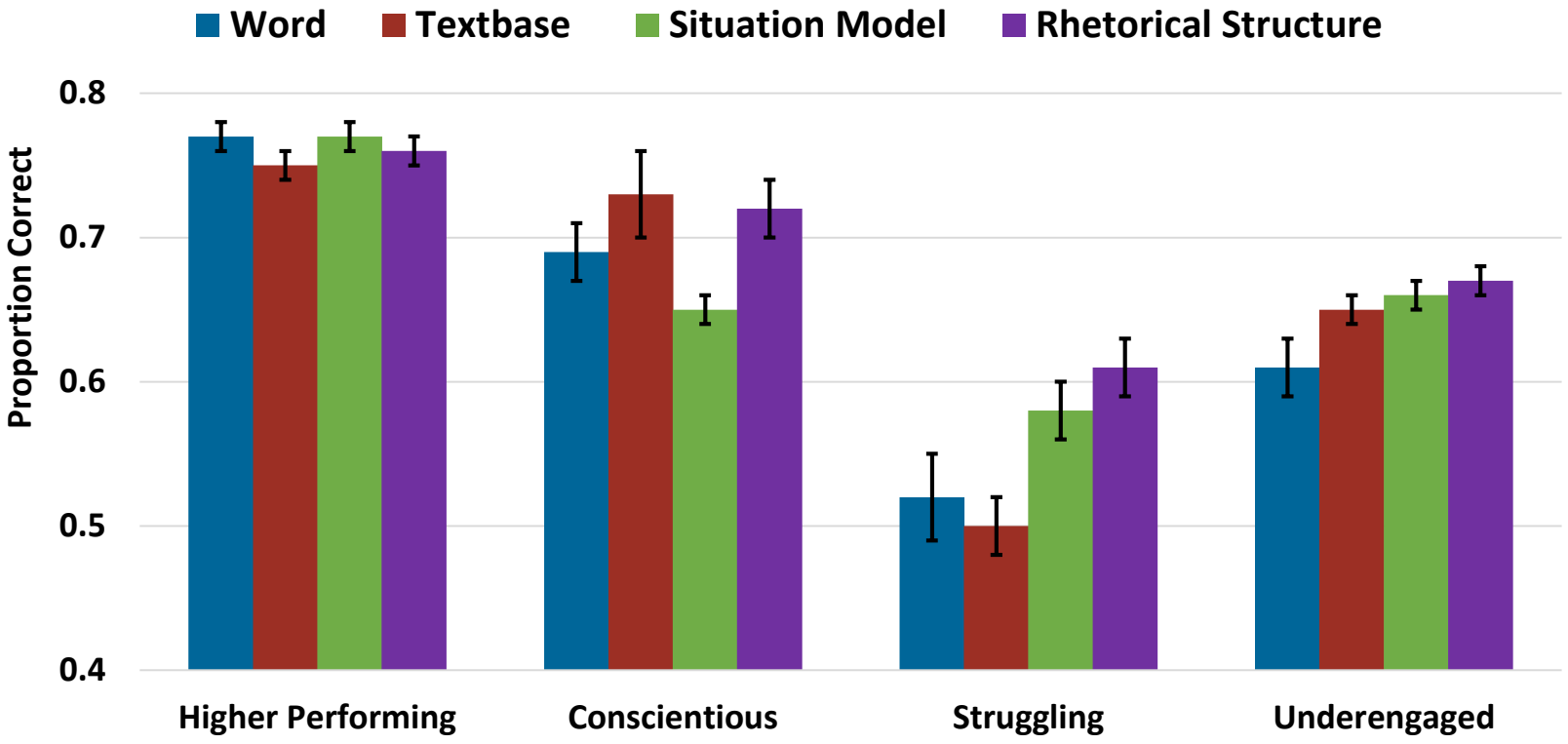
- K-means clustering VS hierarchical agglomerative clustering
  (Connectivity, Silhouette Width, Dunn Index)
- Hierarchical clustering performed better

Fang, Y., Shubeck, K.T., Lippert, A., Cheng,Q., Shi, G., Feng, S., Gatewood, J., Chen, S., Cai, Z., Pavlik, P. I., Frijters, J.C., Greenberg, D., Graesser, A. C. (2018). Clustering the Learning Patterns of Adults with Low Literacy Interacting with an Intelligent Tutoring System. In K.E. Boyer & M. Yudelson (Eds.), *Proceedings of the 11th International Conference on Educational Data Mining* (pp.348-354). Buffalo, NY: Educational Data Mining Society.

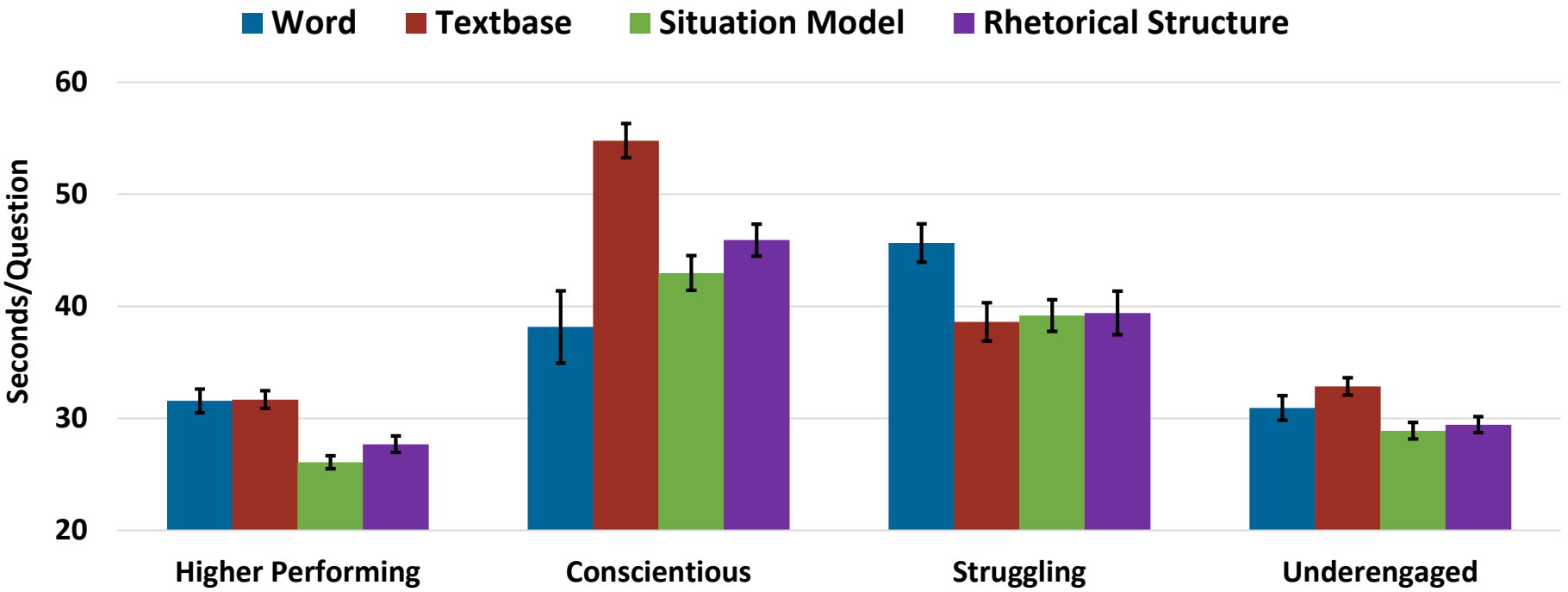
Four Clusters of Readers based on AutoTutor Response Times and Accuracy

1. **Struggling** readers showed minimal gains and may be wheel spinning. Slow plus inaccurate.
2. **Under-engaged** readers don't spend quite enough time that they need. Fast and lower accuracy.
3. **Conscientious** readers are slow and higher accuracy.
4. **Higher performing** readers are relatively fast and accurate.

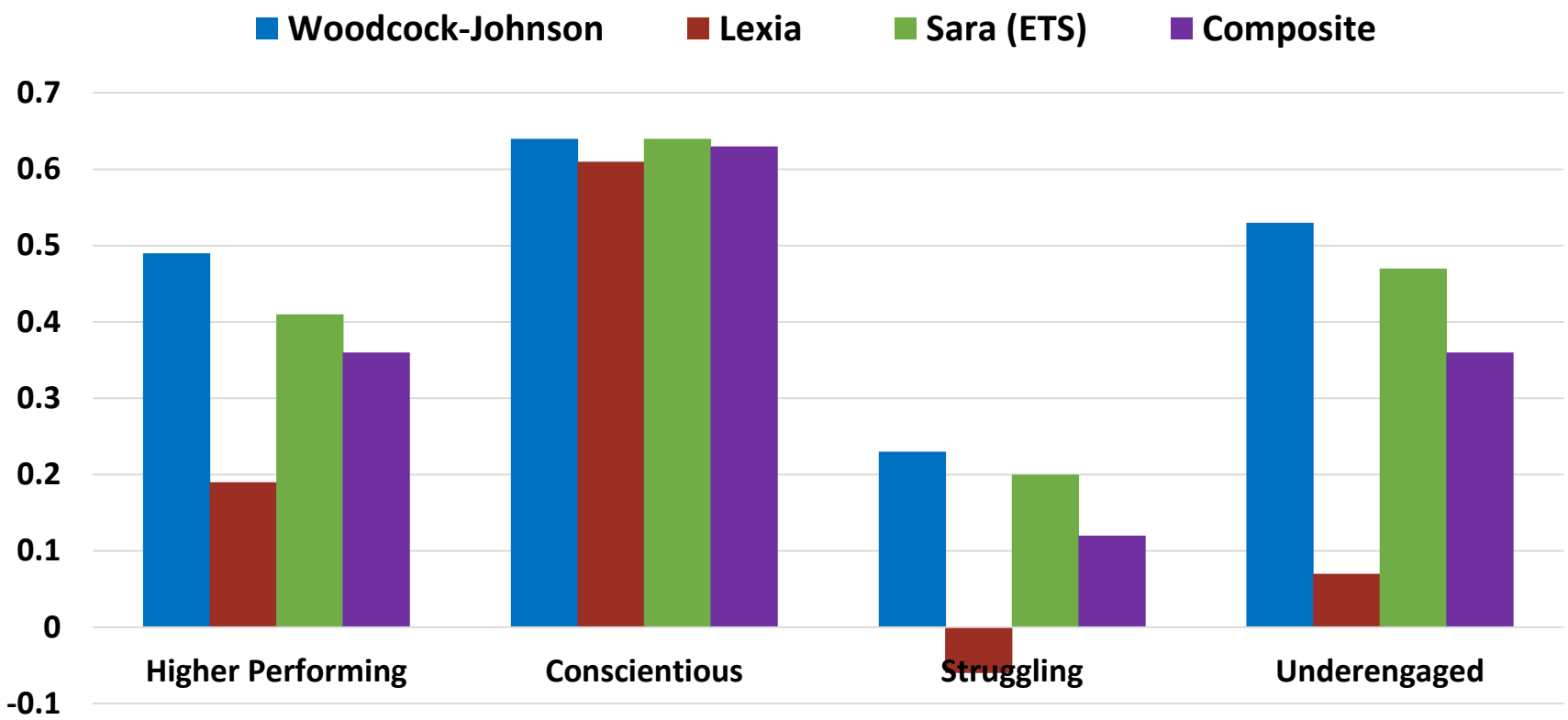
Accuracy as a Function of Theoretical Level and Reader Cluster



Time per Question (seconds) as a Function of Theoretical Level and Reader Cluster



Effect Sizes (posttest minus pretest) on Learning Gains as a Function of Reader Cluster



The four clusters of readers show very different profiles

1. **Struggling** readers showed minimal gains and may be wheel spinning. The intervention is beyond their zone of proximal development.
2. **Under-engaged** readers need to be encouraged to spend more time concentrating or otherwise be motivated more.
3. **Conscientious** readers are the major beneficiaries.
4. **Higher performing** readers may benefit from more challenge and be encouraged to increase reading activities.

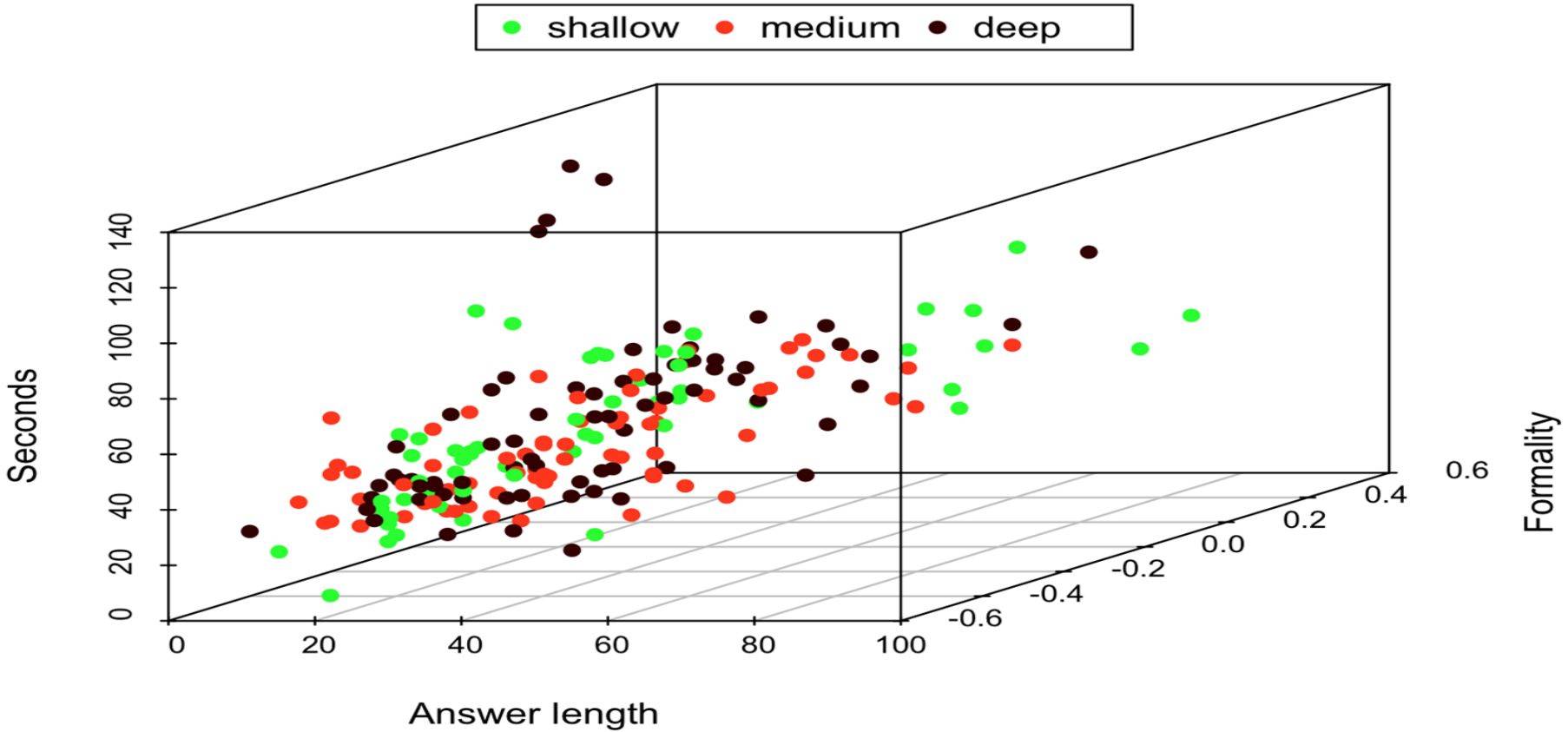
Item Analyses: Mixed-effects Models (Ying Fang)

- **Predictor variables**
  - Text formality score
  - Question depth level (Bloom's taxonomy)
  - Answer length (log of number of words in options)

- **Dependent variables**
  - Time on question in seconds
  - Correctness of answer to question

- **Random effects**
  - Participants
  - Texts

Predicting time in 1st attempts

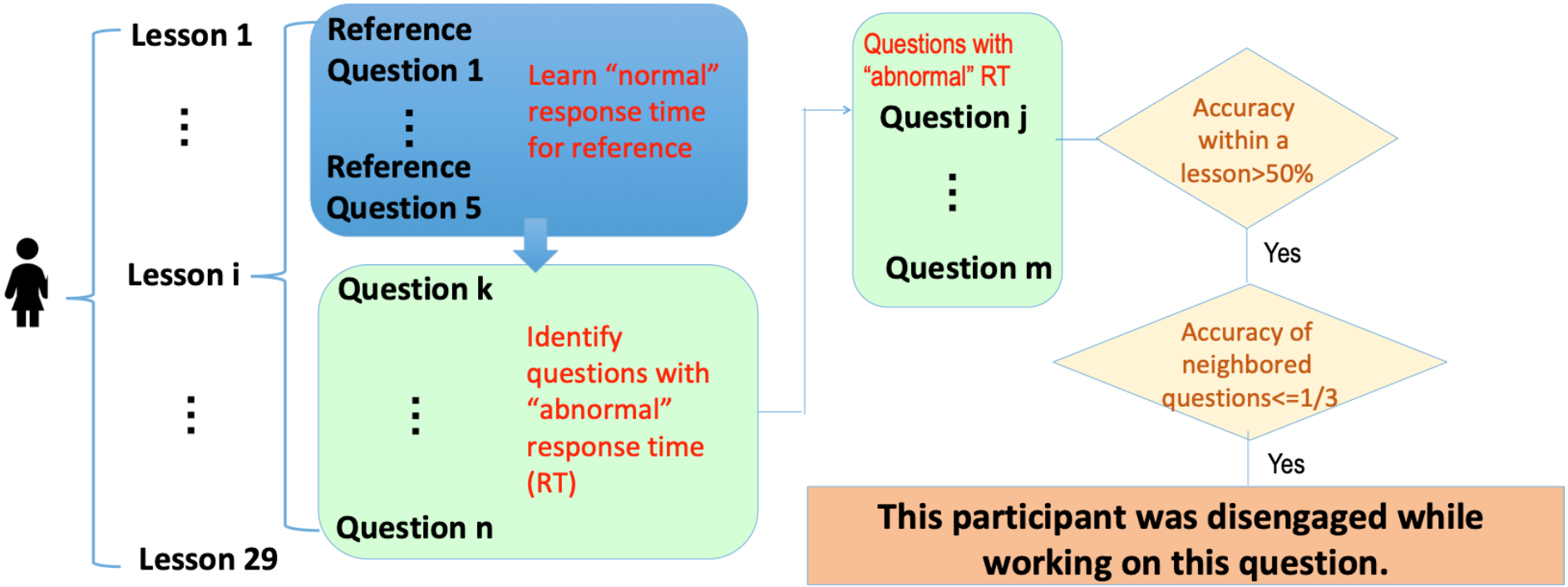


Results on Time and Accuracy of Question Items

	Text Formality	Question Depth	Answer Length
First Attempt Time	+	+	+
Subsequent Attempt Time		+	+
First Attempt Accuracy	-		-
Subsequent Attempt Accuracy		-	-

Disengagement Tracing System (Su Chen)

Algorithm Flow Chart



Upshot of Question Item Analyses

- Identify disengagement time spans of individual readers
- Quickly classify individual readers into one of the four reader clusters (struggling, under-engaged, conscientious, higher performers)
- Design AutoTutor to select materials and trialogue moves that are sensitive to these characteristics

Immediate Next Steps

- **AutoTutor in the Wild**
- **Explore how much human instructor scaffolding is needed?**
- **Scaling up AutoTutor for:**
  - **adult literacy centers**
  - **workforce**
  - **colleges, universities, Department of Defense training**

Long-term Horizon with AI

- **Build a more adaptive AutoTutor**
  - **Sensitivity to engagement and reading clusters**
  - **Sensitivity to interests of the reader (Andrew Olney)**
- **Speech recognition and mobile devices**
- **Social connections through social media:**
  - **Human connections with peers and instructors**
  - **Will they believe intelligent bots?**
- **Integration with Geographical Information Systems**
  - **You are near a literacy center, bookstore, library…**
  - **You like Chinese food. What do you think about this restaurant?**

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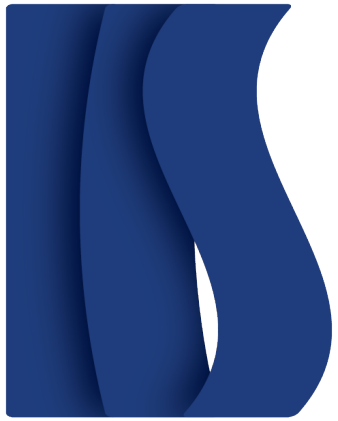

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Thank you!

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