Automated Writing Evaluation:

College Student Perceptions and Future Intentions

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Roscoe, R. D., Wilson, J., Johnson, A. C., & Mayra, C. R. (2017). Presentation, expectations, and experience: Sources of student perceptions of automated writing evaluation. *Computers in Human Behavior*, *70*, 207-221.

Automated Writing Evaluation

- **Natural language processing** (NLP) tools detect linguistic, syntactic, structural, semantic, and rhetorical properties of text

- NLP data can be **statistically modeled** to emulate or predict human judgments of writing quality or specific writing traits

- Statistical models (e.g., regression, DFA, machine learning) guide **scoring and feedback algorithms**

Dikli (2006), Shermis & Burstein (2013)

A Bit of Debate…

Proponents

Scale Up

Speed

Reduce Workload

More Practice with Feedback

Critics

Incomplete Writing Construct

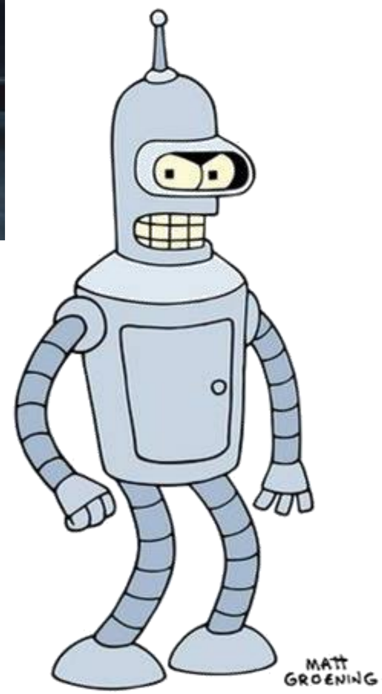
Formulaic Writing

$$x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

Inhuman Audience

A Bit of Debate…

Proponents	Critics



Consequences of Perceptions?

- **Technology acceptance** may be mediated by perceptions of usefulness and ease of use

  Vinkatesh & Davis (2000)

- Beliefs and perceptions about technology can introduce **barriers to implementation**

  Ertmer (1999); Ertmer et al. (2012); Koehler & Mishra (2009)

- Educators' beliefs and attitudes can **influence classroom culture** and student behavior

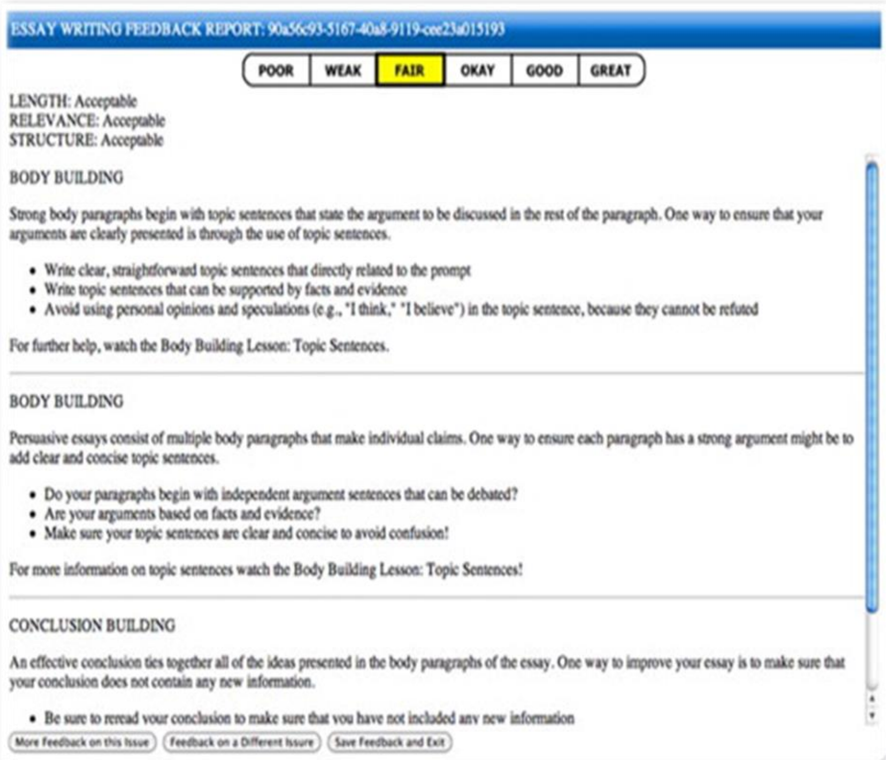
  Li et al. (2015); Webb et al. (2006); Yeager & Dweck (2012)

Current Study

- Explore college student perceptions of AWE (using The Writing Pal tutoring system)
  - **expectations** about scoring and feedback
  - **immediate perceptions** of scores and feedback received
  - **change in perceptions** (better or worse than expected)
- Impact of perceptions on revising (in the paper)
- Impact of perceptions on **future intentions**

The Writing Pal

- **Intelligent tutor for writing strategies**. Includes educational games and formative feedback on student writing (AWE).



- **Feedback topics include**:
  - length/elaboration
  - structure
  - introductions
  - bodies
  - conclusions
  - paraphrasing
  - cohesion
  - revising

Current Study

- 110 undergraduates wrote (20 min.) an essay on "psychology in the media" and revised (10 min.) after receiving a score and feedback from W-Pal

- **Presentation Conditions** (no deception)
  - manipulated whether **scoring system** was presented as "well tested" vs. "in progress"

  - manipulated whether **feedback system** was presented as "well tested" vs. "in progress"

Perceptions

- **Expectations of scoring and feedback**
  - *after* system was introduced
  - *before* any writing or revising

- **Immediate perceptions of scoring and feedback**
  - *after* writing, receiving feedback, and revising
  - i.e., the “full experience”

- **Change in perceptions of scoring and feedback**
  - at the *end* of the study
  - whether final perceptions “better” or “worse”

Future Intentions

- "Would you **use this software again** to help you improve your writing?"
    - "Yes" or "No"
- "Would you **recommend this software** to a friend who needed writing help?"
    - "Yes" or "No"

Effects of Presentation

Mean Ratings of Expectations, Immediate Perceptions, and Final Perceptions by Condition

	Advertised Scoring and Feedback Quality Conditions				Main Effects	
Feedba	Strong Scoring,	Strong Scoring,	Weak Scoring, Feedback = 28)	Weak Scoring, Weak Feedback (n = 29)	Presented Scoring Accuracy $F(1, 106)$	Presented Feedback Quality $F(1, 106)$
Initial I						
Scori			(0.8)	4.1 (0.8)	7.86[b]	2.32
Feed			(0.7)	4.0 (0.7)	< 1.00	3.07[d]
Immed						
Scori			(0.6)	3.2 (0.9)	1.42	< 1.00
Feed			(0.6)	3.1 (0.8)	< 1.00	3.84[d]
Percep						
Scori			(1.0)	+0.2 (1.1)	1.13	< 1.00
Feed			(0.8)	+0.2 (1.1)	1.16	4.86[b]

Note. [a] ... composites computed by averaging individual feedback ratings ... to +2 and are not difference scores.

Presentation only slightly influenced expectations, immediate perceptions, or final perceptions.

Perhaps "low dosage" or lack of authority?

Predicting Scoring Perceptions

Linear Regression Predicting Perceptual Change for Scoring Accuracy

	Coefficients			Model Fit		
Predictor	β	t	p	R^2	F	p
Pres. Scoring Accuracy	-0.08	-0.98	.332	.37	9.99	< .001
Pres. Feedback Quality	0.03	0.37	.710			
Exp. Scoring Accuracy	0.24	2.29	.024			
Exp. Feedback Quality	-0.38	-3.60	< .001			
Imm. Scoring Accuracy	0.47	5.54	< .001			
Imm. Feedback Quality	0.26	2.96	.004			

Note. "Pres." refers to presented system capabilities (dichotomous coding, weak

Expectations and immediate perceptions influenced judgments of the scoring system as "better" or "worse" than expected.

Predicting Feedback Perceptions

Linear Regression Predicting Perceptual Change for Feedback Quality

	Coefficients			Model Fit		
Predictor	β	t	p	R^2	F	p
Pres. Scoring Accuracy	-0.07	-0.88	.383	.44	13.26	< .001
Pres. Feedback Quality	0.10	1.22	.224			
Exp. Scoring Accuracy	-0.01	-0.07	.947			
Exp. Feedback Quality	-0.06	-0.57	.570			
Imm. Scoring Accuracy	0.18	2.25	.027			
Imm. Feedback Quality	0.56	6.69	< .001			

Note. "Pres." refers to presented system capabilities (dichotomous coding, weak =

Only immediate perceptions influenced judgments of the feedback system as "better" or "worse" than expected.

Willingness to Use Again

Logistic Regression Predicting Willingness to Use W-Pal in the Future

	Coefficients				
Predictor	*B*	*SE*	*Wald*	*p*	e^B
Exp. Scoring Accuracy	0.49	0.46	1.09	.296	1.63
Exp. Feedback Quality	0.97	0.63	2.37	.124	2.65
Imm. Scoring Accuracy	0.88	0.61	2.10	.147	2.42
Imm. Feedback Quality	0.42	0.62	0.46	.499	1.52
Scoring Accuracy Change	0.39	0.49	0.62	.432	1.48
Feedback Quality Change	2.10	0.60	12.38	< .001	8.18

Note. “Exp.” refers to students’ expectations, and “Imm.” refers to students’ immediate perceptions. All Feedback Quality ratings are composites computed by averaging

Willingness to use again predicted by perceiving the feedback as “better than expected.”

Willingness to Recommend

Logistic Regression Predicting Willingness to Recommend W-Pal to a Friend

	Coefficients				
Predictor	B	SE	$Wald$	p	e^B
Exp. Scoring Accuracy	1.16	0.56	1.25	.039	3.17
Exp. Feedback Quality	0.29	0.68	0.18	.673	1.33
Imm. Scoring Accuracy	1.37	0.71	3.67	.055	3.93
Imm. Feedback Quality	1.12	0.71	2.50	.114	3.08
Scoring Accuracy Change	-0.27	0.58	0.22	.636	0.76
Feedback Quality Change	2.84	0.78	13.37	< .001	17.12

Note. “Exp.” refers to students’ expectations, and “Imm.” refers to students’
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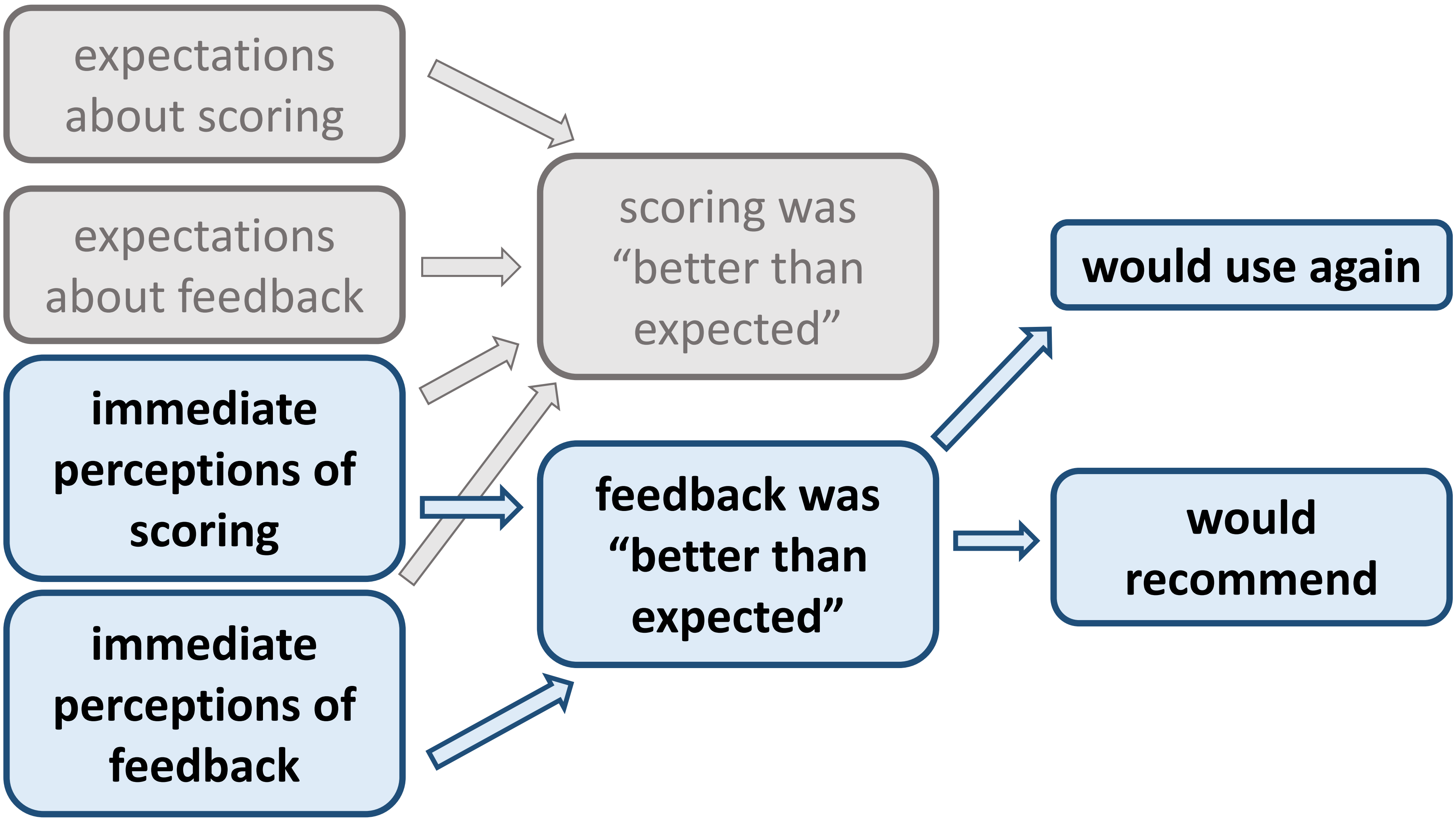
Willingness to recommend predicted by perceiving the feedback as “better than expected.”

Informal "Path"



Winning them Over?

- Effective automated feedback is not just a "learning sciences" issue (e.g., principles of feedback)…

  Hattie & Timperley (2007); Shute (2008)

- … and not just a "computer science" issue (e.g., better NLP detection algorithms)…

  Deane (2013); McNamara et al. (2015); Shermis & Burstein (2013)

- … **might also be a "user science" issue**
  - feedback perceptions, design, classroom integration
  - users' beliefs about methods and appropriateness
  - **direct, positive user experiences are how these perceptions are formed, reinforced, or overturned**

Automation More Broadly

- Beyond automated feedback, what about overall **automation in educational technology**?
    - e.g., intelligent tutoring systems, pedagogical agents, teachable agents, learner modeling, grading, course assignments and placement, etc.
- How are educational technologies running afoul (or taking advantage) of users' beliefs and doubts about computers, automation, and AI?
- **What is the "effect size" of good design and HCI?**

Questions?

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