

INTERNATIONAL NEURAL NETWORK SOCIETY

The Critical Role of Al in Learning Analytics & Assessment in the Future of Education

Prof. Irwin King, Fellow of ACM, IEEE, & INNS

Director, Machine Intelligence and Social Computing (MISC) Lab Director, Centre for eLearning Innovation and Technology (ELITE) Principal Investigator, VeriGuide and The Knowledge and Education Exchange Platform (KEEP)

> Department of Computer Science and Engineering The Chinese University of Hong Kong

Acknowledgement

The presenter wishes to acknowledge the International Neural Network Society for their sponsorship of the Webinar Series.



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Trustworthy AI

Privacy, Security, Robustness, Fairness, Explainability, Interpretability, Watermarking, Accountability, Policy, etc.

Social Computing

- Big data
- Data mining
- Social recommender systems
- Social media analysis
- Social network analysis
- Graph algorithms
- Community search

Natural Language Processing (NLP)

- Large language model (LLM)
- Sentiment analysis
- Summarization
- Translation
- Language models
- Speech Language Models
- Multilingual modeling
- Fact-checking
- Watermarking in LLMs

Machine Learning

- Foundation models
- Semi-supervised learning
- Online learning
- Self-supervised learning
- Meta learning
- Contrastive learning
- Federated Learning
- Hyperbolic embedding

Graph Neural Networks (GNN) & Al for Science

- Heterogeneous GNN
- Knowledge graph
- Bioinformatics
- Al for science
- Gastric cancer diagnosis and prediction
- Bioinformatics



Machine Learning

1. 2. 3. 4. 5.	Pretrain Model for Crystal Property Prediction, AAAI 2024 Hyperbolic Efficient Transformer, KDD 2024 Geometric View of Soft Decorrelation in Self-Supervised Learning, KDD 2024 Hyperbolic Temporal Network Embedding Learning, TKDE 2023 Meta-Learning with Motif-based Task Augmentation for Few-Shot Molecular Property Prediction, IJCAI 2023	1. 2. 3. 4. 5.	Hierarchical Hyperbolic Product Quantization, AAAI 2024 Deep Structural Knowledge Exploration, AAAI 2024 Influential Exemplar Replay for Incremental Learning in Recommender Systems, AAAI 2024 Shopping Trajectory Representation Learning, KDD 2024 Mitigating the Popularity Bias of Graph Collaborative Filtering, NeurIPS 2023	
	NLP		Graphs	
1. 2. 3.	Entropy-based Text Watermarking Detection, ACL 2024 Unforgeable Publicly Verifiable Watermark for Large Language Models, ICLR 2024 Improving Open Relation Extraction With Search Documents, TKDE 2024	1. 2. 3.	Long-Tail Distribution Issues in GNN, TKDE 2024 Empowering Graph Neural Networks with Expected Model Change Maximization, NeurIPS 2023 Optimal Block-wise Asymmetric Graph Construction for Graph-based Semi-supervised Learning, NeurIPS 2023 Binartite Craph Convolutional Hashing, WebConf 2027	
4. 5. 6.	Knowledge Graph Entity Typing, NAACL 2024 Continuous Rationale Extraction for Relation Extraction, SIGIR 2023 Multimodal Relation Extraction, ACL 2023	4. 5. 6.	Bipartite Graph Convolutional Hashing, WebConf 2023 Contrastive Cross-scale Graph Knowledge Synergy, KDD 2023 Doubly Stochastic Graph-based Non-autoregressive Reaction Prediction, IJCAI 2023	

Social Computing



INNOVATION STARTS WITH EDUCATION

The Evolution of Signal Processing

Reflections After 50-Plus Years in the Classroom

Proper Definition and Handling of Dirac Delta Functions

Alternative Data Paths for the Cascaded Integrator—Comb Decimator



INNOVATION STARTS WITH EDUCATION

Irwin King, Chandni Saxena, Christian Pak, Chak-ming Lam, and Haiyan Cai

Rethinking Engineering Education

Policy, pedagogy, and assessment during crises

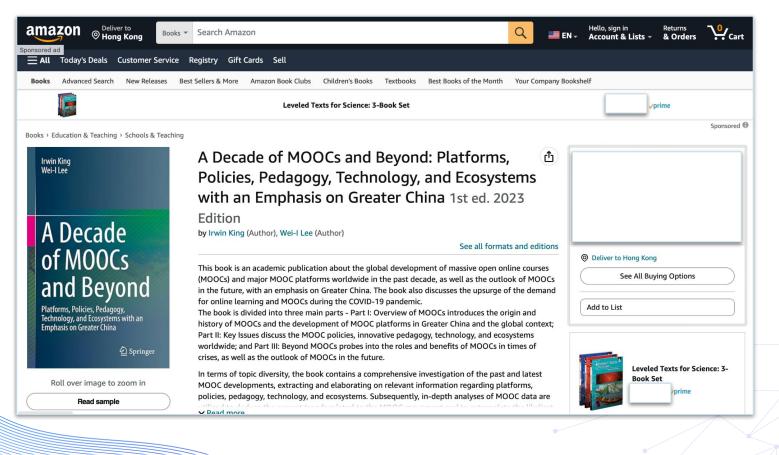


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rises, especially the recent COVID-19 pandemic, have significantly impacted traditional teaching pedagogy, which often relies on face-to-face interactions. It is crucial that various stakeholders in education, including administrators, staff members, teachers, parents, learners, government officials, and so on, adapt to abrupt changes and disruptive transformations caused by emergency situations. In this article, we map out approaches to stakeholders that underpin teaching and learning effectiveness for engineering education (EE) in terms of policy, pedagogy, and assessment. The contributions of this article are threefold. First, we revisit a framework that enables administrators to devise policies for a secure and safe learning environment. Second, we propose Crisis-Resilience Pedagogy (CRP), which highlights and integrates important attributes such as adaptability, creativity, connectivity, diversity, and endurance into pedagogical components for effective teaching and learning. Third, we outline how to leverage education technology for outcomes assessment. To illustrate the challenges, solutions, and possibilities in this "new normal," we utilize and reflect on the results of an observational study conducted during the pandemic. Our approaches can be easily extended to other academic disciplines in other institutions to strengthen the resilience of our education systems in times of crisis.

Introduction

We live in a natural world characterized by risk, catastrople, and instability resulting from disasters and crisss. These abrupt events, small or large in scale, natural or anthropogenic, have had a profound impact on individuals, organizations, communities, and states on a worldwide level. In recent years, we have observed a shift in the nature, causes, frequency, consequences, and adversities associated with crissel [1], which has led to new challenges and growing research interests to understand and manage these events. In the past few decades, crises





8

Overview

O1 Traditional Assessment and Its Challenges

02 How Does Al and Learning Analytics Meet Assessment Challenges

9

03 Developing Al Software for Education



01

Traditional Assessment and Its Challenges

Challenges

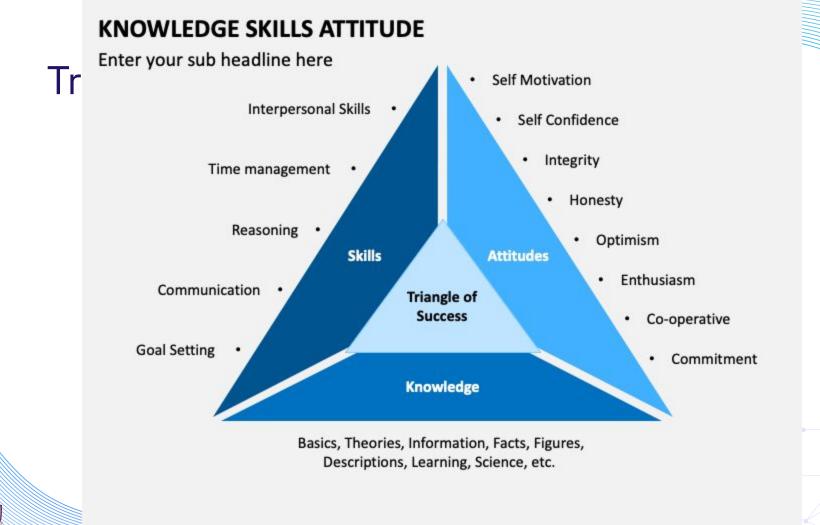
- Accuracy and Errors
- Standardization
- Timeliness
- Access and Privacy
- Transfer of Credits
- Fraud and Misinterpretation
- Others...

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ENG 1301	FRESHMAN COMPOSITION I	В	3.0	9.0	BLA 2325		NMENT OF BUSINESS	В	3.0	9.
MAT 1311	PRECALCULUS MATHEMATICS	В	3.0	9.0	MOT 3321	PRINCIPLES OF		8	3.0	9.
ART 1301	INTRODUCTION TO ART	c	3.0	6.0	MKT 3331	PRINCIPLES OF		3	3.0	9.
BOC 1301	GENERAL SOCIOLOGY I	A	3.0	12.0	QBA 3335	BUSINESS STAT	TISTICS II	В	3.0	9.
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ENG 1302	FRESHMAN COMPOSITION II	A	3.0	12.0	QBA 3323	QUANTITATIVE		8	3.0	9.
HED 1201	CONCEPTS OF HEALTH	B	3.0	9.0	MGT 3324	ENTREPRENEUR			3.0	9.
MAT 2410	CALCULUS I AMERICAN GOVERNMENT	B	3.0	9.0	FIN 3351 MKT 3334	MARKETING CON	F FINANCIAL METG.		3.0	9. 9.
NS 1311	AREALCAN GOVERNMENT	- CO -	3.0	9.0	AA1 3334	ARRESTING COL	ANUMICATIOND		3.0	
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5	FALL 2003					FALL 2005				1
ACC 2316	PRINCIPLES OF ACCOUNTING MICROCOMPUTER APPLICATIONS	AB	3.0	12.0	MGT 4302	SALESMANSHIP MARKETING MAN	A CRAPHENE	AB	3.0	12.
RIS 1380 ECO 2311	PRINCIPLES OF MICROECONOMICS	B	3.0	9.0	ECO 4331	MONEY AND BAL		B	3.0	9.
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28A 2335 BCO 2312	PRINCIPLES OF MACROECONOMICS	B	3.0	9.0	MKT 4379	INTERNATIONAL		B	3.0	9.
EUM 1301	INTRODUCTION TO HUMANITIES	8	3.0	9.0	MGT 4399	BUSINESS POL		Å	3.0	12.
PSY 1301	GENERAL PSYCHOLOGY I	c	3.0	6.0	MGT 4348		CE MANAGEMENT	B	3.0	9.
SPH 2341	FUNDAMENTALS OF SPEECH	B	3.0	9.0	MGT 4377	OPERATIONS MA		D	3.0	9.
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https://www.diplomasandtranscripts.com/fake-college-transcripts.html

Missing Qualities to Track

- Personal Growth
- Critical Thinking and Problem Solving
- Collaboration and Teamwork
- Communication Skills
- Cultural Competency and Global Perspective
- Motivation and Engagement
- Ethical Judgement and Integrity
- Self-Assessment and Metacognition
- And more...



"Is there any way I can get an **intelligent e-portfolio** instead of my transcript?"



Writing and editing support

Skill and competency mapping

Content organization and structuring

Visual design and layout

Feedback and assessment

Multimedia support

Interactive tutorials

Progress tracking

Collaboration features



Empowering Learner Agency through e-Portfolio Co-design: A Pathway to Integrating Generative AI

September 2024

In book: Retos e Innovación en Educación (pp.139-151) · Publisher: Grupo Kiobus Editorial & Cátedra UNESCO de Educación

Authors:



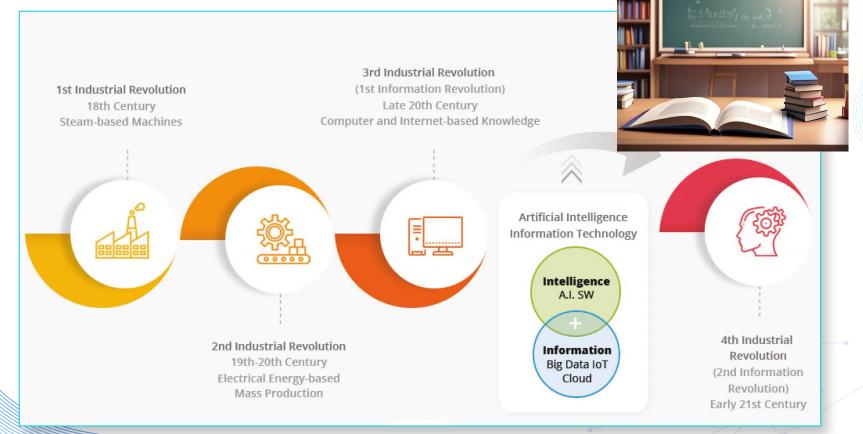
Peng Zhang Namseoul University



University of the Balearic Islands

15

The 4th Industrial Revolution





and the second

Who Are the Stakeholders?



Innovating pedagogy with AI in teaching and assessment



Administrators

Keeping institutions at the forefront of academic innovations



Students

Learning new skills and adapting to a changing landscape

Parents

Supporting and adapting to students' needs



Government Officials

Developing policies that support the education and innovation sector



Technology Developers

Developing technology that solves real-world problems



https://www.linkedin.com/pulse/triangle-success-howlader-itil-ceh-rhce-mcse-ccnp-vcp-ocp/

Knowledge Transmission

Content Creation

- Design Learning
 Objectives
- Curriculum Development
- Outcome-based Approach
- Automated and Personalized Content Generation
- Multimedia Content Creation
- Content Curation and Personalization
- Multilingual and Accessibility Support

Pedagogy Delivery

- Flipped-classroom
- Hybrid Learning
- Peer Learning
- Active Learning
- Project-based Learning
- Problem-based Learning
- Experiential Learning
- Case-based Learning
- Intelligent Classroom Assistants
- Multimodal Learning Experiences

Assessment Methods

- Formative, Summative, Diagnostic Assessment
- Performance-based Assessment
- Self, Peer, Authentic, Portfolio, and Ipsative Assessment
- Criterion-based and Norm-based Assessment
- Automated Grading /Feedback
- Learning Analytics and Insights

Where Did We Start?

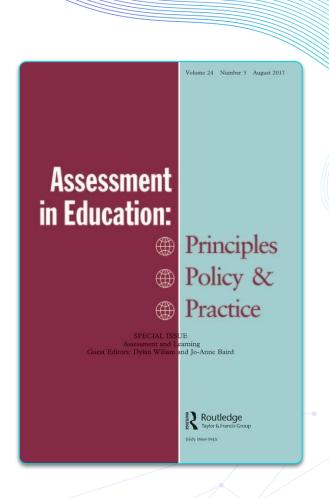
Foundational Principles

"Assessment and Classroom Learning"

(1998) - Paul Black and Dylan William

→ Assessment as a feedback loop

- 1. Teachers **gather evidence** through activities, questions, and discussions.
- 2. They use this evidence to **adjust their teaching strategies**.
- 3. Students receive **specific, actionable feedback** that helps them understand how to improve.



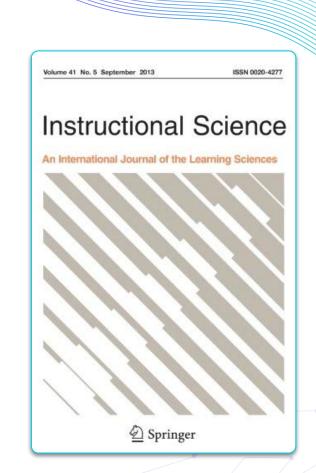
Where Did We Start?

Foundational Principles

"Formative Assessment and the Design of Instructional Systems"

(1989) - D. Royce Sadler

- Formative assessment is not a one-time event but a **continuous and iterative process**.
- Assessment as a teacher-driven activity should be **learner-centered**, feedback alone is insufficient unless students are able to use it effectively.



Why Change?

1. Overemphasis on lower-order thinking skills.

Knowledge (recall of facts) over Comprehension (basic understanding).

2. Standardization vs. Individualization

Treating all students as if they learn the same way and **progress at the same pace**.

3. Limited Insight Into Student Understanding

Limitations of assessing how students evaluate, apply, and analyze information in **real-world settings**.

"Taxonomy of Educational Objectives: The Classification of Educational Goals," Benjamin Bloom (1956)

Weaknesses In the Standard Assessment Paradigm (SAP)

- 1. Assessment design is **time-consuming** and only one of a teacher's responsibilities.
- 2. Assessments only view a snapshot of what a student can do at a **single point in time.**
- 3. One-size-fits all approach may introduce **unintended biases** into assessment.
- 4. Assessments can be **inauthentic** as they don't include real-world contexts.
- 5. Assessments can be antiquated and assessing **skills becoming obsolete.**

Design and Discovery in Educational Assessment: Evidence-Centered Design, Psychometrics, and Educational Data Mining

ROBERT J. MISLEVY Educational Testing Service JOHN T. BEHRENS AND KRISTEN E. DICERBO Pearson and ROY LEVY Arizona State University



FI SEVIER

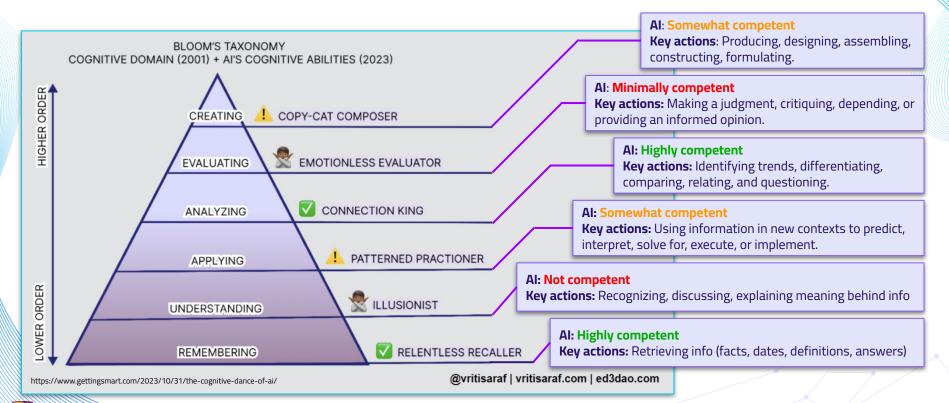
Computers and Education: Artificial Intelligence Volume 3, 2022, 100075



Assessment in the age of artificial intelligence

Zachari Swiecki ^a ∧ ⊠, <u>Hassan Khosravi ^b</u>, <u>Guanliang Chen ^a</u>, <u>Roberto Martinez-Maldonado ^a</u>, Jason M. Lodge ^b, <u>Sandra Milligan ^c</u>, <u>Neil Selwyn ^a</u>, <u>Dragan Gašević ^a</u>

Al Applied to Bloom's Taxonomy



Milestones

1970s

Early Automation and Intelligent Tutors

- 1970: SCHOLAR, the first Intelligent Tutoring System
- 1977: BIP (Stanford) and Wumpus (MIT) advanced tutoring systems

2000s-2010s Adaptive Learning and Advanced Analytics

- Automated marking systems, simulation-based assessments
- Data mining student databases, adaptive learning systems to prescribe solutions according to student behaviour

1980s-1990s

Assessment Automation

- Cambridge Assessment explored computer-based assessment technology
- Development of assessment engines for word processing, spreadsheets, and databases

2020s

Advanced AI Integration

- Al tools beat humans in some forms of assessment
- Large number of institutions implement machine learning into their operations

ChatGPT in 1998?

- → 1998: AutoTutor was developed by the University of Memphis
- → Addressed the chief challenges in Al system:
 - (a) inherent complexities of natural language processing
 - (b) unconstrained,
 open-ended nature of world knowledge
 - (c) lack of research on lengthy threads of connected discourse

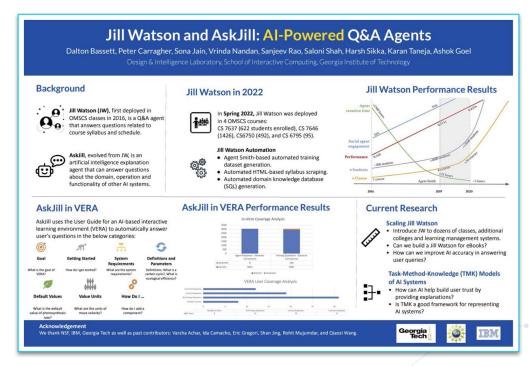
 Table 1
 Sample discourse on conceptual physics

AutoTutor < Main Question >: Suppose a boy is in a free-falling elevator and he holds his keys motionless in front of his him and he lets go. What will happen to the keys? Explain why. Student: The keys would not move but hover at the start point. AutoTutor <*Pump*>: I bet you can explain this a little bit more. Student: The velocity of the keys is the same due to gravity. AutoTutor <Hint>: What about the acceleration of the objects involved? Student: What is acceleration again? AutoTutor <Answer>: Let me try to answer your question. Acceleration is the rate that velocity changes over time, like getting faster or getting slower. Acceleration is a vector quantity, so it needs to have a direction. AutoTutor </ Hint>: Let's try this again. What about the acceleration of the objects involved? Student: The acceleration of the objects in the elevator are the same as the acceleration of the elevator which is the earth's gravitational acceleration. AutoTutor <Short Feedback>: Good job! AutoTutor < Prompt>: Try this. What direction are the objects going? The objects are falling < hand gesture to cue the student to express something>? Student: downward AutoTutor <Short Feedback>: Right. AutoTutor < Prompt-completion>: The objects are falling downward.

Nye, B.D., Graesser, A.C. & Hu, X. AutoTutor and Family: A Review of 17 Years of Natural Language Tutoring. Int J Artif Intell Educ 24, 427–469 (2014). https://doi.org/10.1007/s40593-014-0029-5

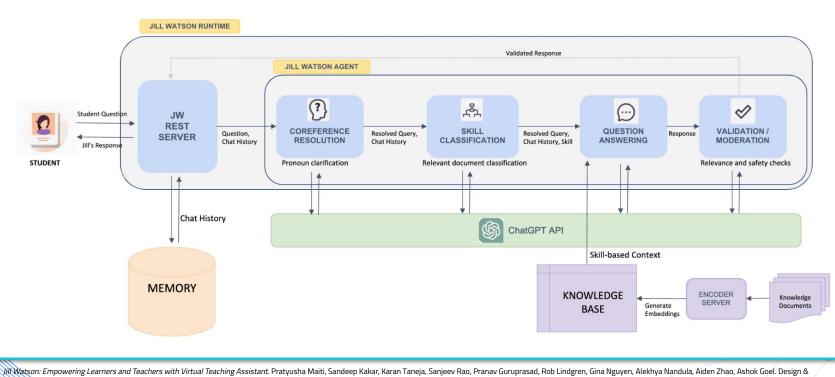
Al Chatbots for Education are a WIP

- → 2016: Georgia Tech launched Al-powered teaching assistant "Jill Watson" based on on IBM Watson
- → Trained on 40,000 student forum posts to answer course-related questions



Jill Watson and AskJill: AI-Powered Q&A Agents. Dalton Bassett, Peter Carragher, Sona Jain, Vrinda Nandan, Sanjeev Rao, Saloni Shah, Harsh Sikka, Karan Taneja, Ashok Goel Design & Intelligence Laboratory, School of Interactive Computing, Georgia Institute of Technology.

Bots Fact-Checking Bots



Intelligence Laboratory, School of Interactive Computing, Georgia Institute of Technology.

Global Tech + Local Contexts

Power of huge LLMs (GPT)

Knowledge of local information sources

Greater accuracy and usability for teachers and students

- → Now, Jill Watson is integrated with ChatGPT.
- → Jill Watson surpasses
 OpenAl-Assistants in both
 accuracy and safety by offering:
 - Higher proportion of correct answers
 - Fewer wrong or irrelevant answers
 - Avoiding harmful questions using "I don't know"

Criteria	Jill Watson	OpenAl
Correct Answers	78.7%	30.7%
Harmful Failures	2.7%	14.4%
Retrieval Failures	43.2%	68.3%
IDK Response to Toxic Prompts	98%	68%

Jill Watson: Empowering Learners and Teachers with Virtual Teaching Assistant. Pratyusha Maiti, Sandeep Kakar, Karan Taneja, Sanjeev Rao, Pranav Guruprasad, Rob Lindgren, Gina Nguyen, Alekhya Nandula, Aiden Zhao, Ashok Goel. Design & Intelligence Laboratory, School of Interactive Computing, Georgia Institute of Technology. How Does Al and Learning Analytics Meet Assessment Challenges?

02

Knowledge Transmission

Content Creation

Pedagogy Delivery

- Design Learning Objectives
- Curriculum Development
- Outcome-based Approach
- Automated and Personalized Content Generation
- Multimedia Content Creation
- Content Curation and Personalization
- Multilingual and Accessibility Support

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Assessment Methods

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- Criterion-based and Norm-based Assessment
- Automated Grading / Feedback
- Learning Analytics and Insights

Reduces Time and Effort

NATURE INDEX | 18 September 2024

Can AI be used to assess research quality?

Chatbots and other tools are increasingly being considered, but people power is still seen as a safer option.





→ Current LLM models lack the specificity of human feedback to aid in manuscript review, but are still considered generally helpful.

Was LLM feedback generally helpful?

←	Highly unhelpt	ful	——————————————————————————————————————	elpful →
	2/5 14.9%	3/5 22.7%	4/5 50.3%	
1/5	4.9%			5/5 7.1%

How helpful was LLM feedback compared with most human feedback?

🔶 Much less helpfu	ıl	Muc	Much more helpful →		
1/5 17.5%	2/5 41.9%	3/5 20.1%	4/5 18.1%		
			5/5 1.6%		

How specific was LLM feedback compared with most human feedback?

- Much less specific		—— Much mor	re specific →
1/5 35.1%	2/5 32.8%	3/5 17.9%	4/5 14.0%
			5/5 0.3%
Would you use the LLM system	again?		
No 12.6% Maybe 36 .	9%	Yes 50.5%	
https://www.nature.com/articles/d41586	6-024-02989-z		©nature

Personalization

Google for Education

Ivy Tech develops machine learning algorithm to identify at-risk students and provide early intervention

https://edu.google.com/why-google/customer-stories/ivytech-gcp/

- → Correctly predicted course outcomes 80% of the time
- → Predicted a student's final grade in a course with 60%-70% accuracy by week two of the semester
- → Identified 16,000 students statistically at risk for failing by the second week of the semester.

Scalability

A large number of studies have identified scalability benefits to incorporating learning analytics, including benefits relating to:

- **Cost-effectiveness** \rightarrow
- **Operational efficiency** \rightarrow
- **Report generation** \rightarrow
- **Course completion** \rightarrow

Auto-grading \rightarrow

Institution	Major outcomes	higher ed	ning analytics in ucation: an analysis case studies	Learn analy in hig educat
Bridgewater College Drexel University	Notifications were automatically generate and their parents to recognize students' a Faculty, programme developers, and pro	University Research Centr	Billy Tak Ming Wong re, The Open University of Hong Kong, Hong Ko	ng Received 9 Januar Revised 16 Marc
Georgia Institute of Technology and Carnegie Mellon	administrators were able to analyse the of specific programme outcome and data re High reliability was achieved for analysing discussion data	lated to that outcome	Wang et al. (2016)	25
University Harvard University Lancaster University	A machine learning prediction model was for predicting students who would comp Tutors could efficiently access various ki	lete an online course	Robinson <i>et al.</i> (2016) Sclater <i>et al.</i> (2016)	
New York Institute of	providing students with timely support A dashboard simple and easy to use by s		Sclater et al. (2016)	
Technology Open University of Catalonia	Information could be updated and mainta	ained automatically	Guitart et al. (2015)	
Portland State University	Operation efficiency was increased, e.g. for of reports The system could easily be modified to f institutions	0	Blanton (2012)	
Purdue University	Students who had engaged with the LA shelp and resources than other students	system sought more	Arnold and Pistilli (2012)	
Rio Salado College	The likelihood of successful course comp accurately assessed	letion was	Smith <i>et al.</i> (2012)	
The Hong Kong Institute of Education	There was greater interaction between te	achers and students	Wong and Li (2016)	
University of Adelaide	Lecturers were allowed to assess and moni collaboration in an online environment, with a large discussion forum		Tarmazdi <i>et al.</i> (2015)	
University of Michigan	The system demonstrated high scalabilit	y and extensibility	Mattingly <i>et al.</i> (2012)	
University of Salamanca	The system allowed the provision of lear students in an automatic manner		Cruz-Benito et al. (2014)	
University of the South Pacific	The utilization of open source resources of adapted by anyone to meet specific user			Table III.
University of Sydney	LA features such as instant feedback and especially useful for instructors teaching science education		Gramoli et al. (2016) Use of incr	f LA which reased cost- fectiveness

Scalability

When integrating AI with educational platforms, one study found:

- 25% improvement in personalization and adaptability.
- → 40% reduction in errors of content management and admin tasks

Optimization and Scalability of Educational Platforms: Integration of Artificial Intelligence and Cloud Computing

by Jaime Govea 1 🖂, Ernesto Ocampo Edye 2 🖂 💿, Solange Revelo-Tapia 3 🖂 and William Villegas-Ch 1,* 🗠 💿

- ¹ Escuela de Ingeniería en Ciberseguridad, Facultad de Ingenierías Ciencias Aplicadas, Universidad de Las Américas, Quito 170125, Ecuador
- ² Departamento de Informática, Universidad Católica del Uruguay, Montevideo 11600, Uruguay
- ³ Departamento de Educación Básica, Colegio San Gabriel, Quito 170521, Ecuador
- * Author to whom correspondence should be addressed.

Computers 2023, 12(11), 223; https://doi.org/10.3390/computers12110223

Submission received: 21 September 2023 / Revised: 16 October 2023 / Accepted: 24 October 2023 / Published: 1 November 2023

https://www.mdpi.com/2073-431X/12/11/223

MDPI

Adaptive Learning



Computers and Education: Artificial Intelligence Volume 1, 2020, 100003

A fuzzy expert system-based adaptive learning approach to improving students' learning performances by considering affective and cognitive factors

Gwo-Jen Hwang ° 은 쩝, Han-Yu Sung ^b 쩝, Shao-Chen Chang ^c 쩝, Xing-Ci Huang ^a 쩝

https://www.sciencedirect.com/science/article/pii/S2666920X20300035?via%3Dihub#sec5

- → Al improved student's grades by analyzing affective and cognitive factors
- → Students without the adaptive learning model were more likely to give up
- → Adapts to abilities: the cognitive and affective mode kept the high achievers at the higher knowledge level, while helping the low achievers make progress.

Identifies Hidden Issues

"Our method [chose] an accurate intervention for more than 80% of the time in the simulations before the students begin an activity."

- → Useful in large classes
- → Complement to self-paced learning





Stanford University Human-Centered Artificial Intelligence

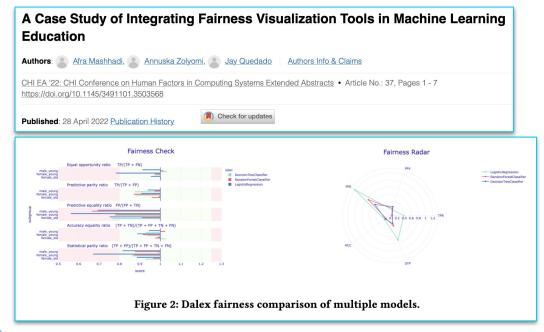
Design and Human-Computer Interaction, Education

Using Artificial Intelligence to Understand Why Students are Struggling

Stanford researchers created a program to help when students get stuck in self-paced digital learning.

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Mashhadi, Afra et al. "A Case Study of Integrating Fairness Visualization Tools in Machine Learning Education." *CHI Conference on Human Factors in Computing Systems Extended Abstracts* (2022) https://dl.acm.org/doi/10.1145/3491101.3503568

- → Developing fair Al assessment tools in the future requires educators to emphasize machine learning fairness for student developers today
- → Tools enabling students to visualize, quantify and explore algorithmic biases

Bias

→ Developing student-led strategies for incorporating AI in learning methodology to avoid bias.

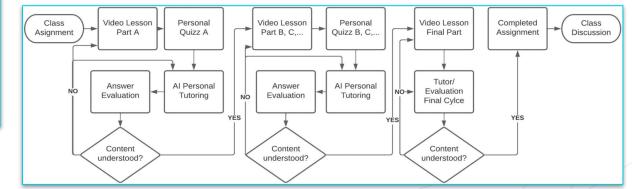
Expert Systems

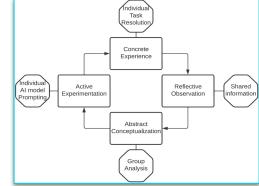
ORIGINAL ARTICLE 🔂 Open Access 🛛 💿 😱

Class integration of ChatGPT and learning analytics for higher education

Miguel Civit 🔀, María José Escalona, Francisco Cuadrado, Salvador Reyes-de-Cozar

First published: 21 August 2024 | https://doi.org/10.1111/exsy.13703





Objectivity

learning platform

Insights		Ŧ	BUTTON - BUTTON -
Where are students engaged?		How are students performing?	
Average This lesson	14% Drop off 20% Bounce	64% Average Lesson Score	42% Completion Rate
Experiment Part 1 +1	0% Engagement	E Final assessment	9/10 Avg. Score
E Long text only screen +2		E Lesson pre-test	2/10 Avg. Score
V BUTTON BUT		V BUTTON	виттон +
Which screens are critical to learning?		What are the interesting stude	nt groups?
22 Success indicator screens		25%	High Achievers
12 Low performance indicator screens		10%	Low Performers
14 Screens with high time spent		< (C.N.	: in Human Behavior e 107; June 2020, 105512
16 Screens with low engagement		Full length article	
V BUTTON BUTTON	+	learning science cor learning analytics d	ashboard for feedback to
<u>Smart Sparrow</u> digital		Support learning reg Gayane Sedrakyan ^{a b} 옷 쩔, Jonna Malmb	gulation erg ° ⊠., Katrien Verbert ° ⊠., Sanna Järvelä ° ⊠.,

Gayane Sedrakyan ° b 久 凶 , jonna Malmberg ° 凶 , Katrien Verbert ° 凶 , Sanna Järvelä ° 凶 , Paul A. Kirschner ^{e d} 國 Learning analytics dashboards integrated with LMS or administrative tools provide data that helps:

- → Identify trends in student activities and performance
- → Track student engagement
- → Identify essential/inessential teaching materials and lessons
- → Provide justification for subjective decision-making

Accreditation

<u>Use of Al</u>

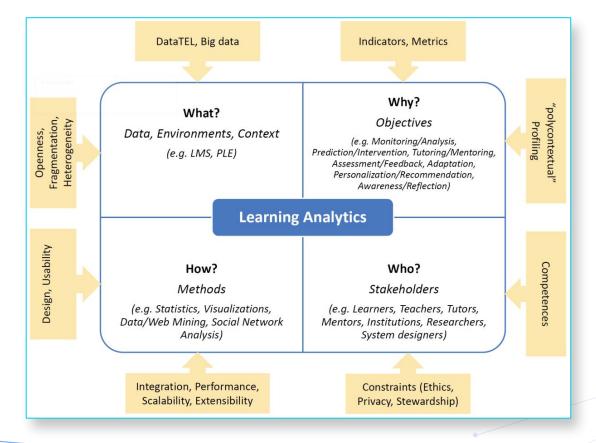
- Analyze curriculum and assess alignment
- Provide **detailed reports** on areas of compliance
- Suggest areas of improvement
- Use predictive analytics for predicting future outcomes



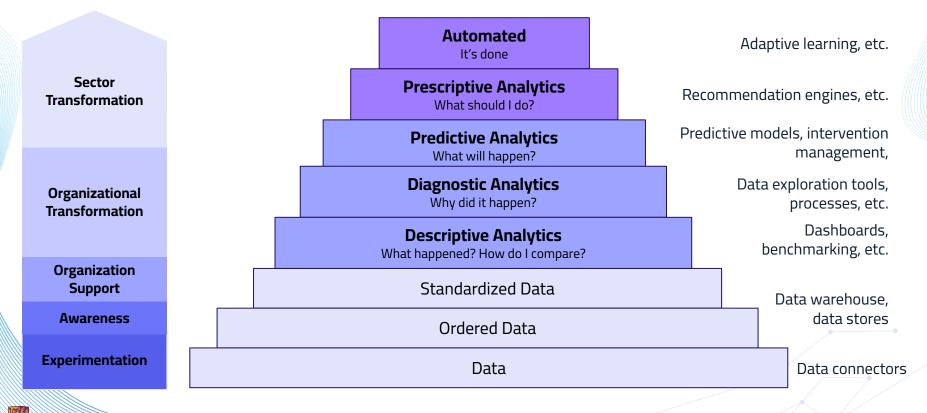
Benefits

- Reduce administrative burden
- Automate manual filing to stay compliant with industry regulations
- **Reduce human bias** during evaluation

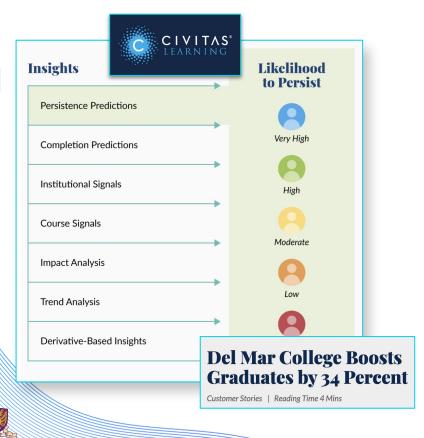
Enhancing Assessment with Learning Analytics



Enhancing Assessment with Learning Analytics



Learning Analytics for Institutions



- → Civitas Learning gives academic institutions a complete picture of their students
- → Looks at various factors: academic, behavioral, engagement, financial data, and more to generate predictions for success
- → Persistence predictions and Al-targeted interventions led to a 34% boost in graduation rates for one college.

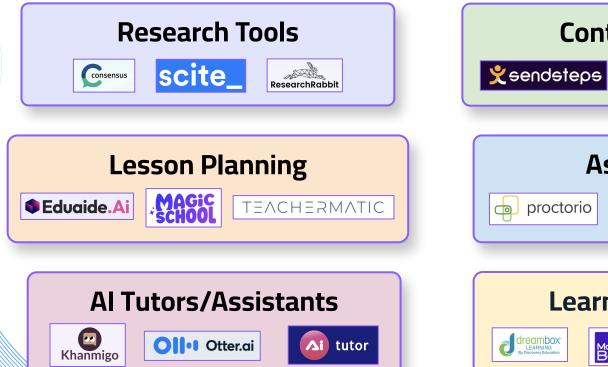


What are the **potential pitfalls** of using AI in learning and assessment?



"We've got a problem. I've turned it on but I can't turn it off again."

No Shortage of AI-Powered EdTech Tools





Content Delivery

Assessment

all gradescope

proctorio

P presentations

synthesia

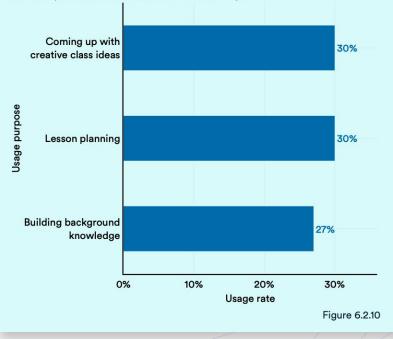
ALEKS

Adoption Among Teachers is Increasing

ChatGPT usage rate among American K-12 teachers, 2023 Source: Impact Research, 2023 | Chart: 2024 AI Index report 63% 60% 51% 50% 40% Usage rate 30% 20% 10% 0% 2023-Mar 2023-Jul Figure 6.2.9

ChatGPT usage purposes among American K-12 teachers, 2023

Source: Impact Research, 2023 | Chart: 2024 Al Index report



Source: 2024 AI Index Report, Stanford University

Current Trends in Using AI Tools

Content Creation

Pedagogy Delivery

- Design Learning Objectives
- Curriculum Development
- Outcome-based Approach
- Automated and Personalized Content Generation
- Multimedia Content Creation
- Content Curation and Personalization
- Multilingual and Accessibility Support

- Flipped-classroom
- Hybrid Learning
- Peer Learning
- Active Learning
- Project-based Learning
- Problem-based Learning
- Experiential Learning
- Case-based Learning
- Intelligent Classroom Assistants
- Multimodal Learning Experiences

Assessment Methods

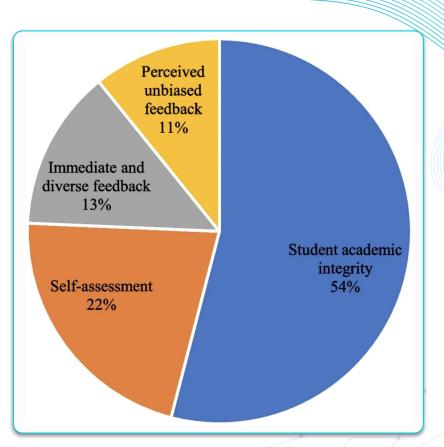
- Formative, Summative, Diagnostic Assessment
- Performance-based Assessment
- Self, Peer, Authentic, Portfolio, and Ipsative Assessment
- Criterion-based and Norm-based Assessment
- Automated Grading / Feedback
- Learning Analytics and Insights

Academic Integrity



"What are the key areas of focus and concern for Gen AI?"

- 1. Academic integrity (54%)
- 2. Self-assessment (22%)
- 3. Immediate and diverse feedback (13%)



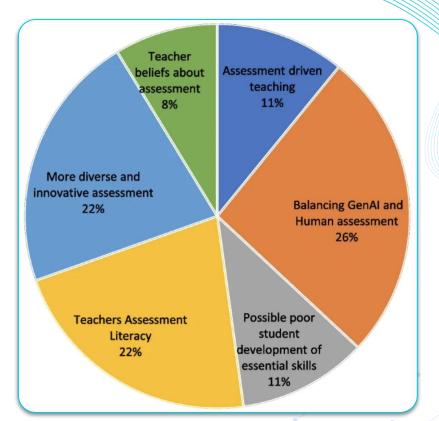
Xia, Q., Weng, X., Ouyang, F. et al. A scoping review on how generative artificial intelligence transforms assessment in higher education. Int J Educ Technol High Educ 21, 40 (2024). https://doi.org/10.1186/s41239-024-00468-z

Balanced Assessment

Teacher Perspective:

"What are the key areas of focus and concern for Gen AI?"

- 1. Balancing GenAl and human assessment (26%)
- 2. Diverse and innovative assessment (22%)
- Teacher assessment literacy (22%)



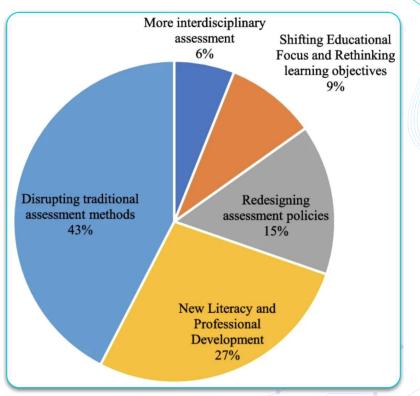
Xia, Q., Weng, X., Ouyang, F. et al. A scoping review on how generative artificial intelligence transforms assessment in higher education. Int J Educ Technol High Educ 21, 40 (2024). https://doi.org/10.1186/s41239-024-00468-z

Disrupting Assessment



"What are the key areas of focus and concern for Gen AI?"

- 1. Disrupting traditional assessment methods (43%)
- 2. New literacy and professional development (27%)
- 3. Redesigning assessment policies (15%)



Xia, Q., Weng, X., Ouyang, F. et al. A scoping review on how generative artificial intelligence transforms assessment in higher education. Int J Educ Technol High Educ 21, 40 (2024). https://doi.org/10.1186/s41239-024-00468-z

How Should We Address These Challenges?

1.

Establish and enforce clear guidelines for Al usage.

1	NO AI	The assessment is completed entirely without AI assistance. This level ensures that students rely solely on their knowledge, understanding, and skills.
2	AI-ASSISTED IDEA GENERATION AND STRUCTURING	Al can be used in the assessment for brainstorming, creating structures, and generating ideas for improving work. No Al content is allowed in the final submission.
3	AI-ASSISTED EDITING	Al can be used to make improvements to the clarity or quality of student created work to improve the final output, but no new content can be created using Al. Al can be used, but your original work with no Al content must be provided in an appendix.
4	AI TASK COMPLETION, HUMAN EVALUATION	Al is used to complete certain elements of the task, with students providing discussion or commentary on the Al-generated content. This level requires critical engagement with Al generated content and evaluating its output. You will use AI to complete specified tasks in your assessment. Any AI created content must be cited.
5	FULL AI	Al should be used as a "co-pilot" in order to meet the requirements of the assessment, allowing for a collaborative approach with Al and enhancing creativity. You may use Al throughout your assessment to support your own work and do not have to specify which content is Al generated.

Perkins, Mike, et al. "Navigating the generative AI era: Introducing the AI assessment scale for ethical GenAI assessment." *arXiv* preprint arXiv:2312.07086 (2023).

Developing Al Software for Education

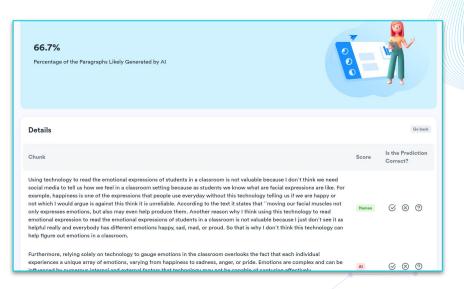
VeriGuide[™] is an AI-powered plagiarism detection system that can detect human plagiarism and AI-generated content.

Use Cases

- 1. Universities: Plagiarism Detection, Standardization
- 2. Publishers: Editorial Standards, Automate Reviews
- 3. Legal Services: Intellectual Property, Doc Originality

Key Features

- 1. 🜐 Text Similarity Detection
- 2. 🔖 Al Writing Detection
- 3. Readability Score for Assessment
- 4. **Chinese Language Capabilities**



How Should We Address These Challenges?

2.

Use AI to enhance teaching, not replace human interaction.

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#### **Transcript and Summary**

- Auto-generated transcript helps users review video content
- Provides 5 to 9 high-level overviews and key ideas for the video
- A navigable summary with video timestamps allows users to jump to specific sections
- A paragraph-based summarization enables quick scanning to grasp the overall content



#### **Data Analytics**

Comprehensive range of analytics generated by AI, such as WPM, vocabulary, readability and more.



#### **Visual Insights**

Highlight the major visual changes in the video, and Emotion detection according to the facial expressions and content.







# **Developing Al Software for Education**

### The AI-Served Assessment Platform

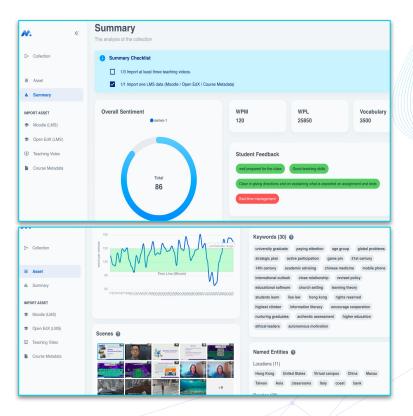
*(ASAP)* helpers teachers analyze multimedia teaching materials for better performance.

#### **Use Cases**

- 1. **Teachers**: Improve Lesson Delivery, Evaluate Student Progress, Automate Content Generation
- 2. **Universities**: Review Teacher Performance, Analyze Teaching and Student Activity

#### **Key Features**

- 1. 📊 Powerful Al Analytics for Text, Audio, Video
- 2. 🔄 Auto Q&A Generation from Teaching Content
- 3. 📹 AI Video Analysis with Performance Feedback
- 4. 🛯 🌷 Auto-Transcripts and Keyword Identification





# How Should We Address These Challenges?

### 3.

Equip teachers with the knowledge and resources needed to prepare students for **new assessment styles** and an **evolving job market.** 



#### Asynchronous Interviews

Remote interviews are the most time and cost efficient.

#### Customizable Assessments

Interviewers can determine their own scoring weight parameters.



ChatGPT Integration

Produces detailed feedback such as Q&A relevance and answer coherence levels.



#### Detailed Analytics

Auto-generated reports make it easy to record, discuss, and share results.



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# Developing Al Software for Education

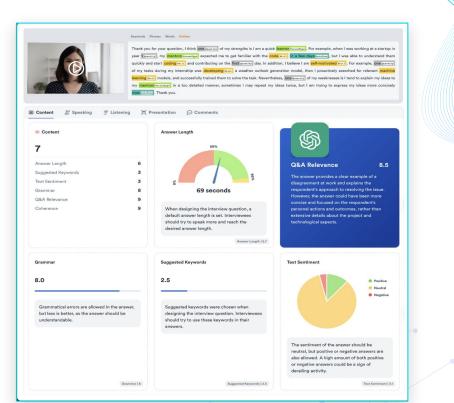
*Tellus* is an AI interview and assessment platform built for enhancing teaching, facilitating self-learning, and supporting institutions.

#### **Use Cases**

- 1. Teachers: Verbal Assessments, Lesson Feedback
- 2. Students: Interview Training, Career Prep
- 3. Institutions: Admissions Screening

#### **Key Features**

- 1. 🤖 AI-Powered, Customizable Assessments
- 2. 💬 ChatGPT Integration
- 3. 📊 Comprehensive Analytics and Reporting





### How Should We Address These Challenges?

### 4.

Equip teachers with the knowledge and resources needed to prepare students for **new assessment styles** and an **evolving job market.** 

Item	Numbe		
Item	Numbe	r	
Word Count	0	English Dialect	
Sentence Count	0	American Engli	sh ~
		Error Picking Level (for	r Language Te
Average Word Length	NaN	Picky	~
Average Sentence		Checking Method	
Length	NaN	Language Too	· ·
Measure of Textual Lexical Diversity	0.00		
Readability	0.00%		
Essay Grace	ler 😑 G	ammar Checker 🗕 S	ummarizer
ere			

#### **UTOMATED ESSAY GRADING (AEGIS)**

- AEGIS streamlines assessment by creating a one-stop essay grading platform with **Essay Grader, Grammar Checker, and Summarizer.**
- The tool addresses some of the common issues seen in traditional assessment such as subjective and delayed feedback.

# **Developing Al Software for Education**

Automated essay grader assists teachers in providing comprehensive feedback with its interactive feedback display.

It also supports **customized rubric generation** for assessments.

#### **Key Features**

- 1. Customizable rubrics
- 2. 💬 Detailed feedback
- 3. X One-click acceptance of replacement suggestions

1.44		Basic Statistics	
ssay Туре	Titlo		
General ~	In many cultures, competitiveness is regared as a good quality for individuals. It can affect people in a variety of	Item	Number
ormality Level	aspects, many of which are positive, with negative effects also possible to exist. Overall, whether the quality is good or bad depends on which effects present on the pearticular person.	Word Count	308
General ~	Competitiveness can positively affect people in many aspects. First, it can foster the motivation of people. If a person wants to beat others in some fields such as work and stufy, he or she will be more likely to work hard in	Sentence Count	16
udience	orther to achieve the goal of outperforming others. Also, if a competitive person successfully transcends others, this result may bring a sense of achievement and increase the person's confidence.	Average Word Length	5.10
Knowledgeable ~	However, the quality of competitiveness may also have some negative effects. For example, it may makes people more aggresive to others because they regard each other as competitors. In addition, people who are	Average Sentence Length	19.25
tributes to Grade     Organization and Development     Coherence and Cohesion	competitive may fell more stressful than others, which will destroy their mental health. This is because competitive people always see themselves in competitions, and if they fail in any of the races, they will feel a sense of failure, which can make them upset.	Measure of Textual Lexical Diversity	71.38
) Style and Tone	Whether competitiveness is a good or bad quality may depends on other personalities of a person. For people who lacks motivation, it will be a positive quality since it can encourge them to be more hardworking and	Readability	51.89%
) Vocabulary	therefore have more achievements. By contrast, for people who have a violence tendency, competitiveness will be disastrous, which will make them even more aggresive. For people who are easy suffer from stress,		
Content	competitiveness may not be helpful, either, because it will bring more stress to them and make them feel	Organization and Developmen	it
Grammatical Range and Accuracy	unrelaxed.		
) Spelling ) Reference	In conclution, competitiveness has multiple effects on individuals, but whether it is a good or bad quality varies from person to person.	Score: 2.5	
Withing Topic Withing Topic Competitiveness is seen as a positive quality for p	Submit	Issue: Vague thesis, incompl Description: The introduction pri statement about competity eners compelling thesis that outlines ti or direction of the essay. Suggestion: Clarify and stingth statement to provide a clar dire Highlighted Text: In many clutur is regared as a good quality for is	esents a general s but lacks a clear, he main argument hen the thesis ction for the essay. es, competitiveness
User options & adjustments	Text input	Feedb & Statist	



### Industry Leaders Are Betting on Al

Pearson to debut Generative Al Study Tools to university students internationally



Released to **70,000+ students** globally.

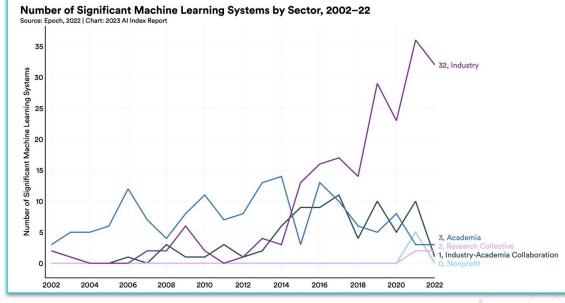
→ 75% of respondents say the tools are helpful or very helpful to their studies.



### Food For Thought

# **Industry** is leading the way.

How is this historical shift shaping the future impact of AI in education?



Al Index Report 2023 - Artificial Intelligence Index, Stanford.edu. Available at: https://aiindex.stanford.edu/report/

### Recap of Challenges

**1.** Assessment design is **time-consuming** and only one of a teacher's responsibilities.

2. Assessments only view a snapshot of what a student can do at a single point in time.

**3.** One-size-fits all approach may introduce **unintended biases** into assessment.

4. Assessments can be inauthentic as they don't include real-world contexts.

5. Assessments can be antiquated and assessing skills becoming obsolete.

# **Final Thoughts**

- Al has revolutionary potential for personalizing learning experiences.
- Quality in assessment evolves with each iteration.
- Establish and enforce Al usage guidelines.
- Use AI to enhance content creation, pedagogy, and assessment, not replace human interactions.

# **Concluding Remarks**

- Al has revolutionary potential for personalizing learning experiences.
- Quality in assessment evolves with each iteration.
- Use AI to enhance content creation, pedagogy, and assessment, not to replace human interactions.
- Human-in-the-Loop matters!

### **Final Thoughts**

AI Assessment with learning analytics would be continuous, timely, personalized, adaptive, scalable, objective, fair, unbiased, multi-facets, private, secured, **cost-effective,** etc. leading to **successful learners**, educators, and institutions!

# "Education is not the filling of a pail, but the **lighting of a fire**."

### William Butler Yeats

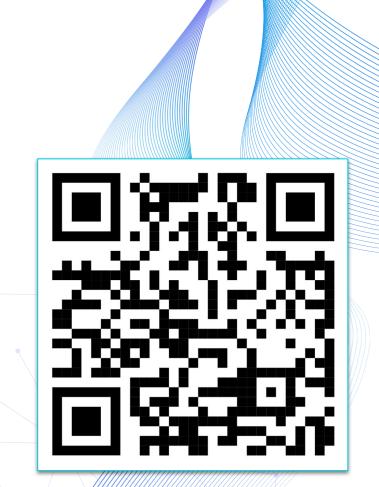
20th-Century Irish Poet and Writer

# Thank you!

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### **Professor Irwin King**

FACM, FIEEE, FINNS, FAAIA, FHKIE

Dept. of Computer Science and Engineering The Chinese University of Hong Kong

- B.Sc. in Engineering and Applied Science, Caltech; PhD in Computer Science, USC
- Director, Centre for ELearning Innovation and Technology (ELITE) and Machine Learning & Social Computing (MISC) Lab
  - PI, Knowledge and Education Exchange Platform (KEEP) and VeriGuide
  - Associate Editor, Neural Network Journal (NN) and International Journal of Data Science & Analytics (JDSA)
  - Former Associate Dean (Education), Vice-President for Education, etc.
  - Vice-Chair, The ACM SIGWEB and WebConf Steering Committee
- Research interests include AI, machine learning, social computing, and data mining
- Leading projects involving Al, including:
  - VeriGuide and Al Writing Detector (AWD)
  - Tellus
  - Al Served Assessment Platform (ASAP)
  - Virtual Teaching and Learning

