# Human-Machine Symbiosis:
# Human Digital Twins for AI-Driven Metacognition in Education

**Roger Azevedo, Ph.D.**

University of Central Florida
College of Engineering and Computer Science
School of Modeling, Simulation, and Training
Learning Sciences Faculty Cluster Initiative
Laboratory for the Study of Metacognition and Advanced Learning Technologies

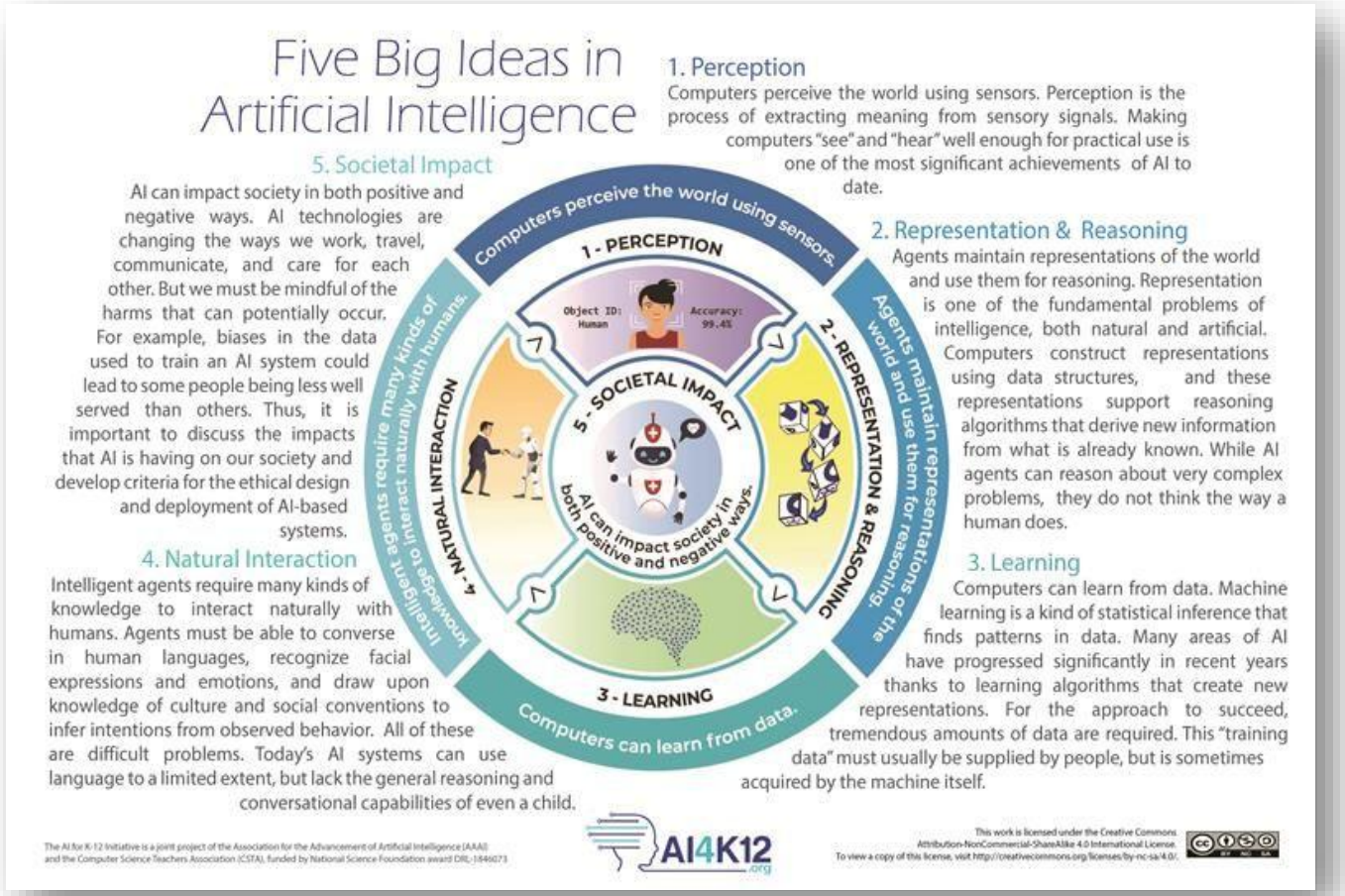


NIH
ies INSTITUTE OF EDUCATION SCIENCES
DEPARTMENT OF EDUCATION UNITED STATES OF AMERICA
NSF
LEADS LEARNING ENVIRONMENTS ACROSS DISCIPLINES
Earli
DEVCOM ARMY RESEARCH LABORATORY
CAPTRS
FULBRIGHT
Social Sciences and Humanities Research Council of Canada
NSERC CRSNG
JACOBS FOUNDATION Our Promise to Youth

# Overview

- Addressing current educational and workforce challenges
- Human-machine symbiosis
- Human Digital Twins (HDTs) to advance science of learning
- Conceptualization of HDTs
  - Designing, developing, testing, and implementing HDTs
- HDTs' roles in augmenting human capabilities, knowledge, and skills
- Role of multimodal multichannel trace data
- Architecture of HDTs
- Examples of HDTs in our work
  - K12 education, healthcare, and military
- Open questions, challenges and future directions

# National Science Foundation's Five Big ideas in AI




## Key Ideas Related to HDTs

- **Perception**
  - Sensor to hear, see, and feel
- **Representations and Reasoning**
  - Representations of the world, tasks, domains, contexts, humans, artificial agents and reason
- **Learning**
  - Learning from data and generate (synthetic) data
- **Natural interaction**
  - Interact naturally with humans
  - Converse, recognize, reason, understand cultural and societal conventions
- **Societal Impact**
  - Positive impact on humans
  - Minimize negative impact on humans
    - Biases, ethics, privacy, etc.

# Why Human Digital Twins (HDTs)?

- **Addressing Major Educational Challenges and Opportunities Across Fields**
  - AI, AIEd, learning analytics, learning sciences, psychological sciences, multimodal learning analytics, data sciences, computer vision, computational modeling, and biomedical sciences
- **Educational and Training Issues & AI**
  - 21st Century skills, focus on self-regulated learning (SRL) skills, and workforce preparation
  - Human-AI teaming, human-AI collaboration, human-machine symbiosis, and hybrid human-AI
- **Adaptive, intelligent systems**
  - New opportunities to significantly advance adaptive, intelligent learning systems
  - GenAI tools, methods, and techniques to accelerate the development of metacognition & SRL
- **Conceptual and Theoretical**
  - Advance models of learning, instruction, teaching, and SRL and their underling processes and mechanisms
- **Methodological and Analytical Issues**
  - HDTs as AI agents designed to learn, teach, model, scaffold, and foster learners' domain and SRL skills
  - New approaches to assess the development, internalization, embodiment, use, and transfer of domain and SRL knowledge and skills

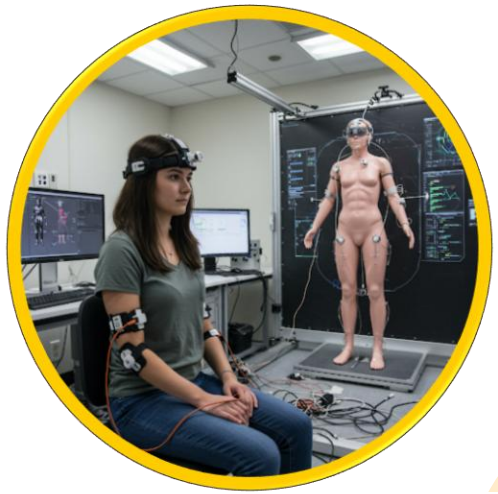
# Human Digital Twins (HDTs)

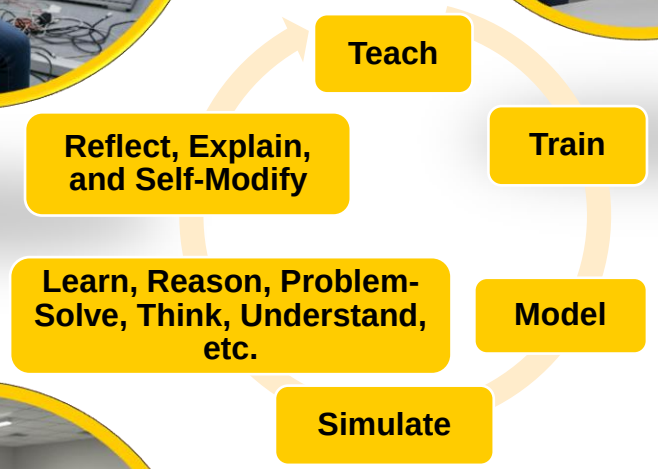
- **The evolution of human-machine integration in educational contexts**
  - From basic tools to intelligent partners in learning
  - The emergence of adaptive, intelligent educational ecosystems
- **The concept of Human Digital Twins (HDTs) as metacognitive scaffolds**
  - Defining HDTs as computational representations of individual learners
  - Moving beyond simple learner profiles to dynamic metacognitive models
- **Current limitations in educational AI implementations**
  - Gap between technological capability and pedagogical application
  - Issues of personalization and adaptation at scale
- **Vision: Symbiotic partnership between humans and AI for enhanced metacognition**
  - Complementary intelligence rather than replacement
  - Augmenting human capabilities while preserving agency
  - Modeling and simulation of metacognitive knowledge and skills across learners, tasks, domains, and contexts

# Understanding Human Digital Twins (HDTs)

- **Definition and conceptual framework of HDTs in educational contexts**
  - Computational, mathematical models of individual cognitive, affective, metacognitive, and motivational (CAMM) processes and learning patterns
  - A continuously updated representation of the learner's knowledge, skills, and states
- **Components of effective educational HDTs**
  - Knowledge representation modules and computational modeling
  - Learning preferences and SRL profiles
  - Cognitive, affective, metacognitive, and motivational (CAMM) modeling systems
- **Technical foundations enabling HDT development**
  - Advanced machine learning (ML) algorithms capturing metacognitive patterns
  - Multimodal data integration from diverse learners and learning environments
  - Metacognitive architectures
- **Distinction from traditional learner profiles or educational data mining**
  - Dynamic rather than static representations of knowledge and skills
  - Predictive capabilities versus historical documentation
  - Focus on CAMM processes rather than content mastery alone

# Human Digital Twins (HDTs)

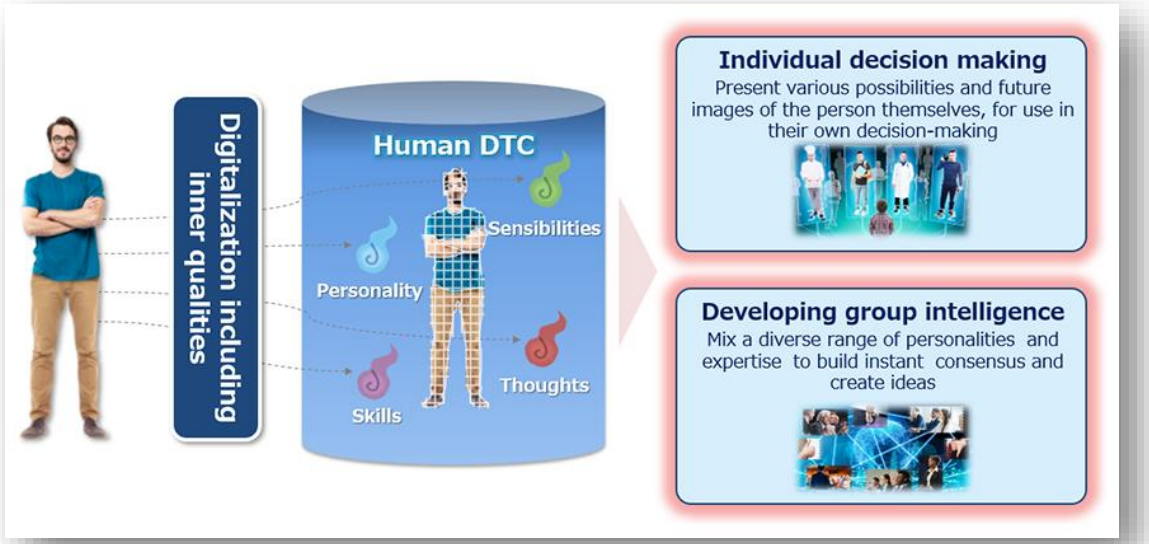





1. Ethical & Privacy Considerations
2. Data Accuracy & Representation
3. Technological Limitations & Validation
4. Interdisciplinary Integration
5. Scalability & Computational Requirements
6. Longitudinal Dynamics & Adaptability
7. Consent & Agency
8. Potential Societal & Psychological Impacts
9. Cross-Domain Application Potential
10. Emergence & Complexity Management

# Overview

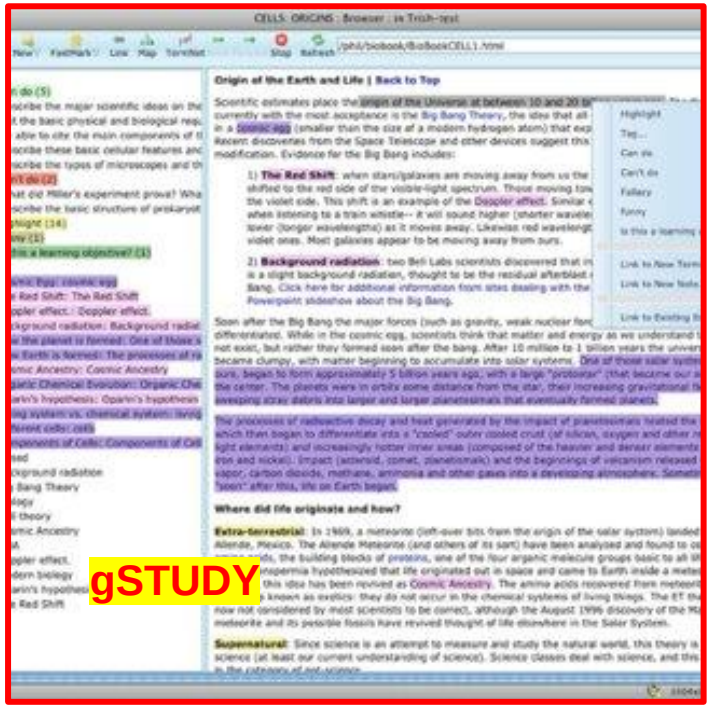
- **Self-regulated learning (SRL), pedagogical agents, multimodal data, and AI**
- **Limitations and challenges with current AI-based SRL environments**
  - Pedagogical agents, modeling dynamics of SRL, and adaptive scaffolding
- **Human Digital Twins (HDTs)**
  - Research platform for designing, developing, testing, and implementing “aspects” of SRL
  - Embodying SRL knowledge and skills in HDTs
    - Modeling, simulating, predicting, and supporting/fostering SRL in learners
    - Challenges and opportunities
  - Application areas
    - Education and training, military, healthcare, K-12, urban planning and smart cities, cybersecurity, aerospace and aviation, gaming and entertainment, learning sciences and human performance, microelectronics and nanotechnology
- **Future directions and open challenges**
  - HDT ecosystems

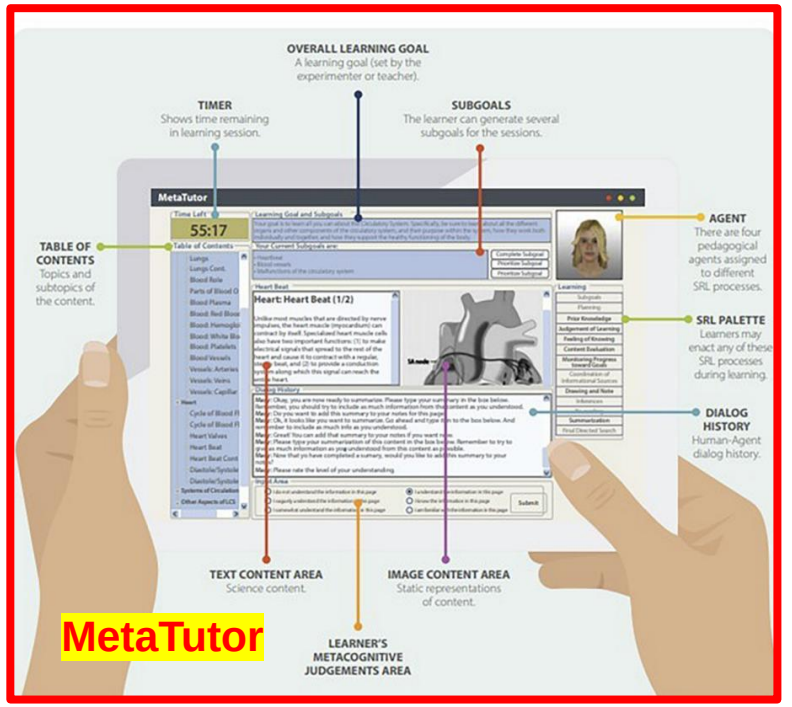


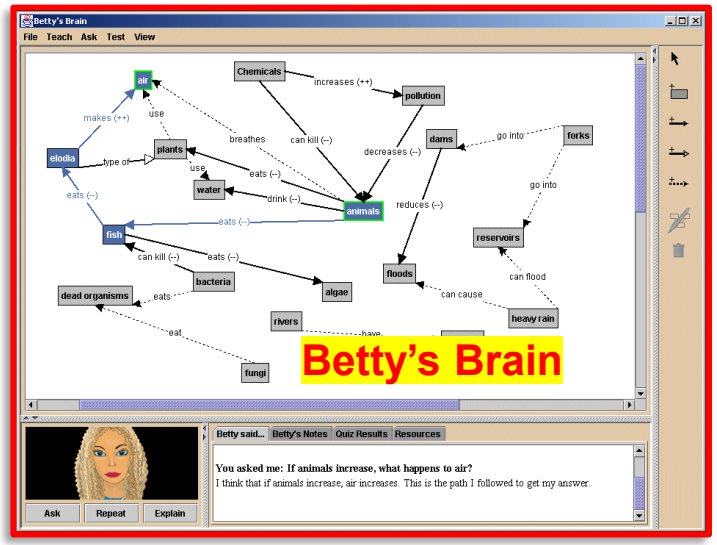

Source: NTT Corporation

# Current AI-based Systems for SRL

(Azevedo & Wiedbusch, 2023)

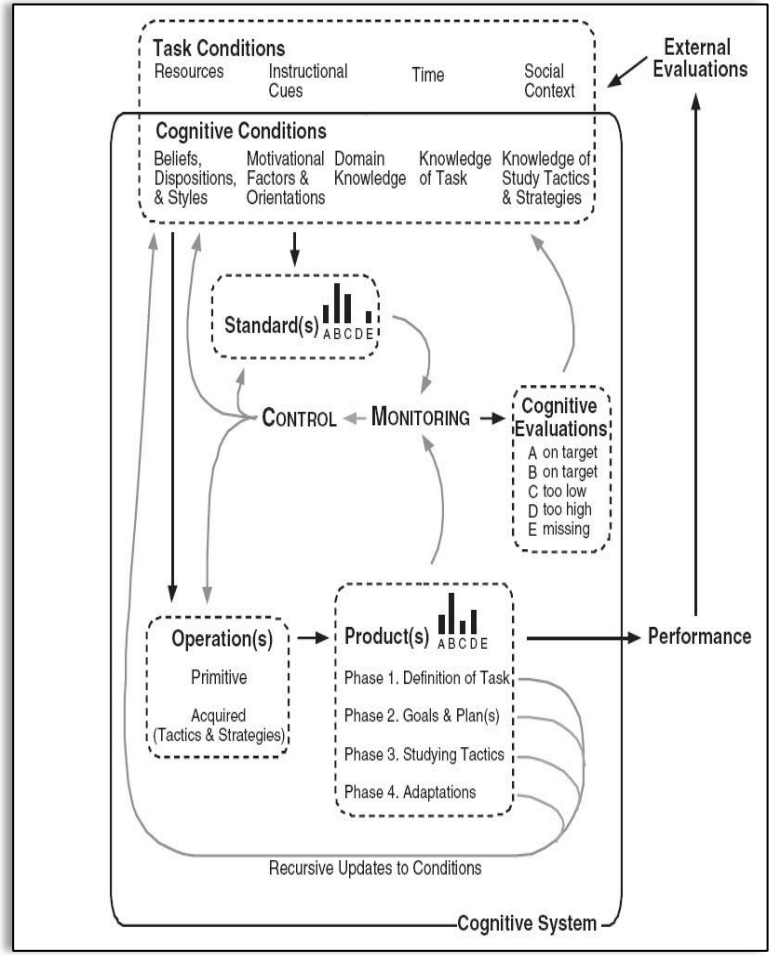


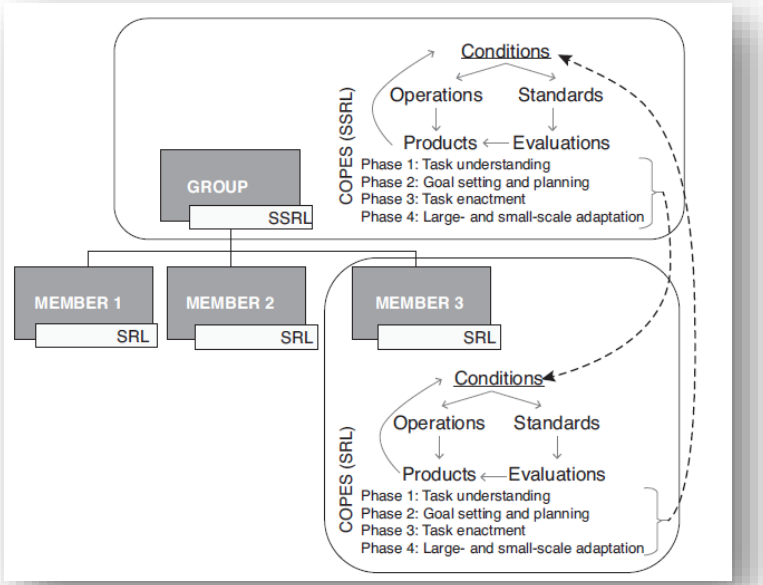



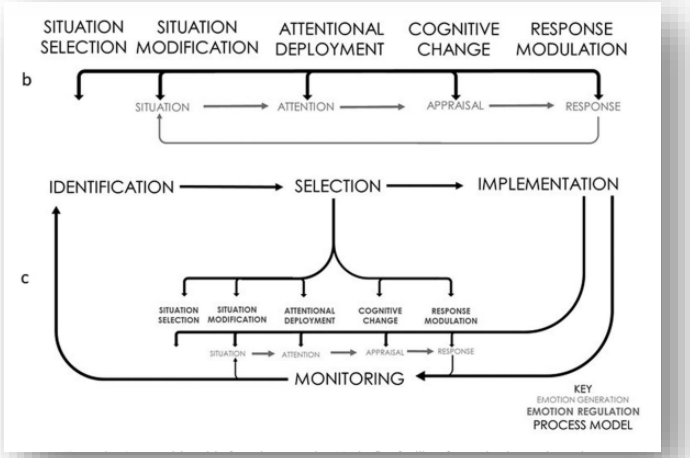



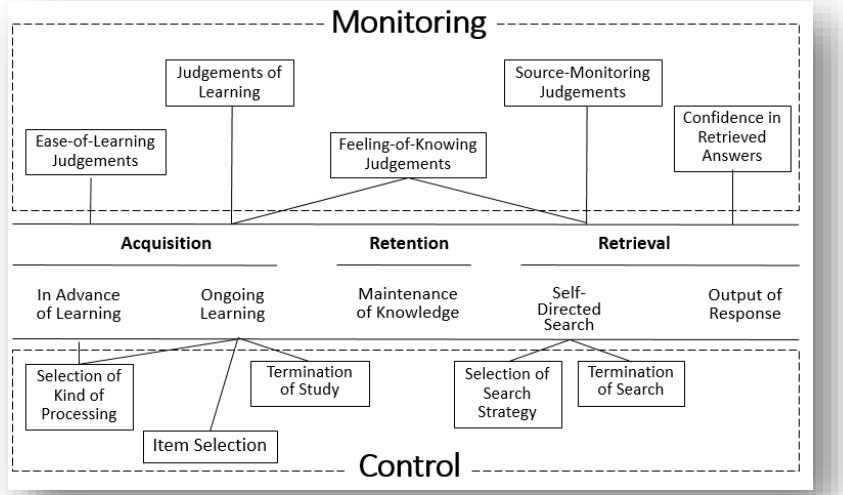
# Models of Self-Regulated Learning (SRL)

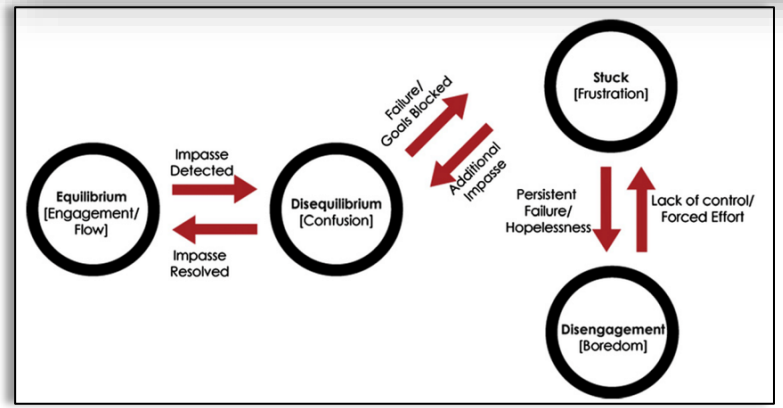
(Azevedo, Bandura, Bjork, Bol, de Bruin, D'Mello, Dignath, Dunlosky, Efklides, Graesser, Graham, Greene, Gross, Hacker, Hadwin, Harris, Järvelä, Kappas, Koriat, Kramarski, Lajoie, Metcalfe, Molenaar, Pekrun, Pintrich, Scherer, Schunk, Veenman, Winne, Zimmerman)

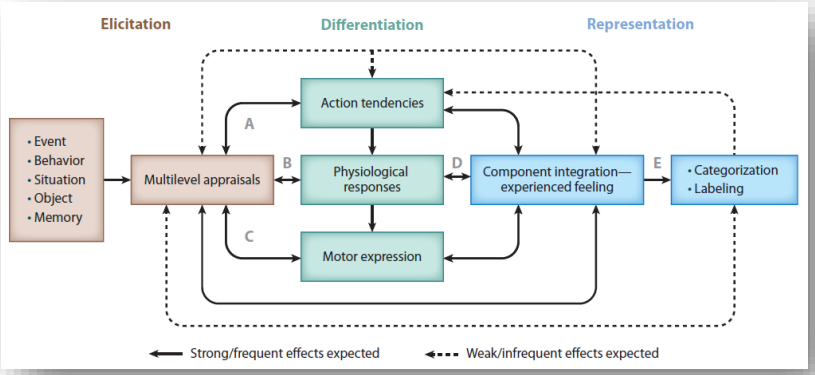


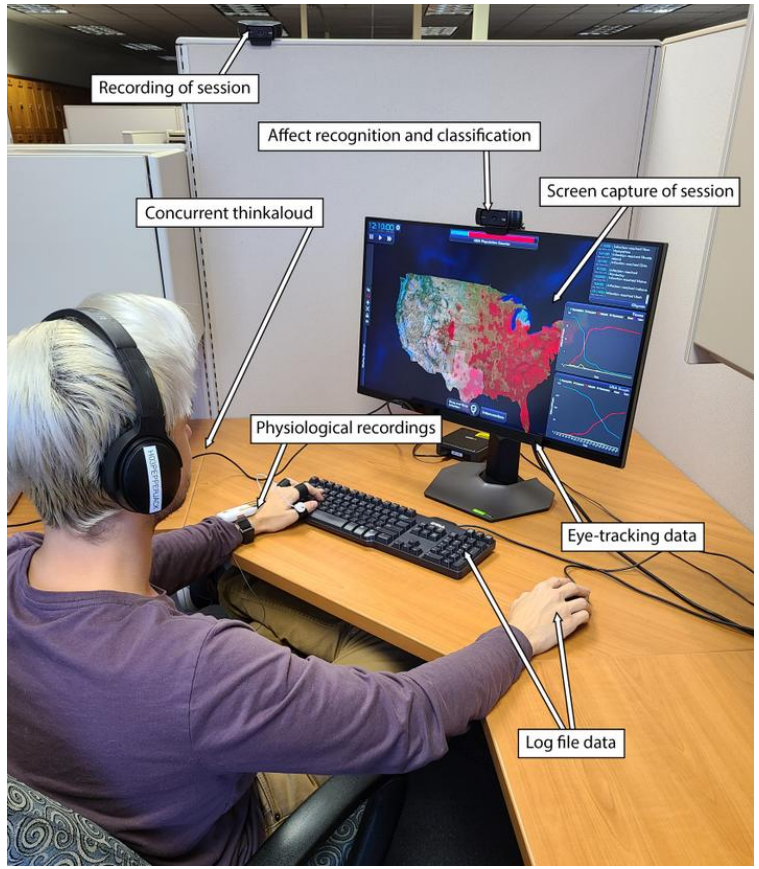






UCF

# Typical Instrumented Learner & Multimodal Data with Outbreak Simulator



Challenges in measuring, detecting, tracking, modeling, inferencing, supporting, and fostering SRL

(Azevedo et al., 2018, 2022, 2023 2024, in press; Azevedo & Gasevic, 2019; Azevedo & Wiedbusch, 2023; Dever et al., 2024; Cloude et al., 2022; Fan et al., 2022; Giannakos et al., 2022, in press; Huang et al., 2023; Järvelä & Bannert, 2022; Järvelä & Hadwin, 2024; Li et al., 2021; Molenaar et al., 2023, 2024; Reimann, 2021; Sharma & Giannakos, 2020; Spikol et al., 2021; Wiedbusch et al., 2023; Winne, 2019; Zhang et al., 2022)

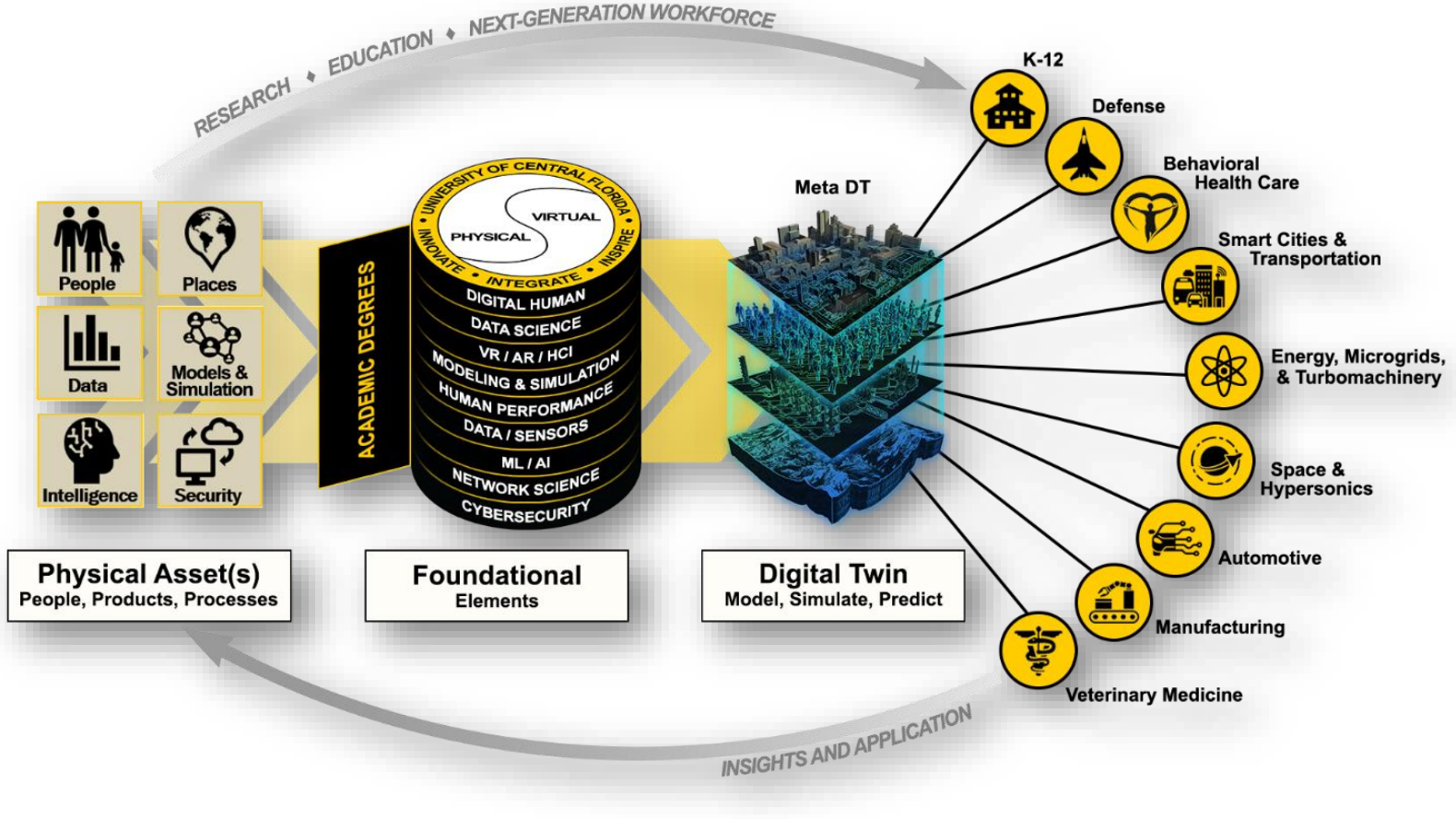
# Multimodal Data—Signals, Metrics, and Indicators

## (Azevedo et al., in press)

- **Physiological Signals**
  - Neurophysiological measurements
  - Biometric indicators
  - Eye-tracking data
  - Cardiovascular and respiratory metrics
  - Electrodermal activity
- **Behavioral Metrics**
  - Learning interaction patterns (e.g., log-files)
  - Engagement duration and intensity
  - Task completion strategies
  - Cognitive effort indicators
  - Emotional responses during learning
  - Motivational self-perceptions
- **Cognitive and Metacognitive Indicators**
  - Problem-solving strategies
  - Metacognitive knowledge and skills
  - Metacognitive strategy deployment
  - Reasoning patterns
  - Attentional focus
  - Cognitive load measurements
- **Affective and Motivational Indicators**
  - Emotion regulation strategies
  - Meta-motivation monitoring and regulation skills
- **Contextual Information**
  - Environmental conditions
  - Social learning interactions
  - Temporal learning patterns
  - Cultural and personal background factors
  - Technological learning environment characteristics

# Conceptual Framework for the Meta Digital Twin @ UCF

(Abdel-Aty, Azevedo, Beidel, Bochenek, & Cruz-Nera, 2022)




**Some Major Challenges:**

1. How, when, and why do we **"share"** humans' multimodal multichannel data with their human digital twins (HDTs)? And which data? Why?
2. How will humans and their HDTs **interact and communicate** with one another?
3. How will we **measure the success** of modeling and simulating humans and their HDTs?
4. What are the roles of **real-world and immersive environments** for modeling and simulating humans and their HDTs?
5. What is the role of **Artificial Intelligence (AI)** in modeling and simulating humans and their HDTs?

# Human Digital Twins (HDTs) and STEM Learning

- Human digital twins (HDTs) are **digital replicas of their human counterparts and their data**
  - goals, needs, beliefs, objectives, etc. data need to be modeled and simulated
- Humans are complex agents that researchers must study, model and simulate to accelerate current STEM learning, problem solving, and transfer

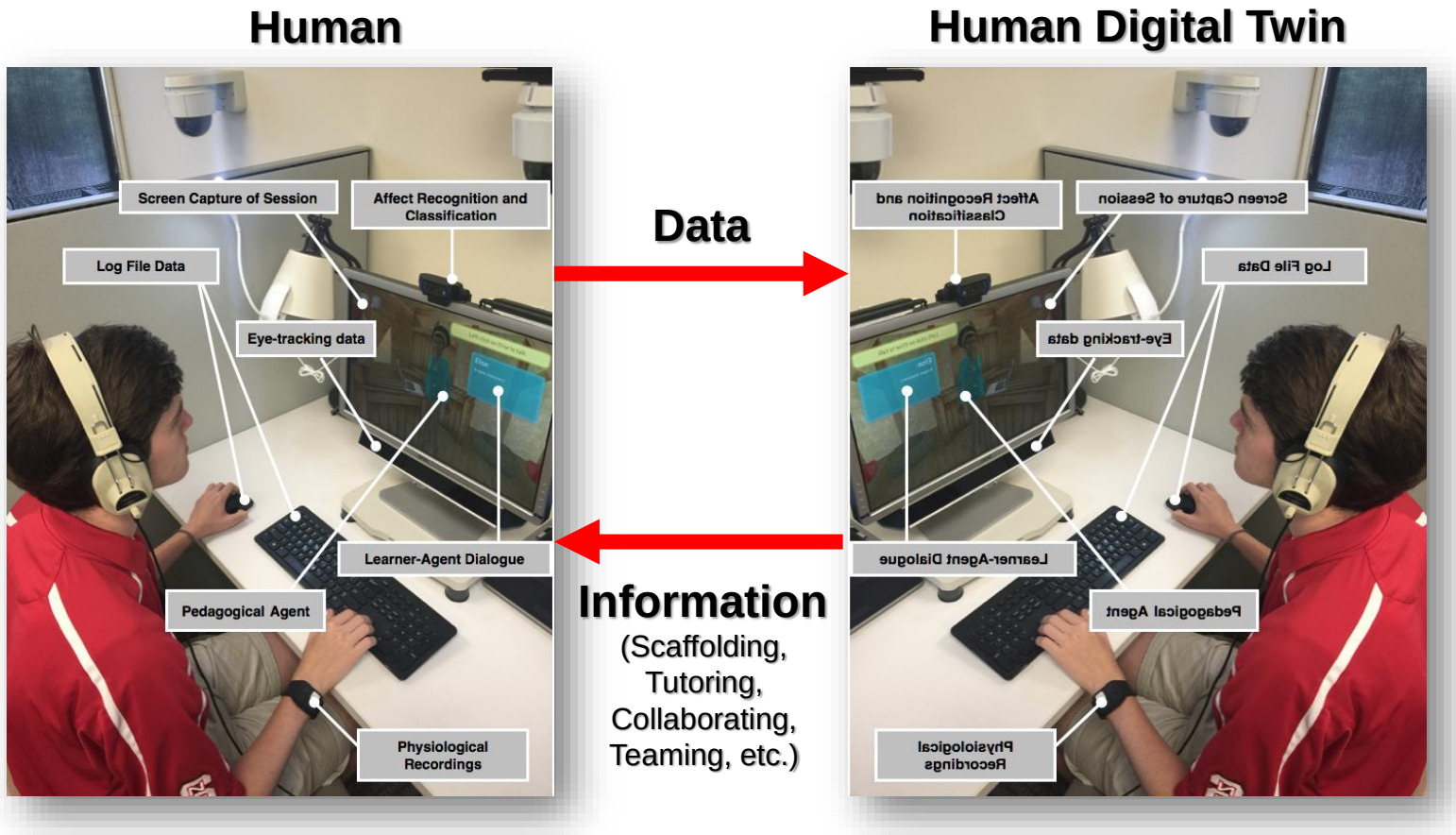
- **But what do we model and simulate?**
  - How do we decide what is important (and not) to model and simulate?
  - It depends, on *what, when, how, why, and for what purpose*?
  - How do we build HDTs that are capable of self-regulation and meta-reasoning?
  - What role do multimodal multichannel data play in the design, modeling, and simulation of HDTs?

# Which Human "Features" need to be Modeled and Simulated in HDTs?

- Multiple Goals, Objectives, & Beliefs
- (Multiple) Roles
- Gender
- Age
- Ethnicity
- Culture
- Socioeconomic Status
- Medical "History
- Language
- Knowledge
- Skills
- Attitudes
- Personality
- Brain
- Perception
- **Cognition**
- **Motivation**
- **Emotions**
- **Metacognition**
- **Social Processes**
- **What else? Why?**
  - Empathy

# Human Data to Model and Simulate in HDTs

## (Azevedo et al., in press)




- Which human data should we measure, detect, capture, model, and simulate in HDTs?
- Multimodal, multichannel human trace data across contexts
- Real world vs immersive virtual environments or combination (e.g., AR)
- Neural, physiological, cognitive, affective, metacognitive, motivational, and social processes and skills

# Detecting, Measuring, and Inferring SRL Processes in Real-Time

(learner AND researcher, teacher, tutor, trainer, or human digital twin [HDT];
based on Azevedo, 2015; Azevedo et al., 2018, 2019, 2022, in press)

**Learner**

**Researcher**
**(or Expert, Teacher, Tutor, Trainer, or HDT)**

# The Metacognitive Framework

- **Defining metacognition in HDTs**
  - Knowledge about cognition (declarative, procedural, conditional)
  - Monitoring and regulation of cognition (planning, monitoring, evaluation)
  - Metacognitive awareness, monitoring, regulation, evaluation, reflection, and adaptivity
- **Current challenges in metacognitive development among learners**
  - Limited self-awareness of cognitive processes
  - Difficulty in objective self-assessment
- **How HDTs can externalize internal cognitive processes**
  - Making thinking visible through computational representations
  - Using a multitude of methods and approaches to external their internal processes
- **Metacognitive feedback loops between the learner and the HDT**
  - Real-time calibration of self-knowledge and skills
  - Development of regulatory strategies through interaction (and feedback)

# AI-Driven Metacognitive Interventions

- **Types of metacognitive scaffolding enabled by HDTs**
  - Cognitive strategy suggestion based on pattern recognition
  - Just-in-time interventions during learning challenges
- **Personalization mechanisms for metacognitive support**
  - Adaptation to individual developmental readiness
  - Contextual awareness of domain-specific requirements
- **The role of explainable AI in metacognitive development**
  - Transparency in the reasoning behind suggestions, recommendations, and scaffolding
  - Building learner trust through comprehensible guidance
- **Examples of successful metacognitive interventions**
  - Systematic analyses of multimodal multichannel trace data
  - Reflection prompts derived from learning patterns
  - Strategy adaptation suggestions based on performance analysis

# Technological Architecture

- **Multi-layered framework for HDT implementation**
  - Data collection and pre-processing systems
  - Inference engines and predictive models
  - User interface and feedback mechanisms
- **Data sources for comprehensive HDT development**
  - Learning management system interactions
  - Biometric and attention monitoring
- **Integration with existing educational technology ecosystems**
  - API standards for interoperability
  - Privacy-preserving data exchange protocols
- **Technical challenges and current limitations**
  - Computational requirements for real-time processing (e.g., SOAR, MIDCA, CARINA)
  - Balancing model complexity with interpretability
  - Addressing data sparsity in early design and testing phases of the HDT
  - Addressing data volume, velocity, veracity, and variety during implementation and scaling-up phases

# Alignment with Winne & Hadwin's (1998, 2018) IPT Model of SRL

| Winne & Hadwin (198, 2018) IPT Model | HDT Architecture Component | Description |
|---|---|---|
| **Task Definition** | Perception Module, Context Model, Student Model | • HDT interprets the problem/task context (e.g., "solving word problems involving systems of equations"), identifies learner needs, and activates task schemas. |
| **Goal Setting & Planning** | Forethought Submodule, Teaching Strategy Repository, Student SRL Profile | • HDT sets conditional instructional goals (e.g., "reduce math anxiety before modeling") based on both external data and prior experience. |
| **Enacting Strategies** | Performance Submodule, Real-Time Control, Strategy Enactment Engine | • HDT selects and executes strategies, scaffolds learner behavior, and adjusts dynamically.<br>• HDT models recursive decision-making using AI control loops. |
| **Adaptation & Reflection** | Reflection Submodule, Meta-Learner, Trace Log Analyzer | • HDT evaluates student outcomes, self-efficacy, and strategy effectiveness.<br>• Uses internal logs to adapt teaching behavior and plan improvements. |

*The architecture incorporates recursive feedback loops, metacognitive condition tracking, and traces to model and adapt the HDT's behavior in authentic ways.*

# Challenges in Designing, Developing, Testing, and Implementing HDTs: High School Math Teacher

- **Capturing and Modeling and Cognitive and Metacognitive Processes**
  - Teacher metacognition
  - Teacher SRL and SRT knowledge and skills
  - Tacit pedagogical knowledge
  - Real-time cognitive adaptivity
  - Modeling phases and stages of SRL processes in real-time
  - Modeling reflective practice
- **Modeling Motivation and Emotion Regulation**
  - Teacher emotion regulation
  - Affectively responsive scaffolding
- **Social and Interpersonal Dynamics**
  - Simulating rapport and social presence
  - Teacher identity and authenticity
  - Power, authority, and trust
- **Psychological fidelity and Human-Likeness**
  - Uncanny Valley ad emotional reactance
  - Cognitive load and misalignment
- **Ethical and Identify-based Concerns**
  - Teacher representation and consent
  - Student perception and bias
- **Representing Pedagogical and SRL Knowledge in HDT**
  - Declarative, procedural, and conditional knowledge and skills
  - Meta-level self-knowledge and meta-teaching skills

# Questions and Challenges for HDTs

1. **What is the value of HDTs as research, modeling, and simulation tools for researchers, learners, teachers, and others to understand SRL? What is their role in the HDT ecosphere?**
   - *When, how, why, and for what purposes?*

2. **Which human multimodal multichannel data should we detect, capture, model, and simulate in HDTs?**
   - *When, how, why, and for what purposes, which contexts, and specific conditions?*
   - *Predicting learning vs. hypothesizing about influences of specific SRL processes during task performance vs. modeling maladaptively to enhance adaptive behavior vs. simulating optimal SRL processing*

3. **Can HDTs advance current models, theories, methods, and analytical techniques used to understand SRL?**
   - *Dynamics of SRL processes over time, across learners, tasks, and contexts*

4. **Can HDTs be used to generate populations of HDTs with varying STEM knowledge and skills** (e.g., middle-school vs. high school; novices vs. experts; developmental ages) **and SRL skills** (e.g., metacognitive declarative, procedural, and conditional knowledge) **to model and simulate their learning, performance, reasoning, understanding, etc. under different instructional conditions using immersive virtual simulation environments?**

# Future Directions and Challenges

- **Technical Challenges**
  - Handling volume, velocity, veracity, variety of high-dimensional, noisy, and incomplete multimodal data
  - Developing robust machine learning and computational architectures
  - Computational complexity in real-time modeling
  - Interdisciplinary approaches to HDT design, development, testing, and implementation
- **Emerging Innovation Areas**
  - Advanced multimodal data fusion techniques
  - Real-time cognitive, affective, metacognitive, and motivational (CAMM) state modeling
  - Personalization and adaptivity at scale
  - Human-AI collaborative (and human-AI teaming) learning paradigms
  - Human-AI hybrid intelligence
- **Empirical Validation and Research Directions**
  - Longitudinal studies on HDT effectiveness
  - Comparing human and AI-driven learning interventions
  - Developing standardized evaluation metrics
  - Continuous model refinement through interdisciplinary research

# Future Vision and Transformative Potential

- Democratizing personalized education through AI technologies
- Empowering learners with self-understanding tools
- Global knowledge networks and collaborative learning ecosystems
- Reimagining education as a dynamic, adaptive human-AI partnership
- Future of education characterized by
  - Hyper-personalized learning pathways
  - Proactive SRL support systems
  - Dynamic, responsive educational environments
  - Individualized developmental strategies
  - Comprehensive understanding of learning processes

# Acknowledgements


- **Funding Agencies**
  - NSF, NIH, U.S., Department of Education, IES, NIH, SSHRC, NSERC, CRC, CFI, CCR, Fulbright, EARLI, Jacobs Foundation, Army Research Lab, and CAPTRS
- **Current and former members of the SMART Lab**
  - Dr. Megan Wiedbusch, Dr. Daryn Dever, Dr. Elizabeth Cloude, Dr. Matthew Moreno, Annamarie Brosnihan, Camaron Marano, Tara Delgado, Maral Karimi, Milouni Patel, Evan Naderi, Milla Sherman, Oscar Tidwell, Anna Cevallos, Andrea Llanas, Sophia Capelllo, Kevin Smith, Emily Bright, Nicole Enamorado, Saeork Park, Nathan Sonnenfeld, Fiorella Rodriguez, Sarah Grace Schmorrow, Dr. Nicholas Mudrick, Megan Price, Dennis Hernandez, Carina Tudela, Mitchell Moravec, Alex Haikonen, Pooja Ganatra, Sarah Augustine, Daniel Baucom, Franz Wortha, Kimani Hoffman, Lahari Revuri, Rosy Almanzar, and Jonathan Schertz
- **National and international collaborators**
  - Engin Ader, Mary Jean Amon, Mindi Anderson, Anila Asghar, Maria Bannert, Reza Feyzi Behnagh, Gautam Biswas, Grace Bochenek, François Bouchet, Rafael Calvo, Analia Castigliani, Min Chi, Cristina Conati, Jennifer Cromley, Carolina Cruz-Nera, Shane Dawson, Francesca de Rosa, Lisa Dieker, Melissa Duffy, Dragan Gašević, Arthur Graesser, Jeffrey A. Greene, Alexander Groeschner, Frank Guido-Sanz, Varadraj Gurupur, Jason Harley, Caridad Hernandez, Bari Hoffman, Danial Hooshyar, Charles Hughes, Eunice Jang, Sanna Järvelä, Joseph Kider, Susanne Lajoie, Joseph LaViola, Ronald Landis, James Lester, Ryan McMahan, Amanda Major, Rebeca Cerezo Menéndez, Tova Michalsky, Inge Molenaar, Daniel Moos, Krista Muis, Susanne Narciss, Magy Seif El-Nasr, Mark Neider, Soonhye Park, Reinhard Pekrun, Jose Carlos Núñez Pérez, Ghaith Rabadi, Ramkumar Rajendran, Dirk Reiners, Barrie Robison, Jonathan Rowe, Michael Serra, Kshitij Sharma, Mindy Shoss, George Siemens, Bryan Smith, Terrence Soule, Michelle Taub, Dario Torre, Damla Turgut, Gregory Trevors, Philip Winne, Jichen Zhu, and Joerg Zumbach