

From Bored to Floored: Utilizing Profiles in Adaptive Learning Technology to Increase Student Engagement and Motivation

Presenters



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Experiencing ALT through Google Forms

https://forms.gle/KSnQJfigZ4cFqeb26

Escape the Conference

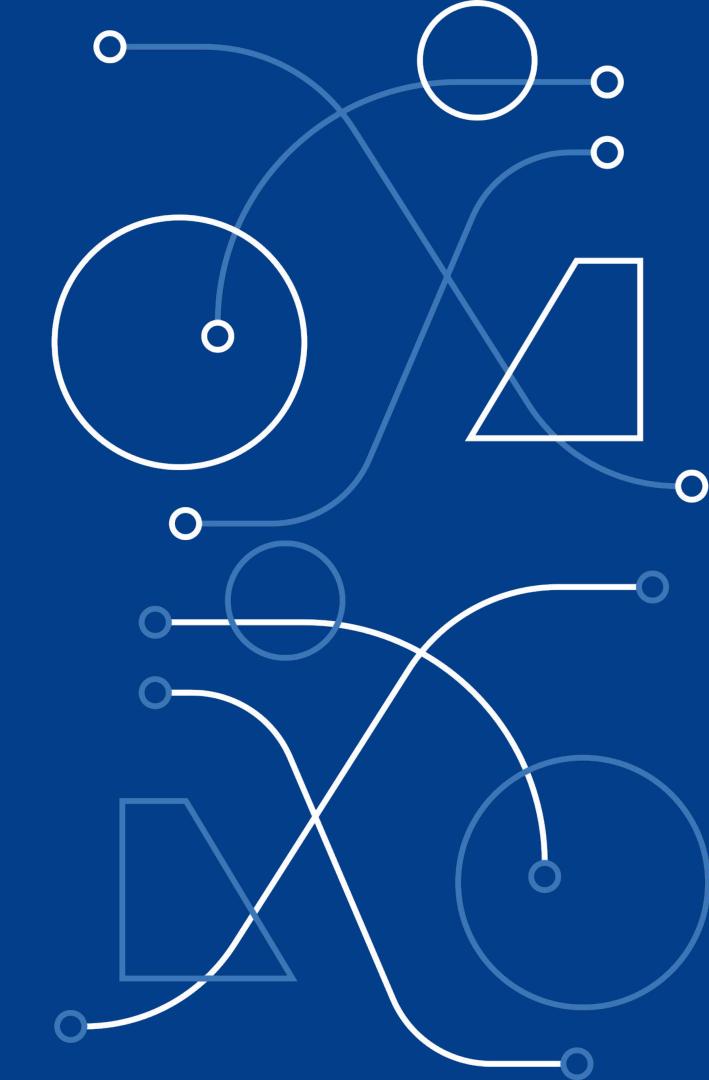
Form description

Of the special days listed below, what is your favorite? *

- Fourth of July
- New Years Eve
- Halloween



An overview of Adaptive Learning Technology (ALT) Personalized Learning



Scope of Literature Review



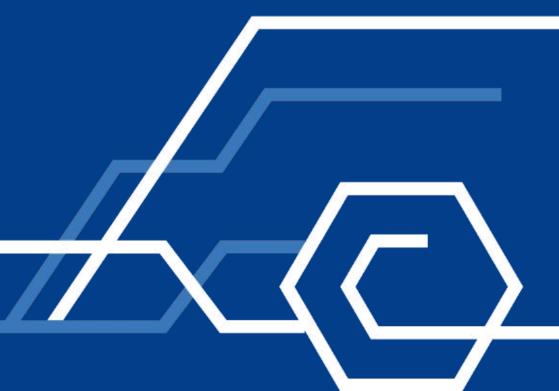


Learner Motivation & Engagement



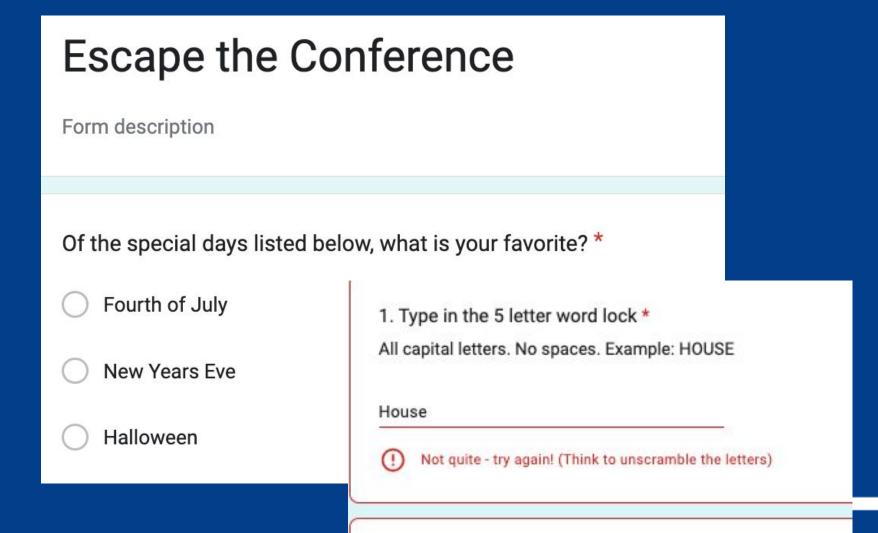
Various subjects across formal learning settings in K-12 & higher education





Four Categories of Adaptive Technology

- 1. adaptive learning system,
- 2. adaptive learning application,
- 3. adaptive teaching approach, and
- 4. adaptive design solutions



4-Digit Number Lock *

1234

No spaces or commas. Example: 6789

Note quite - HINT: Look at the stars

(Martin et al., 2020)

Adaptive Learning (AL) vs. Personalized Learning (PL)

- Both terms used interchangeably. Vague distinction in technology-enhanced learning.
- PL can be used to identify individual characteristics, regardless of adapting to learner tasks.
- AL can be used to adapt to learner performance without the need for personalized information.
- Affection sub-classified into learner intention, learning attitudes, engagement expectations, motivation, self-efficacy, satisfaction, cognitive load, learning anxiety, learning experiences.

(Xie et al., 2019)

Personalized Adaptive Learning (PAL)

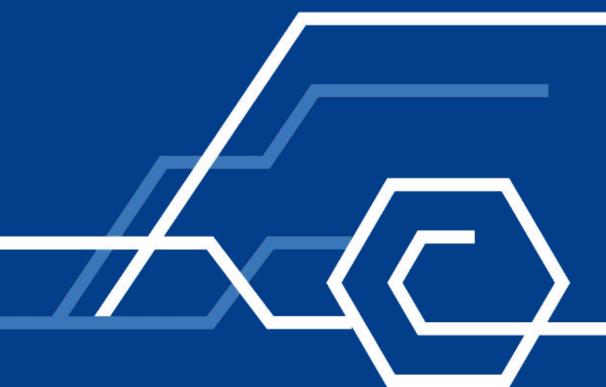
Core elements:

- 1. Individual characteristics
- 2. Individual performance
- 3. Personal development
- 4. Adaptive adjustment

(Peng et al., 2019)

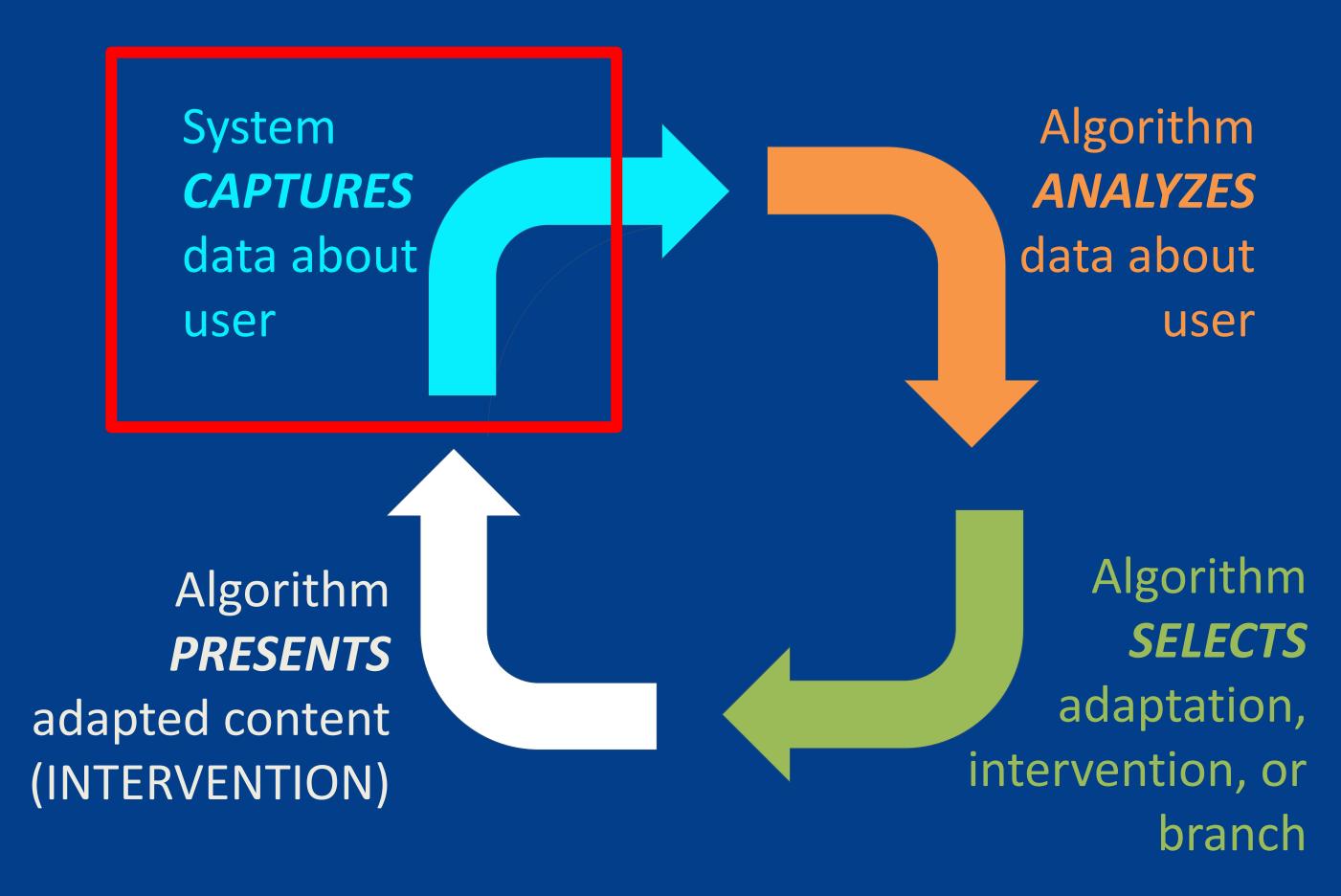
Constructed from four aspects:

- 1. Learner profiles
- 2. Competency-based progression
- 3. Personal learning
- 4. Flexible learning environments





Current Uses of Learner Profiles in ALT



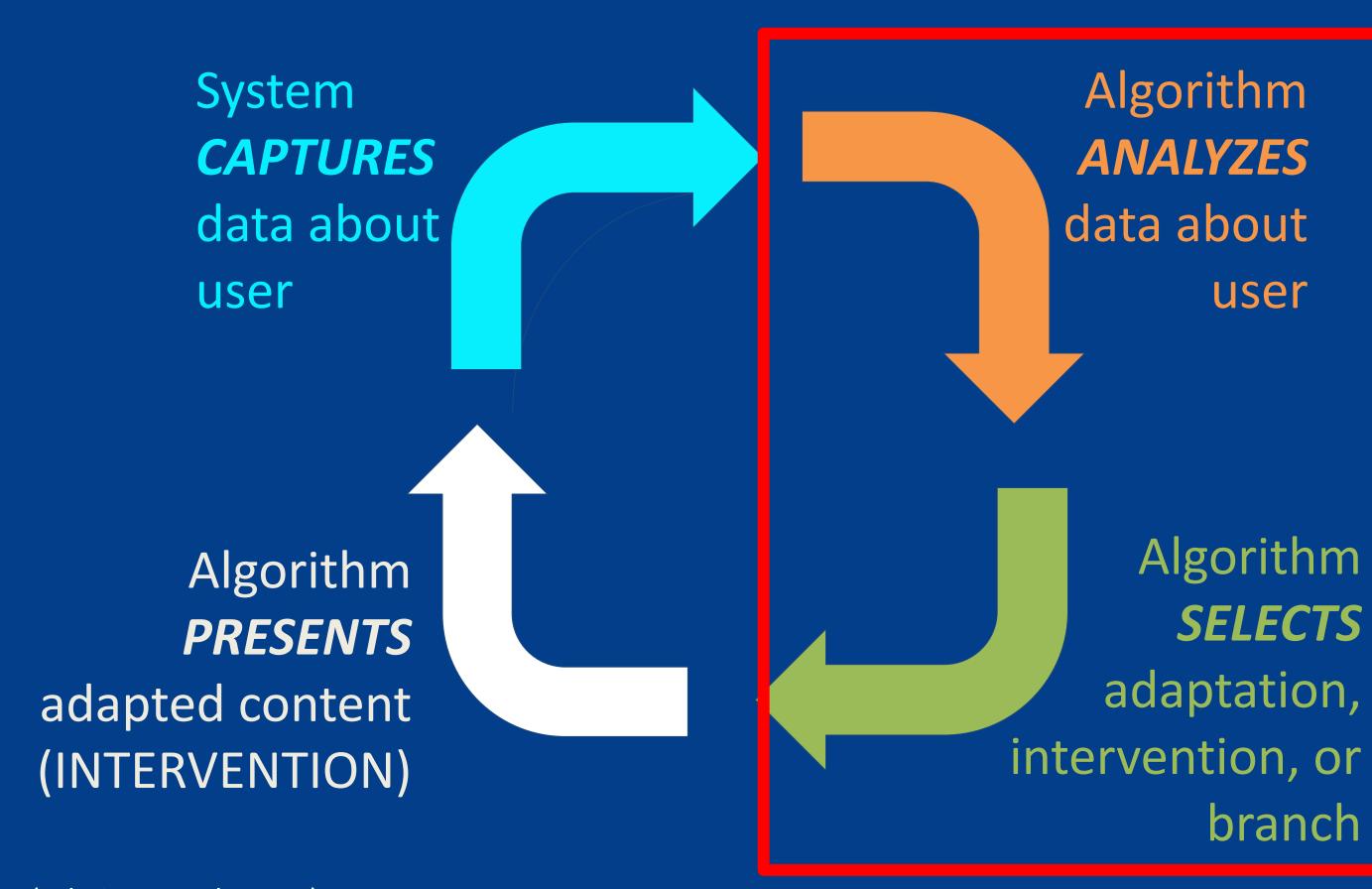
"It is important to identify those elements that relate to each of the stages of a collective application: selection, capture, aggregation, processing, and presentation" (Dron & Anderson, 2014, p. 229)

- Non-Al Powered ALS

Capturing Data about User Before & During Interaction with ALT

- Relevant Questionnaire (Scheiter et al., 2019)
 - VARK Questionnaire (learning styles) (El-Sabagh, 2021).
- Pre-assessment / Test (Scheiter et al., 2019)



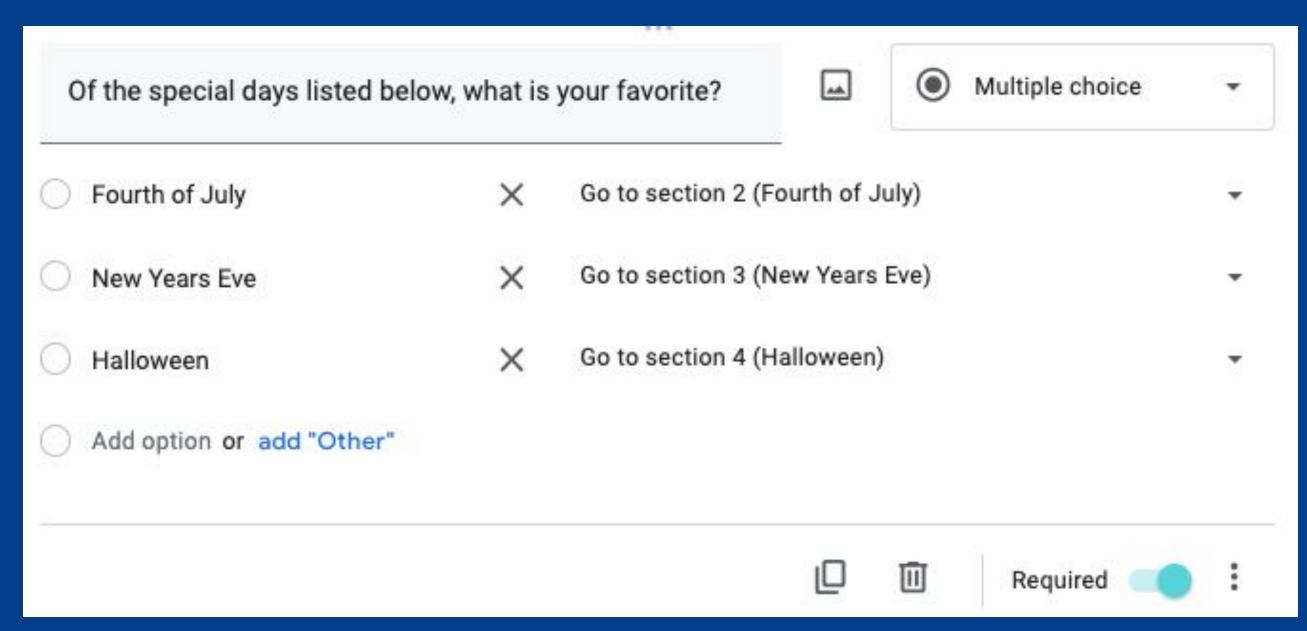


"It is important to identify those elements that relate to each of the stages of a collective application: selection, capture, aggregation, processing, and presentation" (Dron & Anderson, 2014, p. 229)

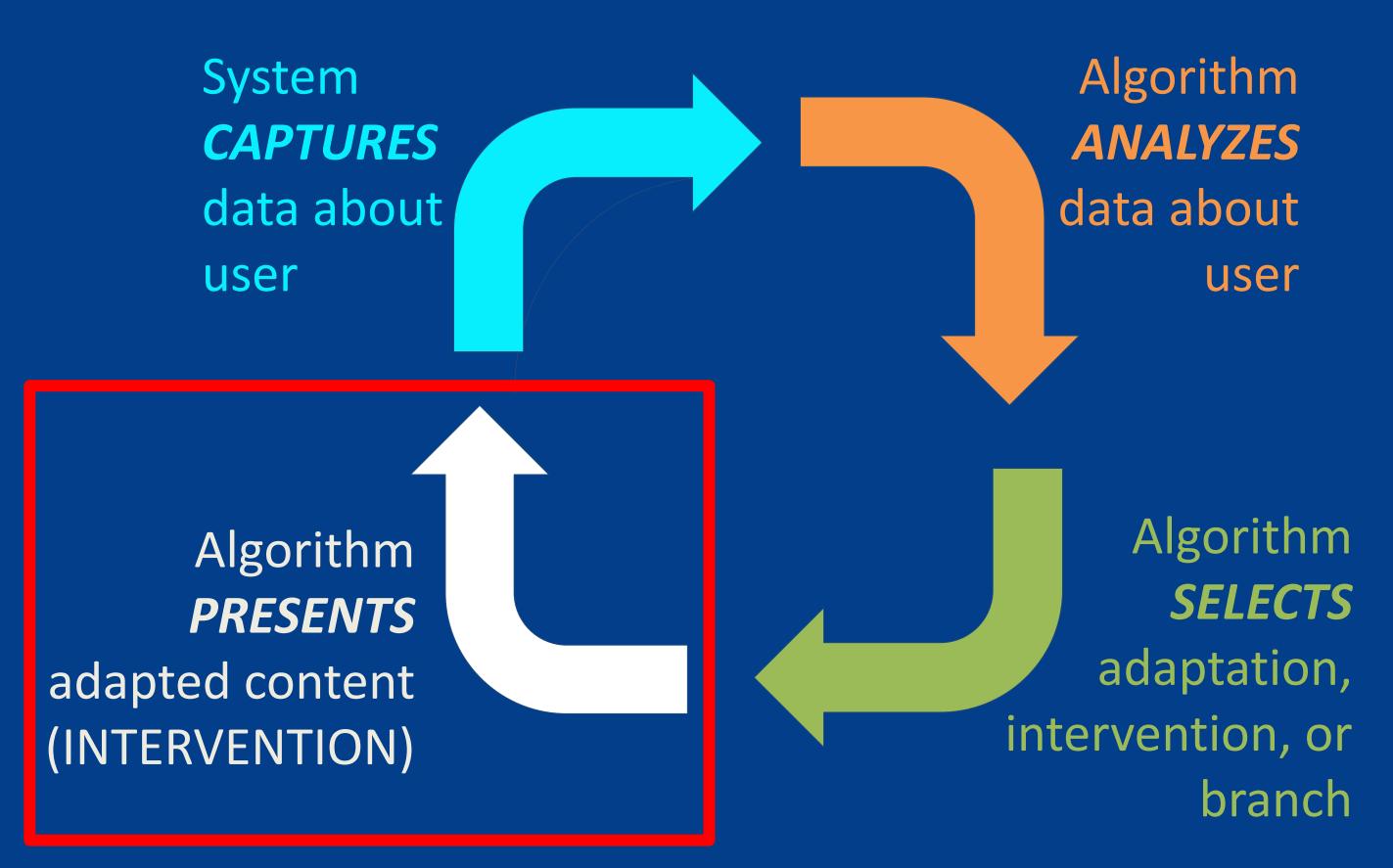
- Non-Al Powered ALS

(Scheitera et al., 2019)

Capturing Data about User Before & During Interaction with ALT



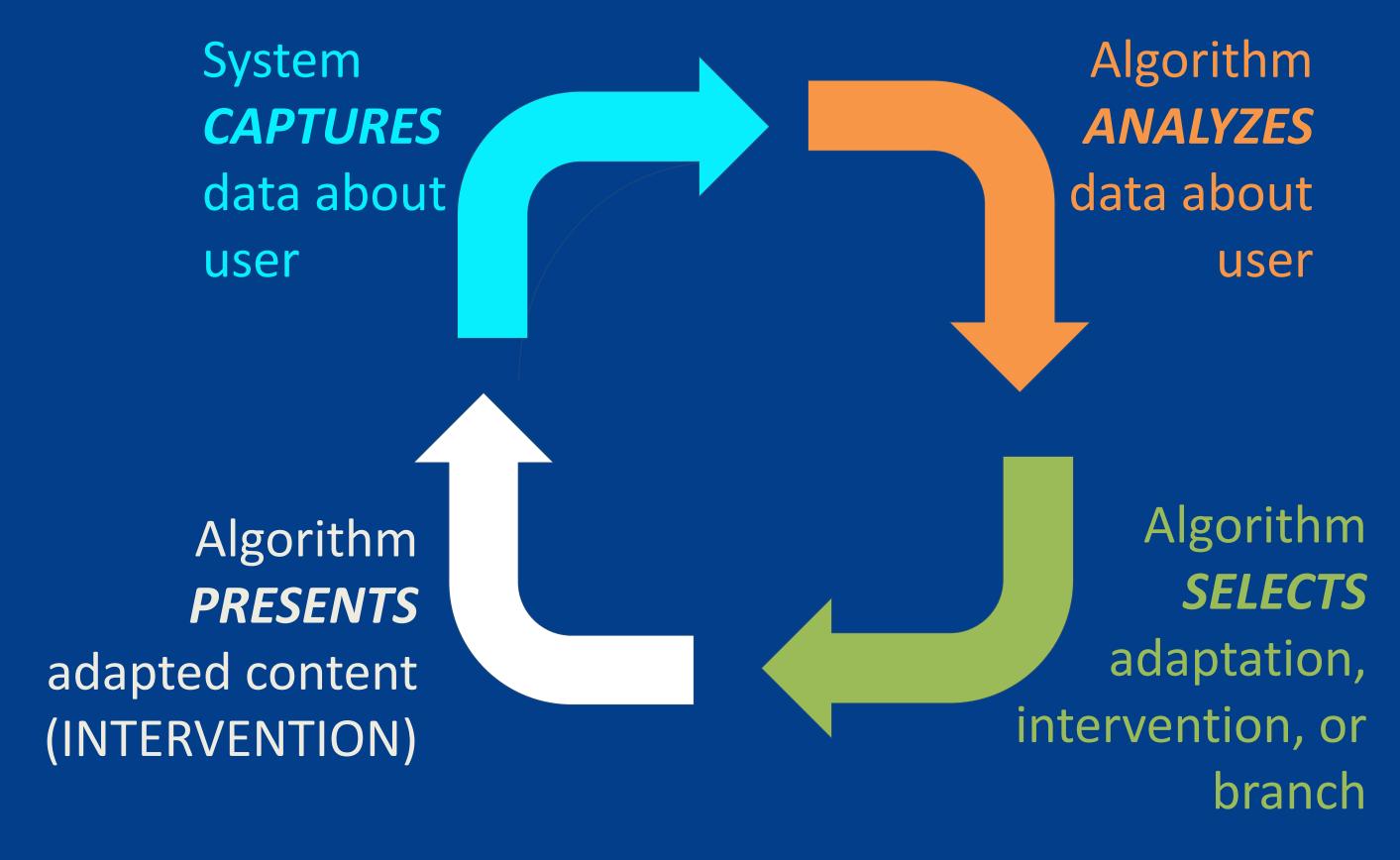
System design and development following instructional design models (El-Sabagh, 2021)



"It is important to identify those elements that relate to each of the stages of a collective application: selection, capture, aggregation, processing, and presentation" (Dron & Anderson, 2014, p. 229)

- Non-Al Powered ALS

And the cycle continues again and again....



"It is important to identify those elements that relate to each of the stages of a collective application: selection, capture, aggregation, processing, and presentation" (Dron & Anderson, 2014, p. 229)

- Non-Al Powered ALS

Capturing Data about User Before & During Interaction with ALT

- System draws conclusions about the learner while the learner interacts with the system (Scheiter et al., 2019)
- Al-recommendation system implemented in three phases: the information collection phase the learning phase, and the recommendation phase p (Huang et al., 2023).
- Adaptive intelligence engines should build on outer loop to set learning parameters (student data), middle loop (tasks), inner loop (organized steps within task)(VanLehn and Boulay in Dziuban et al., 2018)
- Data mining and machine learning to classify learners and predict needs (Missaoui et al.,
 2021)

Capturing Data about User Before & During Interaction with ALT

1. Type in the 5 letter word lock *

All capital letters. No spaces. Example: HOUSE

House

1. Not quite - try again! (Think to unscramble the letters)

2. 4-Digit Number Lock *

No spaces or commas. Example: 6789

1234

Note quite - HINT: Look at the stars

Research: ALT & Engagement

- * Effective Profiling Techniques
- ★ Considerations for System Design



Research: ALT & Engagement & Motivation



- Research shows adaptive learning based on learner profiles can positively impact student motivation, engagement, and outcomes compared to one-size-fits-all approaches. Measures like participation, effort, motivation were higher with personalized learning (El-Sabagh, 2021; Liu et al., 2017; Mirari, 2022)
 - Students require varying amounts of time to acquire knowledge despite having similar motivation and abilities
 (Dziuban et al., 2018)
 - Personalization key to helping students learn material while increasing engagement (Dziuban et al., 2018)
- ★ Findings on the efficacy of adapting to learning styles are mixed:
 - Learning adapted to styles increased engagement (El-Sabagh, 2021 experimental study)
 - Students were driven by curiosity and desire to refresh their knowledge, showing adaptive learning can tap into
 intrinsic motivation (Lui et al.,, 2017)
 - System design flaws (e.g., misalignment & technical issue) caused issues (Liu et al., 2017 adaptive intervention study)
 - o Gender differences, cognitive styles, and prior knowledge may lead to different reactions in PAL (Xie et al, 2019)
 - Effects were most pronounced in higher education settings with mature, self-motivated learners (Mirari, 2022)

Effective Profiling Techniques

- VARK model classify learners into four groups based on visual, auditory, read/write, and kinesthetic learning styles (El-Sabagh, 2021).
- Tracking gaze to measure ongoing user interaction with system (Scheiter et al., 2019)
- Selecting appropriate tool based on the user's profile, prior knowledge, Zone of Proximal Development (Scheiter et al., 2019; Alamri et al., 2020)
- Data mining and machine learning to classify learners and predict needs through Ontology-based
 Semantic Profiling (Missaoui & Maalel, 2021)
 - Ontologies: Structured ways of representing knowledge that computers can read
 - Semantic technologies: Tools for linking data and adding meaning that computers can interpret

Designing the Technology

EXTRINSIC MOTIVATORS

Digital Badge for completion (Alamri et al., 2020)

Timer / Gaze Tracker for real-time user engagement (Scheiter et al., 2019)

Design flaws caused issues (Liu et al.)

Direct feedback provided by learner (Alamri et al., 2020; Scheiter et al., 2019)

Understanding that the user is interacting with ALT (Scheiter et al., 2019)

INTRINSIC MOTIVATORS

Metacognitive
awareness /
Judgment of Learning
(JOL) Assessment
(Scheiter et al., 2019)

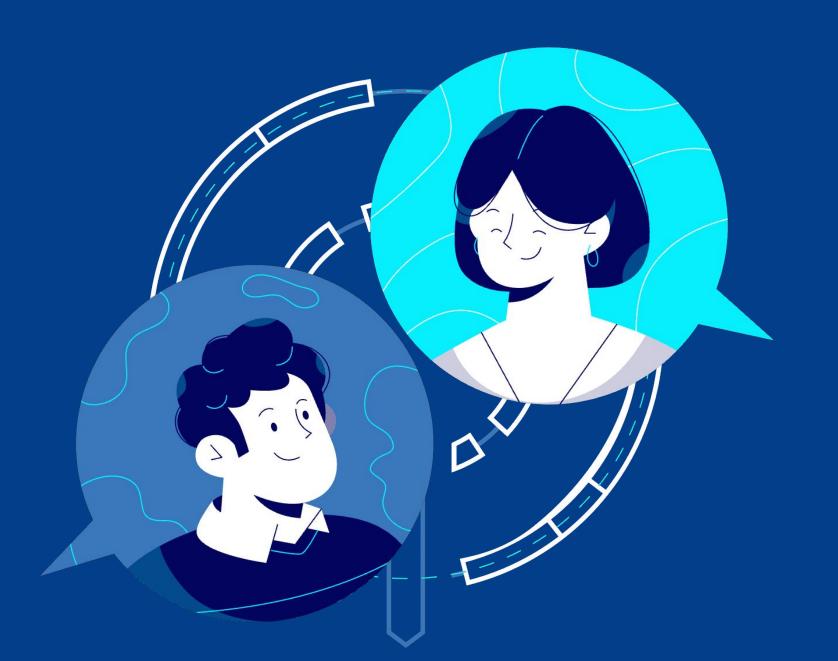
Autonomy provided by ALT increases motivation (Lim et al., 2022; Alamri et al., 2020)

Zone of Proximal
Development (Alamri et al., 2020)

Best Practices for ALT Design

- ★ Bayes theorem / SPRT test for AI-enabled personalized video recommendations (Huang et al., 2023)
- ★ Learner understanding of rules and expectations at start of course a prerequisite for engagement. More agency and executive control to reduce uncertainty for students (Dziuban et al., 2018)
- ★ Immediate feedback engages the user to think about their learning and remain engaged to do better (Alamri et al., 2020; Scheiter et al., 2019)
- ★ Testing the system design before rolling it out (Scheiter et al., 2019)
- ★ Including an instrument that measures student motivation and regard for the content, as part of the ALT (Lim et al., 2022)
- ★ Opportunity for user to give feedback to developers within ALT (Battou et al., 2018; Alamri et al., 2020)

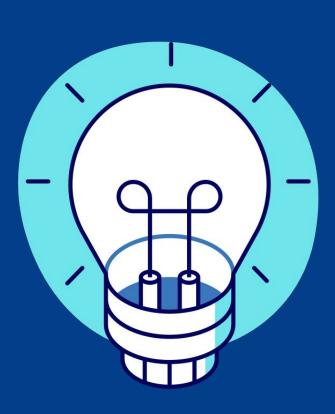
Escape the Conference



Pause & Reflect:

How did the DESIGN of our Google Form at the beginning incorporate the outlined profiling techniques and systems design tips discussed so far?

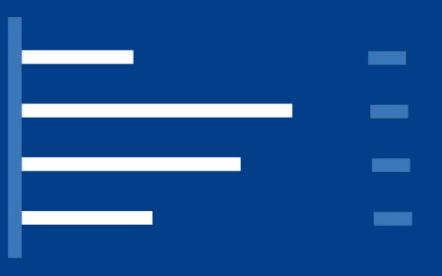
- 1. Informing user of the "Escape the Conference" activity → Intentional communication with user
- 2. Selecting preferred holiday \rightarrow Matching tool to learner's interests
- 3. Timing the activity \rightarrow Gaze study with timer and forced intervention
- 4. Challenging "enough" activity to challenge your thinking \rightarrow ZPD
- 5. Likert scale at end \rightarrow Opportunity for reflection & feedback
- 6. Digital Badge at end
- 7. Testing the design of the form





Key Challenges & Implications



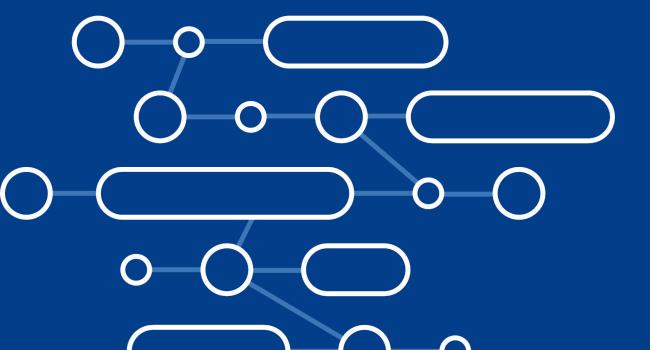


Research Limitations

- Small sample sizes (El-Sabagh, 2021; Liu et al., 2017; Scheiter et al., 2019 gaze study;)
- Limited contexts and populations studied (El-Sabagh focused on one course at a university)
- Reliance on self-reported data for some measures (Liu et al., 2017; El-Sabagh, 2021)
- Limited longitudinal data on longer term impacts (all studies were quite short duration)
- Lack of studies on motivation of user while interacting with ALS (Alamri et al, 2020)
- Lack of studies of ALS in higher education (Alamri et al., 2020)
- Studies about user engagement and motivation conducted by textbook companies or the developers themselves (lack of independently-driven studies) (Alamri et al., 2020)
- Adaptive learning is an idealized cognitive model (ICM) and boundary object (Dziuban et al., 2018)
- Few studies on wearable devices, smartphones, and tablets. Need for more studies using virtual reality (Xie et al., 2019)



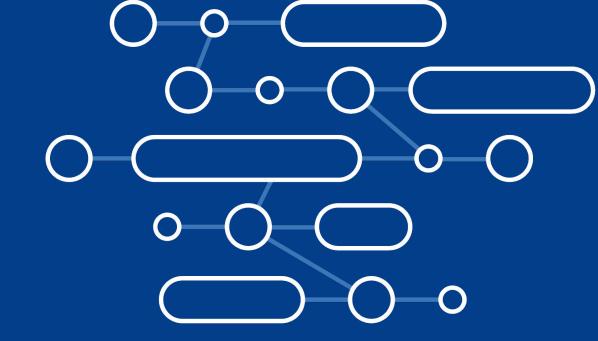
What the Research Says...



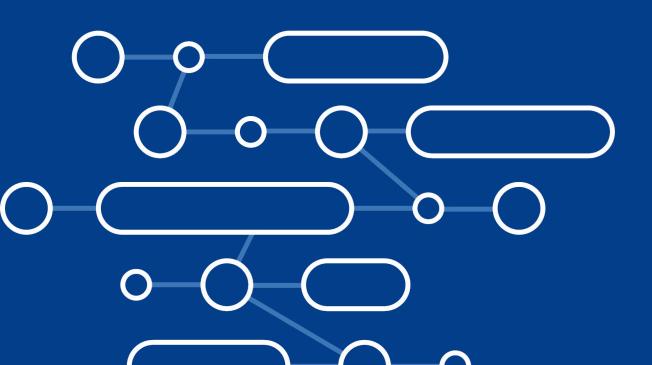
- → Learning improvements in students with moderate motivation levels were significantly higher than those in students with high and low levels of motivation (Huang et al., 2023)
- → Those with poor motivation appear to need additional design incentives to engage with recommended content (Huang et al., 2023).
- → Some learners may not neatly fit into one of the VARK categories (El-Sabagh, 2021).

- The effectiveness of adaptive learning depends heavily on the quality of the system design and implementation.
 - Need better profiling methods
 leveraging AI (Missaoui & Maalei,
 2021 machine learning)
 - Improved algorithms and modeling (Liu et al., 2017) - predictive accuracy issues)
 - Alignment of assessments,
 materials, objectives with learner
 needs is crucial, as is usability
 testing (Liu et al., 2017).

- → Using digital badges as means of pre-existing data regarding user to automatically generate content in ALT (Alamri et al., 2020)
- → Collecting a variety of data efficiently and using all of it to create appropriate ALS (Scheiter et al, 2019)
- → Need for tool built into ALT to measure engagement with content (Lim et al, 2022).
- → ALS had no impact on users with low prior knowledge (Scheiter et al,
 2019)

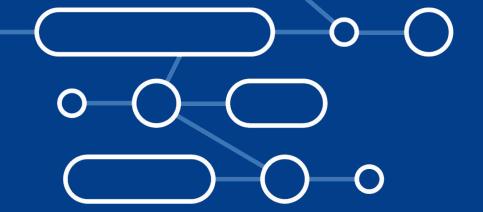


Application: Escape the Conference Activity

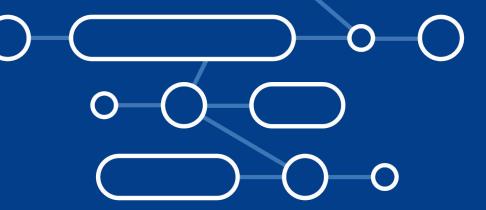


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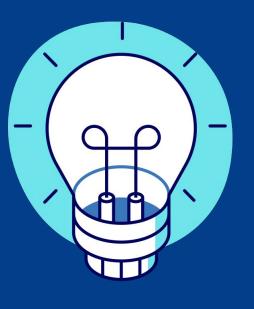
Applying ALL of these various findings to any ALT is important for developers to consider to ensure student engagement, motivation, and even metacognition



Future Research



- → What system design features are most important for adaptive learning success? How can the machine learning and AI behind adaptive systems be improved?
 - More work needed on the learning algorithms, user interfaces, and optimal balance between learner control vs. system adaptation.
 - Robust learner modeling and predictive capabilities are still limited.
- → How effective is adapting to different learner traits beyond just learning styles?
 - More research needed on adapting to knowledge levels, goals, interests etc. (Liu et al., 2017)
 - ◆ More studies needed on applications across new contexts (El-Sabagh, 2021)
 - ◆ Need for design framework (Battou et al., 2018)
- → What motivates learners to share profile information needed by adaptive systems?
 - ◆ More work needed on privacy perceptions. Collection of personalized information from learners may potentially impede their progress (Peng et al., 2019)



Conclusions

- ★ Personalized adaptive learning (PAL) shows promise for improving motivation, engagement and outcomes but more research is needed on optimal design, implementation, and use cases across contexts.
- ★ Students learned more and were more engaged through the adaptive system based on learning styles. They reported more opportunities to recall learned content than the conventional system.
- ★ In summary, learner profiles enable customization in e-learning that can benefit engagement and learning. But high quality adaptive system design is equally critical for success. More research would further understanding of how to best leverage learner profiles in adaptive learning environments.



Escape the Conference User Results





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