On the Road to Personalized Learning: Applications of Machine Learning Algorithms

Okan Bulut

Measurement, Evaluation, and Data Science

University of Alberta

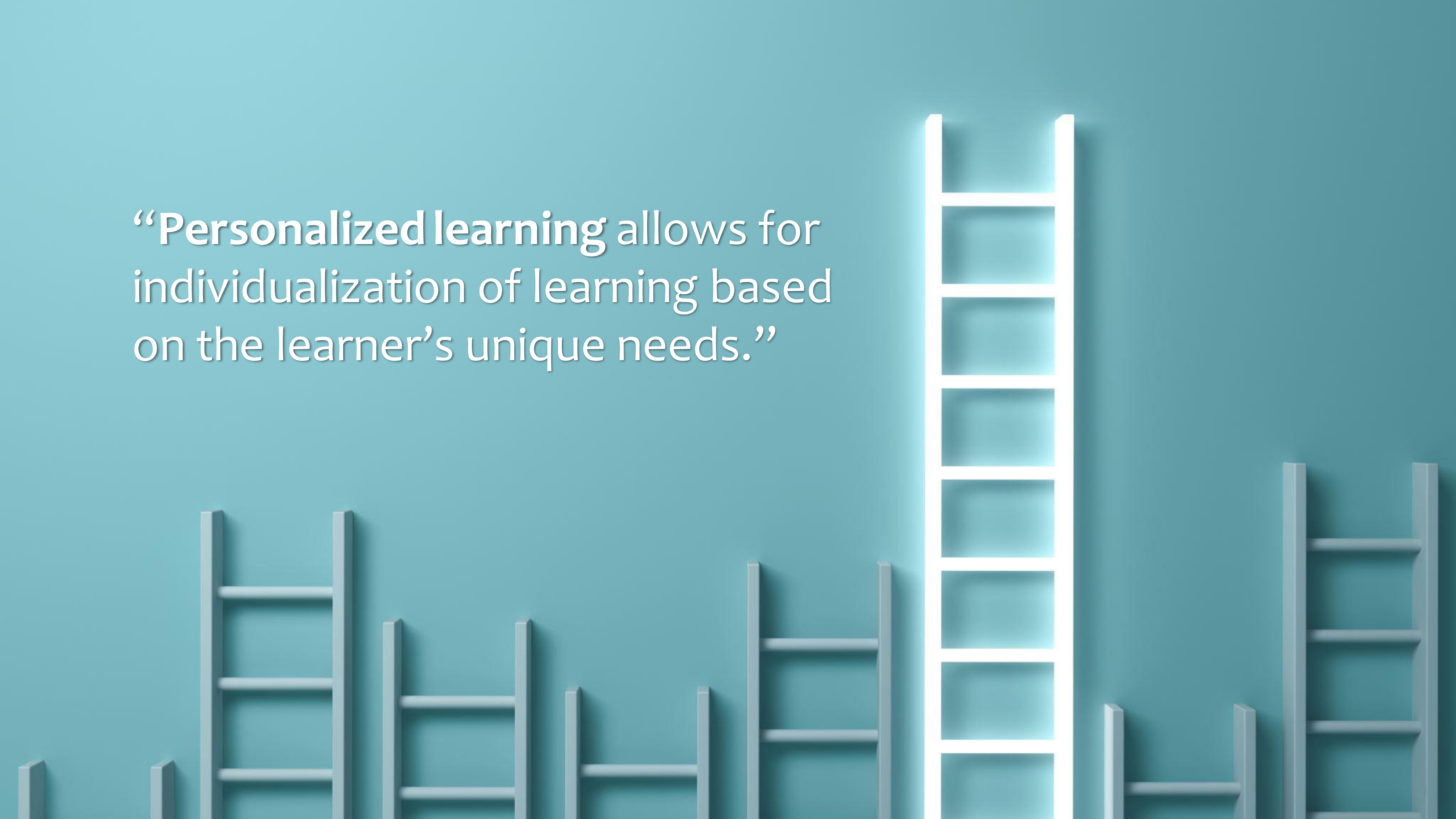
bulut@ualberta.ca

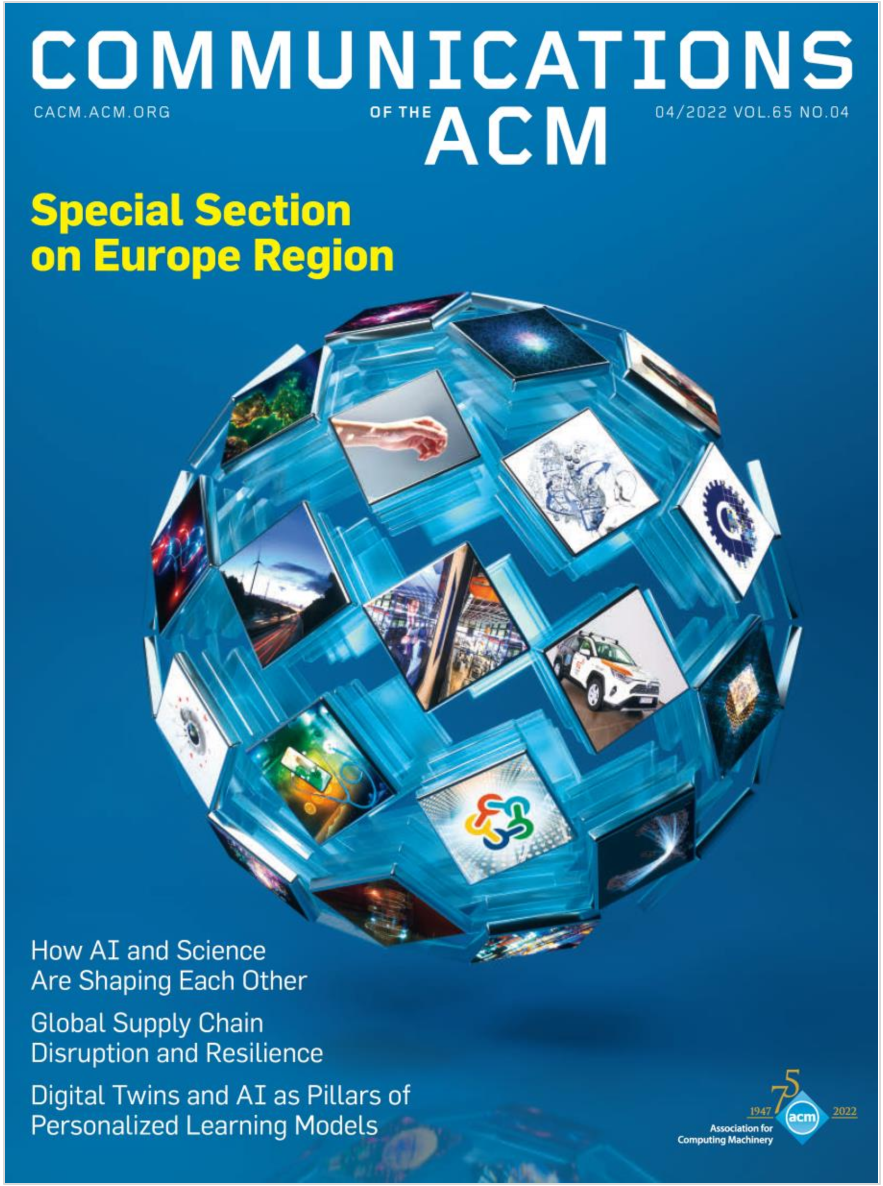
www.okanbulut.com

@drokanbulut

Outline

1. Why personalized learning?
2. Personalization through adaptivity
3. Three applications of personalization
4. Concluding remarks and future research


“**Personalized learning** allows for individualization of learning based on the learner’s unique needs.”



https://dl.acm.org/toc/cacm/2022/65/4

DOI:/10.1145/3478281

Personalized learning models can cut student dropout rates, boost student success, improve the integration of online and on-site students, better support teachers in mixed-teaching modalities, enhance accessibility, and more.

BY MARCO FURINI, OMBRETTA GAGGI, SILVIA MIRRI, MANUELA MONTANGERO, ELVIRA PELLE, FRANCESCO POGGI, AND CATIA PRANDI

Digital Twins and Artificial Intelligence

as Pillars of Personalized Learning Models

MODERN EDUCATIONAL SYSTEMS have not really evolved enough to meet the needs of modern students.[21] No wonder, the percentage of dropouts from university studies is quite high (40% in the U.S. and 10% in Europe[7,9]). The university student profile has changed over the years. While yesterday's students were mainly full-time, today's students face challenges such as work commitments, family obligations, financial constraints, physical impairments, and learning models that do not adequately engage students or help them understand core concepts.[11] One might think that this issue concerns only those who fail to complete their studies, but this is view is shortsighted. Today's educational system deficiencies will affect the welfare of tomorrow's society.

To improve current learning models, academic institutions around the world agree that the time has come to improve the world of education, moving from a traditional approach—where learning is standardized and available only to those with access to educational buildings—to a new paradigm that enables students to personalize their educational pathway, so they can progress at their own pace.[19,21] Future learning models must address key concerns, such as reducing dropout rates, supporting students with psycho-physical impairments, integrating on-site and online students, and personalizing the learning experience.

Digital twins—digital replicas of students—and artificial intelligence (AI) will be the pillars of innovation, accessibility, and personalization in future learning models.[19] The good news is that we can build these models today: AI algorithms have made great strides in recent years, and the use of technology in education has increased enormously. Indeed, while the COVID-19 pandemic has, on one hand, strongly hampered the learning process for many people around the world, it has, on the other

» key insights

- **The time has come to revolutionize current educational systems, which are too rigid and cannot adequately support students who have work commitments, family obligations, financial constraints, and physical impairments.**
- **AI and digital-twin technology are helping to transform cities into smarter versions of themselves, supporting the Industry 4.0 revolution, and improving health services, but these technologies have rarely been used in the educational sector.**
- **AI and the digital-twin approach can be used to build personalized, inclusive, and accessible learning models. These models will have a tremendous social, cultural, and economic impact, and they will make it possible to meet some sustainable development goals set by the United Nations General Assembly.**

IMAGE BY ANDRIJ BORYS ASSOCIATES, USING PHOTO BY DEAN DROBOT

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contributed articles

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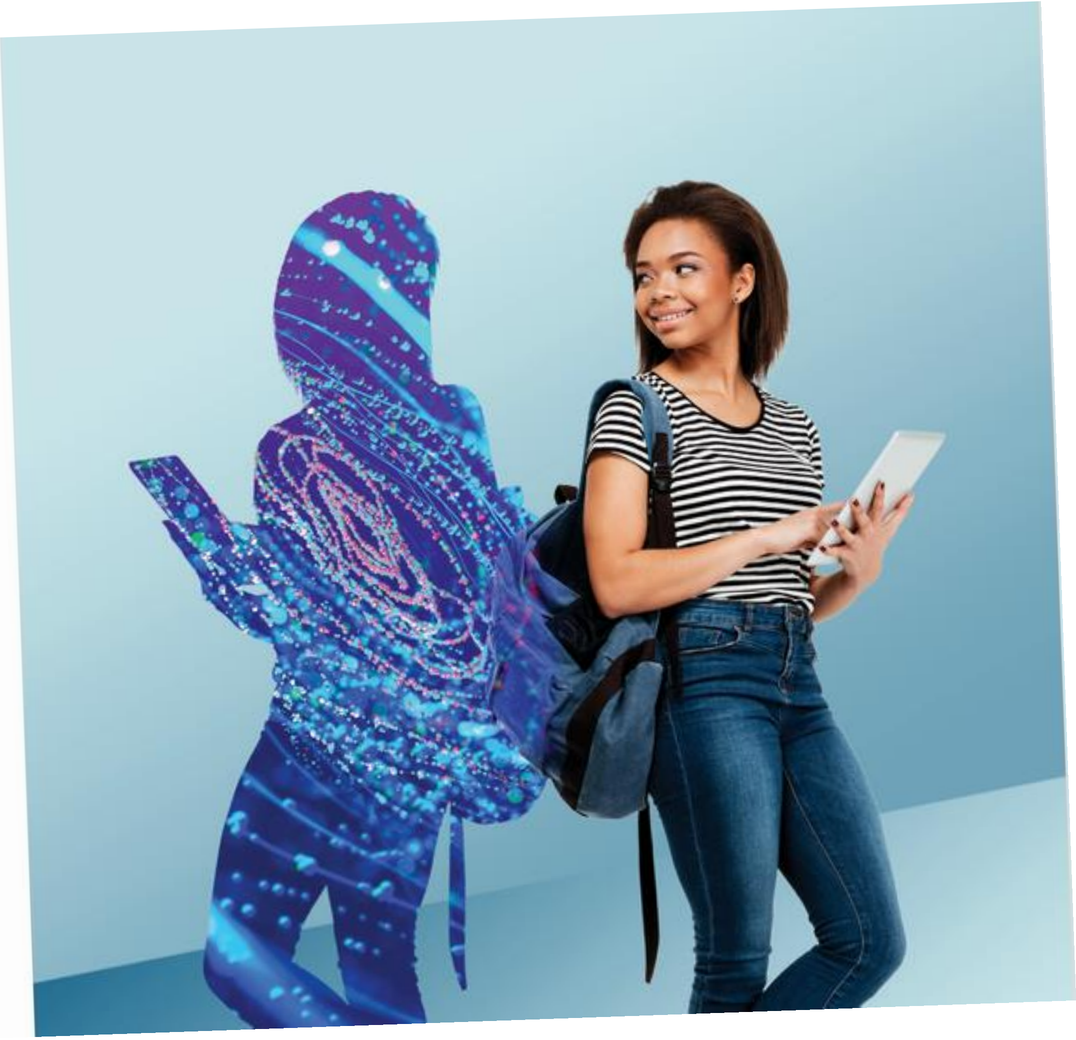
- The time has come to revolutionize



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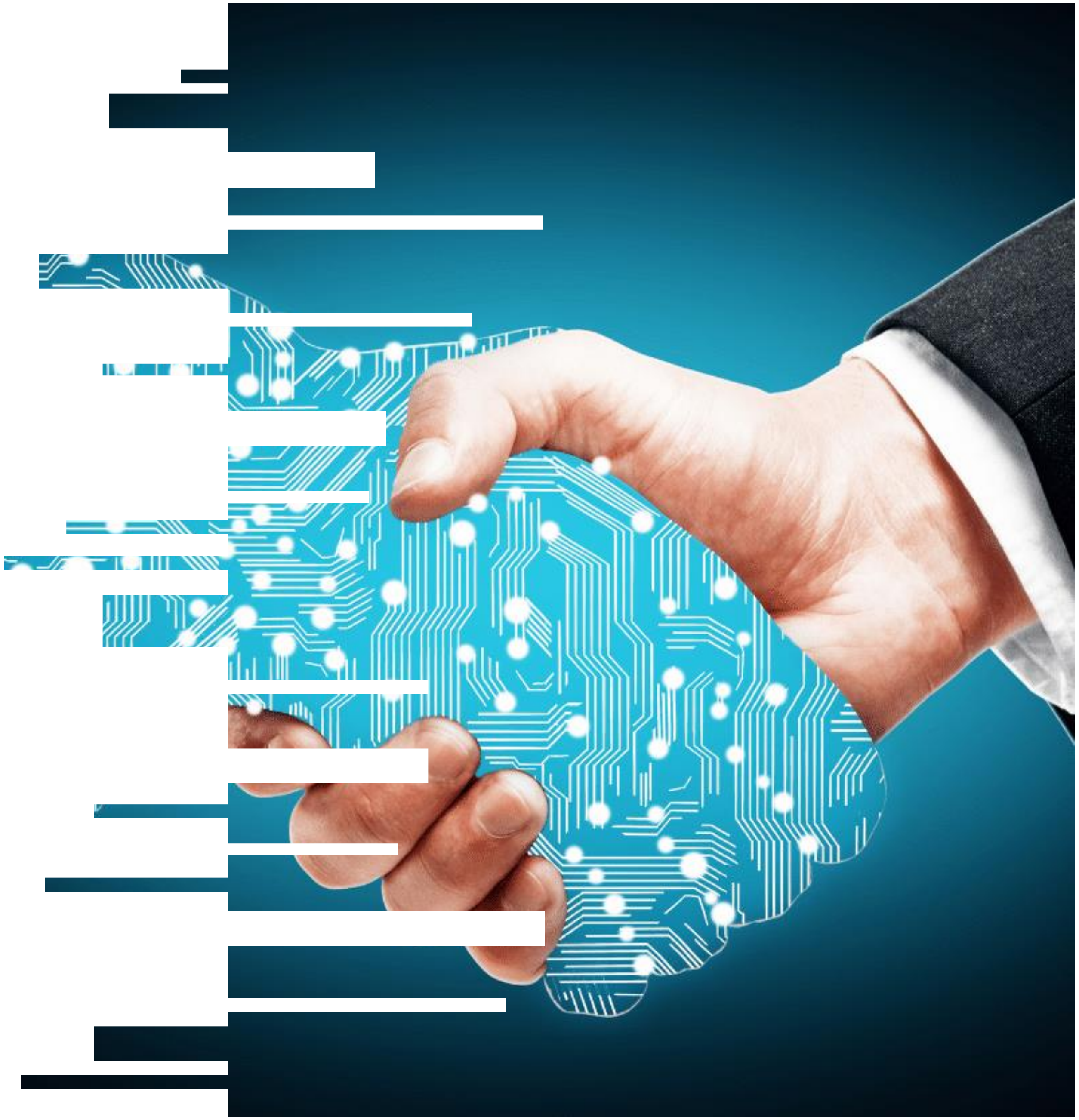
“A **digital twin** is a digital replica of a physical entity, and it is created by combining pieces of data from various sources.”

Furini et al. (2022)



STUDENT

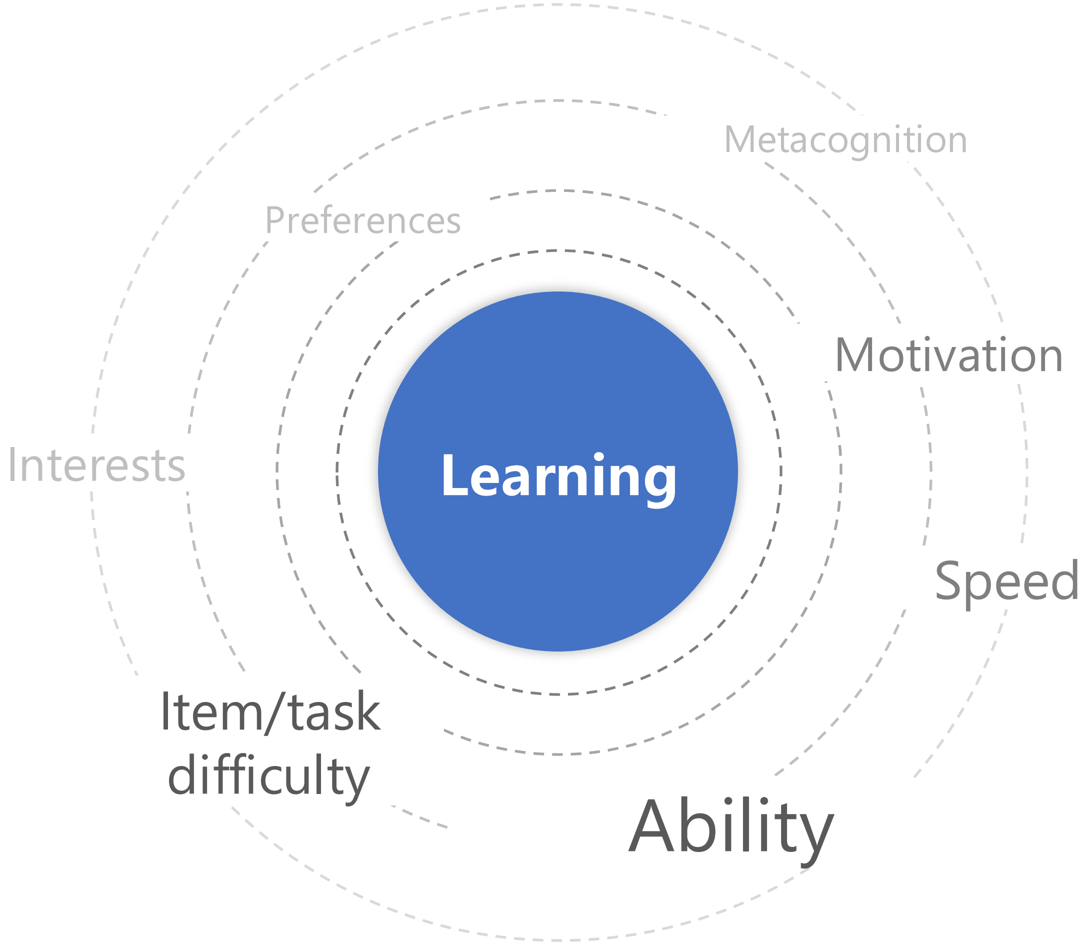
- Academic background
- Study habits
- Subject preferences
- Cognitive characteristics
- Learning behaviors
- Digital educational material consumption

DIGITAL TWIN

- Digital student records
- Online learning activities
- Digital learning behaviors
- Data from digital assessments
- Learner knowledge space
- Interactions with learning materials

Personalization through Adaptivity

Algorithmic Adaptivity



Computerized Adaptive Tests

- In computerized adaptive testing (CAT),
  - Select and administer the best item from the item bank
  - Update the test-taker's provisional ability estimate
  - Select the best item based on the updated ability

- "Limited personalization" because CAT relies only on item parameters and the test-taker's ability.

- What about test-takers' interests, preferences, and meta-cognitive skills?

Gorgun and Bulut
Large-scale Assessments in Education (2023) 11:27
https://doi.org/10.1186/s40536-023-00177-5

Large-scale Assessments in Education

METHODOLOGY **Open Access**

Incorporating test-taking engagement into the item selection algorithm in low-stakes computerized adaptive tests

Guher Gorgun[1*] and Okan Bulut[2]

*Correspondence: gorgun@ualberta.ca

[1] Measurement, Evaluation, and Data Science, Faculty of Education, University of Alberta, 6-110 Education Centre North, 11210 87 Ave NW, Edmonton, AB T6G 2G5, Canada
[2] Centre for Research in Applied Measurement and Evaluation, Faculty of Education, University of Alberta, 6-110 Education Centre North, 11210 87 Ave NW, Edmonton, AB T6G 2G5, Canada

Abstract

In low-stakes assessment settings, students' performance is not only influenced by students' ability level but also their test-taking engagement. In computerized adaptive tests (CATs), disengaged responses (e.g., rapid guesses) that fail to reflect students' true ability levels may lead to the selection of less informative items and thereby contaminate item selection and ability estimation procedures. To date, researchers have developed various approaches to detect and remove disengaged responses after test administration is completed to alleviate the negative impact of low test-taking engagement on test scores. This study proposes an alternative item selection method based on Maximum Fisher Information (MFI) that considers test-taking engagement as a secondary latent trait to select the most optimal items based on both ability and engagement. The results of post-hoc simulation studies indicated that the proposed method could optimize item selection and improve the accuracy of final ability estimates, especially for low-ability students. Overall, the proposed method showed great promise for tailoring CATs based on test-taking engagement. Practitioners are encouraged to consider incorporating engagement into the item selection algorithm to enhance the validity of inferences made from low-stakes CATs.

Keywords: CAT, Low-stakes, Test-taking engagement, Response time, Maximum fisher information

The tacit assumption when administrating an assessment is that examinees will invest maximal effort while attempting the items (AERA et al., 2014; Rios & Soland, 2021). The effort here refers to the individuals' investment of mental exertion to achieve a task (Inzlicht et al., 2018). For example, an examinee who knows how to decode a particular word may fail to do so during a test due to insufficient effort or disengagement (Frederick, 2005). The effort exerted by examinees during a test is usually defined as *test-taking engagement*. Therefore, the response behavior characterized as effortful is referred to as solution or engaged response behavior (e.g., Pastor et al., 2019; Schnipke & Scrams, 2002), whereas the response behavior characterized as non-effortful is known as disen-

https://doi.org/10.1186/s40536-023-00177-5

Algorithmic Adaptivity

Ability

+

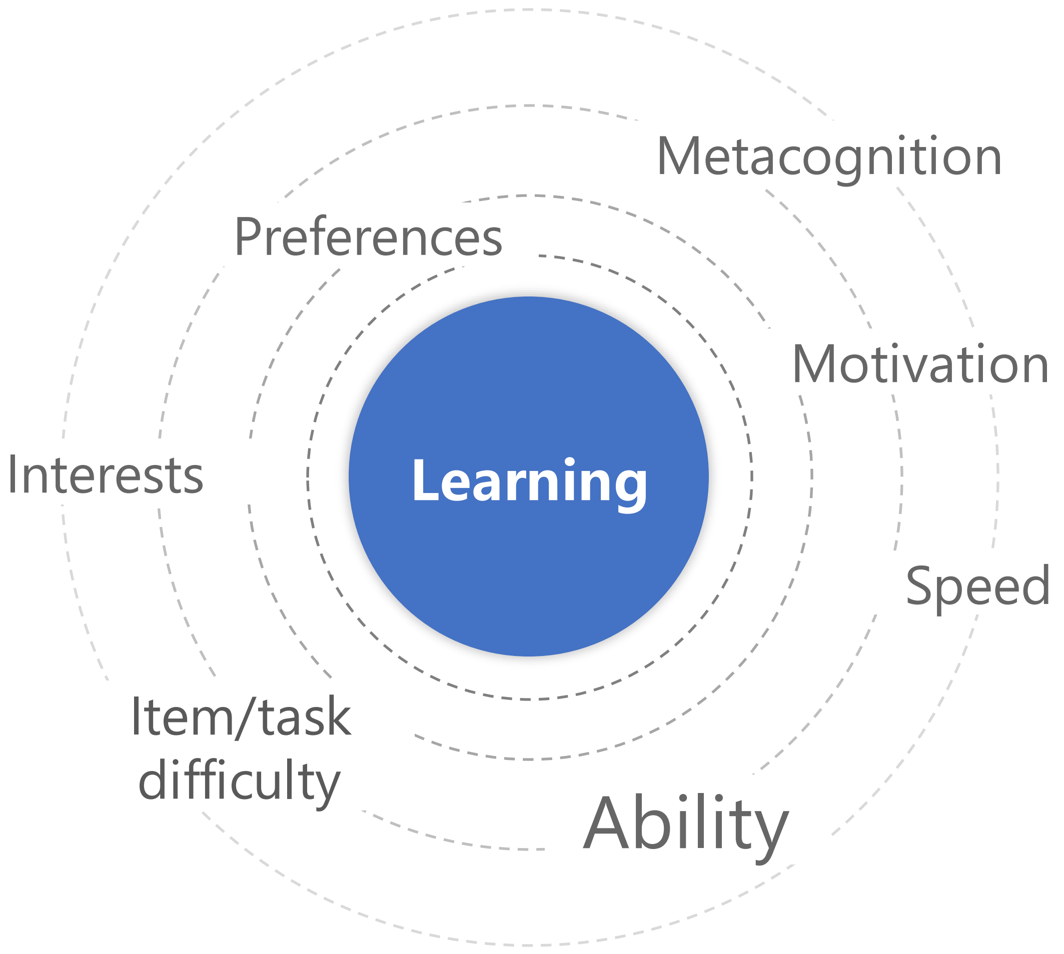
Test-taking engagement

Personalization through Adaptivity

Algorithmic Adaptivity

+

Designed Adaptivity



On the Road to Stronger Adaptivity

"Adaptive" Variables

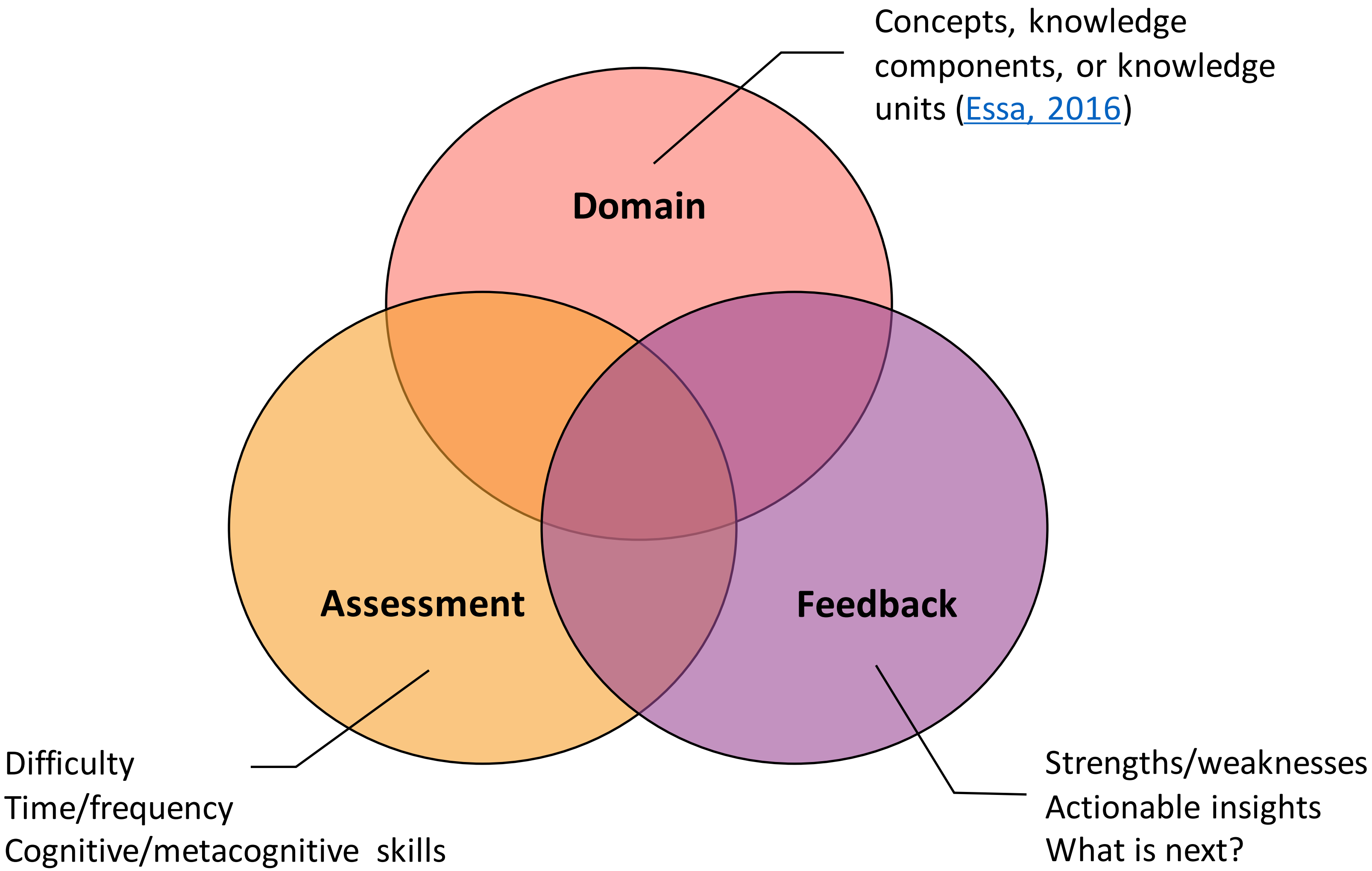
Metacognition

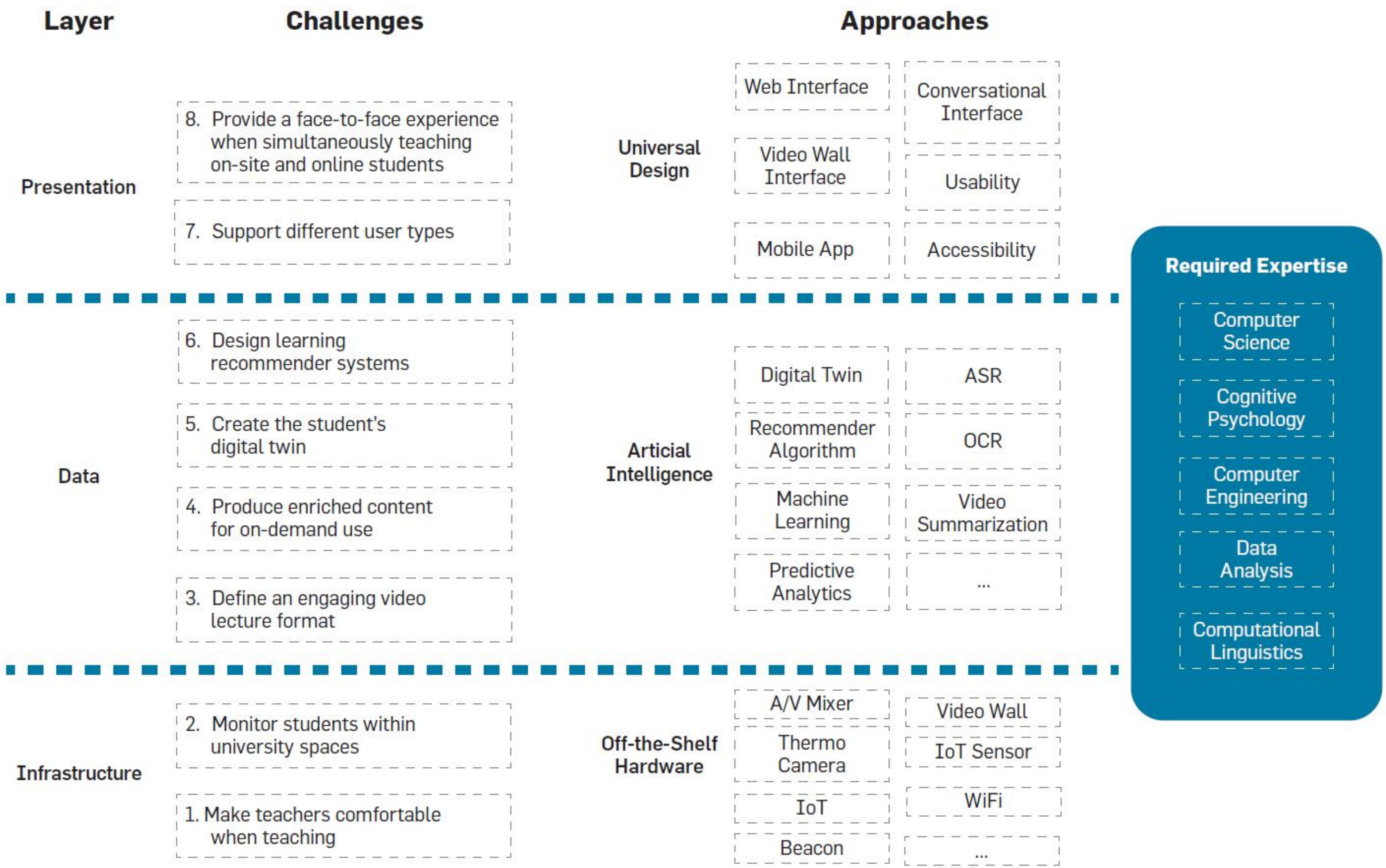
Preferences and interests

Learning progression

Demographic variables

(Triantafillou et al., 2007)





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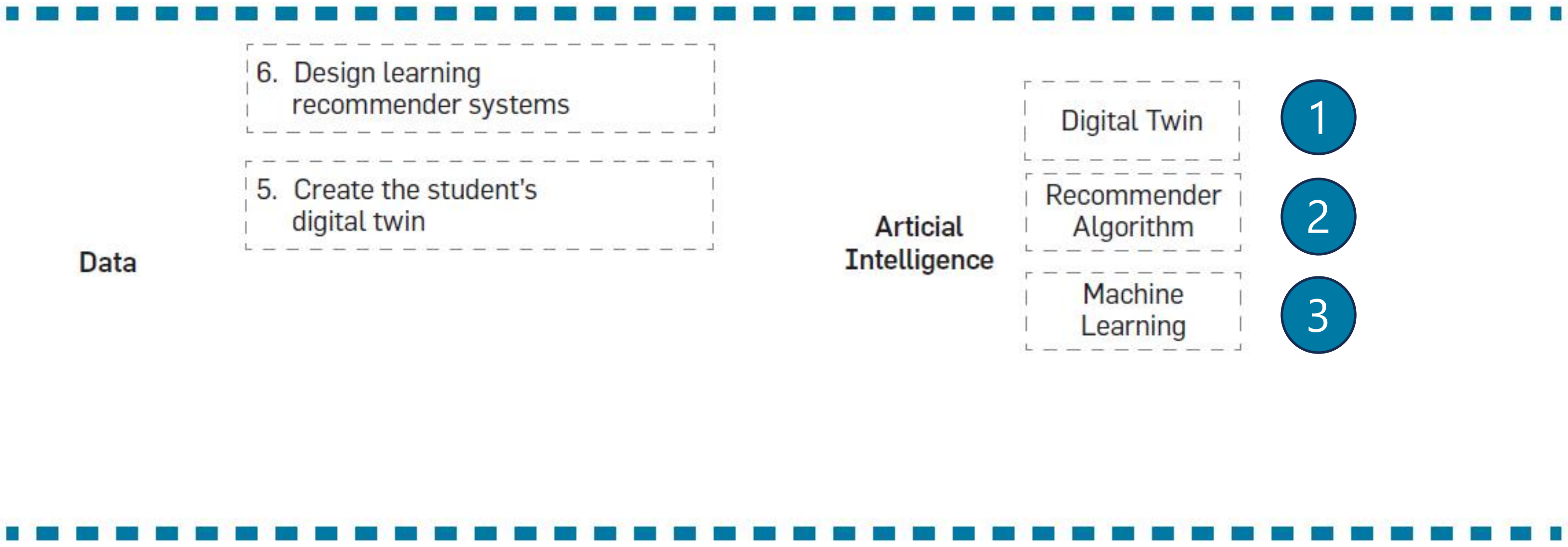

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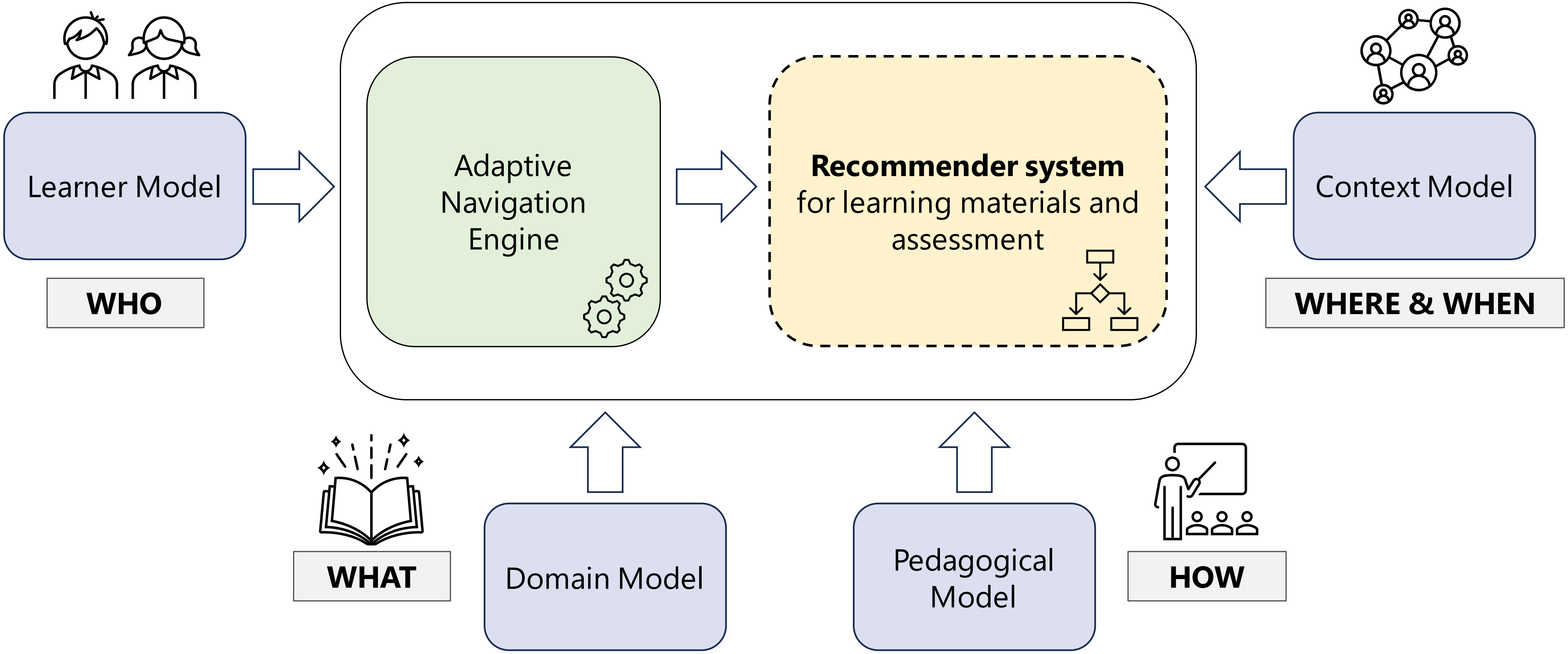
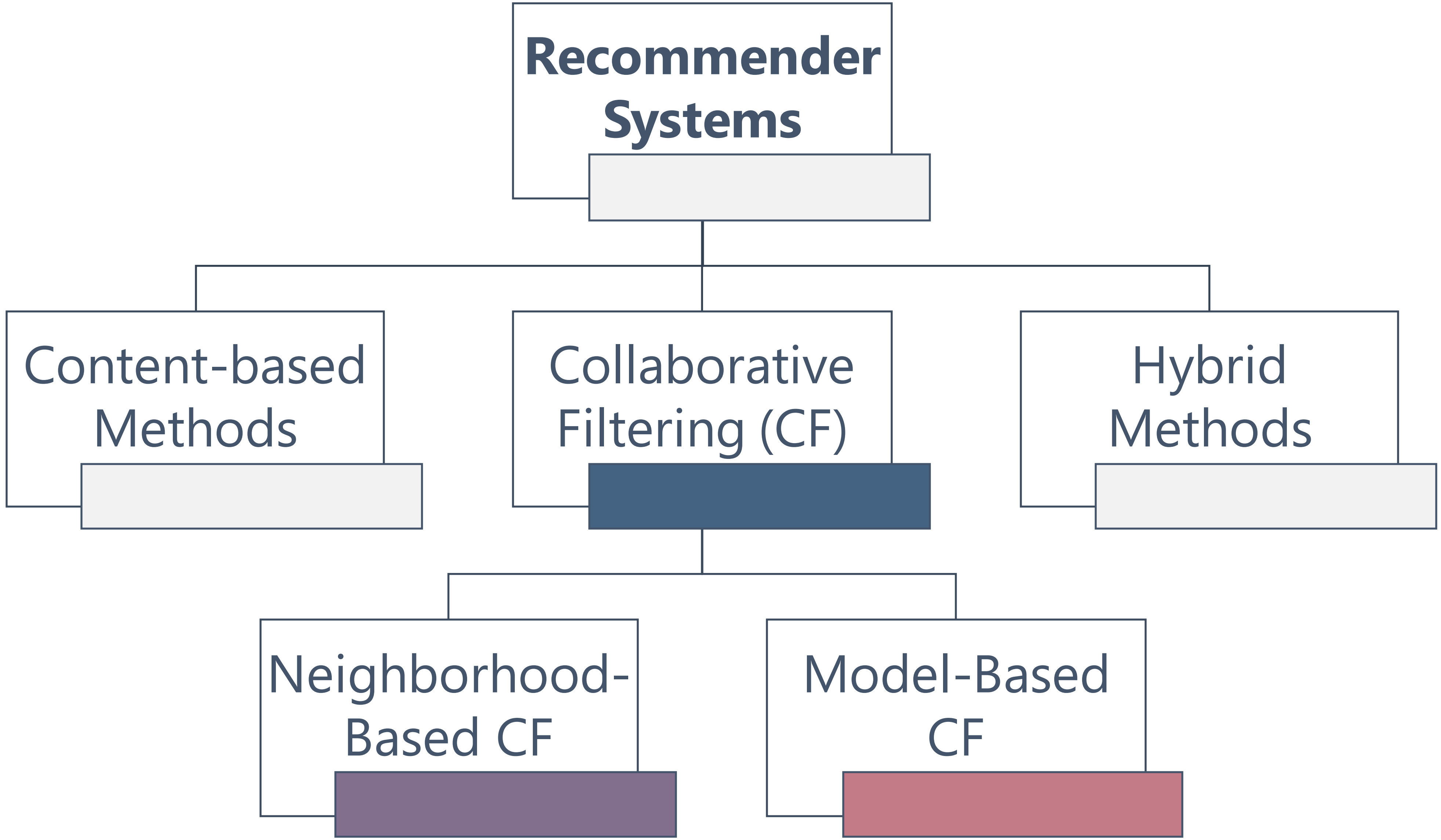
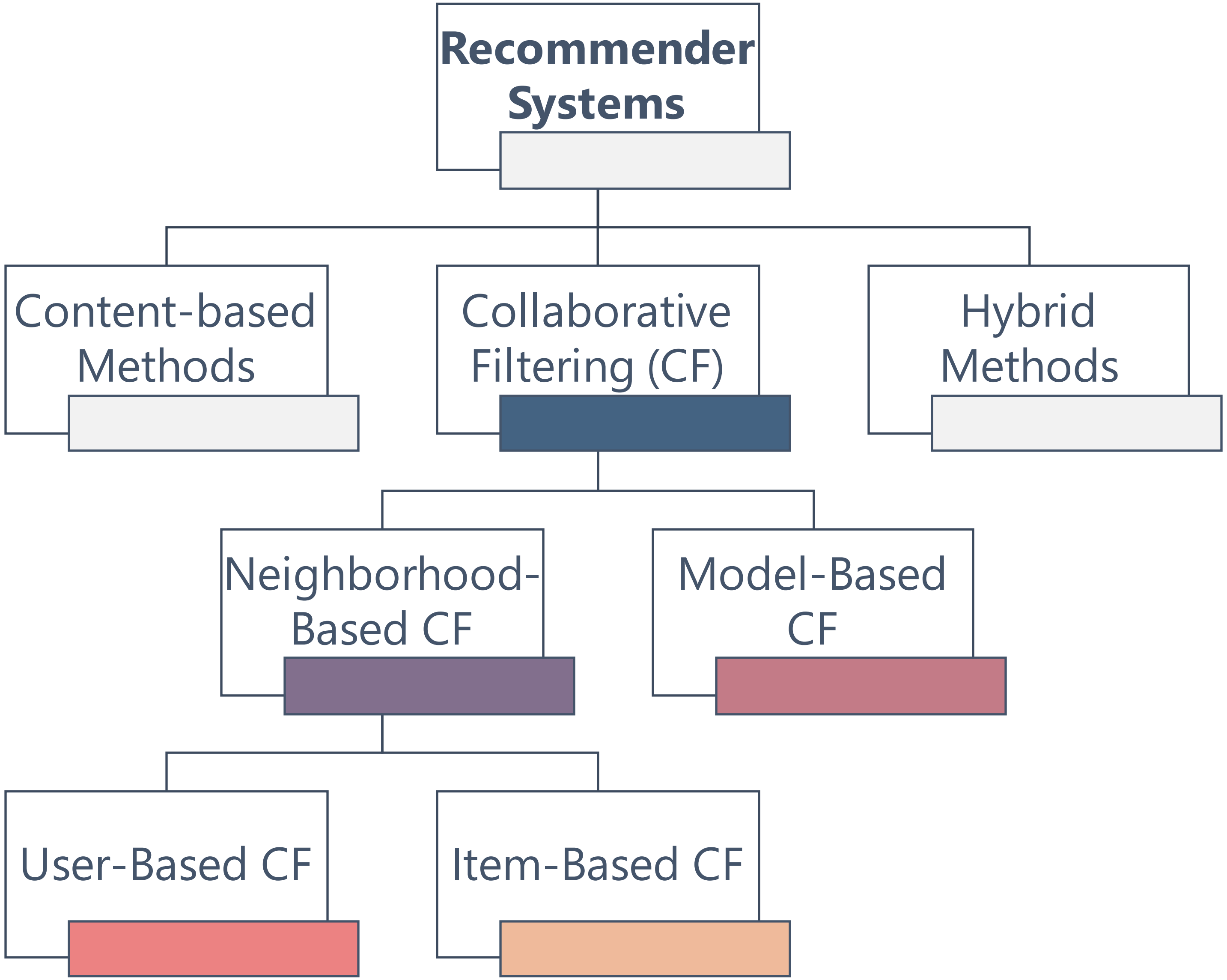
Adaptive Learning Systems



Recommender systems

"… personalized information agents that provide recommendations: suggestions for items likely to be of use to a user" (Burke, 2007)


Recommender Systems
Content-based Methods
Collaborative Filtering (CF)
Hybrid Methods
Neighborhood-Based CF
Model-Based CF


Recommender Systems
Content-based Methods
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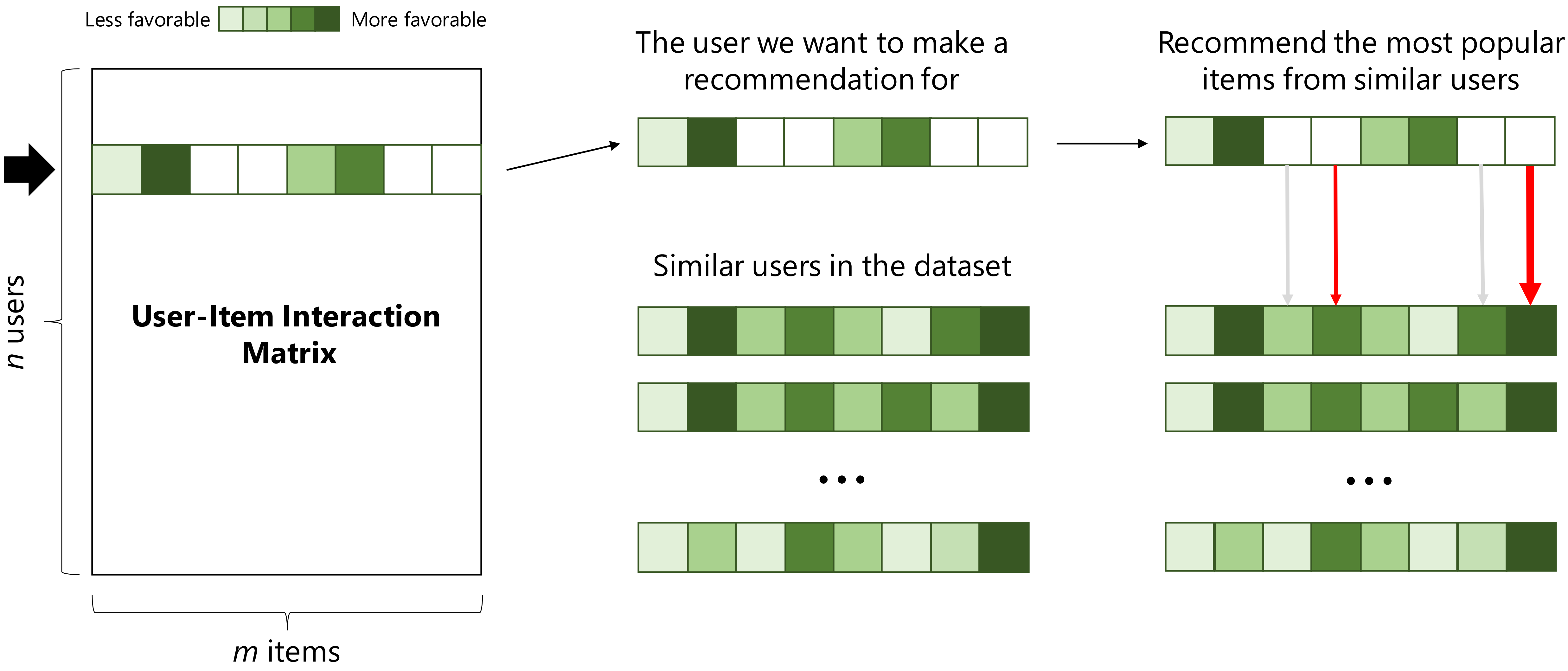
Model-Based CF
User-Based CF
Item-Based CF

User-Based Collaborative Filtering



User-Based Collaborative Filtering

- **user** u_i, $i = 1, \dots, n$
- **item** p_j, $j = 1, \dots, m$
- **rating** r_{ij}

Step 1

$$sim(u_i, u_k) = \cos(u_i, u_k) = \frac{\sum_{j=1}^{m} r_{ij} r_{kj}}{\sqrt{\sum_{j=1}^{m} r_{ij}^2 \sum_{j=1}^{m} r_{kj}^2}}, \text{ or}$$

$$sim(u_i, u_k) = cor(u_i, u_k) = \frac{\sum_{j=1}(r_{ij} - \overline{r_i})(r_{kj} - \overline{r_k})}{\sqrt{\sum_{j=1}(r_{ij} - \overline{r_i})^2 \sum_{j=1}(r_{kj} - \overline{r_k})^2}},$$

Step 2

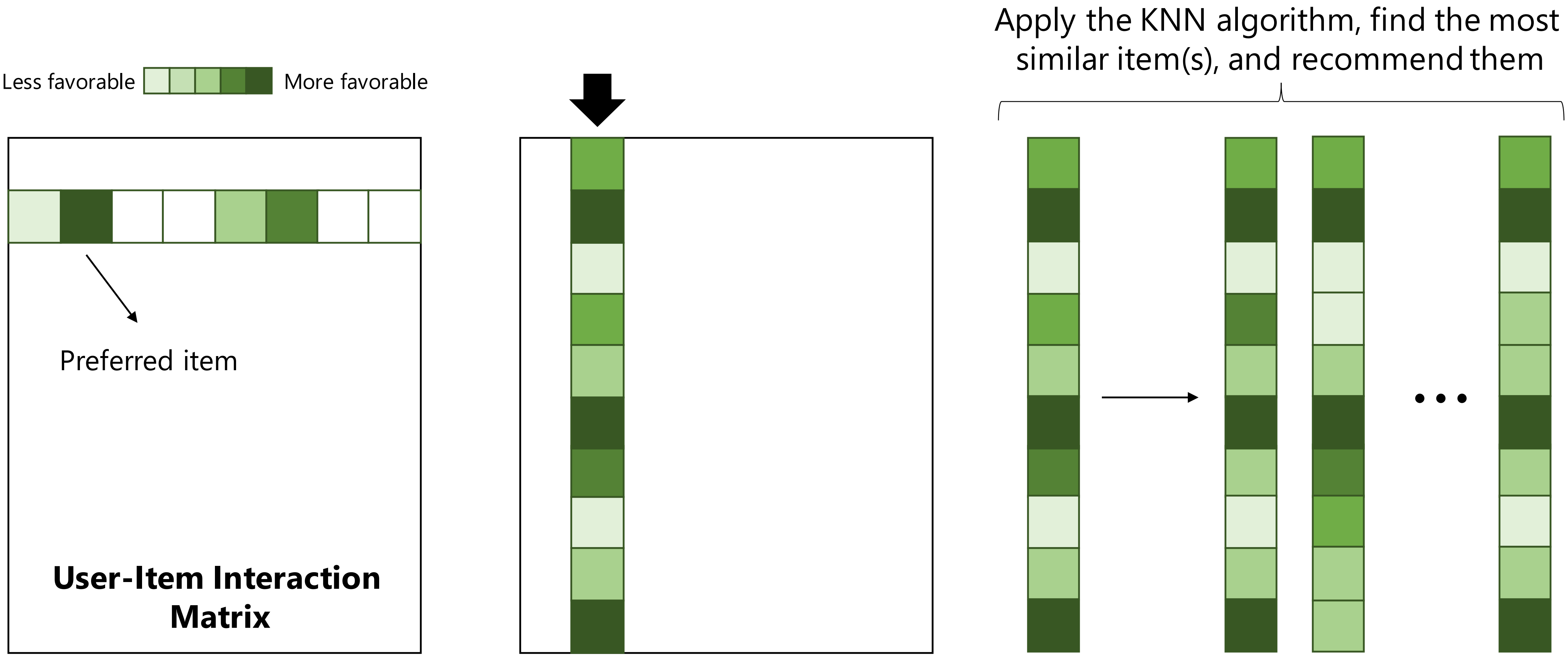
Perform k-nearest neighbors (KNN) to select the best neighbors of the target user (alternatively, use a similarity threshold)

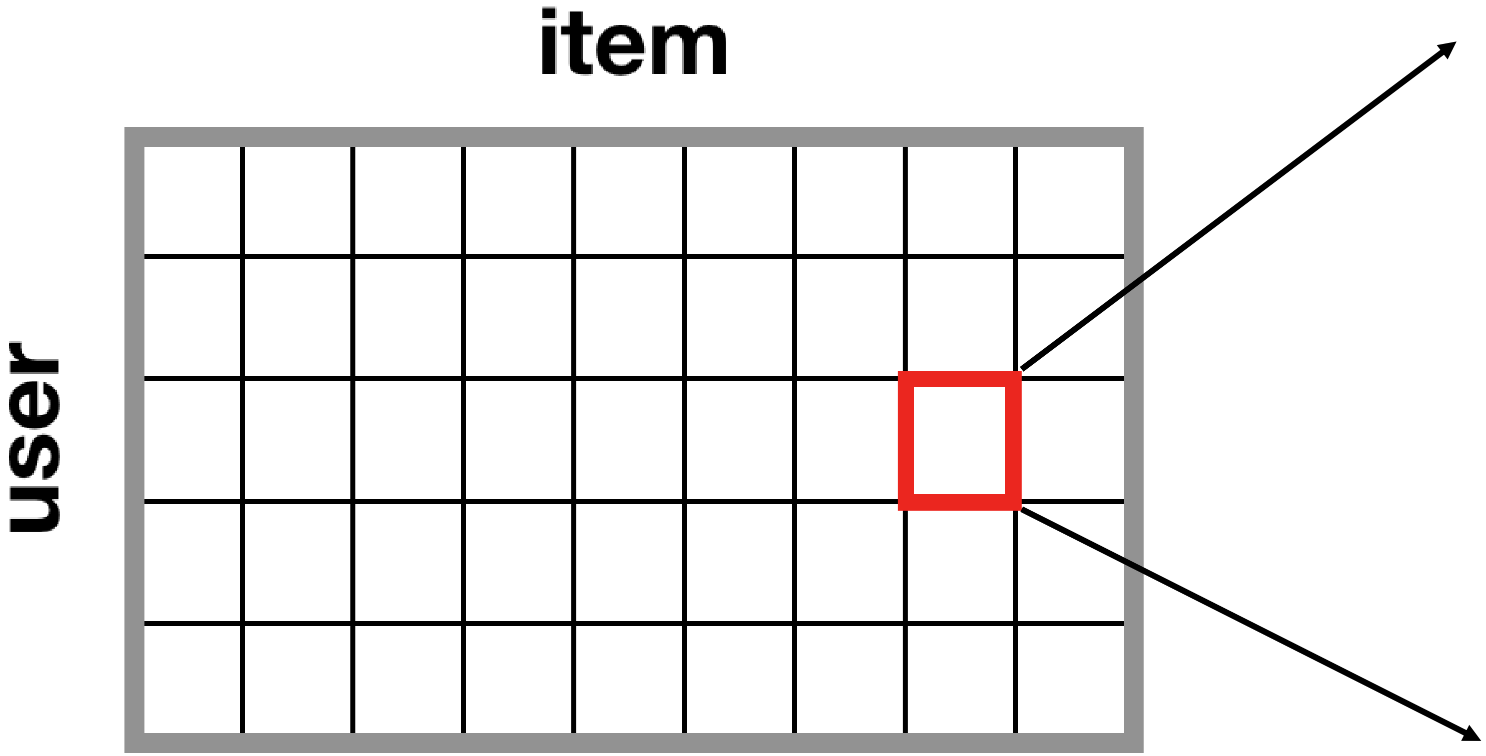
Step 3

Predict an unknown rating for the target user based on the best neighbors identified in Step 2 (i.e., weighted average of ratings from the best neighbors).

$$\hat{r}_{ij} = \frac{\sum_k sim(u_i, u_k) r_{kj}}{\#\, of\, ratings} \quad \text{or} \quad \hat{r}_{ij} = \overline{r_i} + \frac{\sum_k sim(u_i, u_k)(r_{kj} - \overline{r_k})}{\#\, of\, ratings}$$

Item-Based Collaborative Filtering





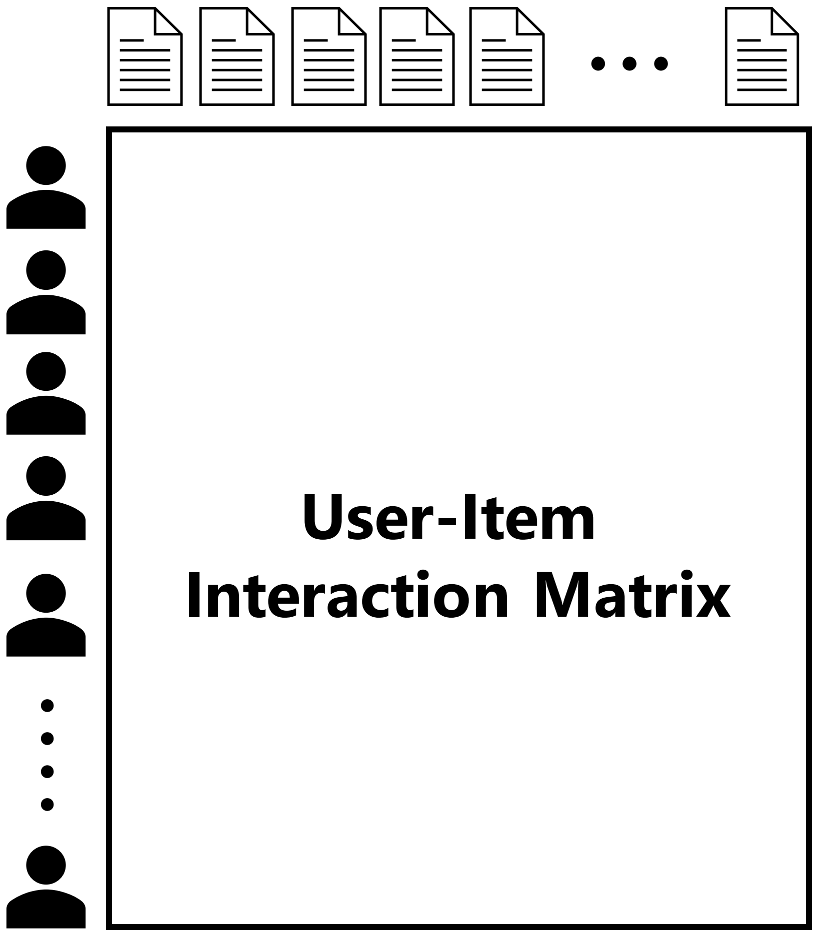
Implicit Feedback

Direct feedback towards an item (e.g., learner ratings on materials)

Explicit Feedback

Indirect behavior towards an item (e.g., browsing or search history, clicks, duration)

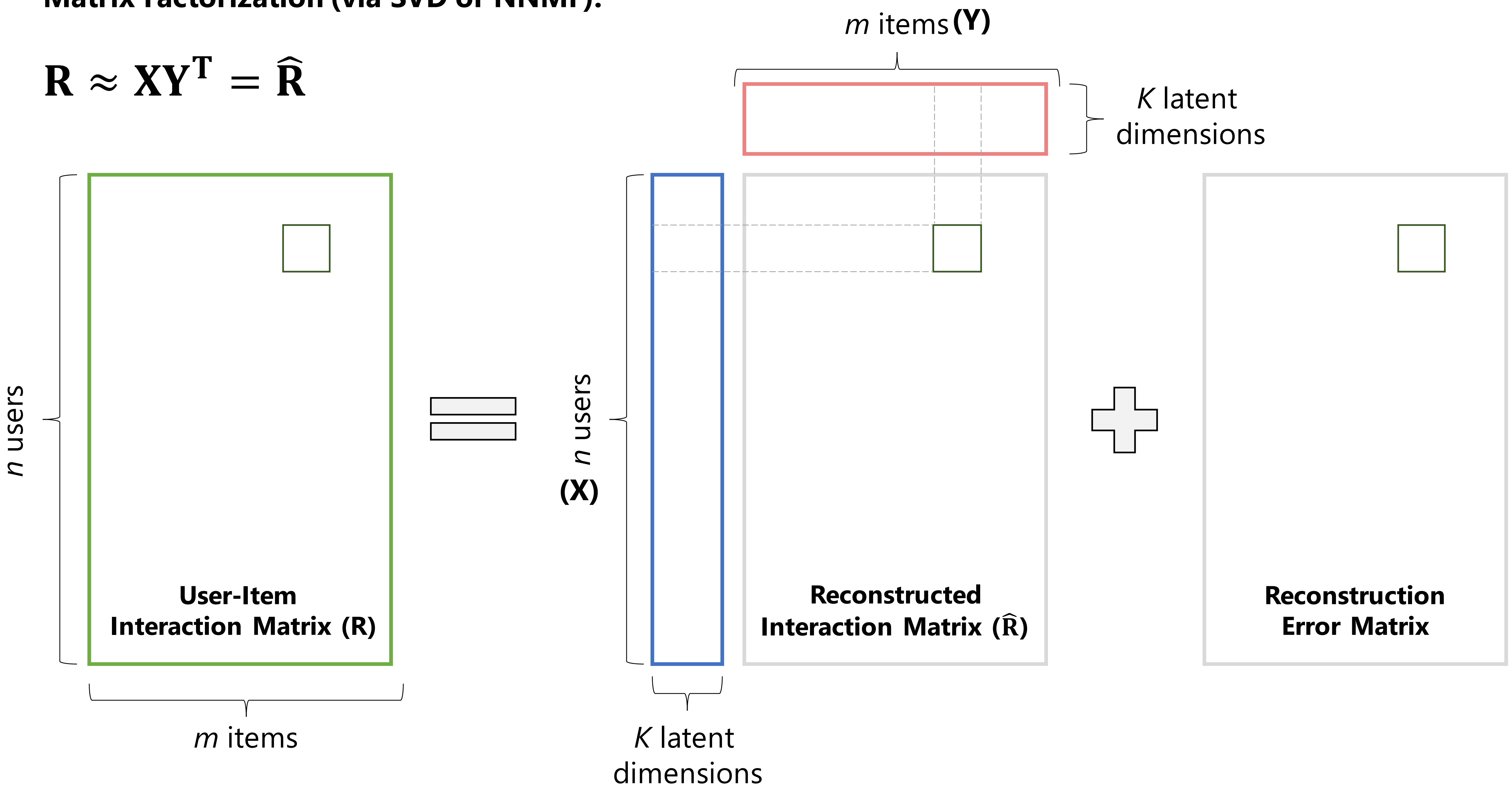
Model-Based Collaborative Filtering

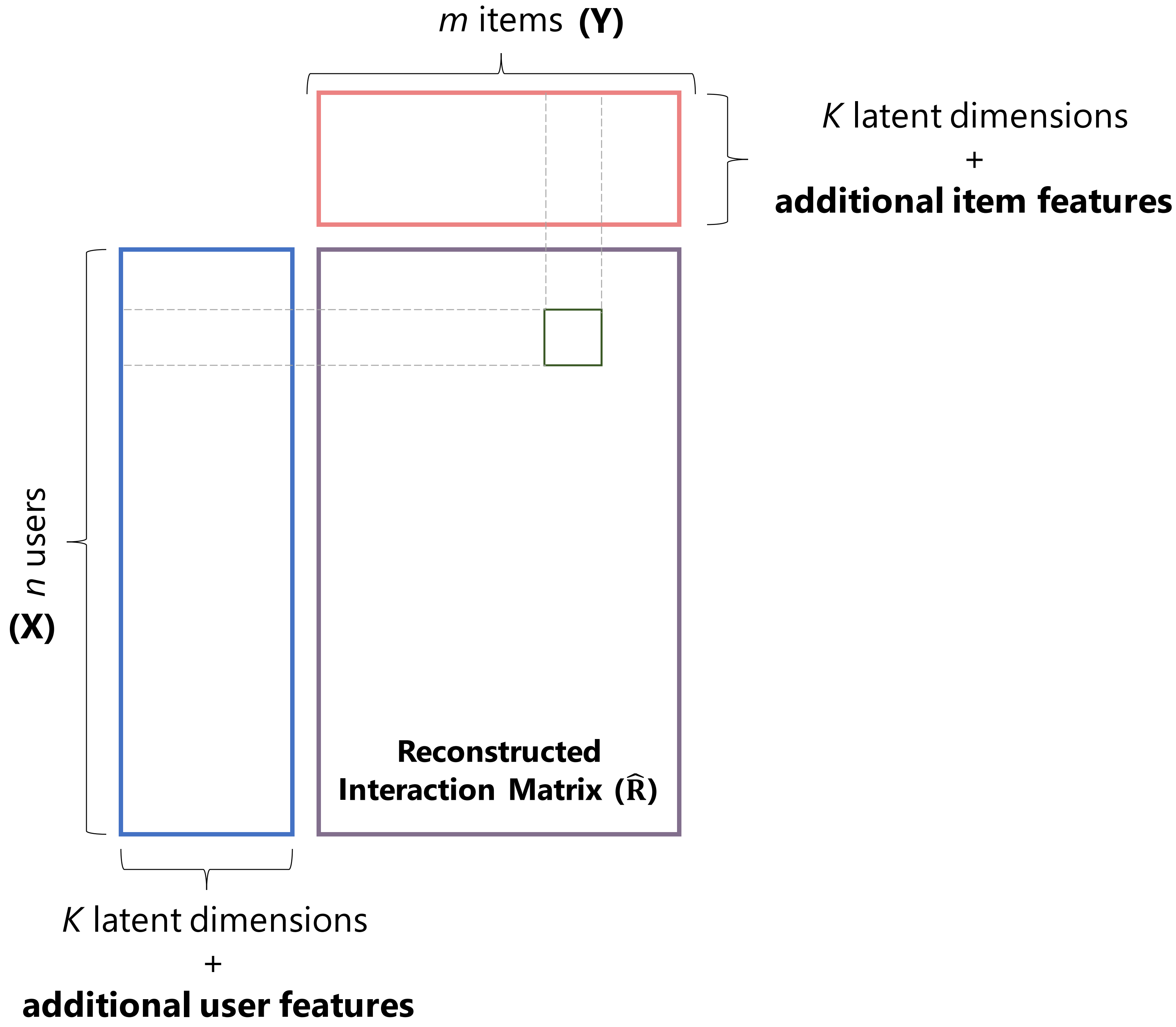


An underlying **generative** model that explains the user-item interactions.

Matrix Factorization (via SVD or NNMF):

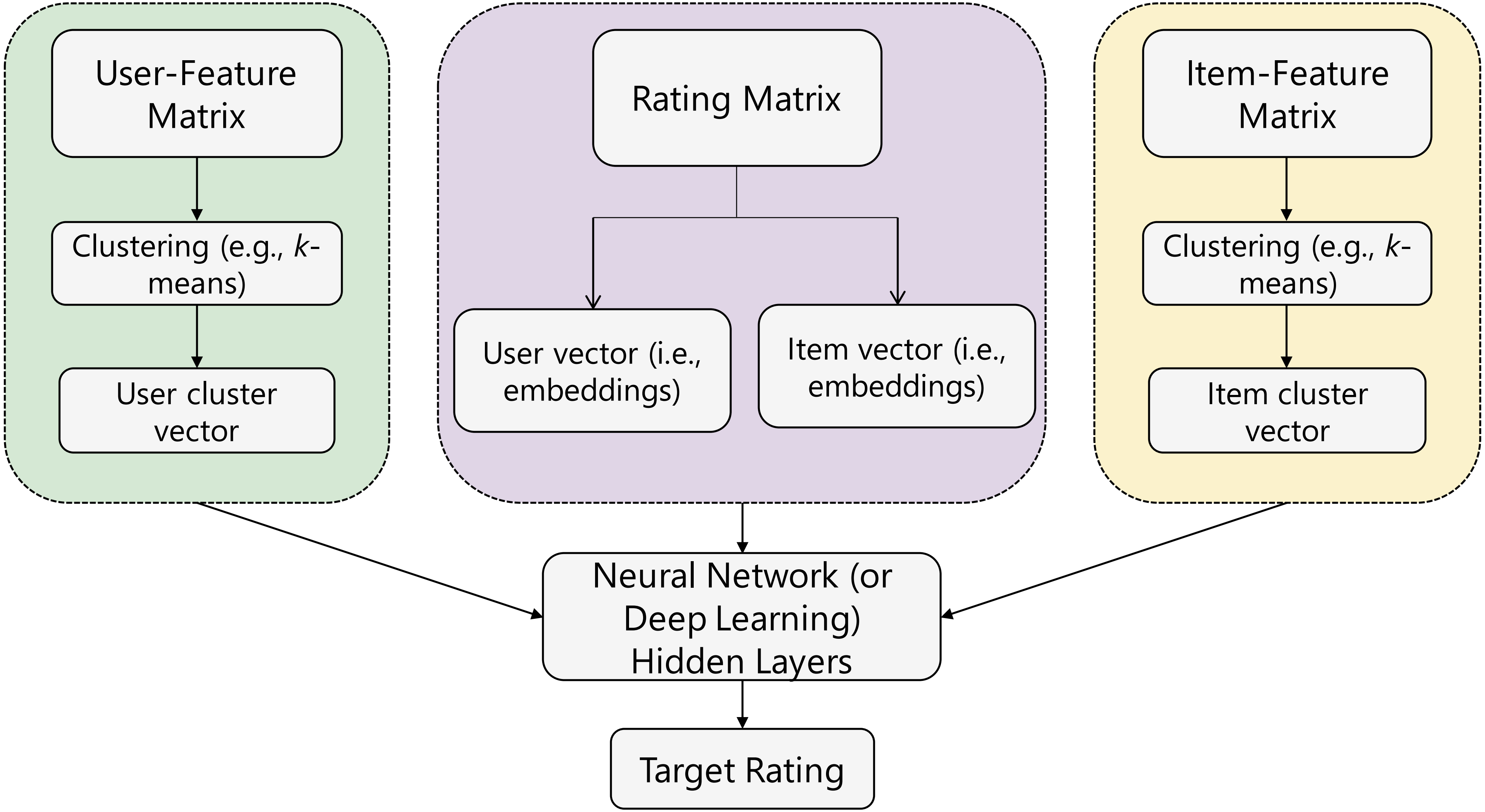
$$\mathbf{R} \approx \mathbf{X}\mathbf{Y}^{\mathrm{T}} = \hat{\mathbf{R}}$$





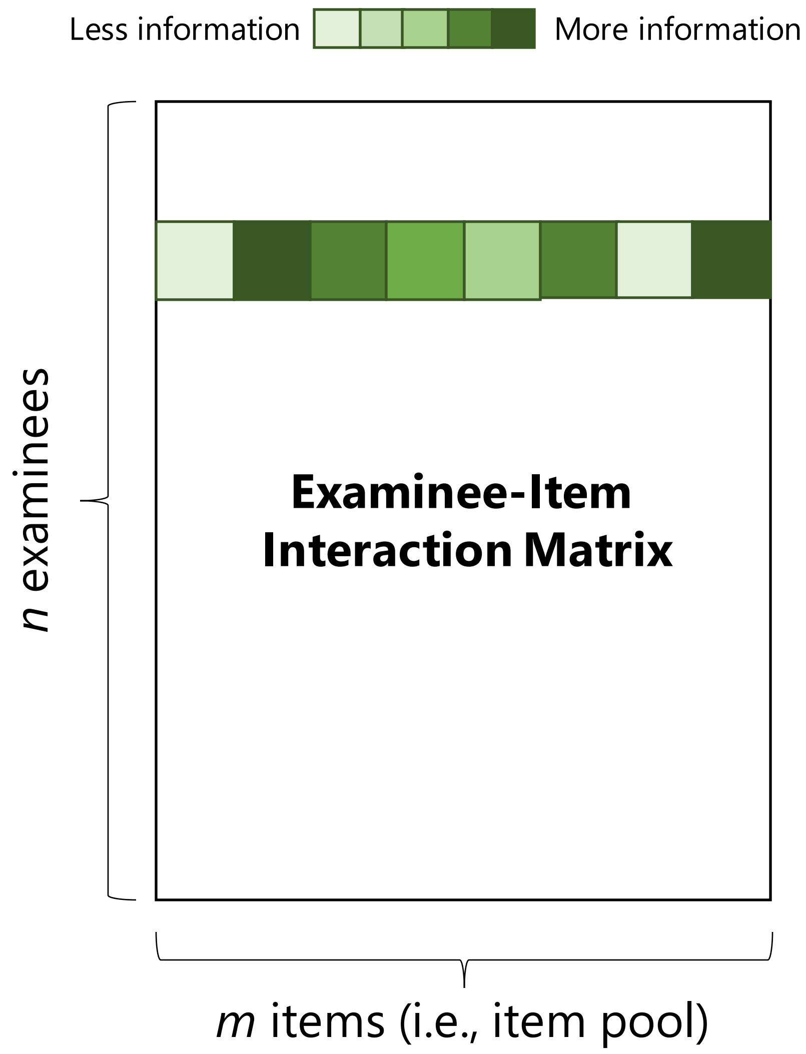
m items (Y)
K latent dimensions
+
additional item features
n users
(X)
Reconstructed
Interaction Matrix ($\hat{R}$)
K latent dimensions
+
additional user features

Hybrid Recommender Systems

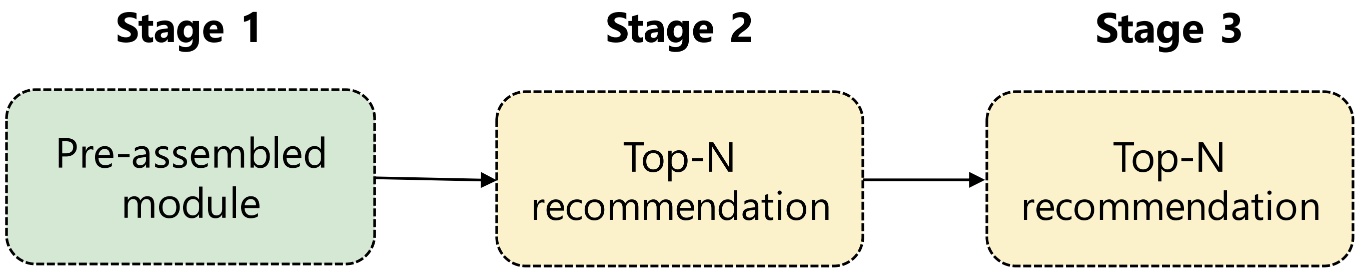


1 Adaptive Item Recommendation

Adaptive Item Recommendation



Item selection with collaborative filtering in on-the-fly multistage adaptive testing (Xiao & Bulut, 2022)



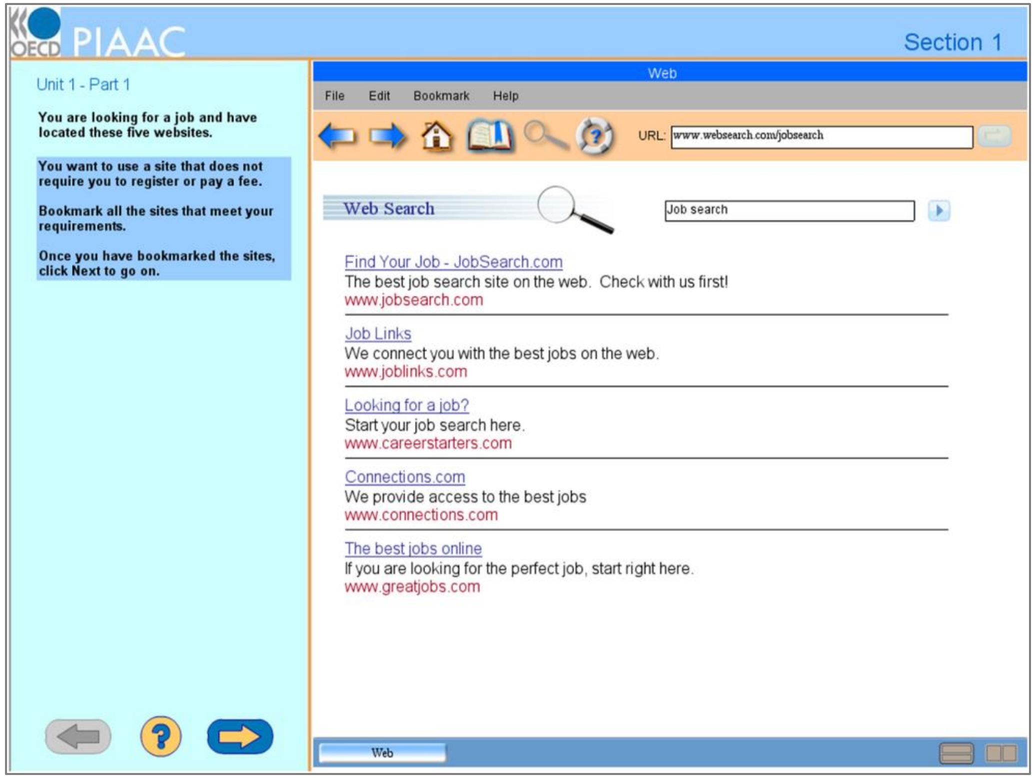
On-the-fly module assembly using:

- User-based CF (UBCF)
- Item-based CF (IBCF)
- Traditional approach (Maximum Fisher information; MFI)

Results:

- Measurement accuracy: UBCF > MFI
- Item bank utilization: IBCF > MFI

Adaptive Item Recommendation with Process Data

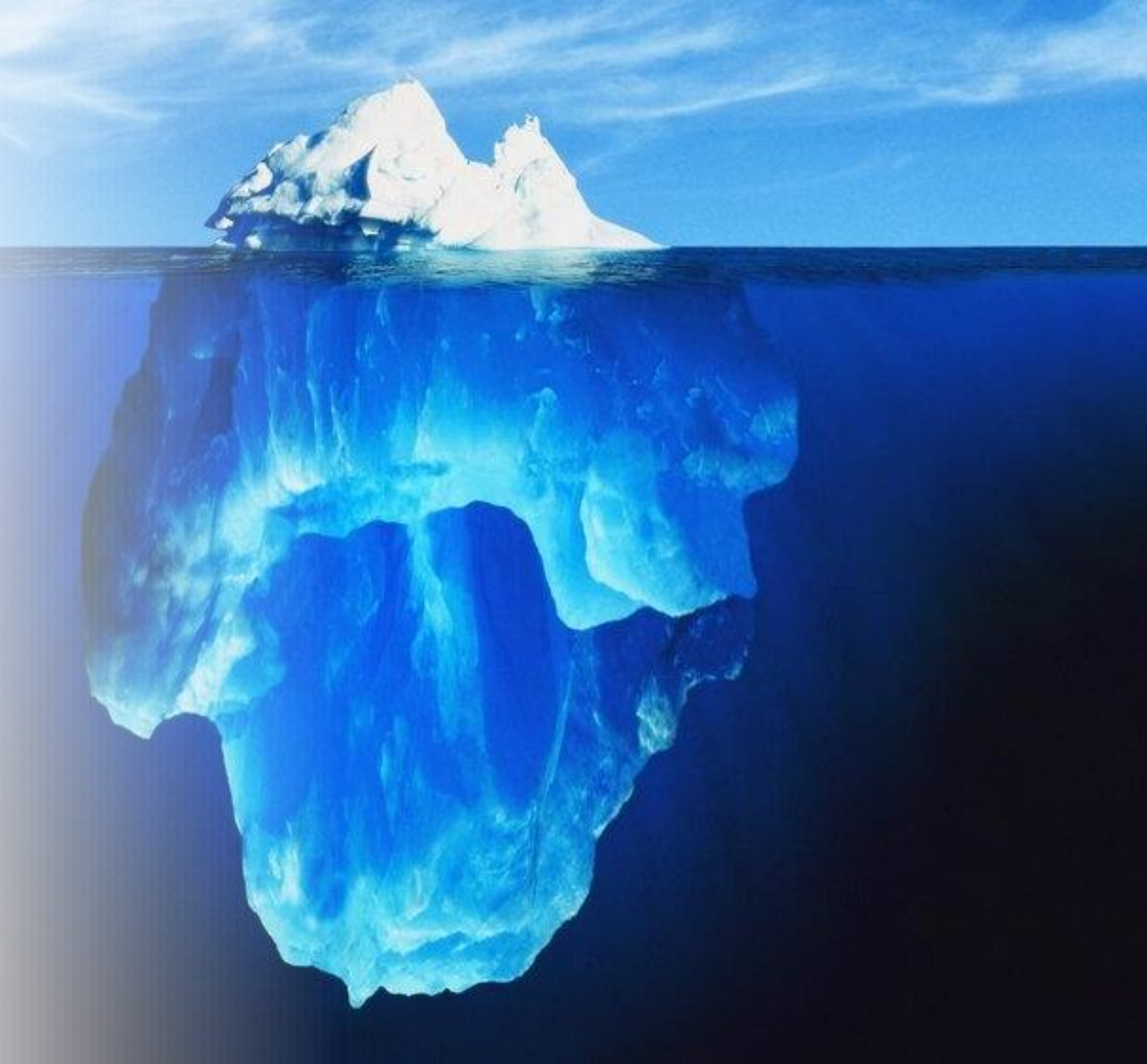


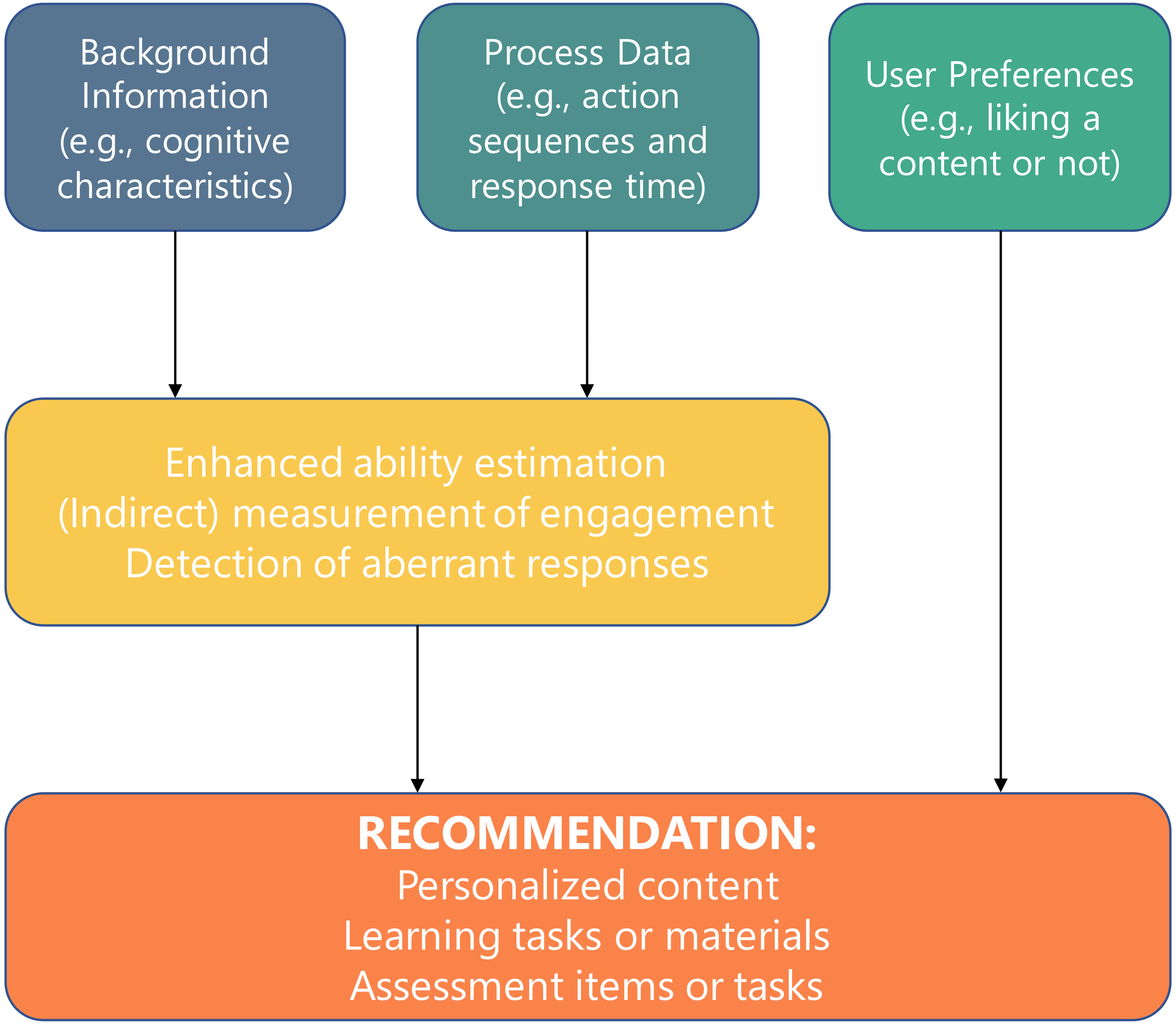
https://www.oecd.org/skills/piaac/

- Individuals may use different strategies when navigating through multiple web search results.
- Foraging patterns (Gao, Cui, Bulut, Zhai, & Chen, 2022)
  - Sequential search of information
  - Continue intensive search until finding a solution
  - Giving up early
- Process data (e.g., actions taken to solve a task) can inform the selection of the optimal item for each learner (Bulut et al., 2023).

Bulut, O., Yildirim-Erbasli, S. N., He, S., Tan, B., & Gao, Y. (2023, April). Adaptive item recommendation using process data and examinee background characteristics. In Q. He & O. Bulut (Chairs), *Empowering process data for data-informed decision-making in measurement*. Paper presented at the annual meeting of the National Council on Measurement in Education, Chicago, IL.

Adaptive
Item
Recommendation





DIGITAL TWIN

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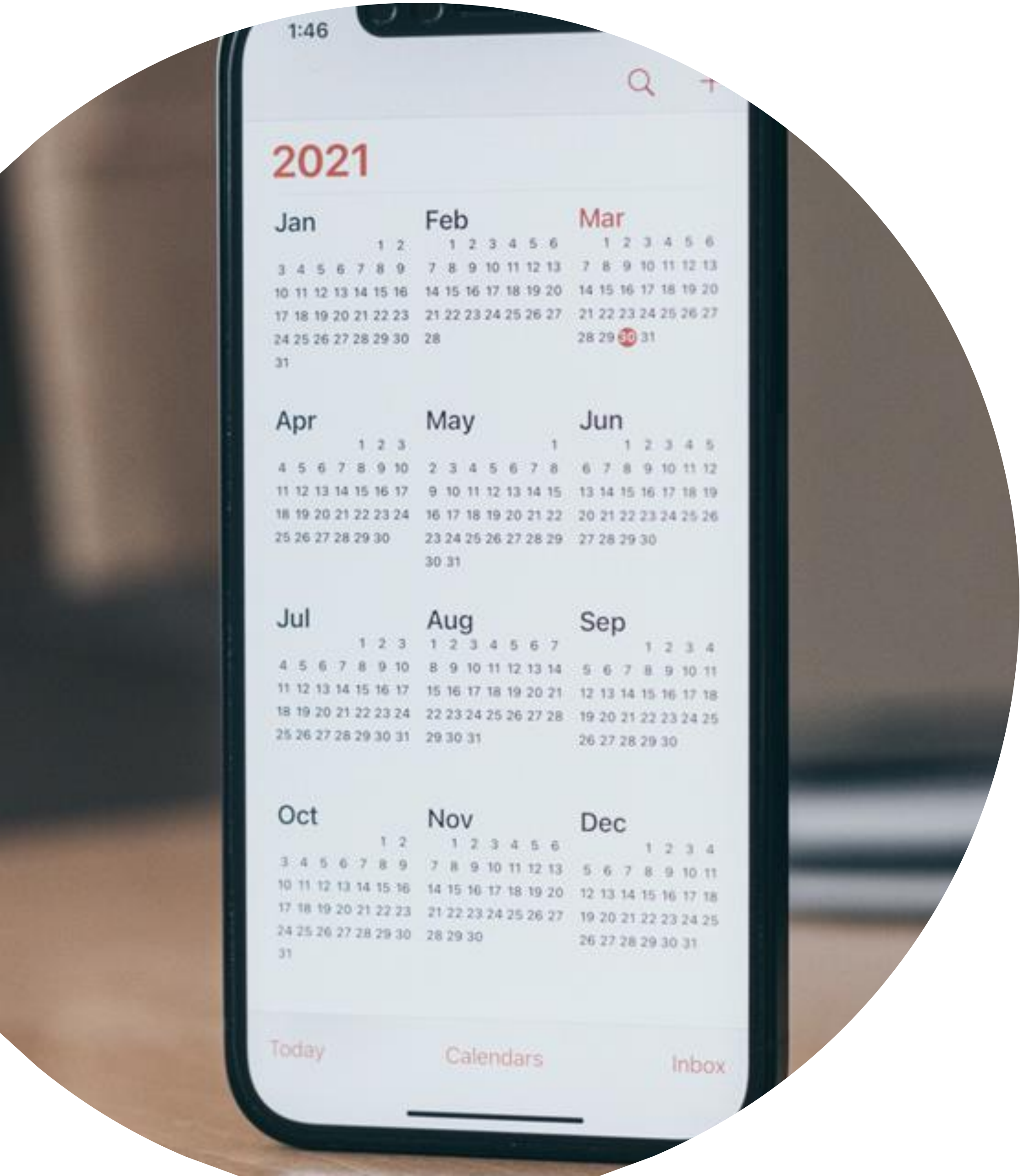
Furini et al. (2022)

2 Personalized Assessment Scheduling



Personalized Assessment Scheduling

What is the optimal test schedule for each student based on their learning progress?

Progress monitoring with Renaissance's Star Reading and Star Math adaptive tests for K-12

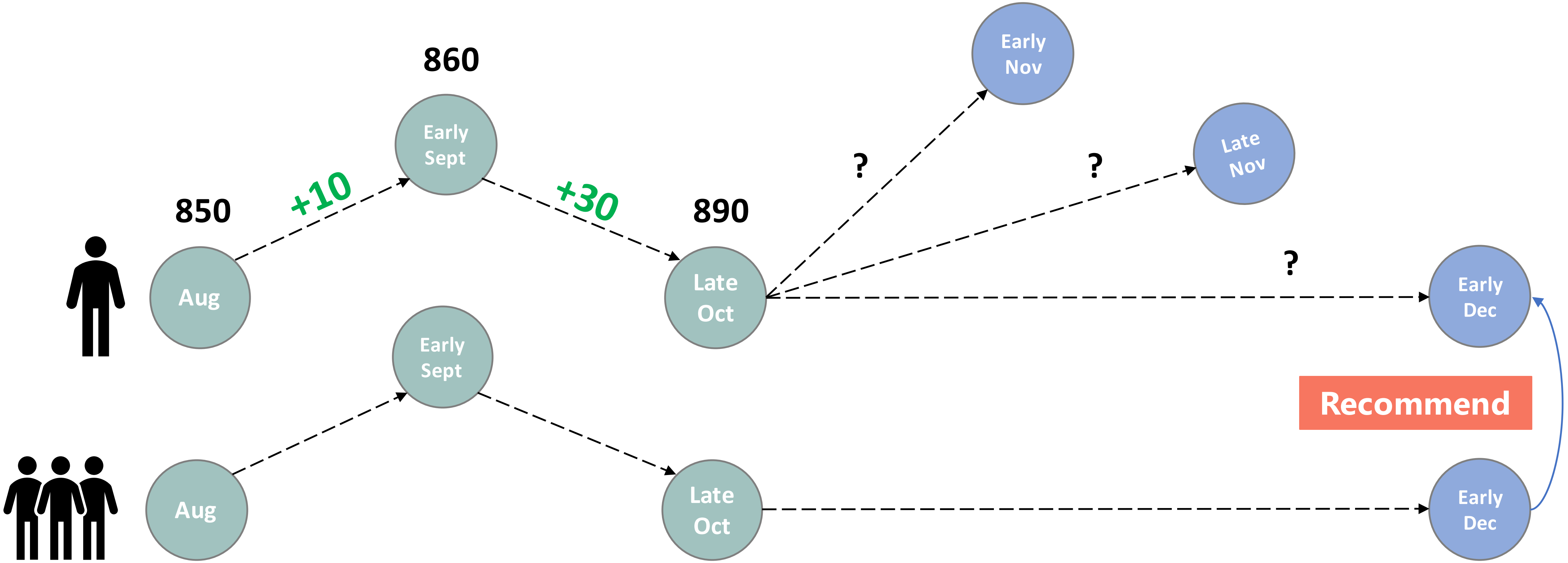
Grade 2 (n = 668,324) and Grade 4 (n = 727,147)

2 to 18 test administrations per student

(Bulut, Shin, & Cormier, 2022; Shin & Bulut, 2022; Bulut, Cormier, & Shin, 2020)

User-Based Collaborative Filtering with Dijkstra's Shortest Path First Algorithm

- **Maximize** the positive and absolute score change between test administrations
- **Minimize** the number of test administrations



- Find similar students (with max score change + fewest test administrations)
- Select the most similar students based on Euclidean distance and recommend their schedule

Standard Practice = Schedules Determined by Teachers **RS** = Recommender System

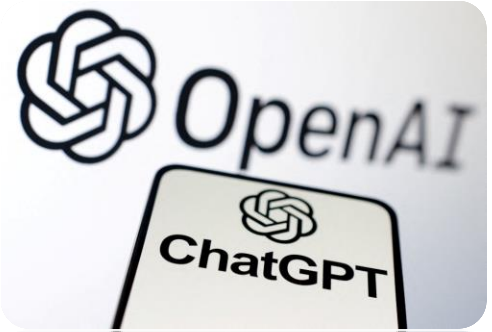
Evaluation Criteria	Grade 2			Grade 4		
	Standard Practice		RS	Standard Practice		RS
Average number of tests administered	5.42	→	**3.51**	5.37	→	**3.84**
Average score change between tests	8.32	→	**12.25**	3.49	→	**4.63**
Range of tests required	(1, 18)	→	(1, 5)	(1, 17)	→	(1, 6)
Non-recommendable cases	-		0.05%	-		0.10%

3

Conversation-Based Assessment

ANTHROPIC CLAUDE 2

GOOGLE BARD



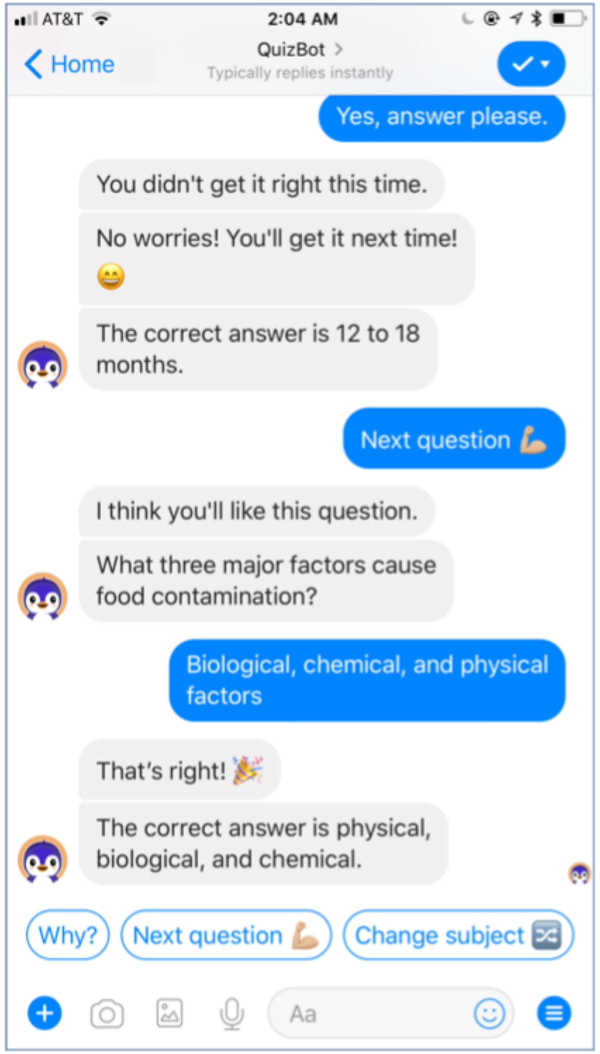
LLaMA by Meta

Bing

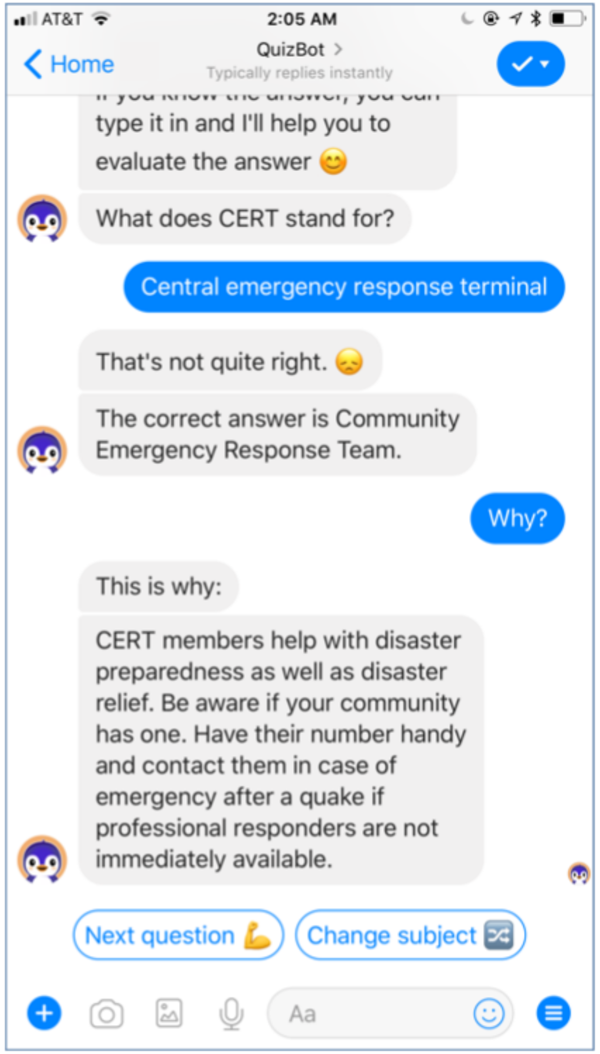
QuizBot (Ruan et al., 2019)

Conversation-Based Assessment

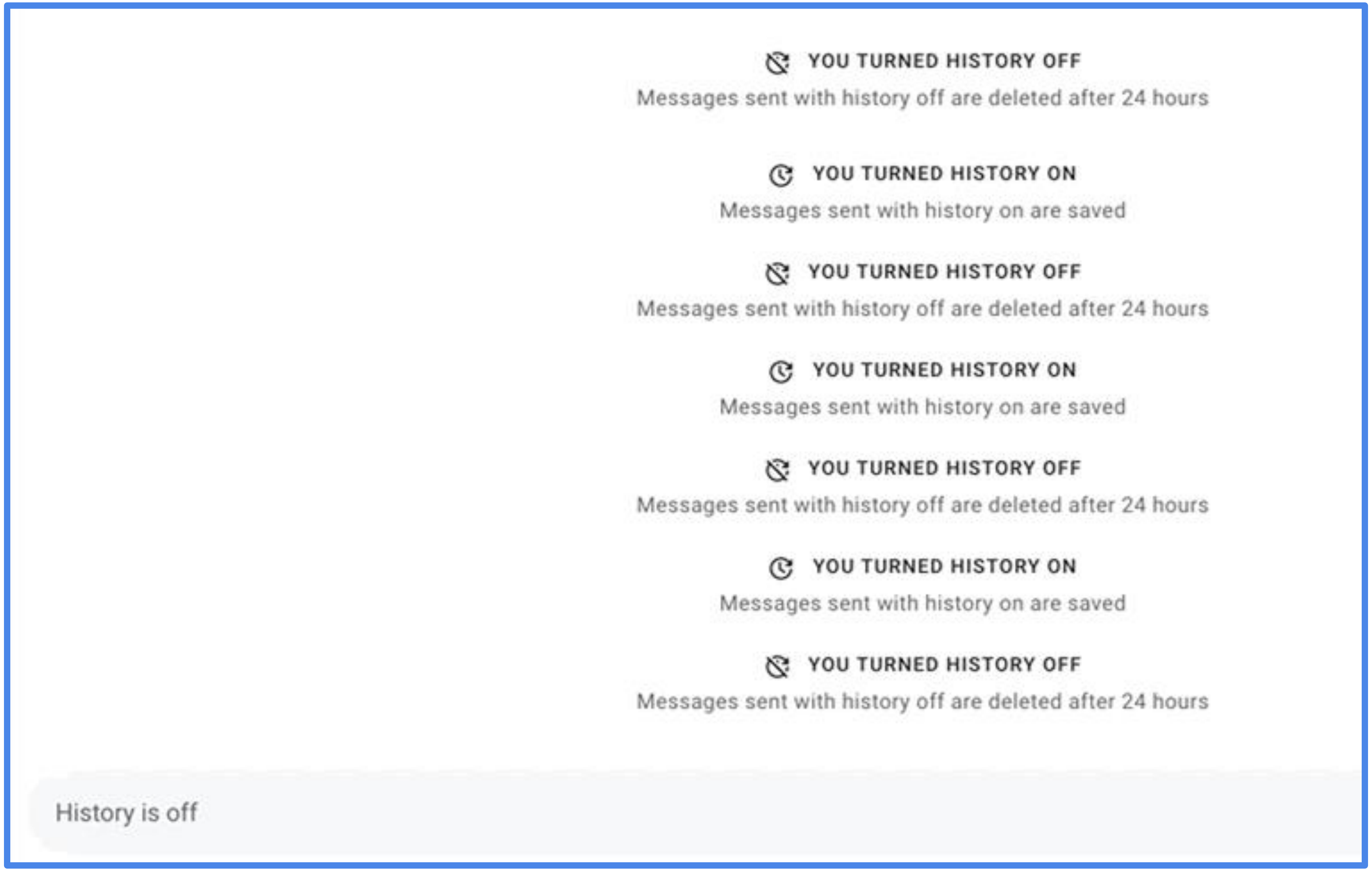
- Conversational AI
- Automatic feedback for learners
- Option to ask for hints or explanations



Feedback after a **wrong** answer



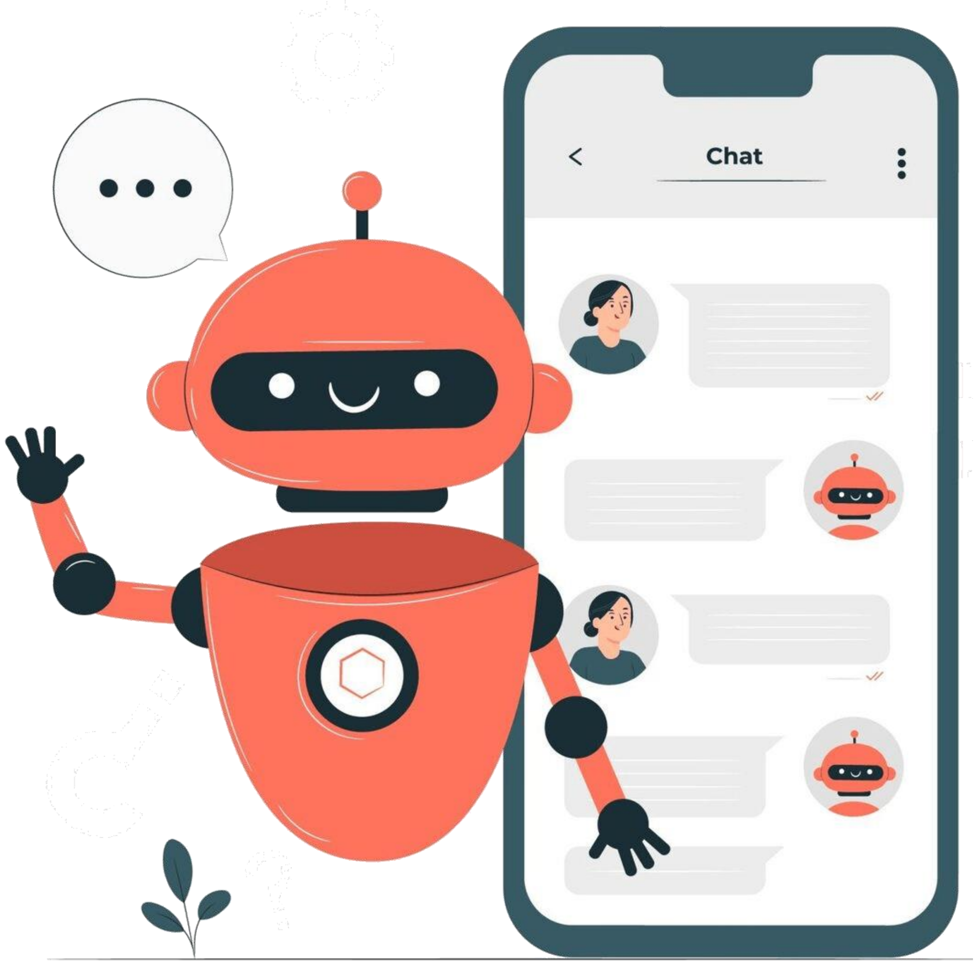
Feedback after a **correct** answer



Yildirim-Erbasli, S. N., & Bulut, O. (2023). Conversation-based assessment: A novel approach to boosting test-taking effort in digital formative assessment. *Computers & Education: Artificial Intelligence, 4*, 100135. doi:10.1016/j.caeai.2023.100135

Self-Directed PD for Teachers

- Ongoing project funded by the Social Sciences and Humanities Research Council (SSHRC) in Canada
- Professional development for pre-service and early-career teachers
- Conversational AI
    - Acting like a student or a parent
    - Real-life decision-making situations
    - Automated feedback



Concluding Remarks

- With large volumes of learner data, personalized learning has turned from myth to reality.
- Amalgamation of algorithmic and designed adaptivity is necessary.
- There are still many unknown aspects of personalization.
  - What is the impact of personalization on learner experience?
  - How much choice is too much?

Future Research

- Augmented and virtual reality combined with large language models

- Generative AI for students with learning disabilities (grant submitted)
    - Support
    - Motivation & encouragement

- Fairness of AI systems for personalized learning
    - Does personalization lead to any fairness problems?
    - How to de-bias AI

Images created with DALL-E 2

Thank You!