Transparent and Controllable Adaptive Systems in Education

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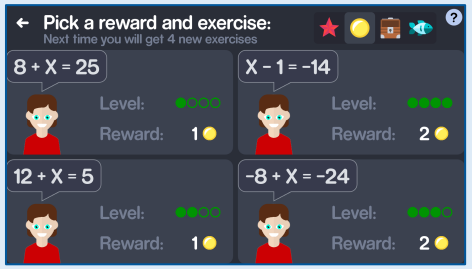
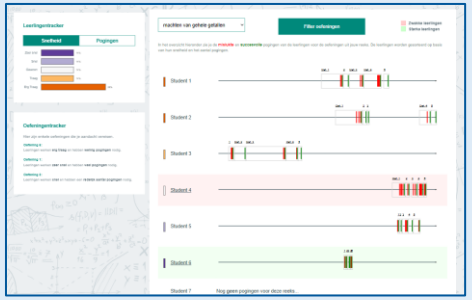
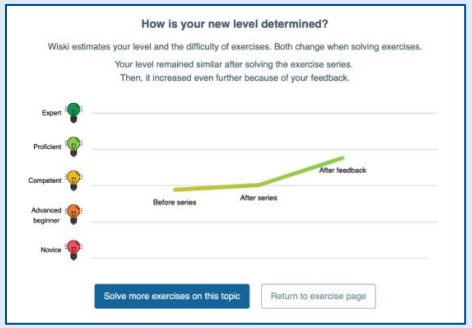
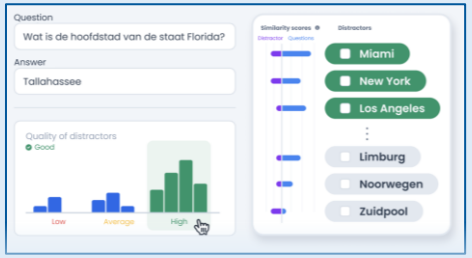
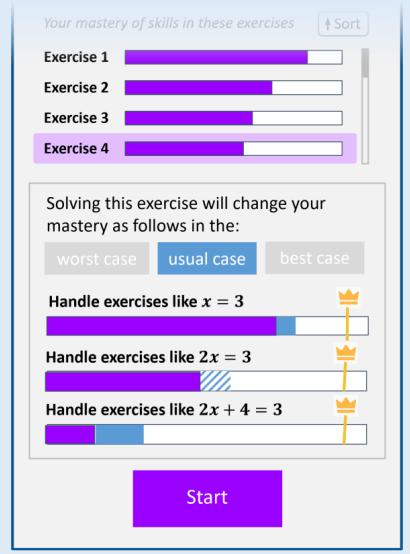
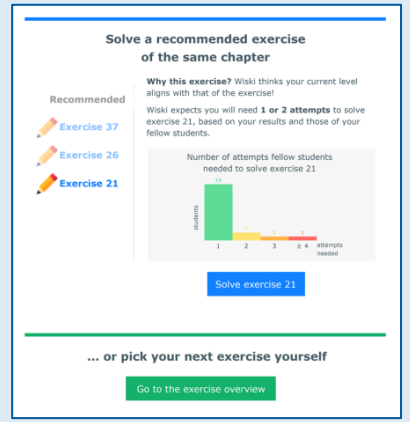


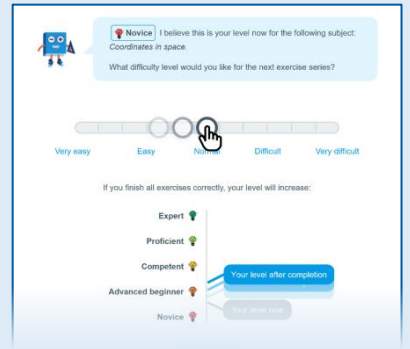












Lecture 1 Introduction
Lecture 2 User Modelling ✅
Lecture 3 Context Modelling
Lecture 4 Recommender Systems 1 - Collaborative ✅
Lecture 5 Recommender Systems 2 - Content-based ✅
Lecture 6 Group Recommender Systems
Lecture 7 Adaptive Interfaces and Visualization ✅
Lecture 8 Explanations ✅
Lecture 9 Evaluation - Metrics and Reproducibility
Lecture 10 Evaluation - Layered Evaluation ✅
Lecture 11 Impact and Ethics
Lecture 12 - Music Recommender Systems
Lecture 13 Application Area - Intelligent Interactive Health Systems
Lecture 14 ???

I'm looking for a guest speaker…

Hmm, I should do it! 💪

About Me

Create AI systems and make them explainable and controllable, particularly in education

My short career

MSc fundamental mathematics
MSc applied informatics
2012-2019

KU LEUVEN

PhD in computer science
2019-2023

Assistant professor
in computer science
2023-now

Universiteit Utrecht

Jeroen Ooge
jeroenooge.be

I How to adapt education?

Examples of adaptation in education

II What is my research about?

Transparent and controllable

AI systems for education

III How can you contribute?

Exercise & ideas for master’s theses

AI can help make education adaptive in many ways

Teaching

Teaching-aid
Teaching quality
Pedagogical agents
Training of teachers
Personalised teaching
Improving teaching

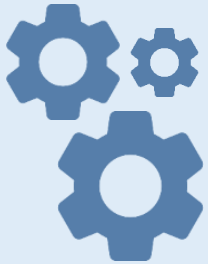
Student performance

Dropout prediction
Assessment
Cognitive diagnosis
Achievements
Grading
Reading ability
Creativity
Engagement
Feedback
Argumentation

"AI" consists of algorithms with specific tasks

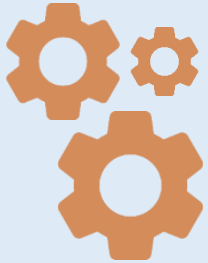
Mostafa Zafari, Jalal Safari Bazargani, Abolghasem Sadeghi-Niaraki, and Soo-Mi Choi. 2022. Artificial Intelligence Applications in K-12 Education: A Systematic Literature Review. *IEEE Access* 10: 61905–61921. https://doi.org/10.1109/ACCESS.2022.3179356

Available exercises



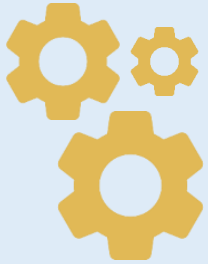
Recommended exercise

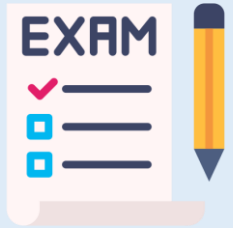
Learner profile



Predicted progress/risk

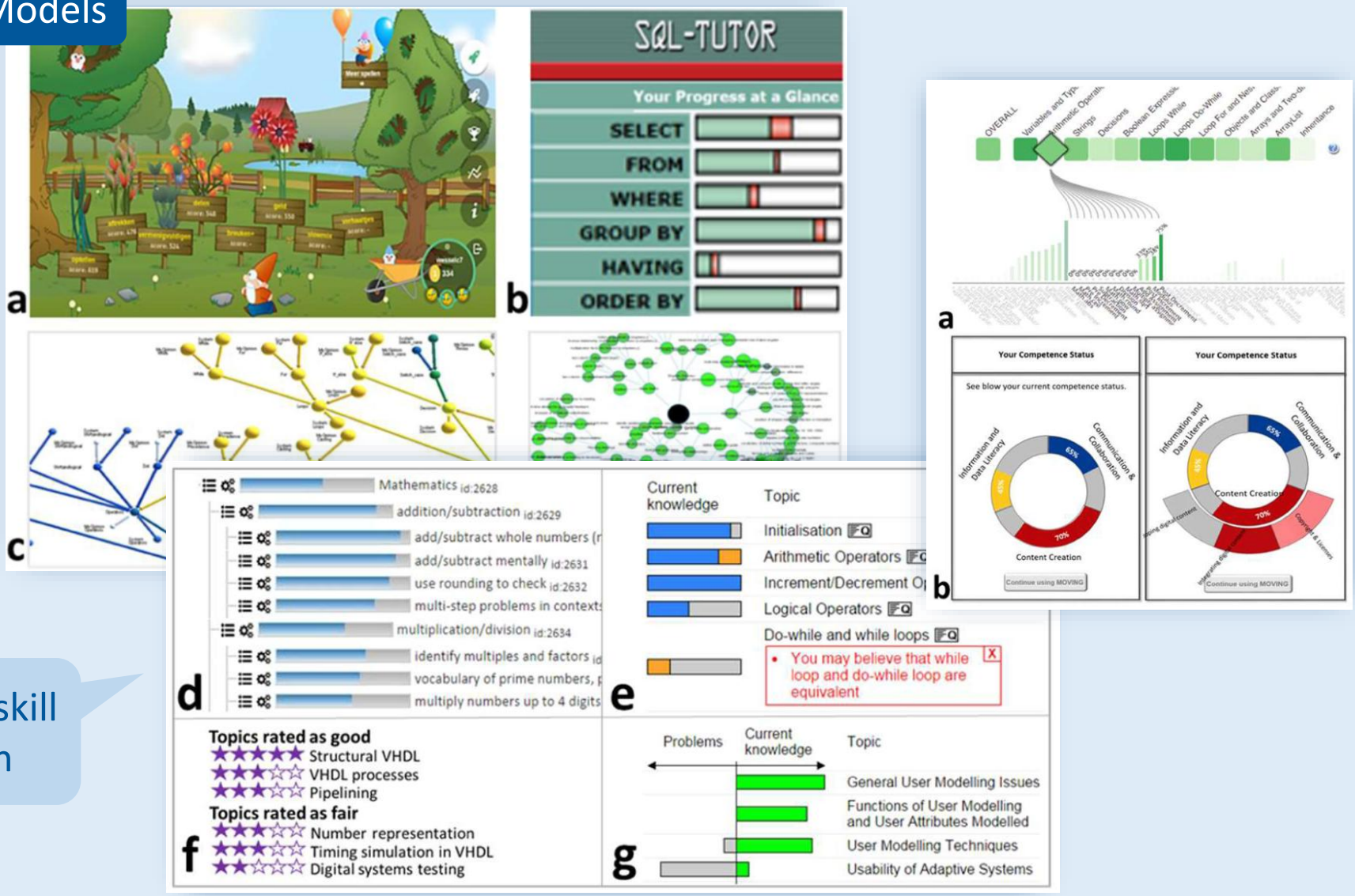
Textual prompt





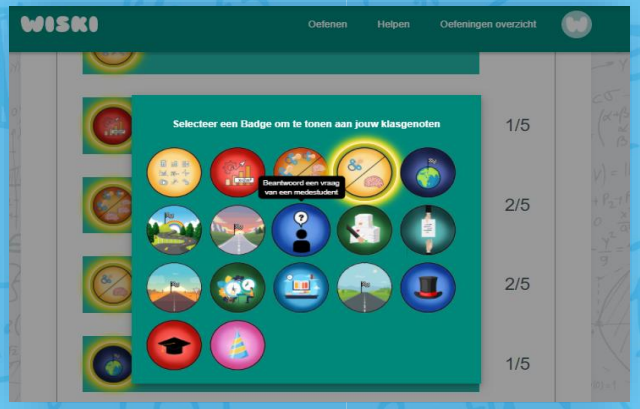
Exam question

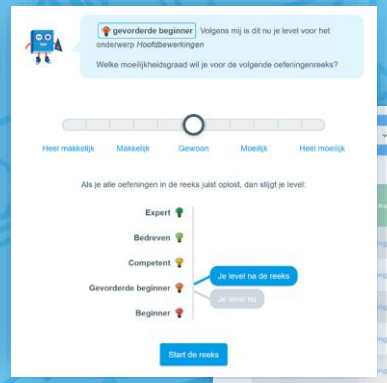
Open Learner Models

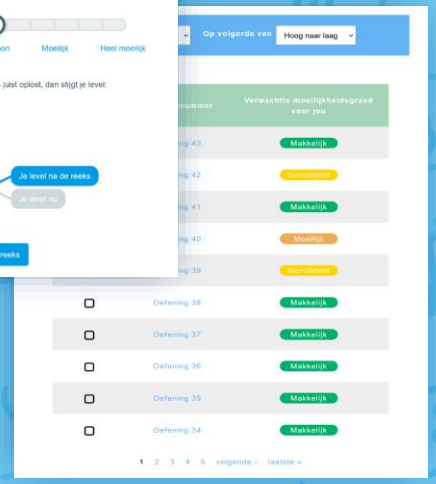


Algorithmic skill estimation

Susan Bull. 2020. There are Open Learner Models About! *IEEE Transactions on Learning Technologies* 13, 2: 425–448. https://doi.org/10.1109/TLT.2020.2978473

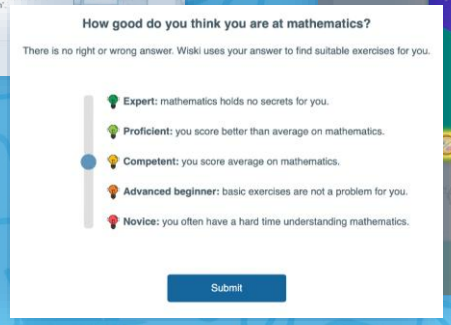


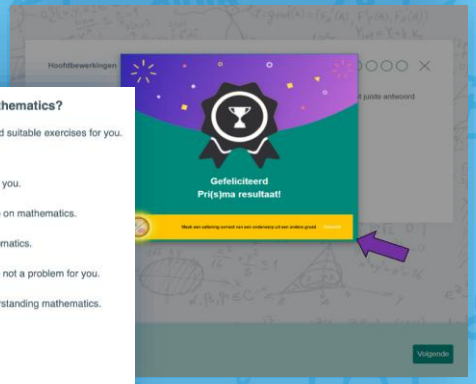


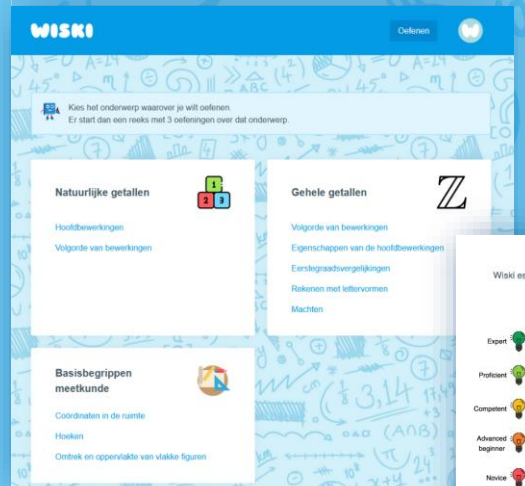


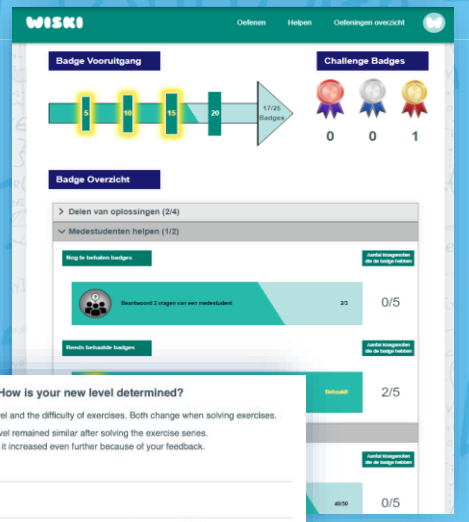
WISKI

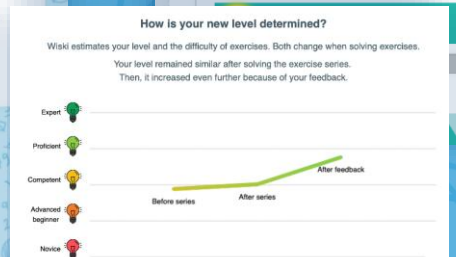
personalised maths practice with AI











Volgorde van bewerkingen

$6 \cdot (-12) + 36 \cdot 2 = \ldots$ Bereken en tik de juiste oplossing aan.

- (•) 0
- ( ) -144
- ( ) 72
- ( ) 144

Correct

Top-π!

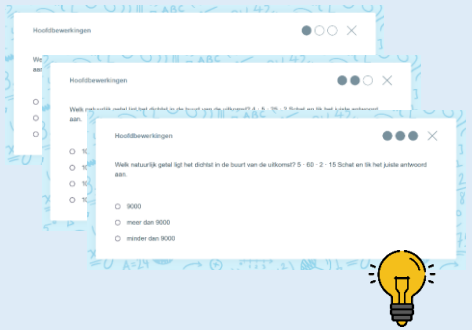
Overslaan Volgende

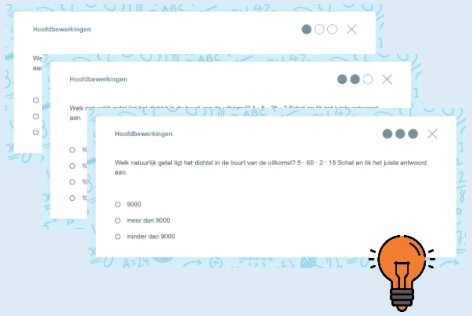
expert

competent

beginner

Recommender system





Estimating mastery and difficulty with Elo ratings

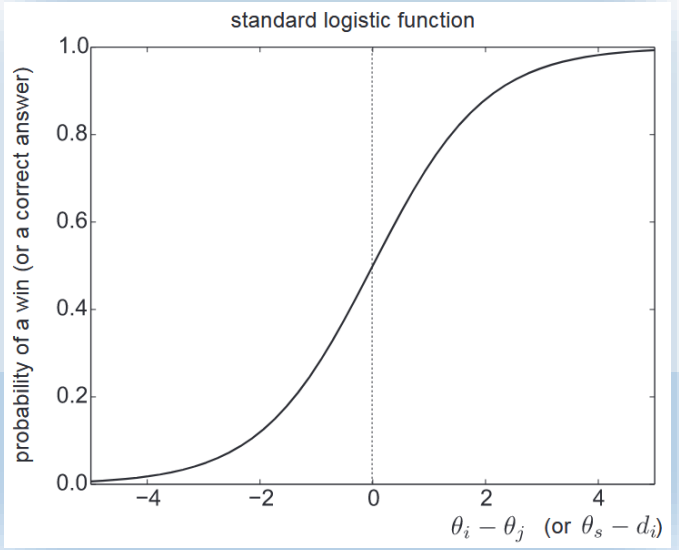
2.2. The Elo rating system in an educational setting

To apply the Elo rating system in the context of educational systems, we interpret a student's answer to an item as a match between the student and the item. In this context it is natural to slightly change the notation while keeping the basic principle the same. We denote skill of a student s as θ_s, difficulty of an item i as d_i, and the correctness of an answer of a student s on an item i as $\text{correct}_{si} \in \{0,1\}$. The probability of a correct answer is given by the logistic function with respect to the difference between skill and difficulty (Fig. 1 left):

$$P(\text{correct}_{si} = 1) = 1 \Big/ \left(1 + e^{-(\theta_s - d_i)}\right)$$

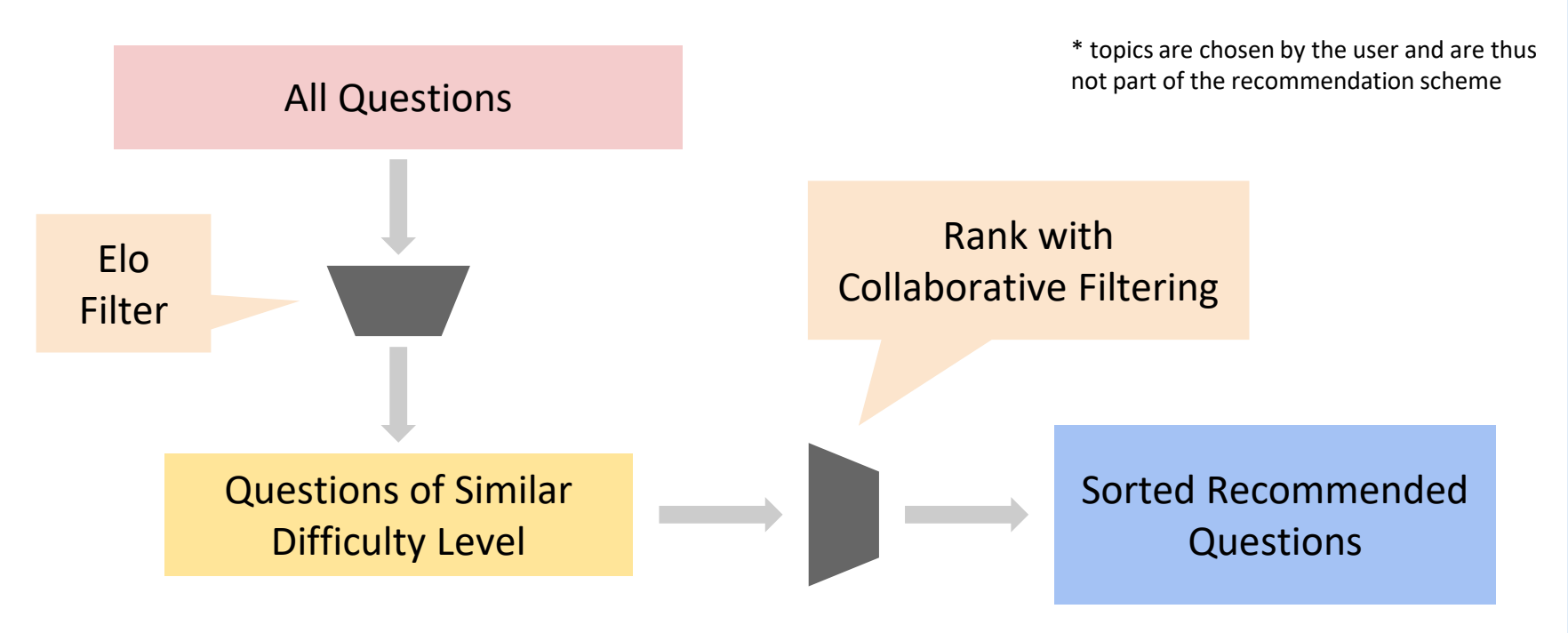
The skill and difficulty estimates are updated as follows:

$$\begin{aligned} \theta_s &:= \theta_s + K \cdot (\text{correct}_{si} - P(\text{correct}_{si} = 1)) \\ d_i &:= d_i + K \cdot (P(\text{correct}_{si} = 1) - \text{correct}_{si}) \end{aligned}$$



Radek Pelánek. 2016. Applications of the Elo rating system in adaptive educational systems. *Computers & Education* 98: 169–179.
https://doi.org/10.1016/j.compedu.2016.03.017

Recommending with Elo and collaborative filtering



Jeroen Ooge*, Shotallo Kato*, and Katrien Verbert. 2022. Explaining Recommendations in E-Learning: Effects on Adolescents' Trust. In *27th International Conference on Intelligent User Interfaces* (IUI '22), 93–105. https://doi.org/10.1145/3490099.3511140


TIME FOR
QUESTIONS

I How to adapt education?

Examples of adaptation in education

II What is my research about?

Transparent and controllable

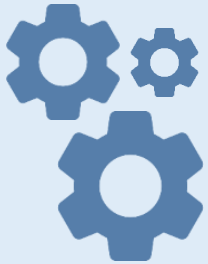
adaptive AI systems for education

III How can you contribute?

Exercise & ideas for master's theses

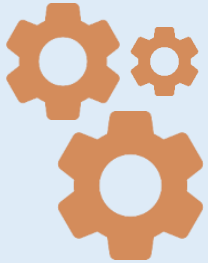
Call it *adaptive* systems

Available exercises



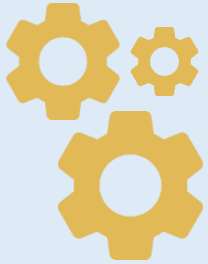
Recommended exercise

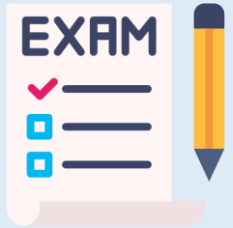
Learner profile



Predicted progress/risk

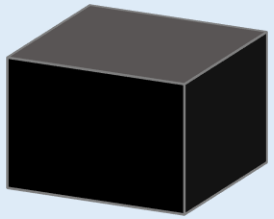
Textual prompt





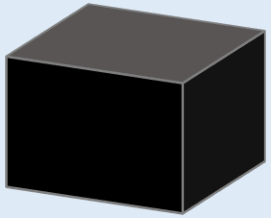
Exam question

Available exercises



Recommended exercise

Learner profile



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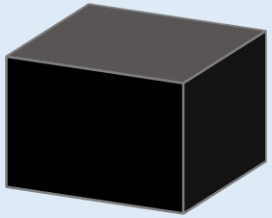
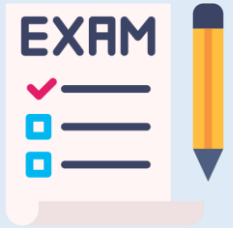
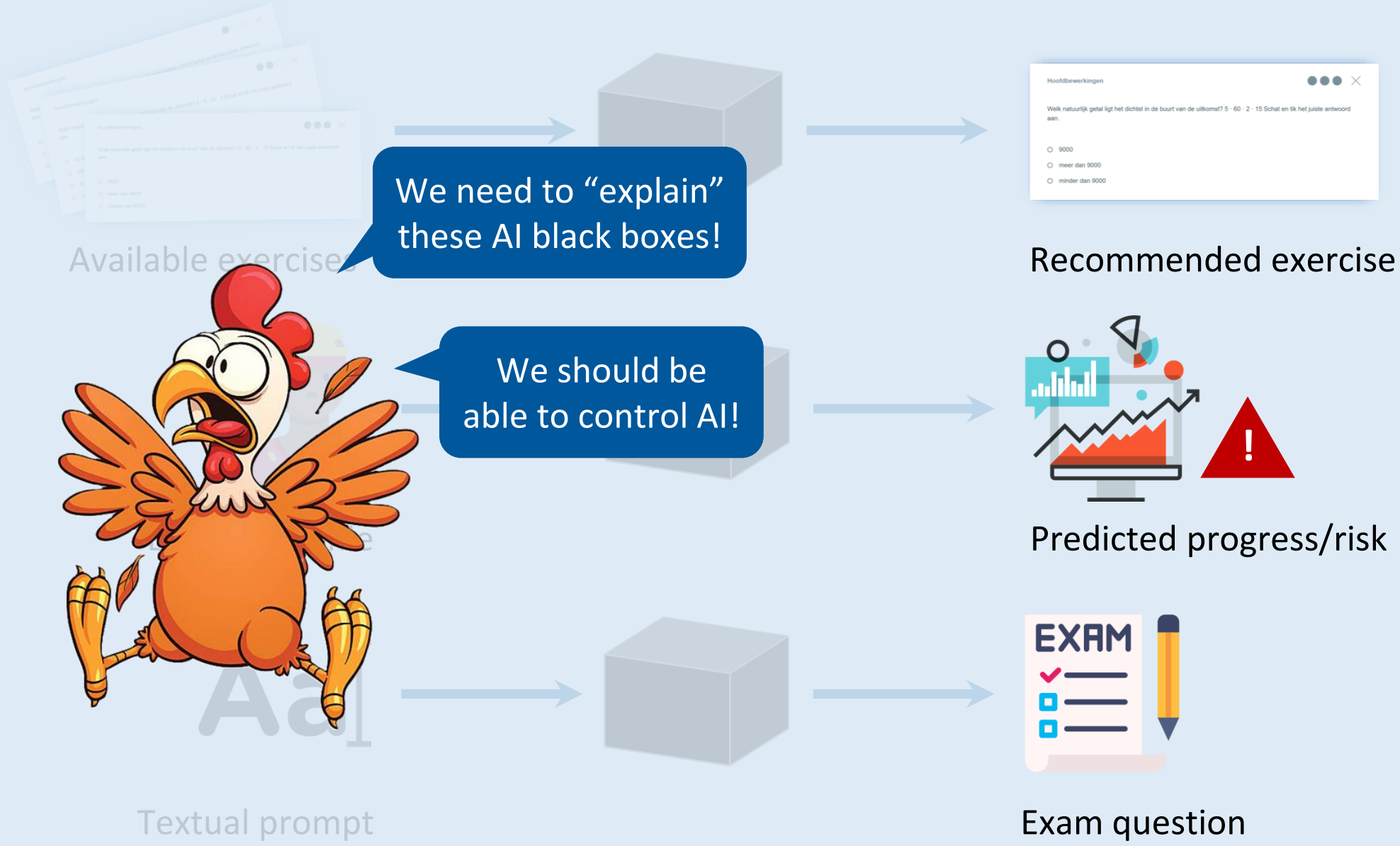
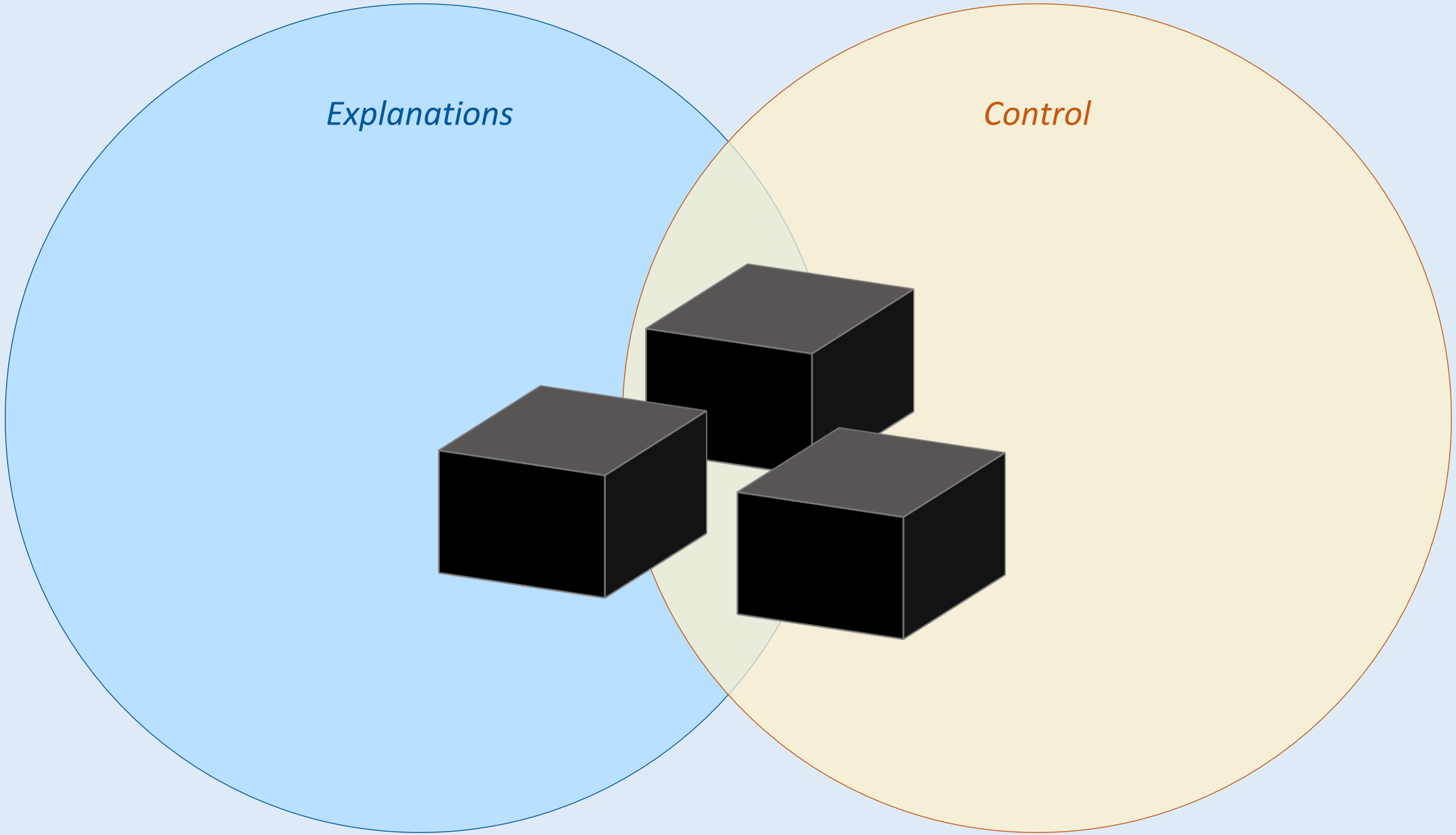
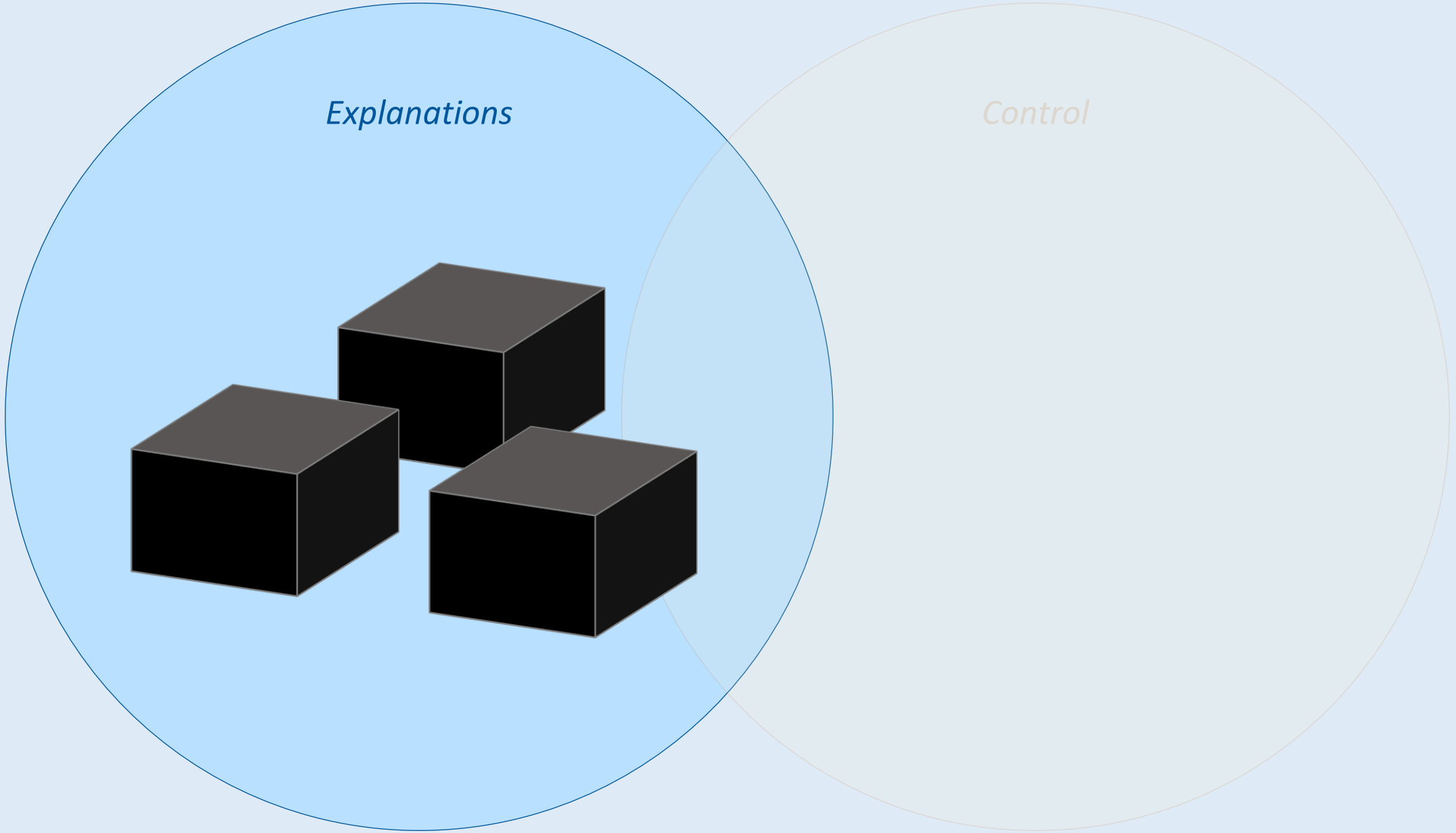




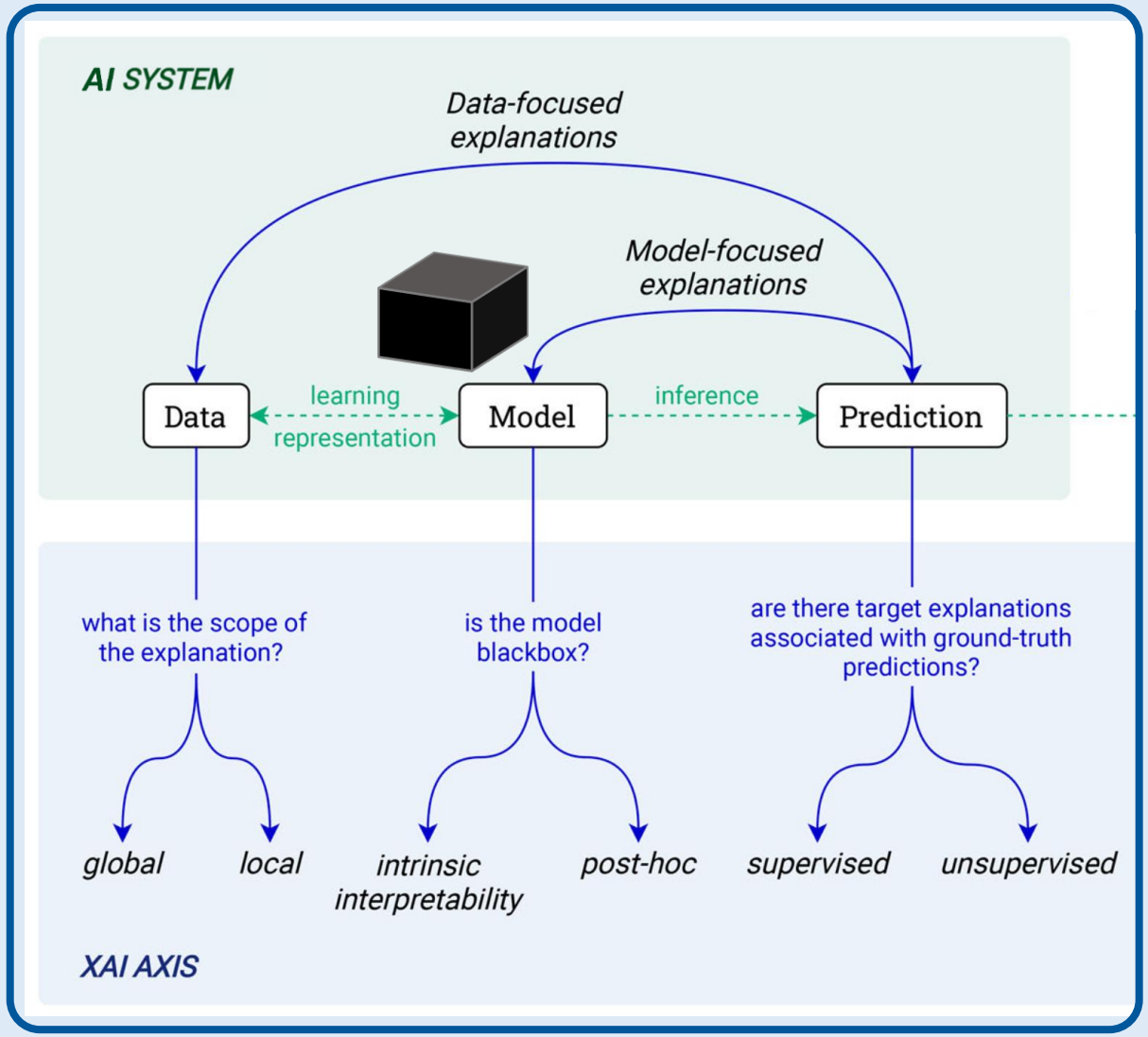
Exam question


We need to “explain” these AI black boxes!
We should be able to control AI!
Available exercises
Textual prompt
Recommended exercise
Predicted progress/risk
Exam question
EXAM


Explanations
Control

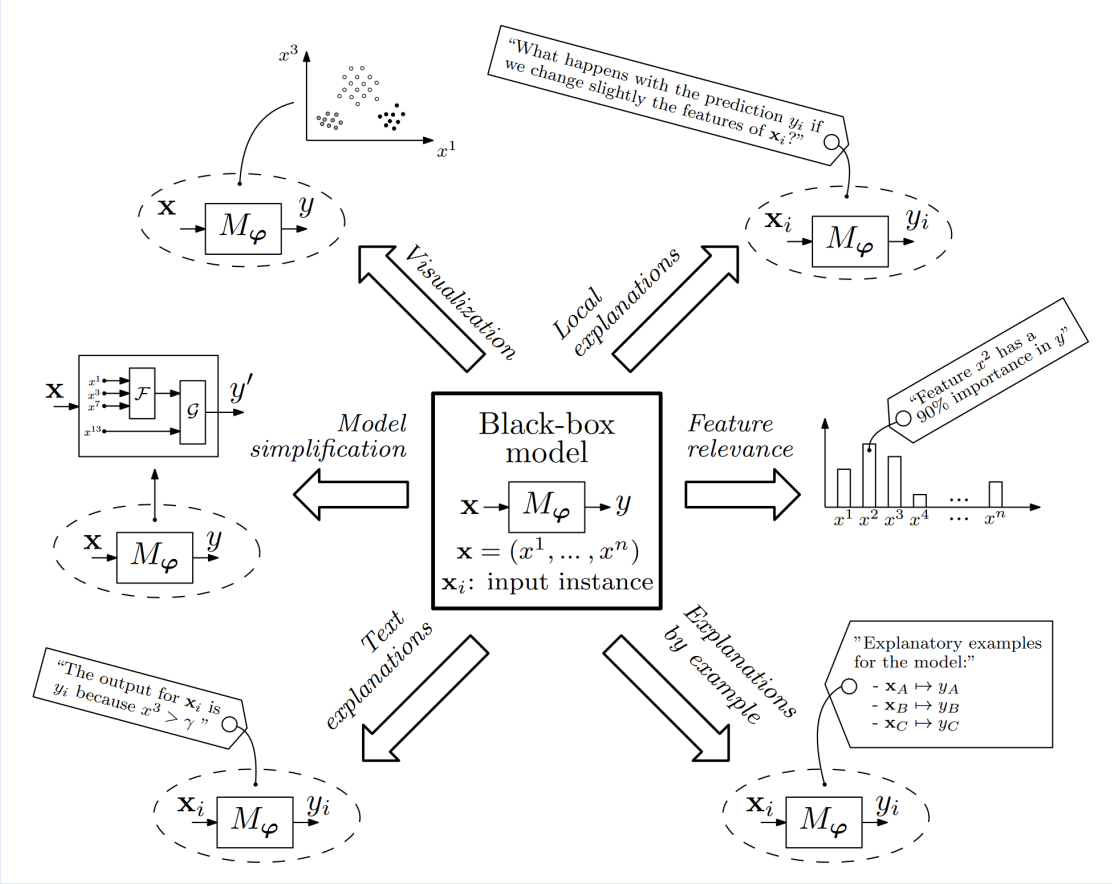

Explanations
Control

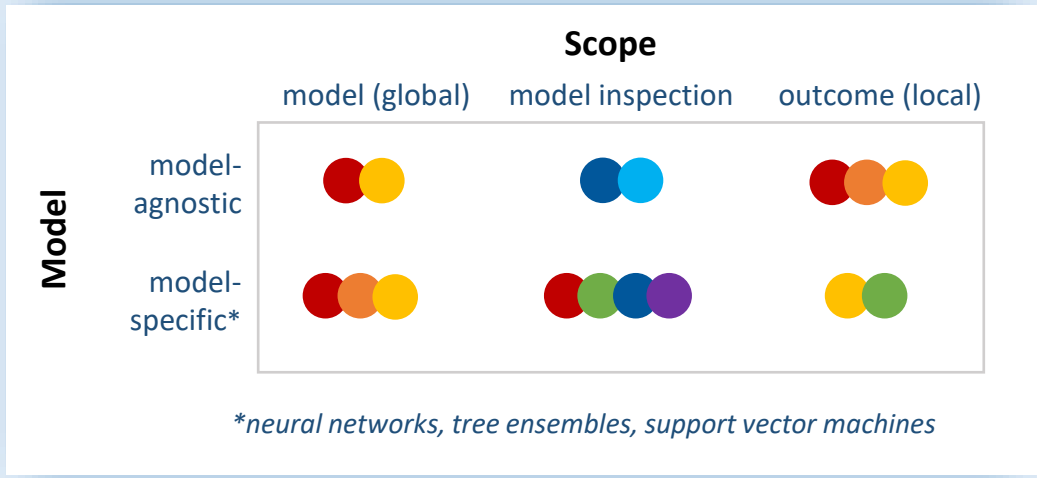
Algorithmic Explainability



Darius Afchar, Alessandro Melchiorre, Markus Schedl, Romain Hennequin, Elena Epure, and Manuel Moussallam. 2022. Explainability in Music Recommender Systems. *AI Magazine* 43, 2: 190–208. https://doi.org/10.1002/aaai.12056

Algorithmic Explainability



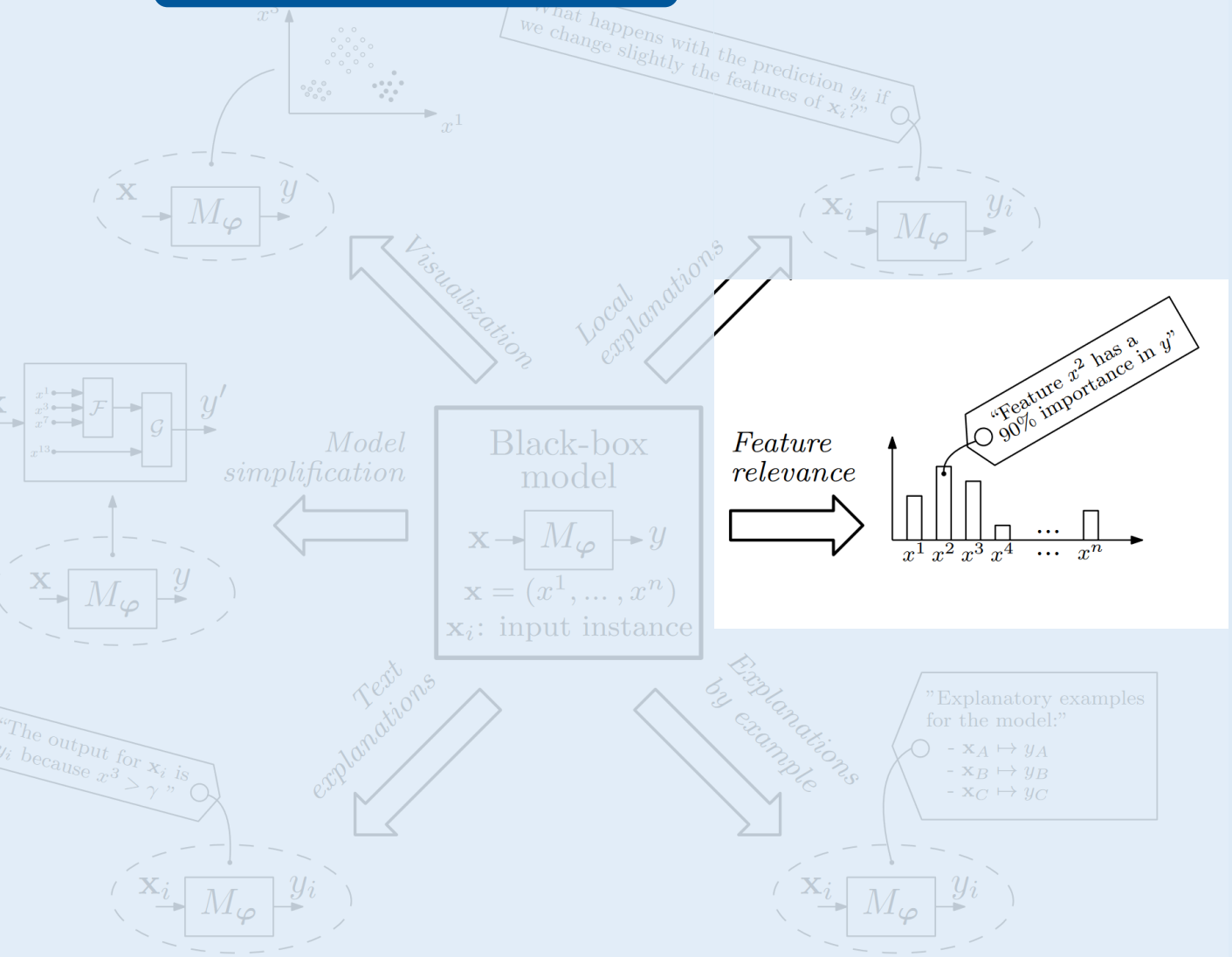


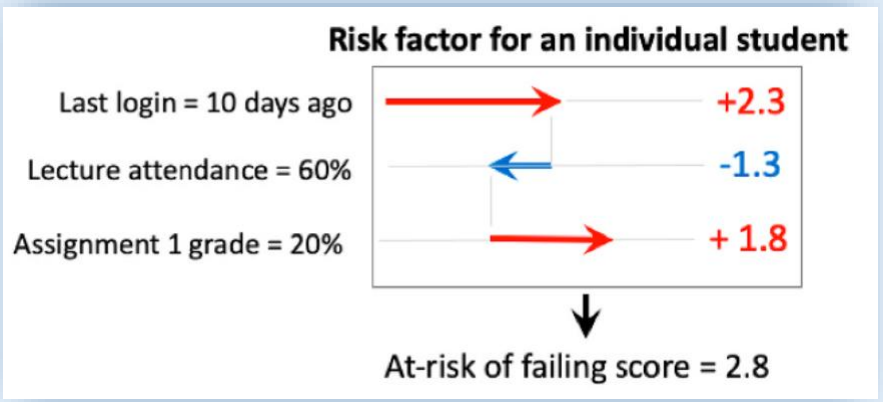
- Decision tree
- Decision rules
- Feature importance
- Saliency mask
- Partial dependence plot
- Sensitivity analysis
- Activation maximisation

Alejandro Barredo Arrieta et al. 2020. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion 58: 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Riccardo Guidotti, Anna Monreale, Salvatore Ruggieri, Franco Turini, Fosca Giannotti, and Dino Pedreschi. 2019. A Survey of Methods for Explaining Black Box Models. *ACM Computing Surveys* 51, 5: 1–42. https://doi.org/10.1145/3236009

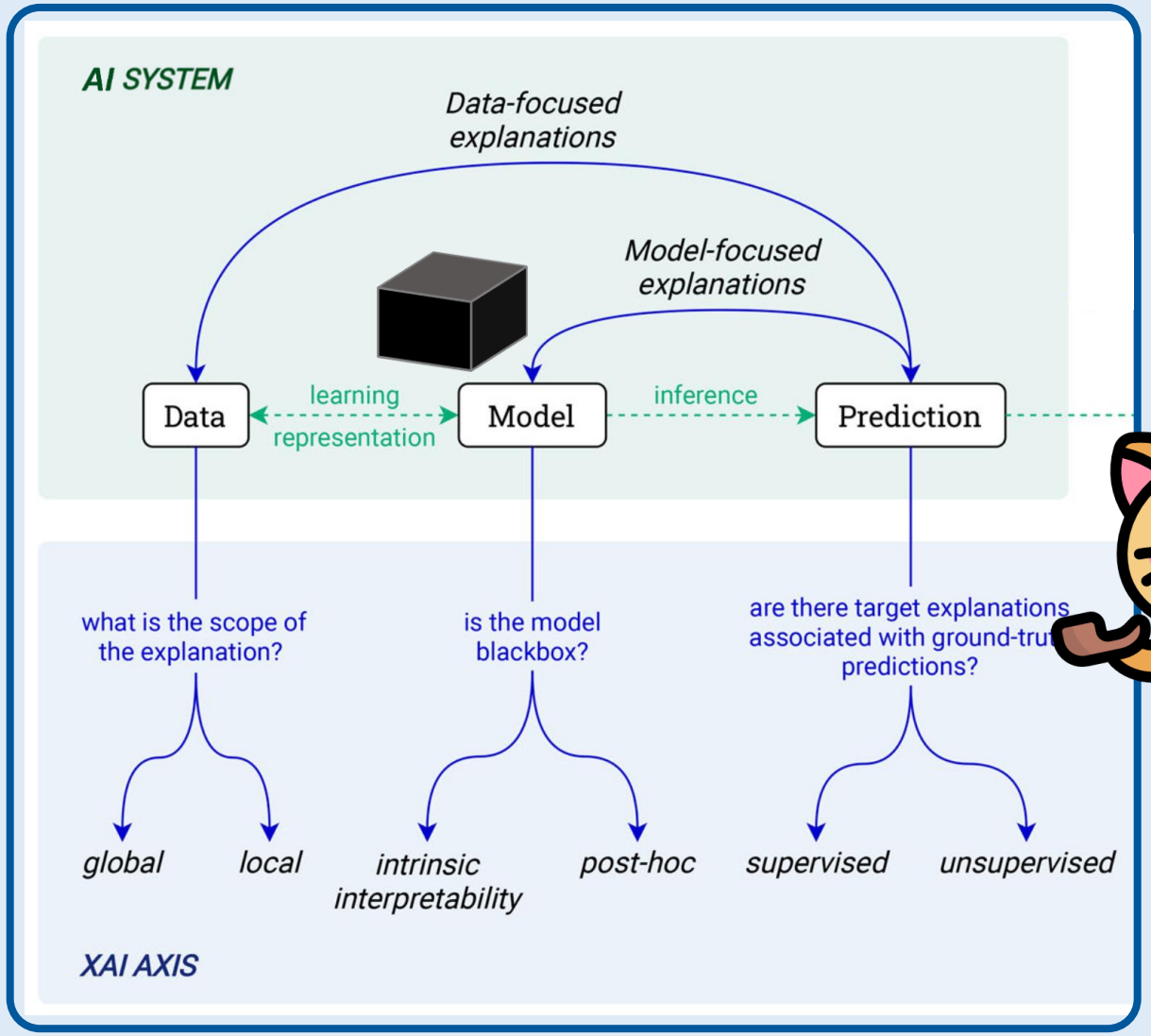
Algorithmic Explainability

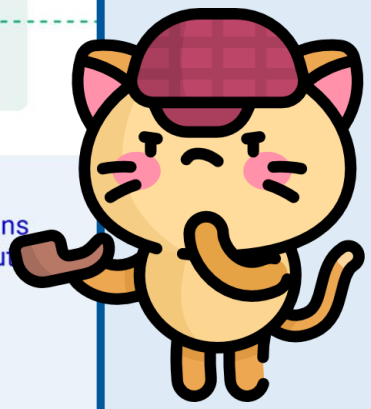




Hassan Khosravi, Simon Buckingham Shum, Guanliang Chen, Cristina Conati, Yi-Shan Tsai, Judy Kay, Simon Knight, Roberto Martinez-Maldonado, Shazia Sadiq, and Dragan Gašević. 2022. Explainable Artificial Intelligence in education. Computers and Education: Artificial Intelligence 3: 100074. https://doi.org/10.1016/j.caeai.2022.100074

Algorithmic Explainability



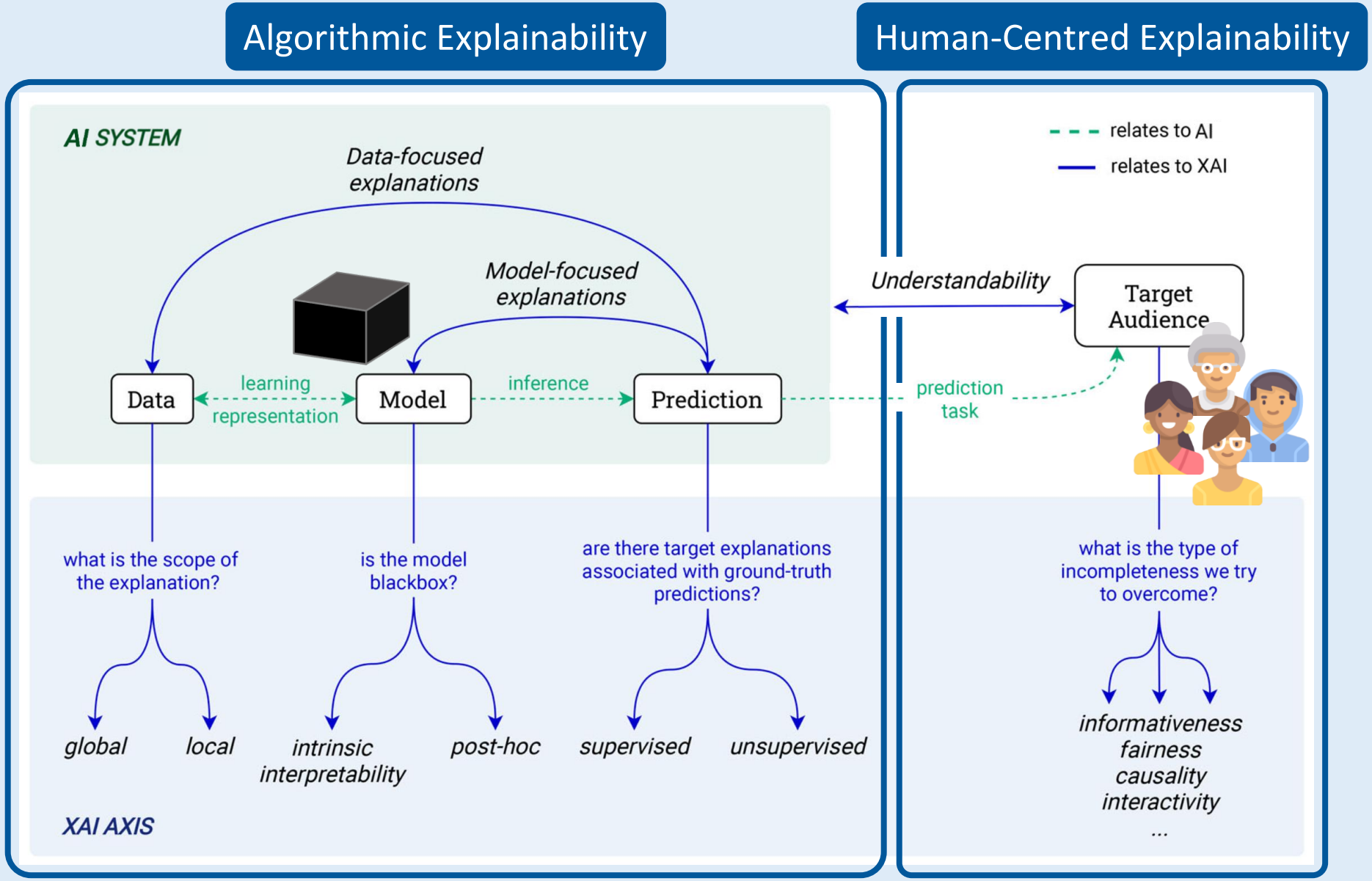


Which explanation do we use?

Who is the audience?

What is their context?

Darius Afchar, Alessandro Melchiorre, Markus Schedl, Romain Hennequin, Elena Epure, and Manuel Moussallam. 2022. Explainability in Music Recommender Systems. *AI Magazine* 43, 2: 190–208. https://doi.org/10.1002/aaai.12056



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Human-Centred Explainability

Different people and contexts
need different explainability solutions

Research goal: Design tailored explanations and evaluate how they affect people's behaviour (e.g., trust, understanding, motivation, learning)

Data

What kind of data was the system trained on?
What is the source of the training data?
How were the labels/ground-truth produced?
What is the sample size of the training data?
What dataset(s) is the system NOT using?
What are the potential limitations/biases of the data?
What is the size, proportion, or distribution of the training data with given feature(s)/feature-value(s)?

Output

What kind of output does the system give?
What does the system output mean?
What is the scope of the system's capability? Can it do. . . ?
How is the output used for other system component(s)?
How should I best use the output of the system?
How should the output fit in my workflow?

Performance

How accurate/precise/reliable are the predictions?
How often does the system make mistakes?
In what situations is the system likely to be correct/ incorrect?
What are the limitations of the system?
What kind of mistakes is the system likely to make?
Is the system's performance good enough for. . . ?

How

How does the system make predictions?
What features does the system consider?
Is [feature X] used or not used for the predictions?
What is the system's overall logic?
How does it weigh different features?
What kind of rules does it follow?
How does [feature X] impact its predictions?
What are the top rules/features that determine its predictions?
What kind of algorithm is used?
How were the parameters set?

Why

Why/how is this instance given this prediction?
What feature(s) of this instance determine the system's prediction of it?
Why are [instance A and B] given the same prediction?

Why not

Why is this instance NOT predicted to be [a different outcome]?
Why is this instance predicted [P instead of a different outcome Q]?
Why are [instance A and B] given different predictions?

How t

How sl differe
What is instanc
How sh instanc
What differen

How t

What instanc
What is feature
What value(s) predicti
What k tion?

What if

What instanc
What v feature
What w instanc

Other

How/w prove/c
Can I, a (improv
Why i algorith
What c mean?
What a system?

Why

Why/how is this instance giving this prediction?
What feature(s) of this instance determine the system's prediction of it?
Why are [instance A and B] given the same prediction?

What if

What would the system predict if this instance changes to. . . ?
What would the system predict if a given feature changes to. . . ?
What would the system predict for [a different instance]?

What insights are people looking for?

Q. Vera Liao et al. 2020. Questioning the AI: Informing Design Practices for Explainable AI User Experiences. https://doi.org/10.1145/3313831.3376590

Explanations are typically…

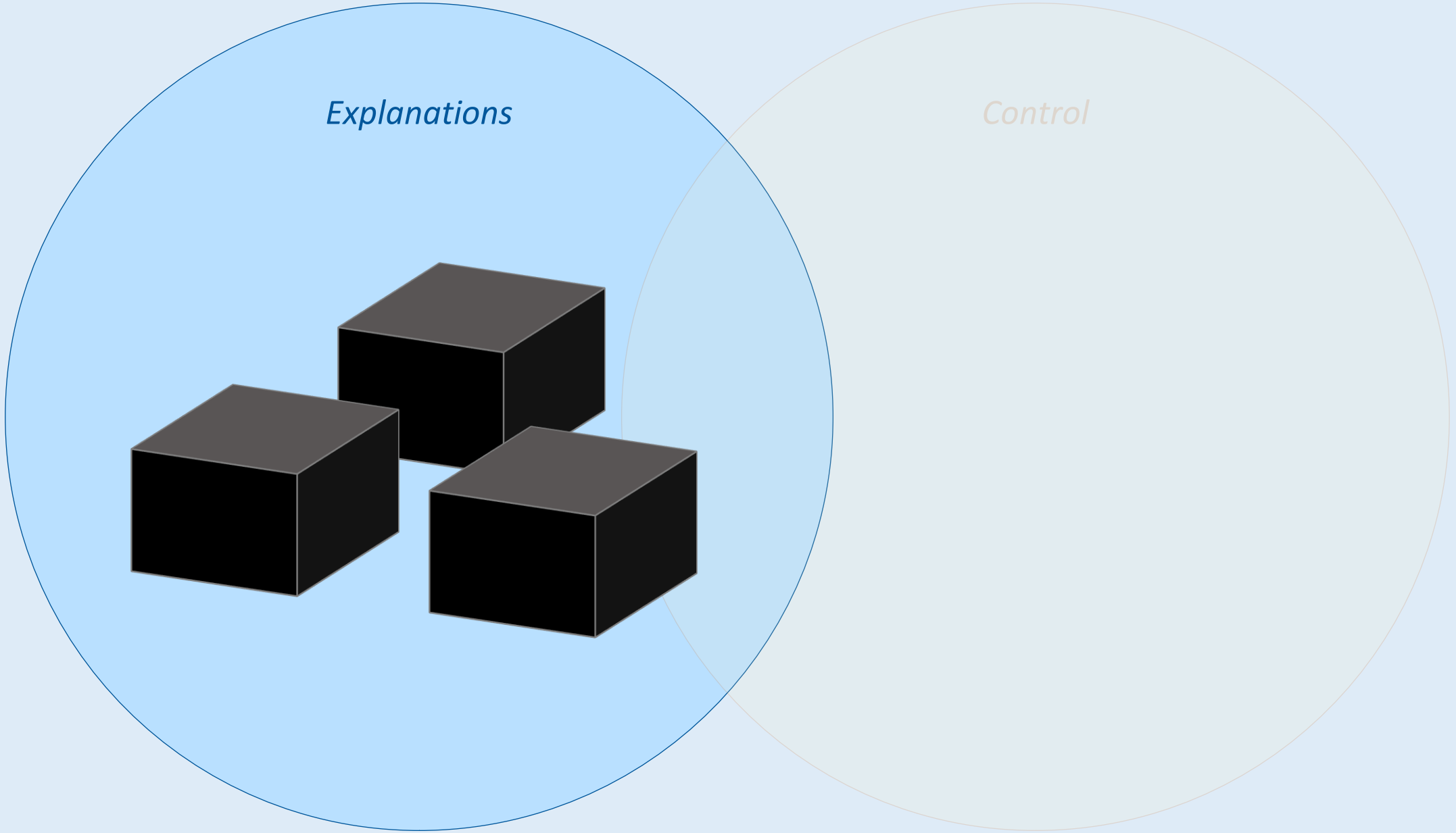
… **contrastive**: people don't ask why an event has taken place, but why another event *didn't*

… **selected**: people select one or two causes of an event and consider those to be *the* explanation

… **social**: people adapt to listeners' current beliefs and knowledge in a conversation

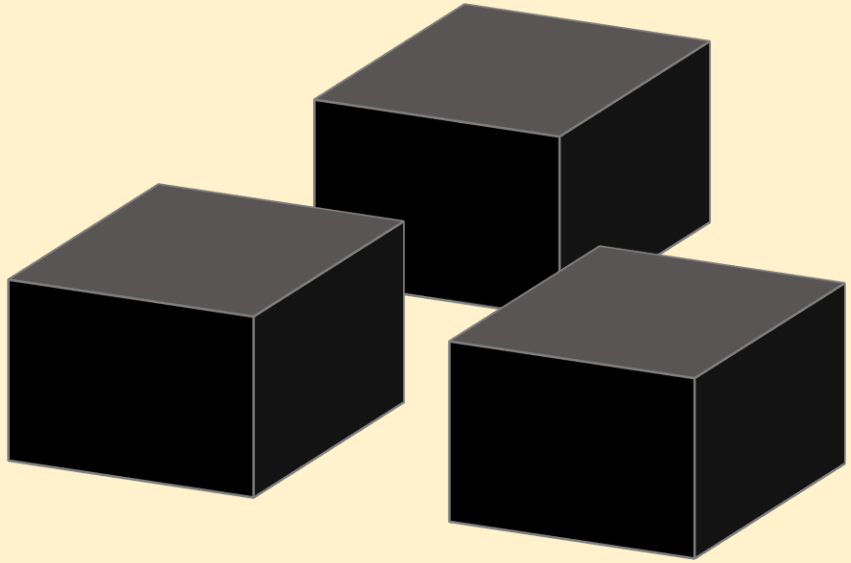
What can we learn about explaining from the social sciences?

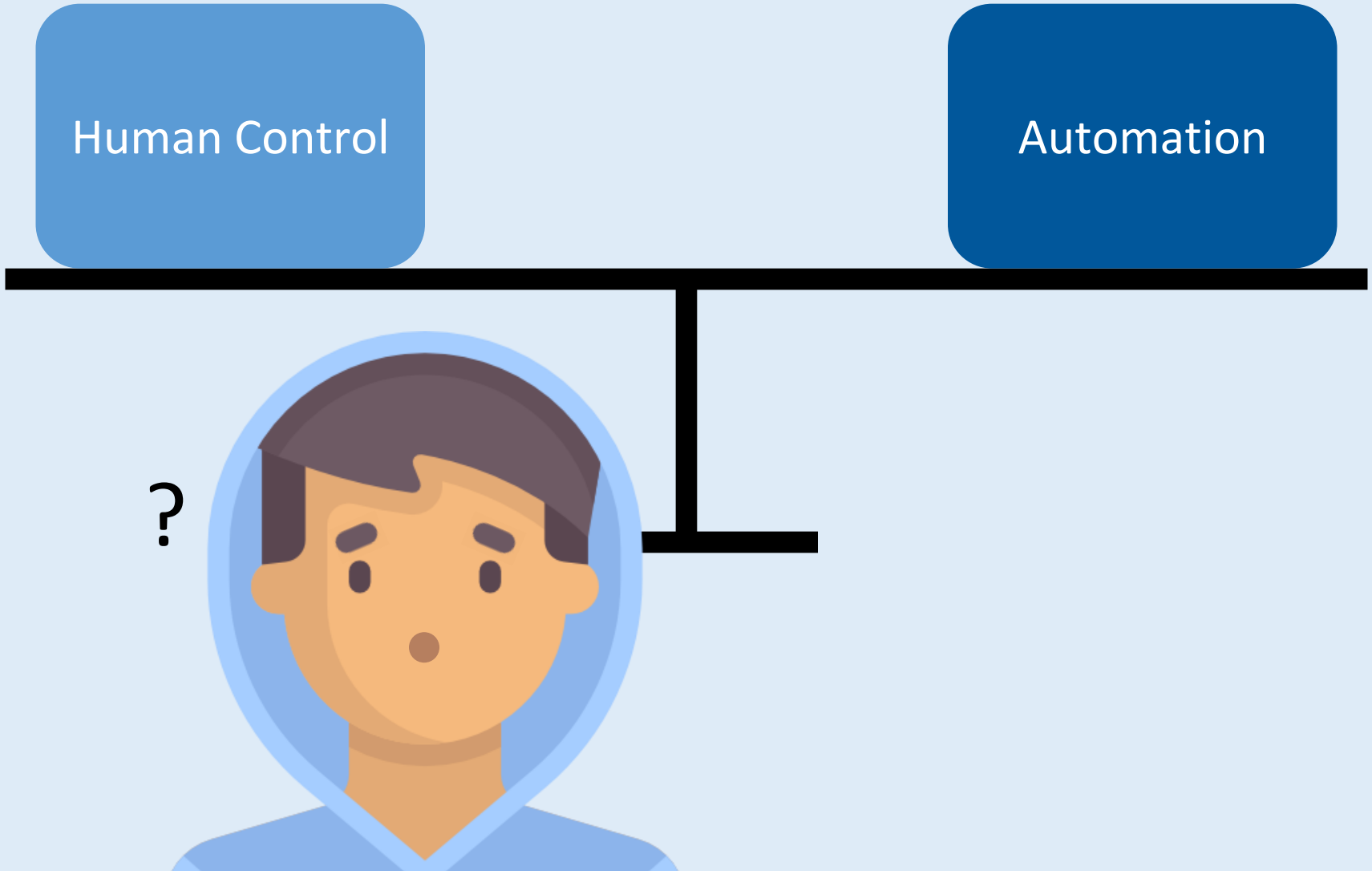
Tim Miller. 2019. Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence* 267: 1–38. https://doi.org/10.1016/j.artint.2018.07.007

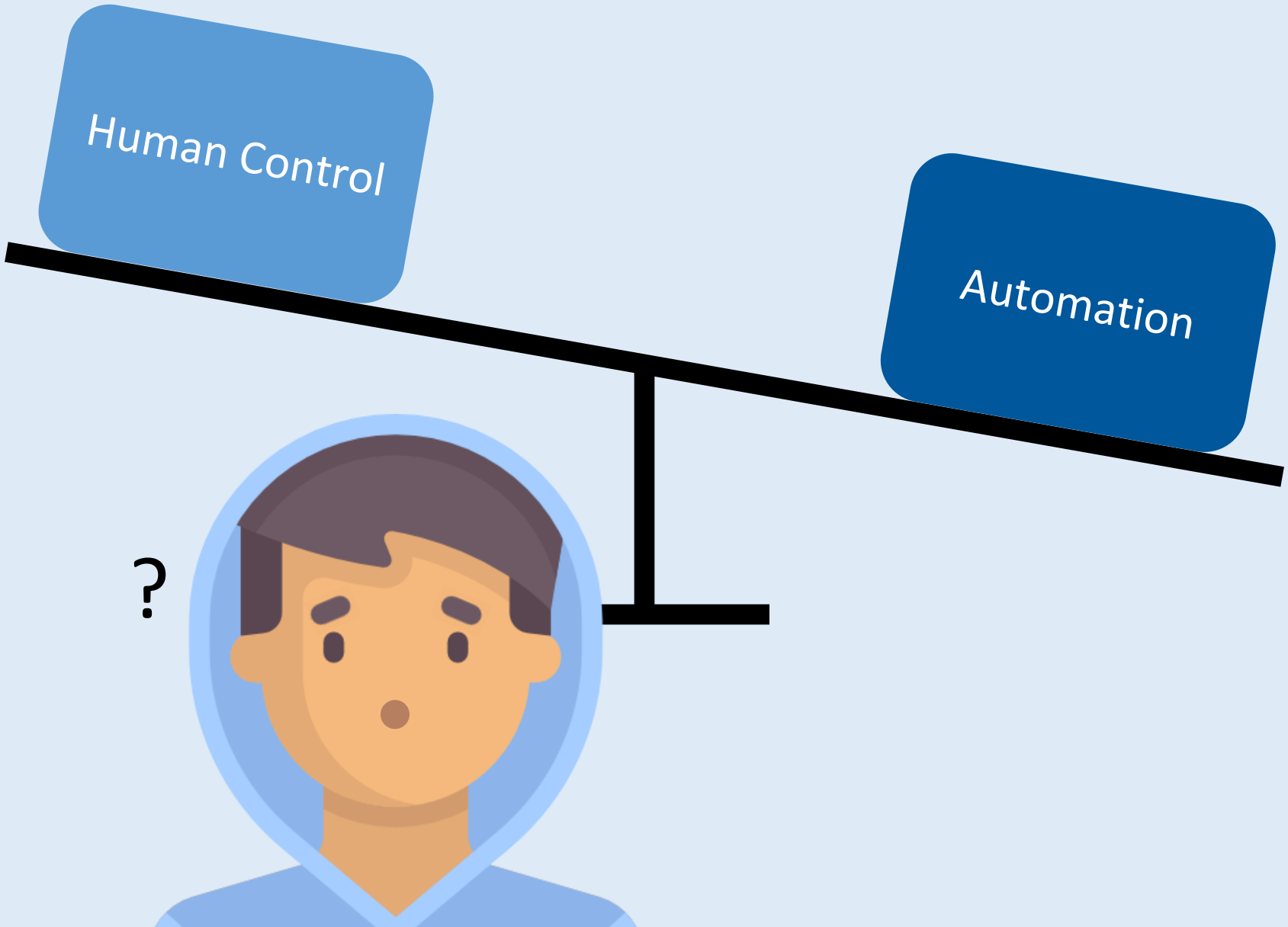

Explanations
Control

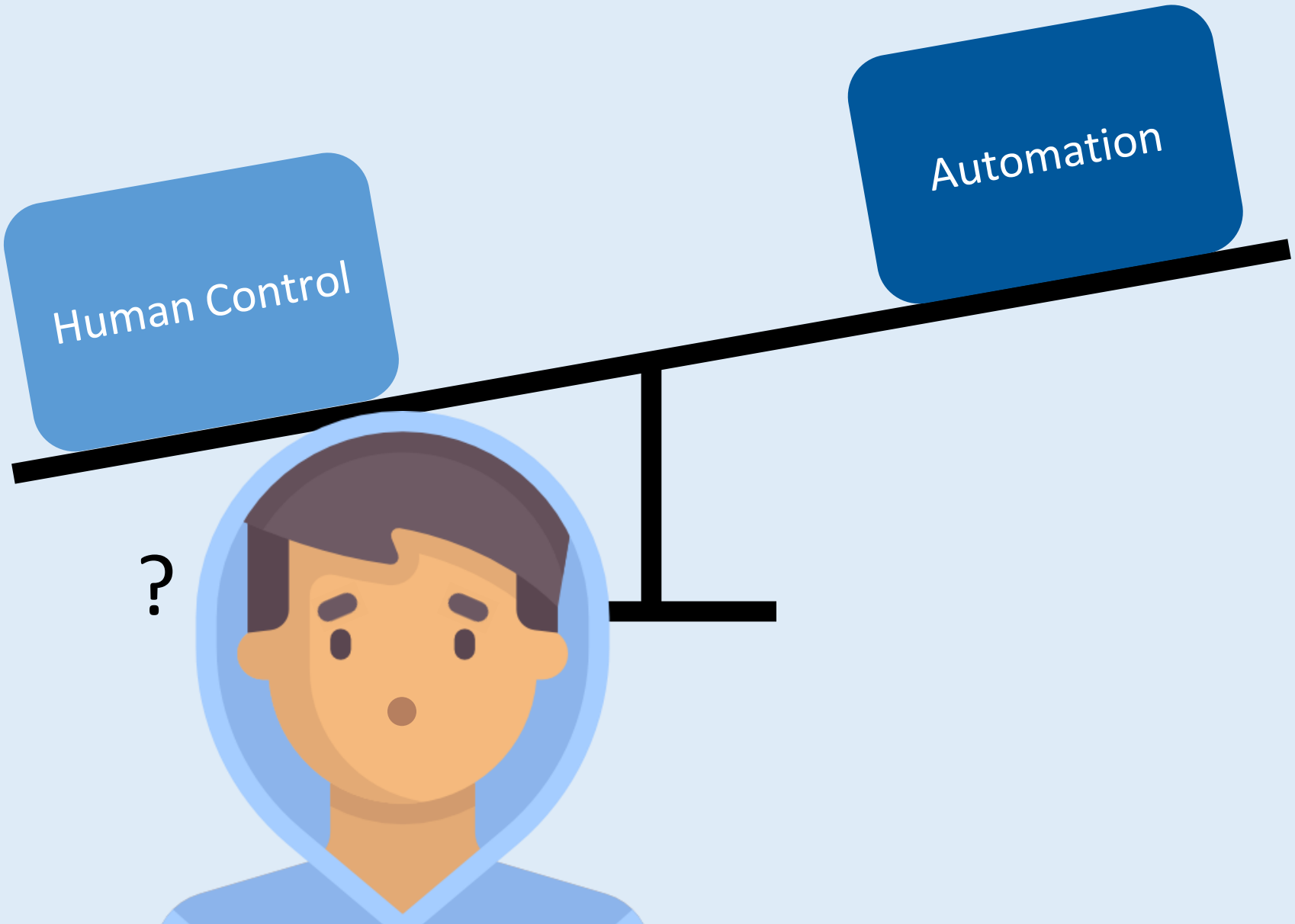
Explanations

Control




Human Control
Automation
?


Human Control
Automation
?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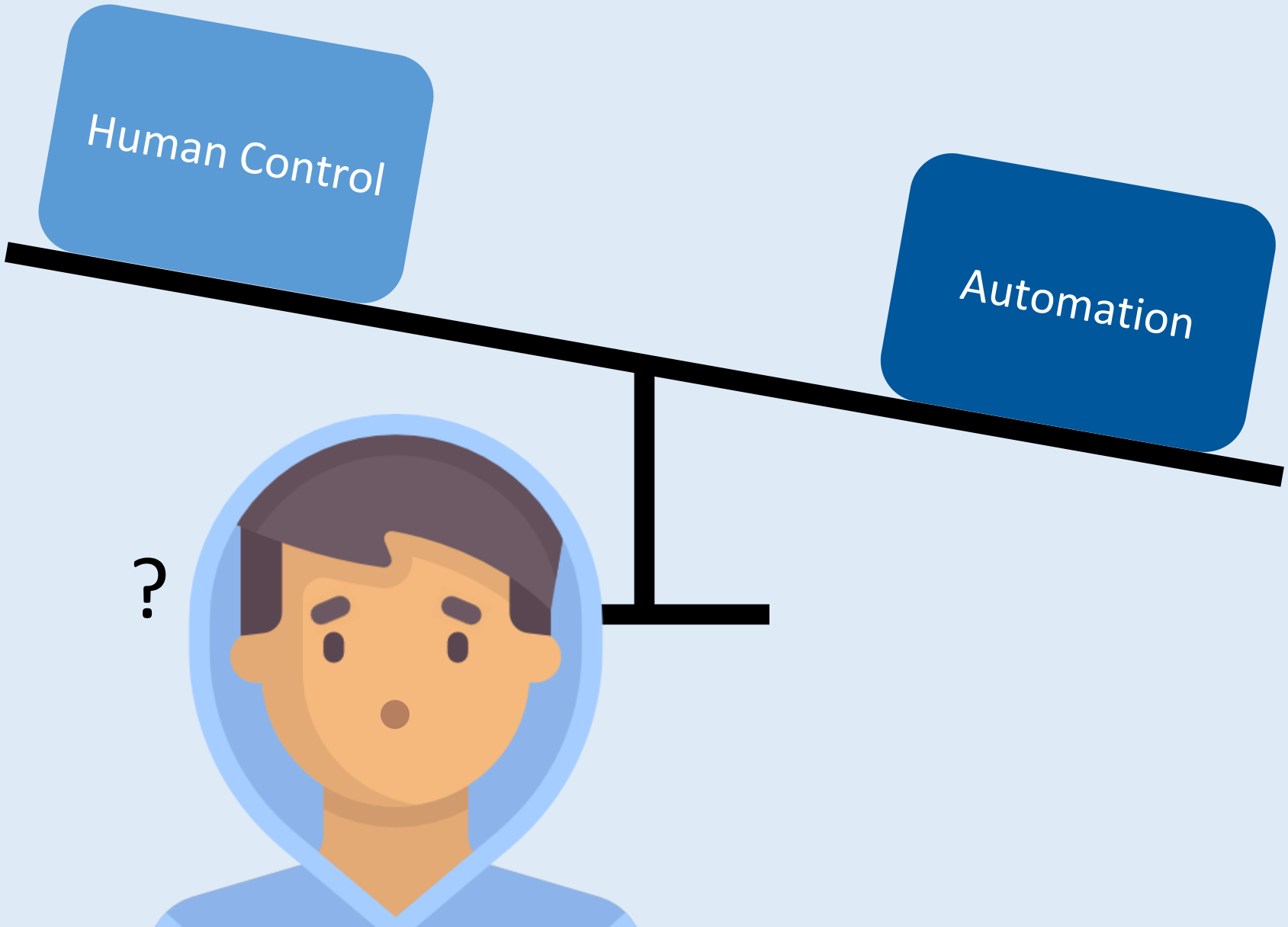
?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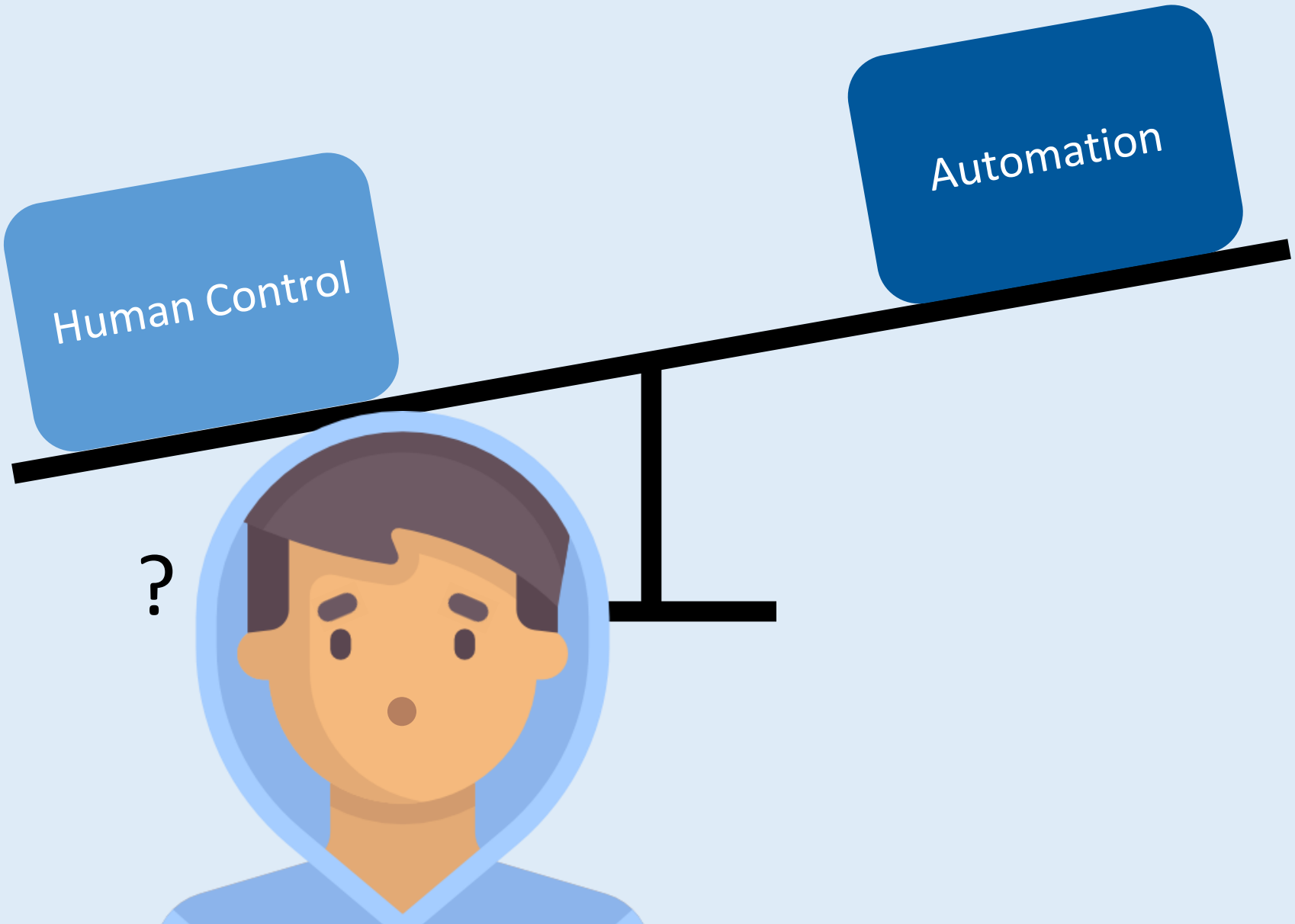
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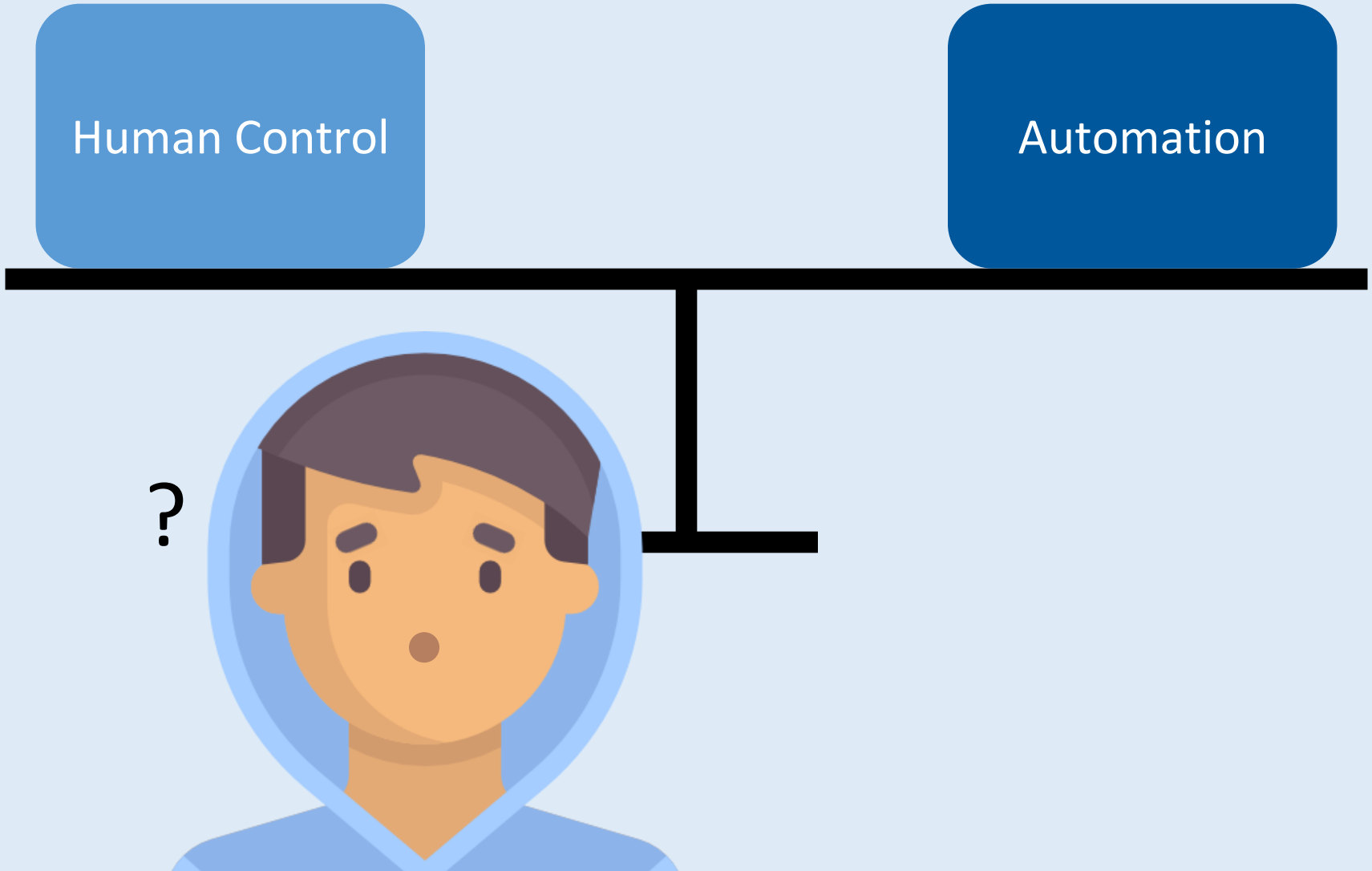
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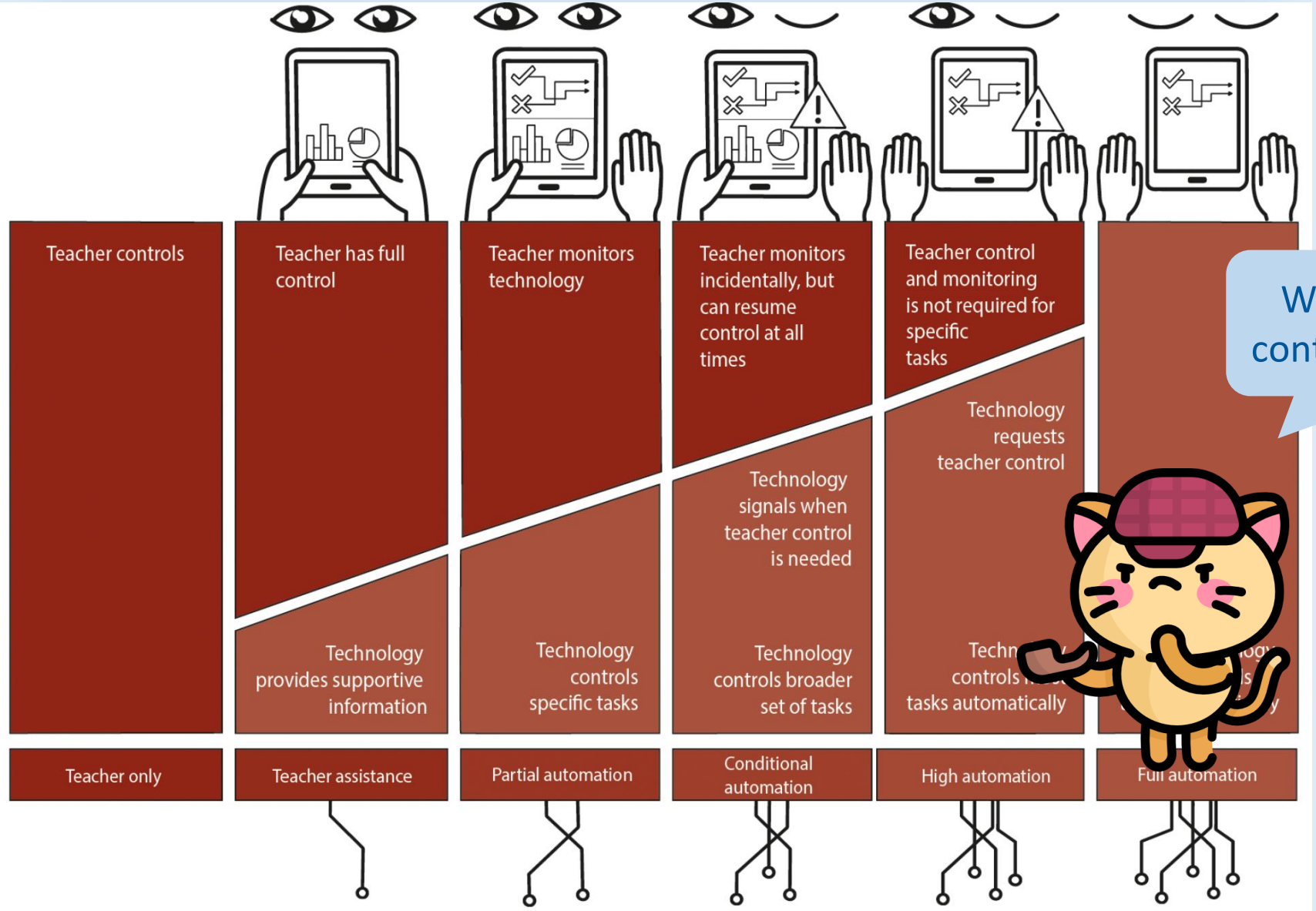


Also applies to other educational stakeholders

What are suitable control mechanisms?

Who is the audience?

What is their context?

Inge Molenaar. 2022. Towards hybrid human-AI learning technologies. *European Journal of Education* 57, 4: 632–645. https://doi.org/10.1111/ejed.12527

Human-Centred Explainability

Different people and contexts
need different explainability solutions

Research goal: Design tailored explanations and evaluate how they affect people's behaviour (e.g., trust, understanding, motivation, learning)

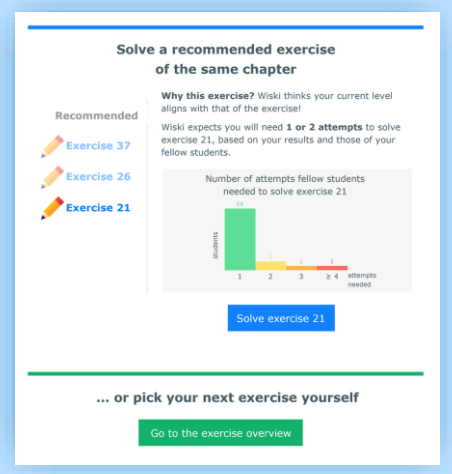
Human-Centred Explainability *and Controllability*

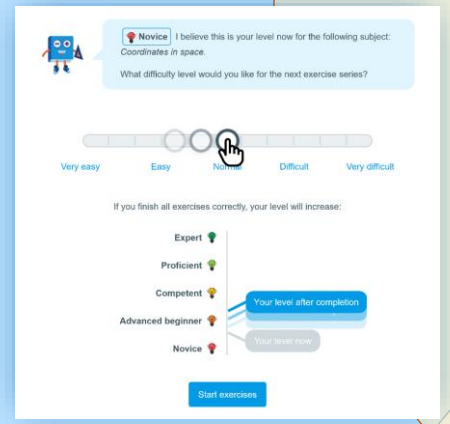
Different people and contexts need different explainability *and controllability* solutions

Research goal: Design tailored explanations *and control mechanisms* and evaluate how they affect people's behaviour
(e.g., trust, understanding, motivation, learning)

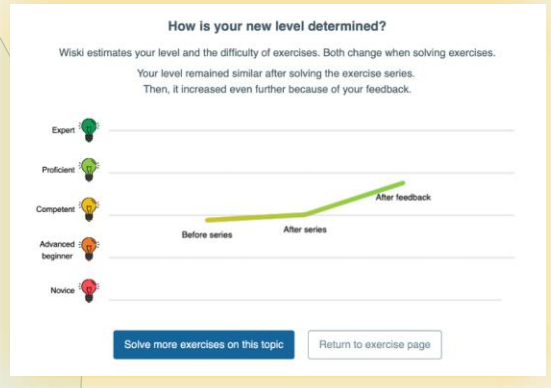

TIME FOR
QUESTIONS

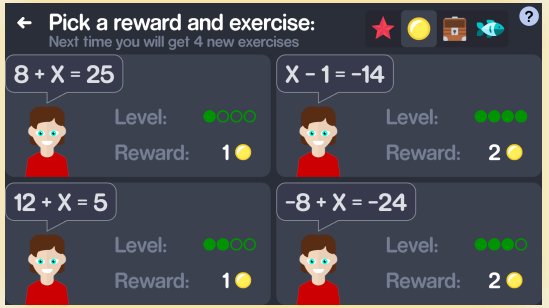
Explanations



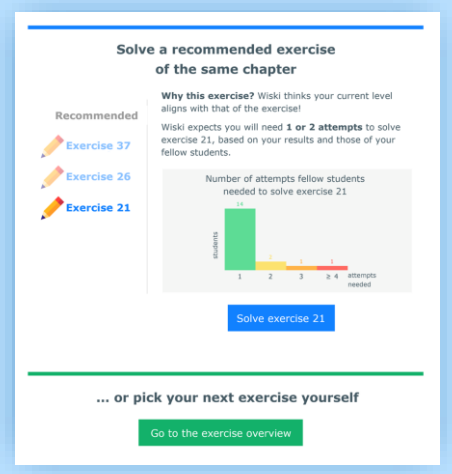


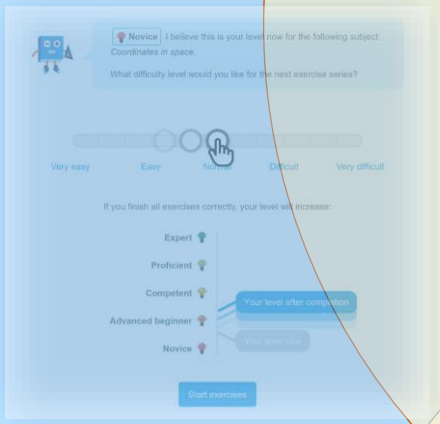
Control



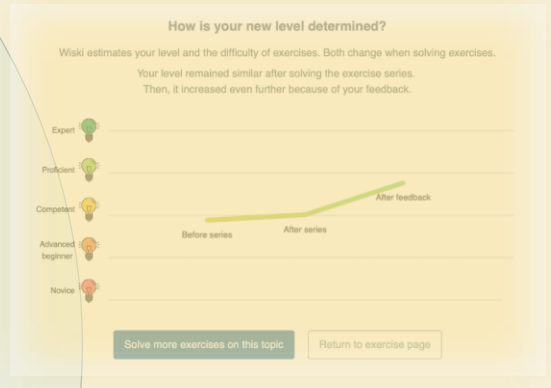


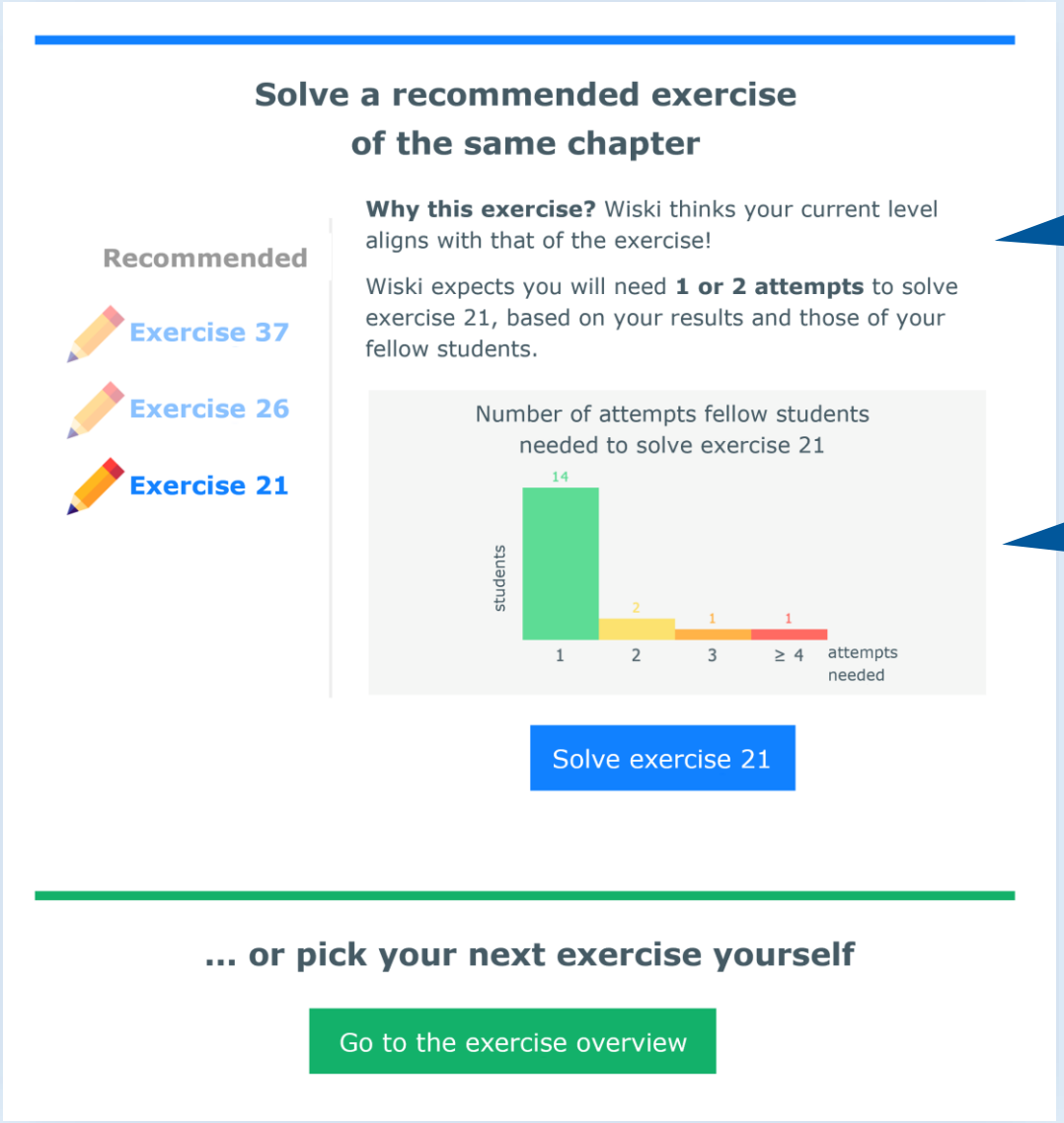
Explanations





Control





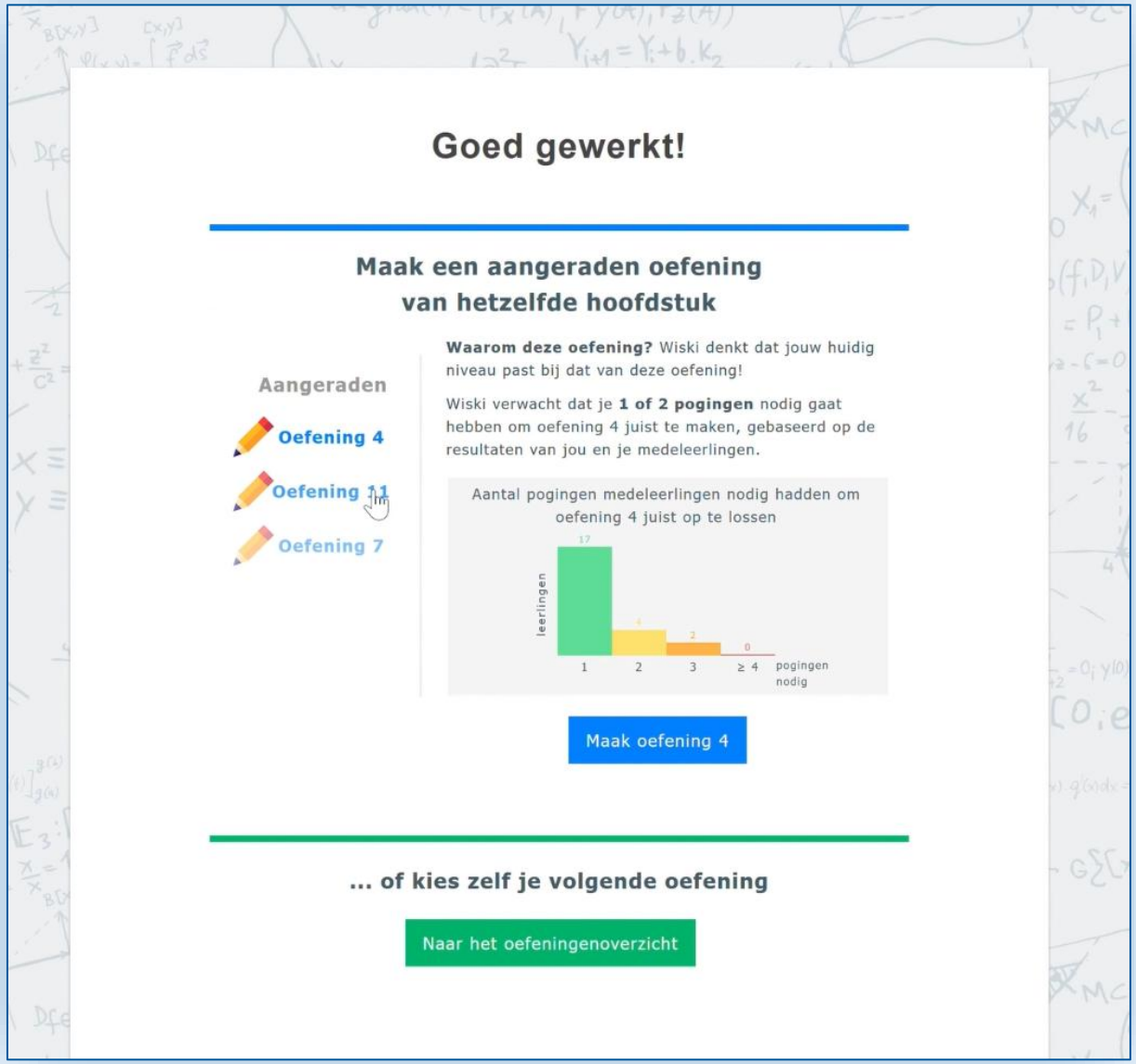
Textual explanation

Visual explanation

Explanations: *why* explanations for recommendations

Control: choose next exercises

Jeroen Ooge*, Shotallo Kato*, and Katrien Verbert. 2022. Explaining Recommendations in E-Learning: Effects on Adolescents' Trust. In *27th International Conference on Intelligent User Interfaces* (IUI '22), 93–105. https://doi.org/10.1145/3490099.3511140



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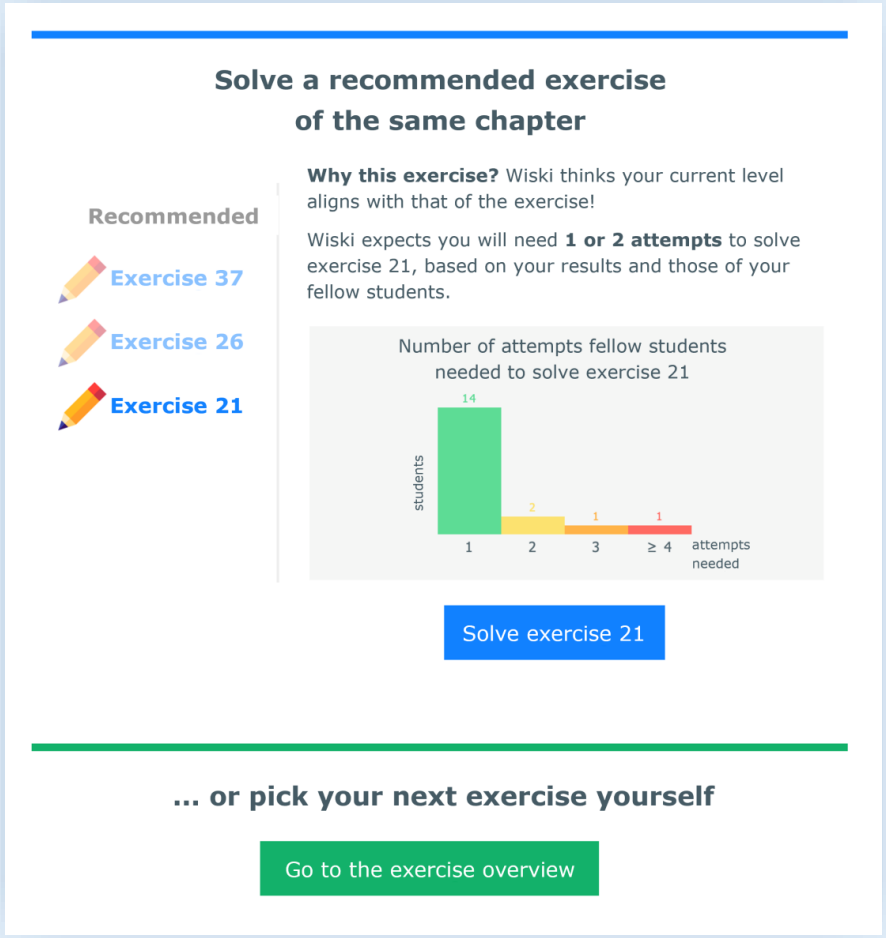
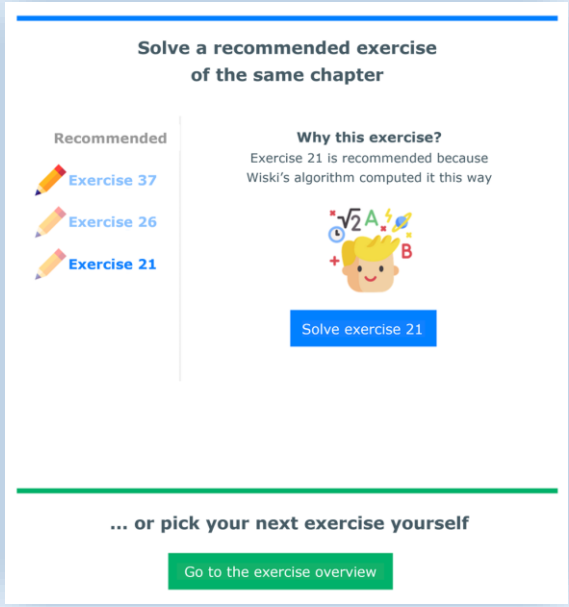
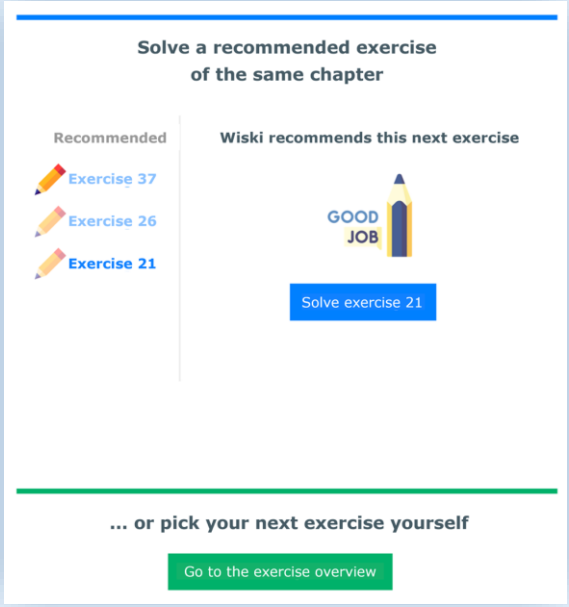
How was trust in the platform affected?



Real explanation



Placebo explanation



No explanation

Jeroen Ooge*, Shotallo Kato*, and Katrien Verbert. 2022. Explaining Recommendations in E-Learning: Effects on Adolescents' Trust. In *27th International Conference on Intelligent User Interfaces* (IUI '22), 93–105. https://doi.org/10.1145/3490099.3511140

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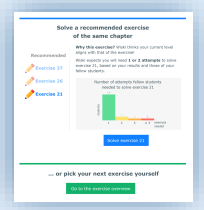
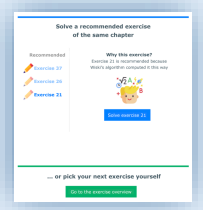




Real vs no explanation

trust increased

trust unchanged

trust decreased

Placebo vs no explanation

trust increased

trust unchanged

trust decreased

Jeroen Ooge*, Shotallo Kato*, and Katrien Verbert. 2022. Explaining Recommendations in E-Learning: Effects on Adolescents' Trust. In *27th International Conference on Intelligent User Interfaces* (IUI '22), 93–105. https://doi.org/10.1145/3490099.3511140

Competence

Q1 Wiski is like an expert (for example, a teacher) for recommend exercises.

Q2 Wiski has the expertise (knowledge) to estimate my math level.

Q3 Wiski can estimate my math level.

Q4 Wiski understands the difficulty level of math exercises well.

Q5 Wiski takes my math level into account when recommending e

Benevolence

Q6 Wiski prioritizes that I improve in math.

Q7 Wiski recommends exercises so that I improve in math.

Q8 Wiski wants to estimate my math level well.

Integrity

Q9 Wiski recommends exercises as correctly as possible.

Q10 Wiski is honest.

Q11 Wiski makes integrous recommendations.

Trust (one-dimensional)

Q12 I trust Wiski to recommend me math exercises.

Intention to return

Q13 If I want to solve math exercises again, I will choose Wiski.

Q14 If I want to be recommended math exercises again, I will choos

Perceived transparency

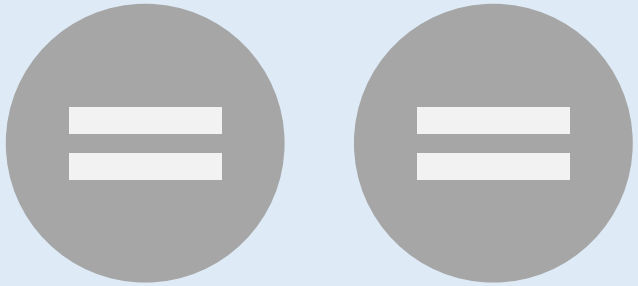
Q15 I find that Wiski gives enough explanation as to why an exercise recommended.

Trusting beliefs

Multidimensional trust

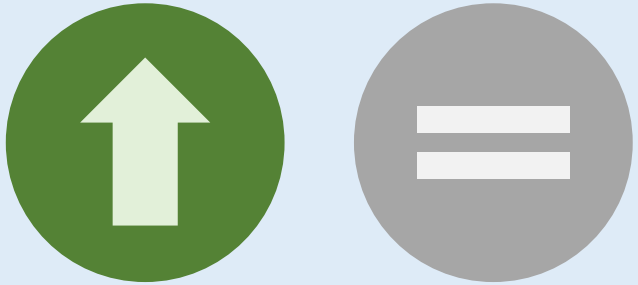
Real vs no explanation

MD trust *1D trust*



Placebo vs no explanation

MD trust *1D trust*



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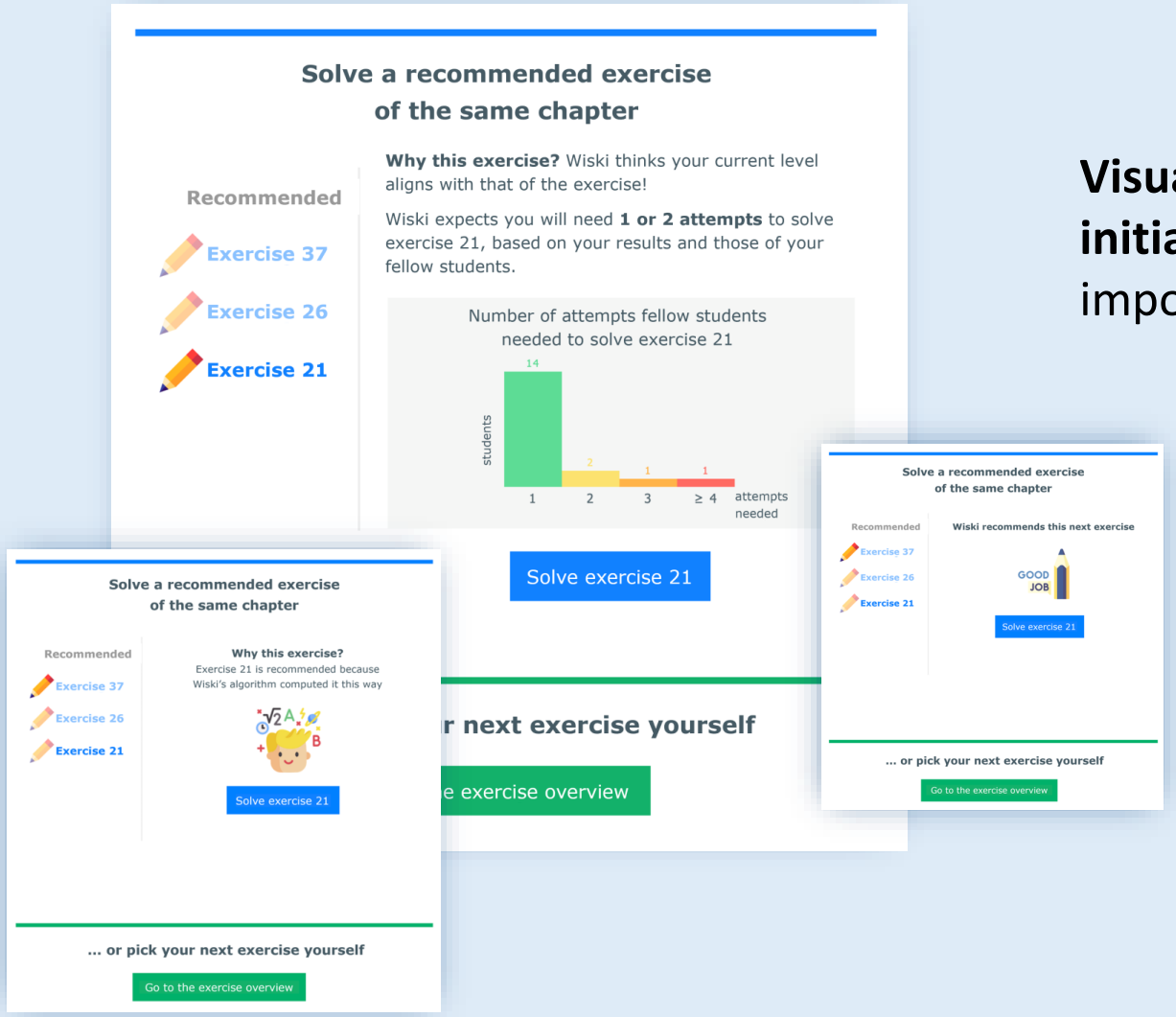
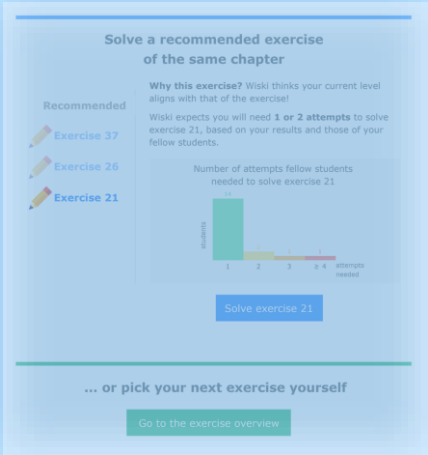
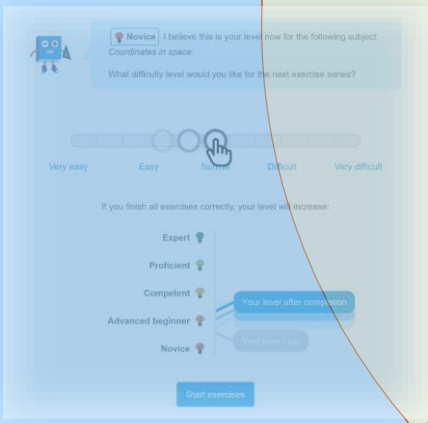


Visual explanations can increase initial trust but may not be the most important factor for building it

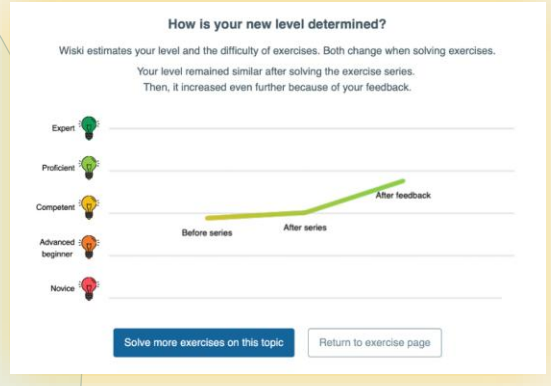
Jeroen Ooge*, Shotallo Kato*, and Katrien Verbert. 2022. Explaining Recommendations in E-Learning: Effects on Adolescents' Trust. In *27th International Conference on Intelligent User Interfaces* (IUI '22), 93–105. https://doi.org/10.1145/3490099.3511140

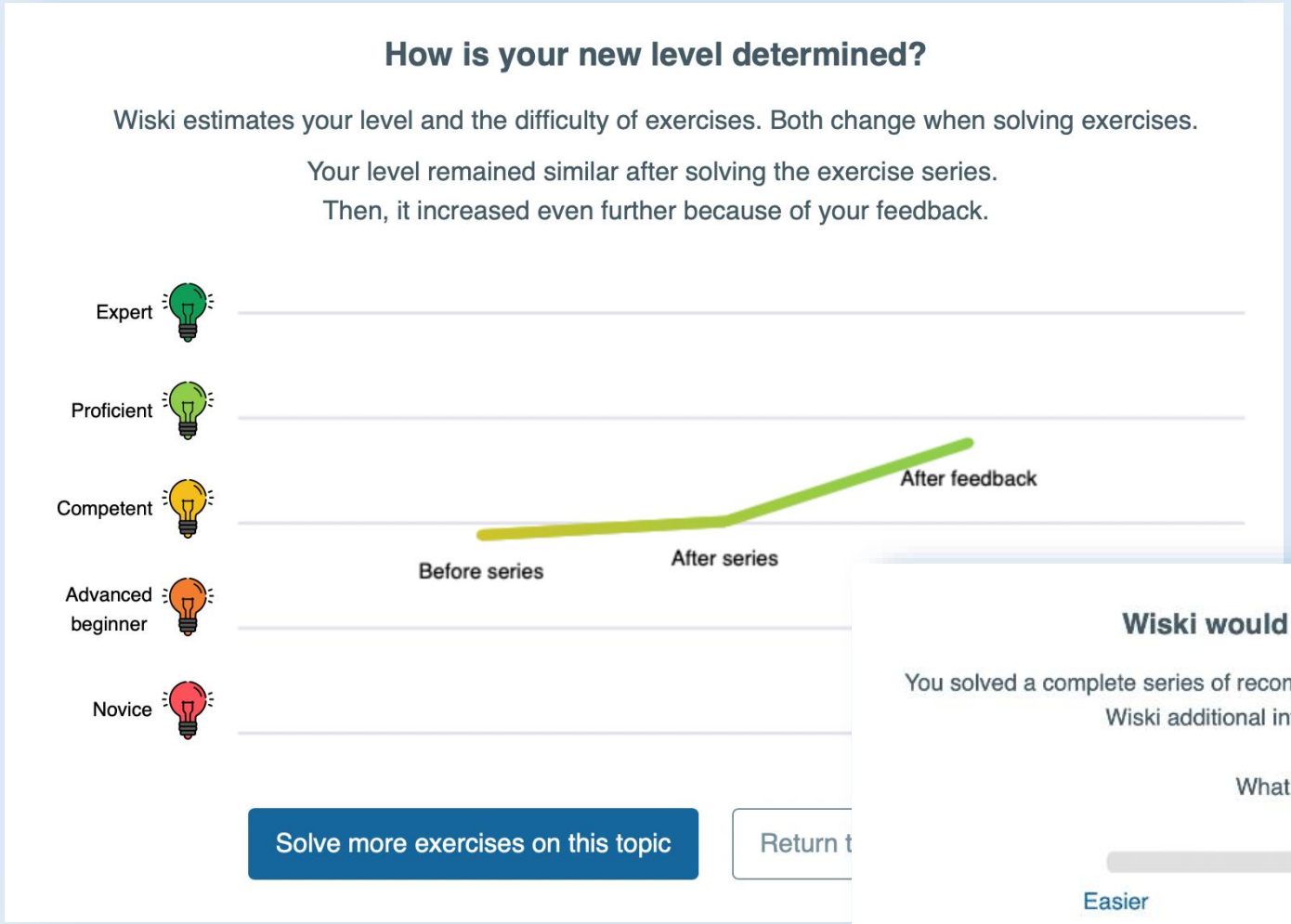
Explanations





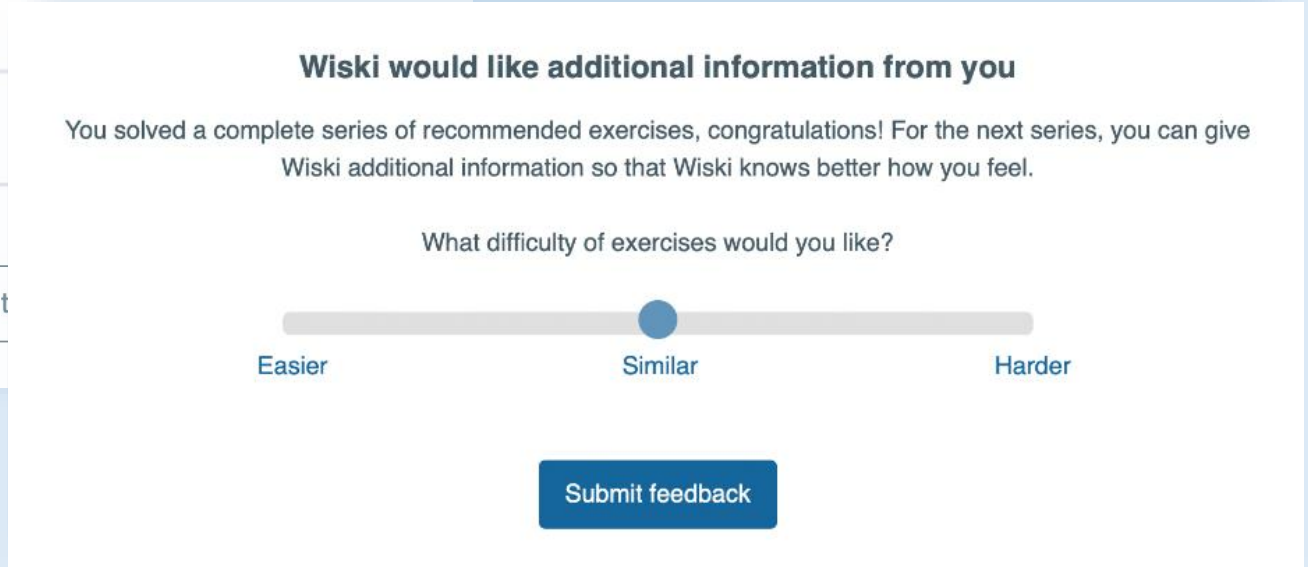
Control





Explanations: control impact in *output* explanations

Control: steer mastery level



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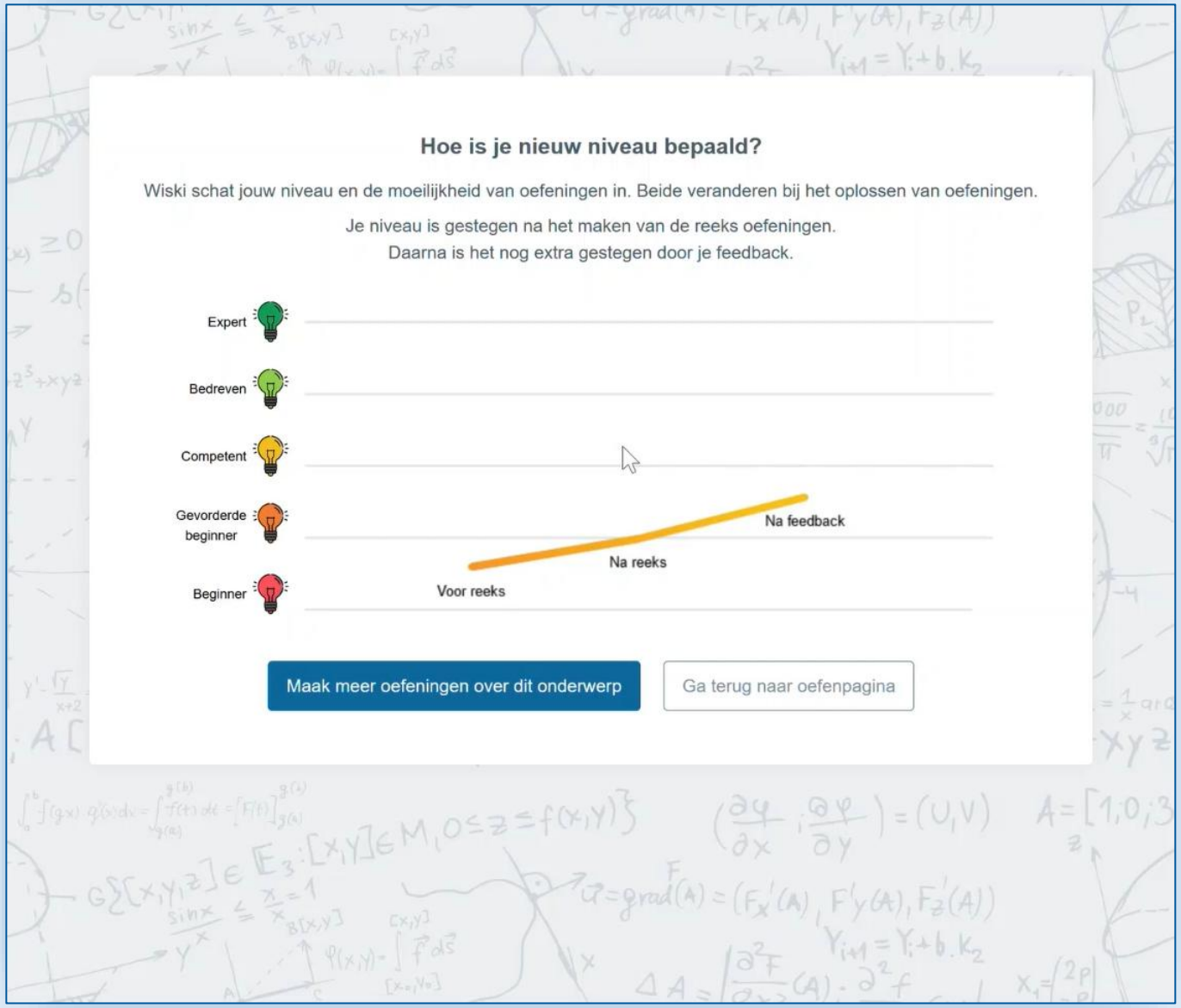

Explanations: control impact in *output* explanations

Control: steer mastery level

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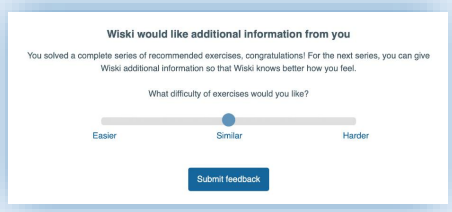

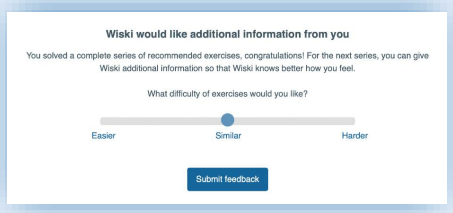

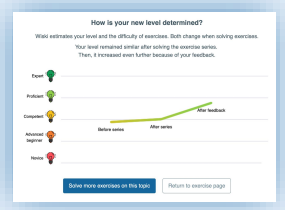

Control vs no control

- trust increased
- trust unchanged ✓
- trust decreased

Control with impact vs no control

- trust increased ✓
- trust unchanged
- trust decreased

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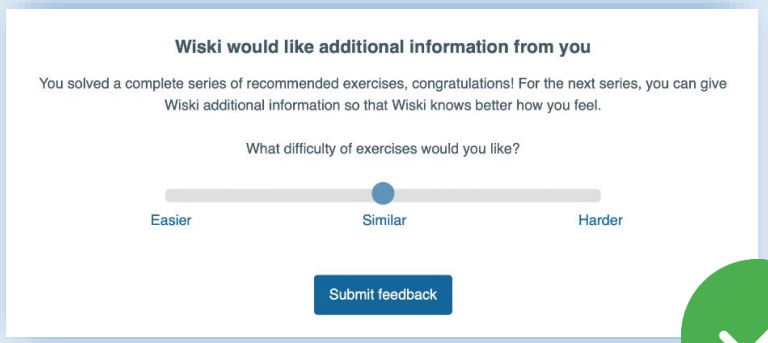

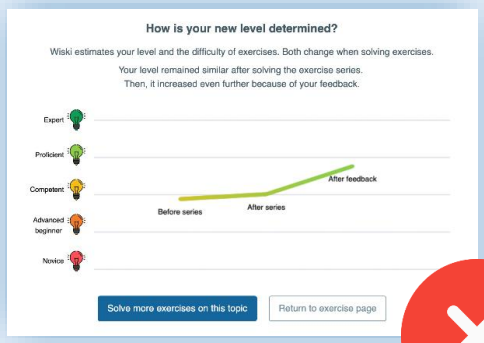

Trust in the platform

Reflection on own mastery and recommendations

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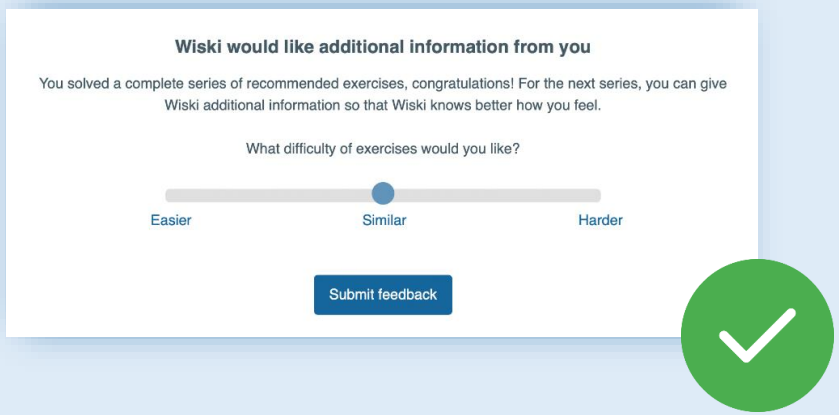

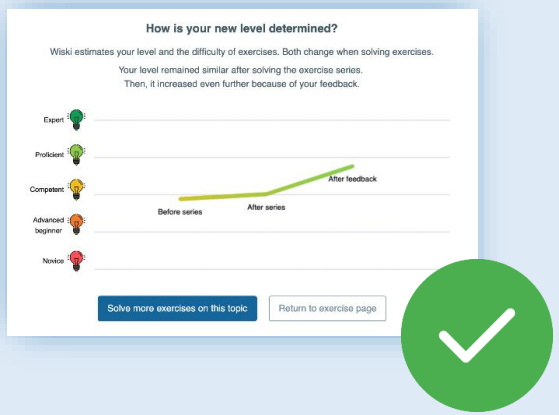

Trust in the platform due to more perceived transparency

Reflection on own mastery and recommendations

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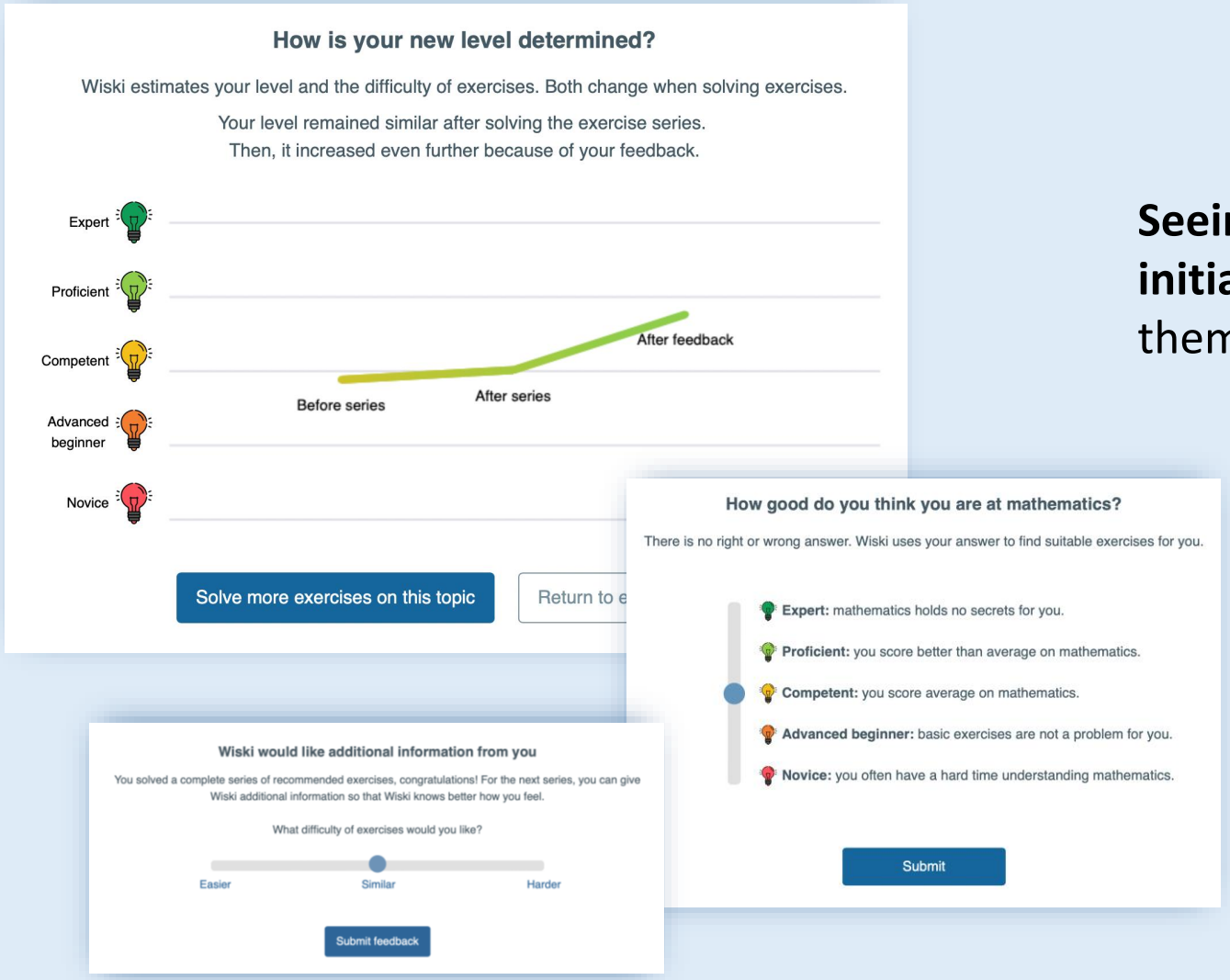


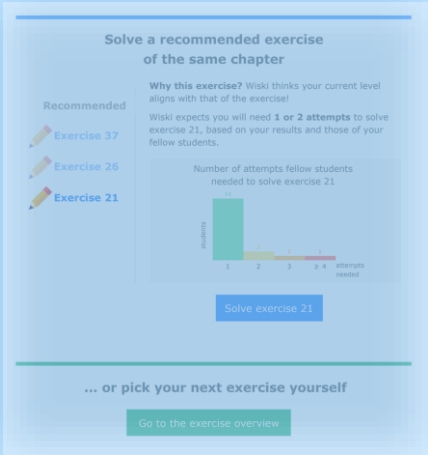
Seeing the impact of control can increase initial trust, but control mechanisms by themselves do not necessarily

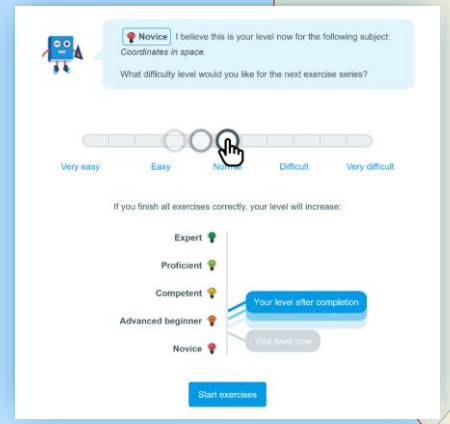
Jeroen Ooge, Leen Dereu, and Katrien Verbert. 2023. Steering Recommendations and Visualising Its Impact: Effects on Adolescents' Trust in E-Learning Platforms. In *Proceedings of the 28th International Conference on Intelligent User Interfaces* (IUI '23), 156–170. https://doi.org/10.1145/3581641.3584046


BRAIN
BREAK

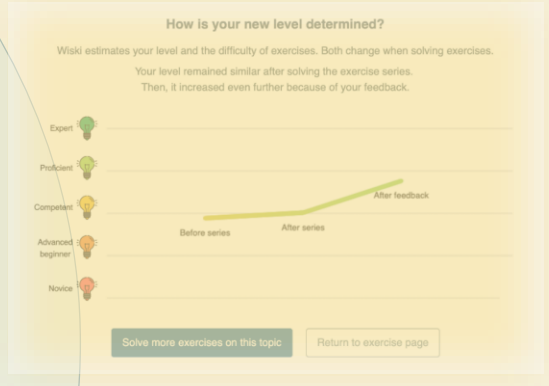

TIME FOR
QUESTIONS

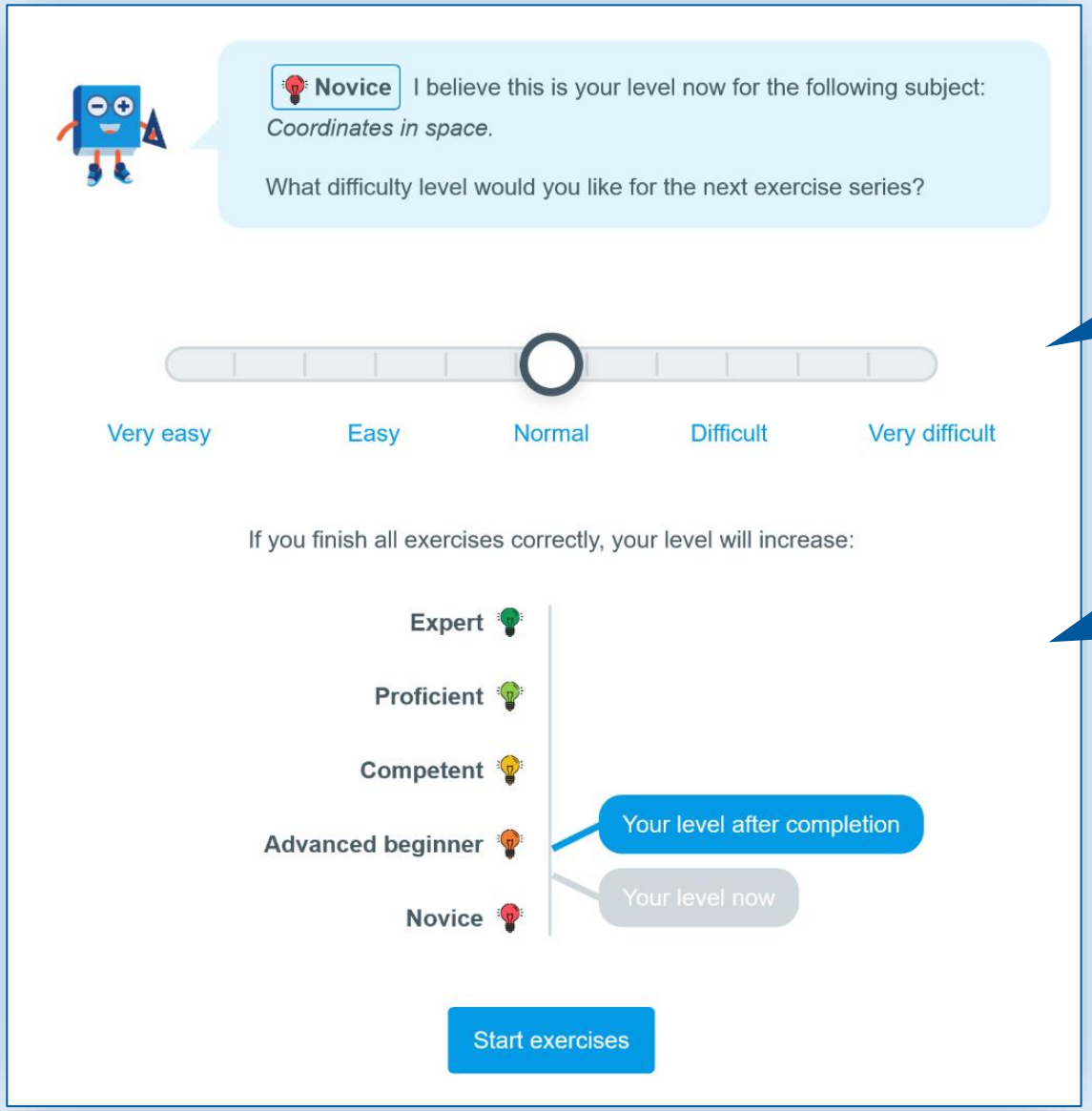
Explanations





Control

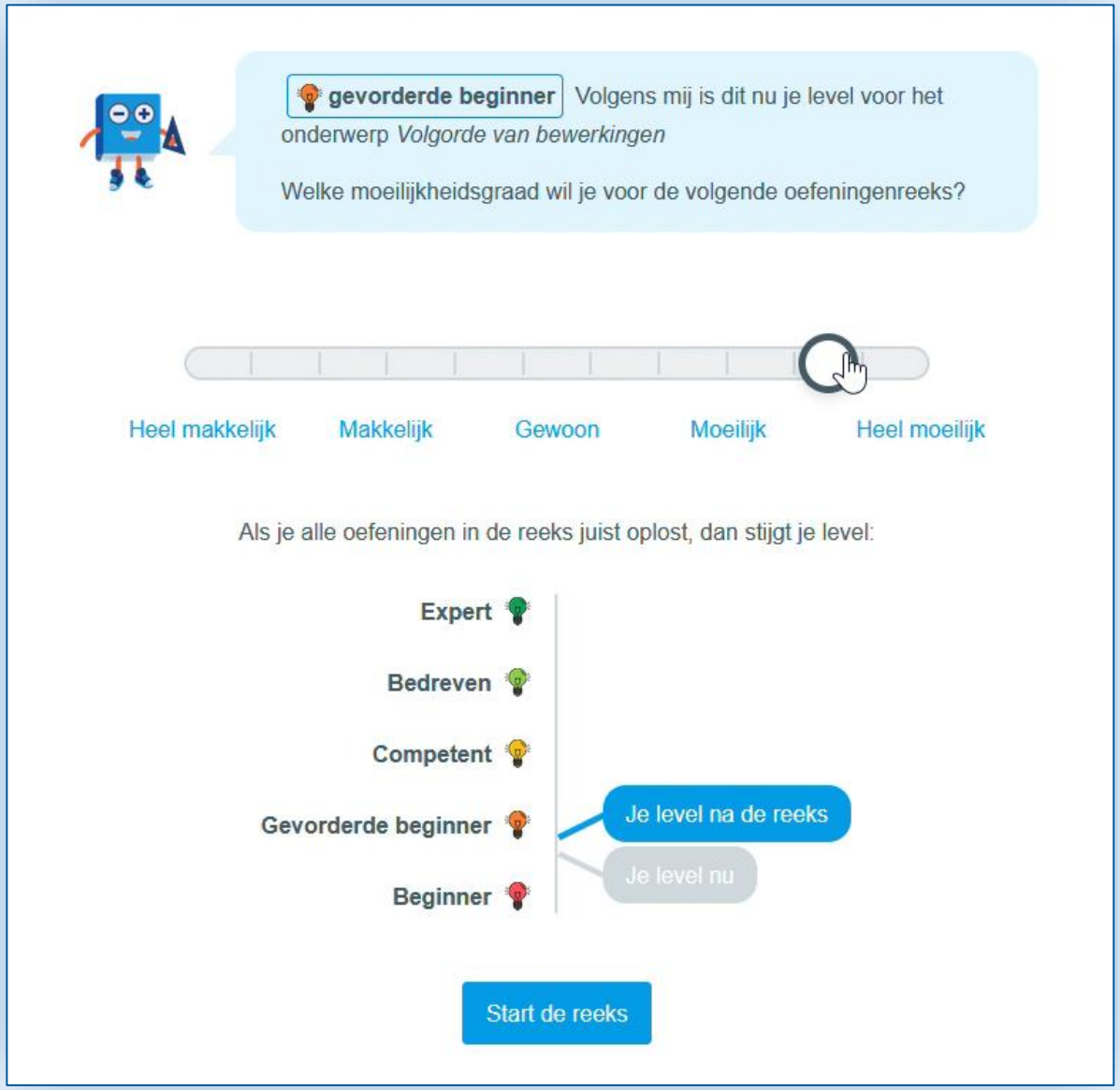




Learner control: choose difficulty of exercise series

What-if explanation: what is the impact on my level if I solve this series correctly?

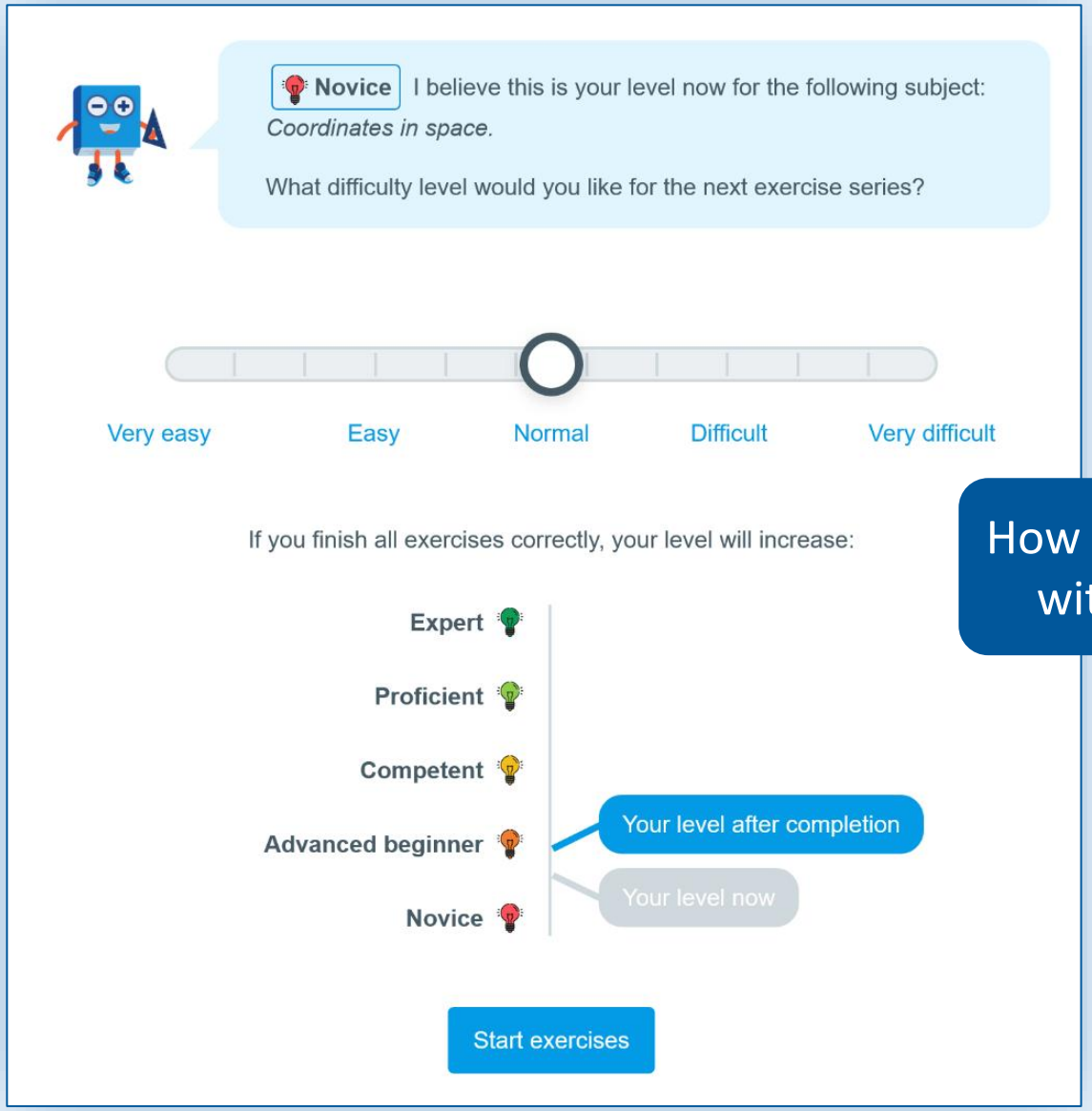
Jeroen Ooge, Arno Vanneste, Maxwell Szymanski, and Katrien Verbert. Designing Visual Explanations and Learner Controls to Engage Adolescents in AI-Supported Exercise Selection. In *Proceedings of the 15th Learning Analytics and Knowledge Conference*, March 2025. https://arxiv.org/abs/2412.16034



Explanations: real-time *what-if* explanations

Control: choose difficulty of recommended exercises series

Jeroen Ooge, Arno Vanneste, Maxwell Szymanski, and Katrien Verbert. Designing Visual Explanations and Learner Controls to Engage Adolescents in AI-Supported Exercise Selection. In *Proceedings of the 15th Learning Analytics and Knowledge Conference*, March 2025. https://arxiv.org/abs/2412.16034



How did you come up with this design?

Jeroen Ooge, Arno Vanneste, Maxwell Szymanski, and Katrien Verbert. Designing Visual Explanations and Learner Controls to Engage Adolescents in AI-Supported Exercise Selection. In *Proceedings of the 15th Learning Analytics and Knowledge Conference*, March 2025. https://arxiv.org/abs/2412.16034

Study 1: Group Discussion

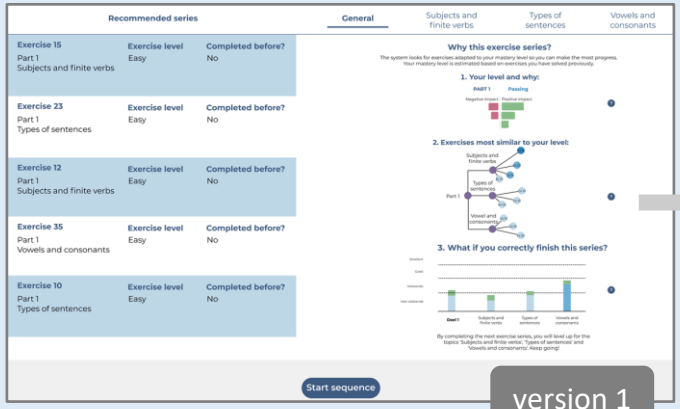
- 3 teachers and 6 EdTech professionals
- Collect learning and explainability needs; test understandability

Study 2: Think-Aloud Studies

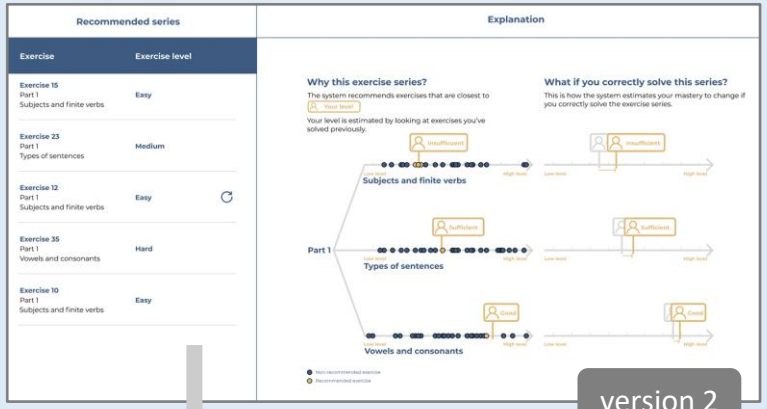
- 6 adolescents
- Collect explainability needs; test understandability and usability

Study 3: Focus Groups

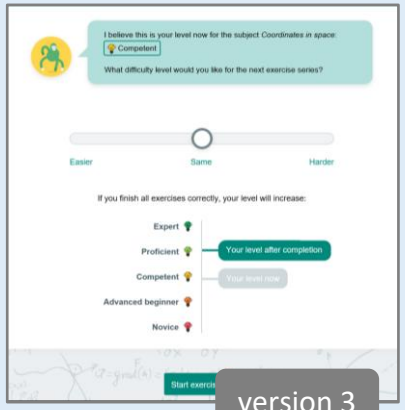
- 7 teachers and pedagogical experts
- Collect explainability and control needs; assess pedagogical value



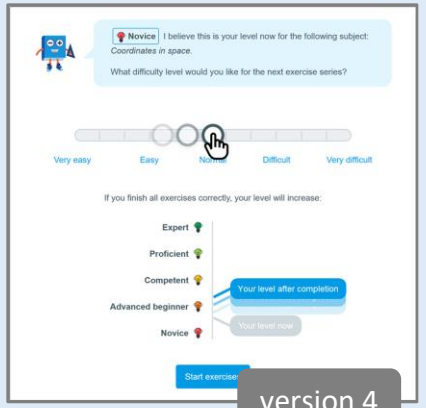
version 1



version 2



version 3



version 4

Study 4: Think-Aloud Studies

- 6 adolescents
- Collect explainability and control needs; test understandability and usability

Jeroen Ooge, Arno Vanneste, Maxwell Szymanski, and Katrien Verbert. Designing Visual Explanations and Learner Controls to Engage Adolescents in AI-Supported Exercise Selection. In *Proceedings of the 15th Learning Analytics and Knowledge Conference*, March 2025. https://arxiv.org/abs/2412.16034

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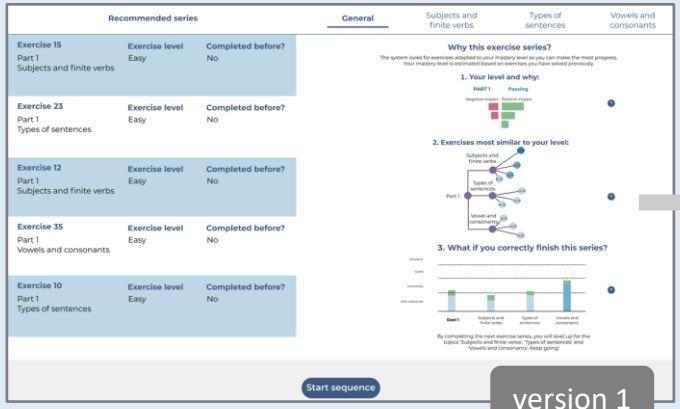

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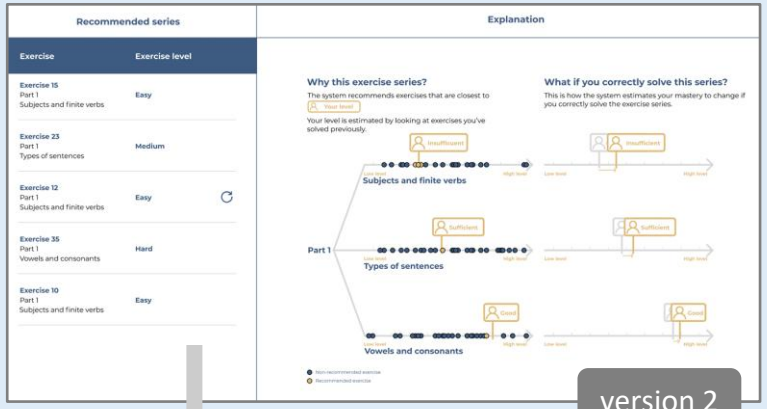

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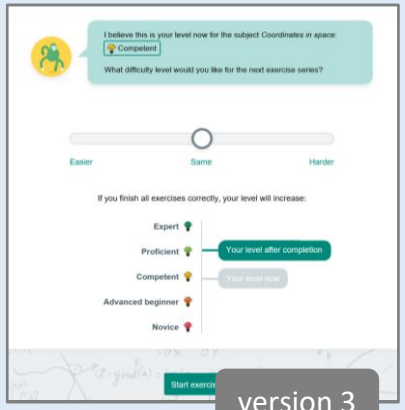

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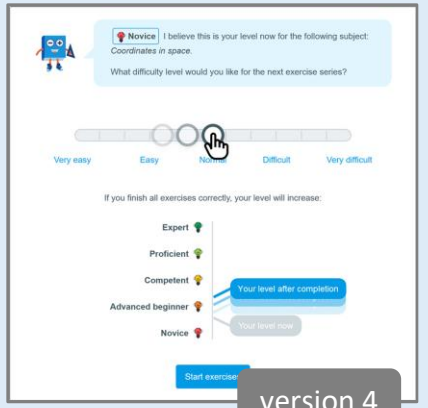


version 4

Study 4: Think-Aloud Studies

- 6 adolescents
- Collect explainability and control needs; test understandability and usability

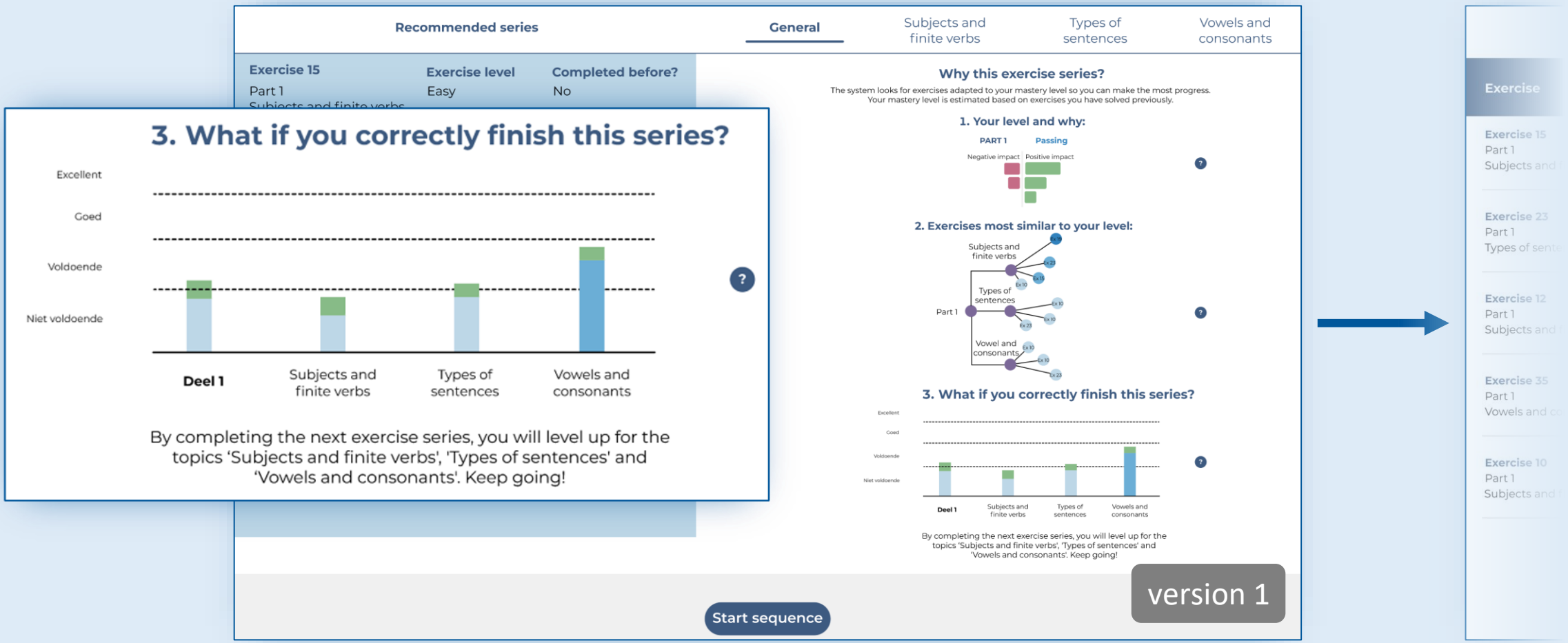
Long **iterative design process** with many educational stakeholders!

Study 1: Group Discussion

- 3 teachers and 6 EdTech professionals
- Collect learning and explainability needs; test understandability

Clarify visualisations and restrict information

What-if explanations might boost motivation



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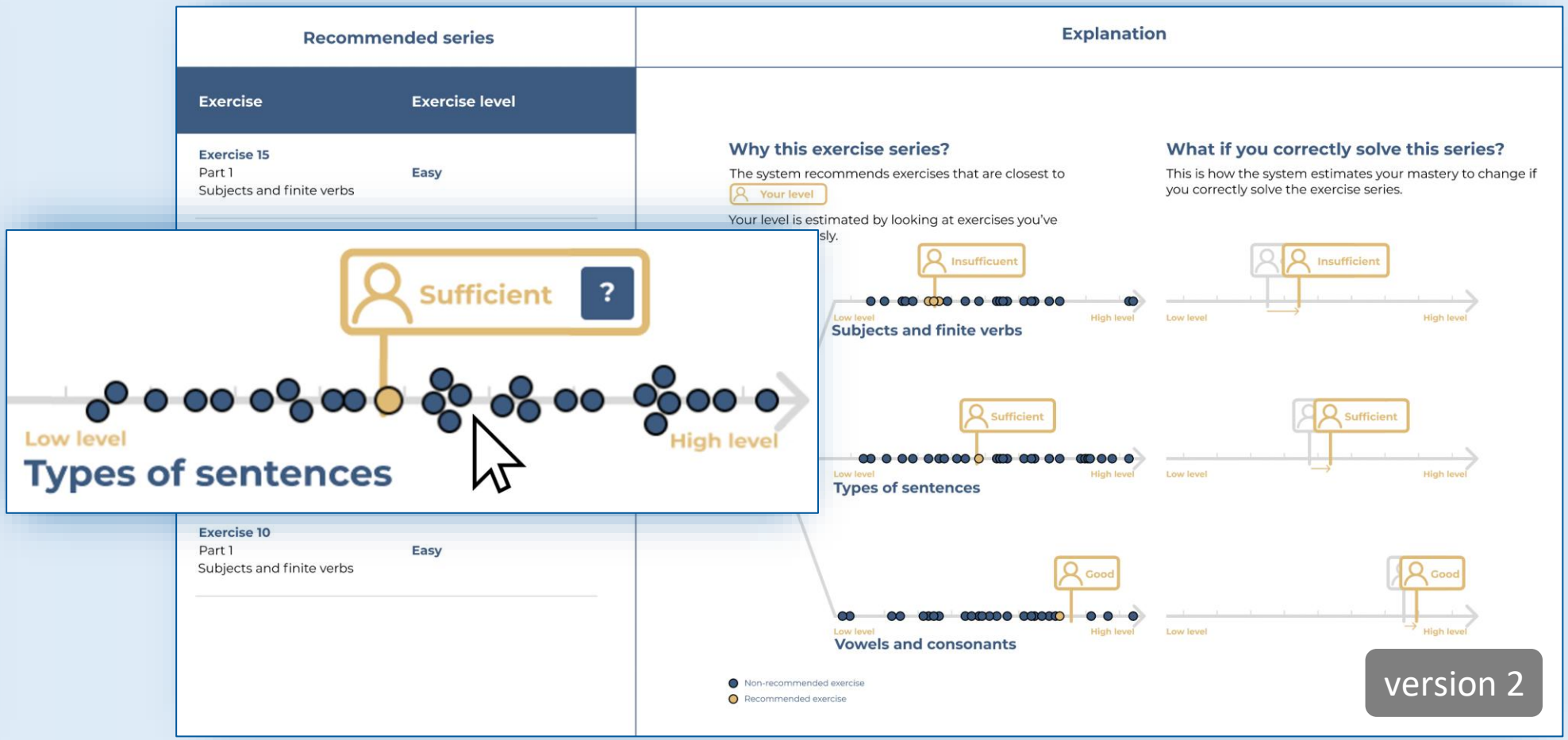
Study 2: Think-Aloud Studies

- 6 adolescents
- Collect explainability needs; test understandability and usability

Minimise text, tightly integrate explanations

Inattentiveness can harm mental models

Adolescents want control and motivation supports



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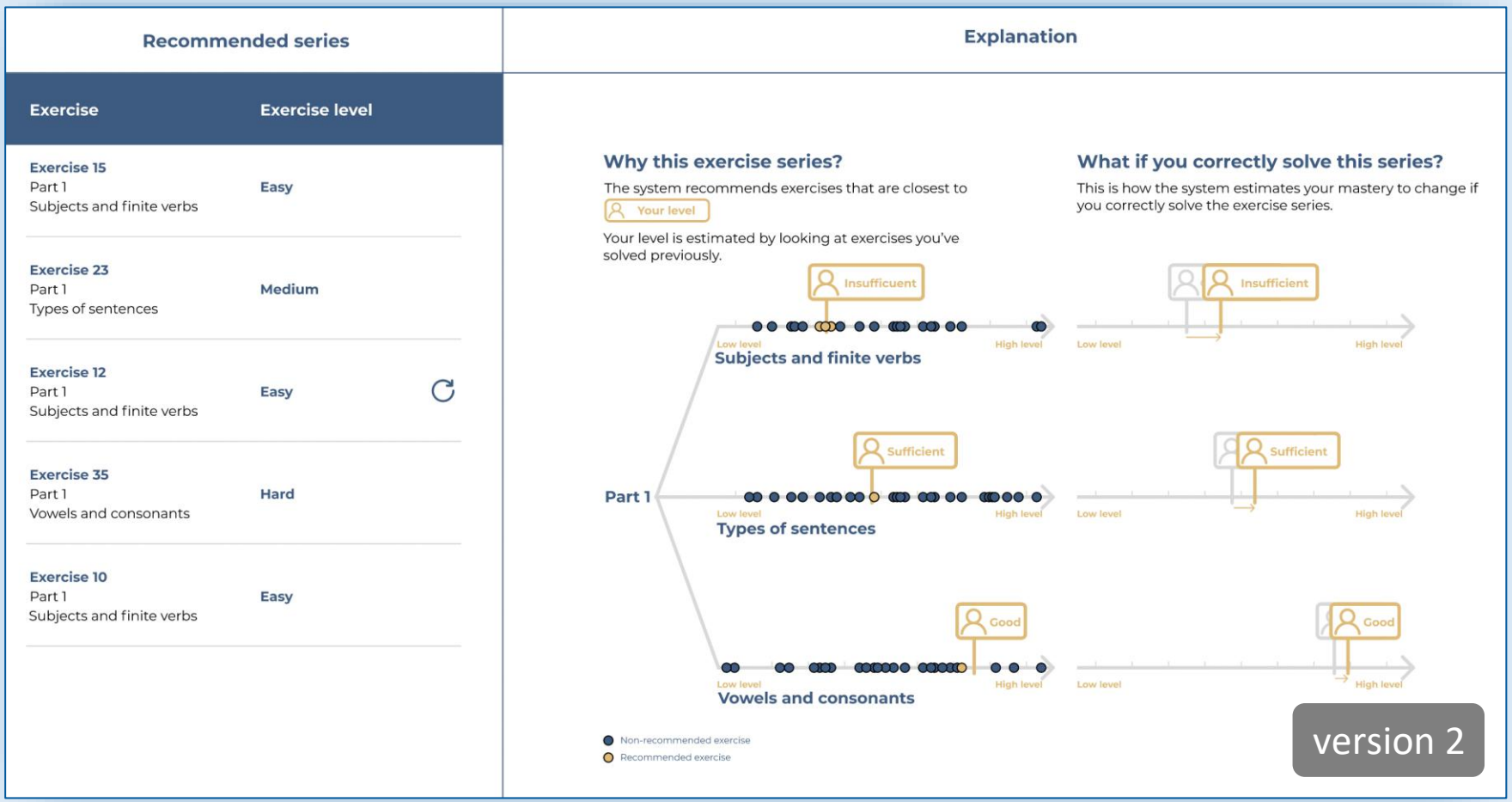
Study 3: Focus Groups

- 7 teachers and pedagogical experts
- Collect explainability and control needs; assess pedagogical value

Students need goal-oriented, motivating explanations

How appropriate is learner control?

Why explanations can empower teachers



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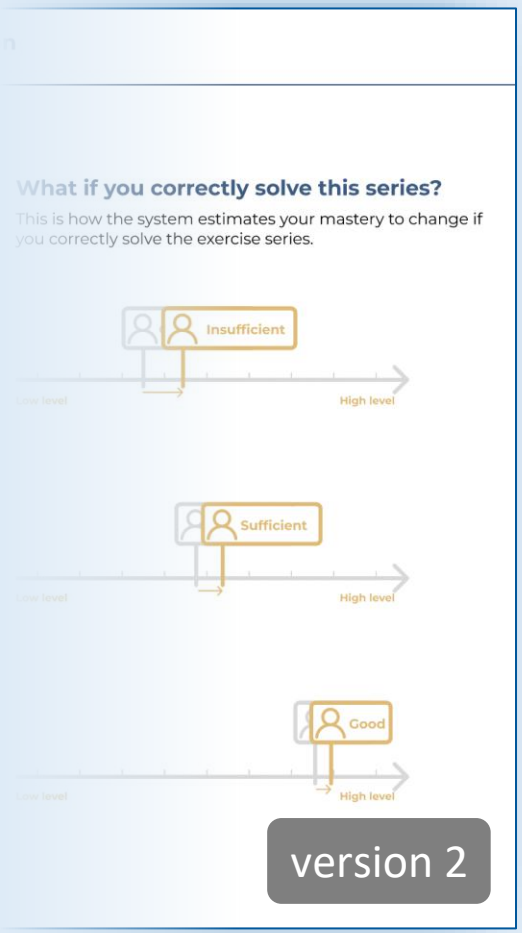
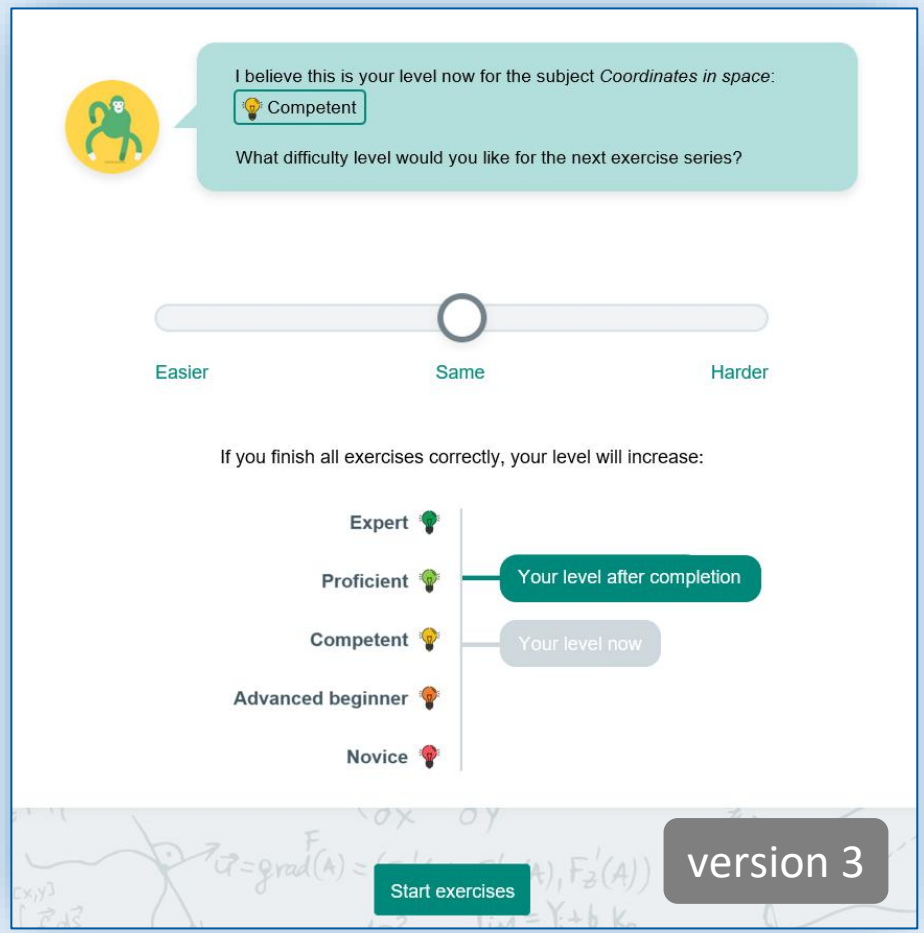
Study 4: Think-Aloud Studies

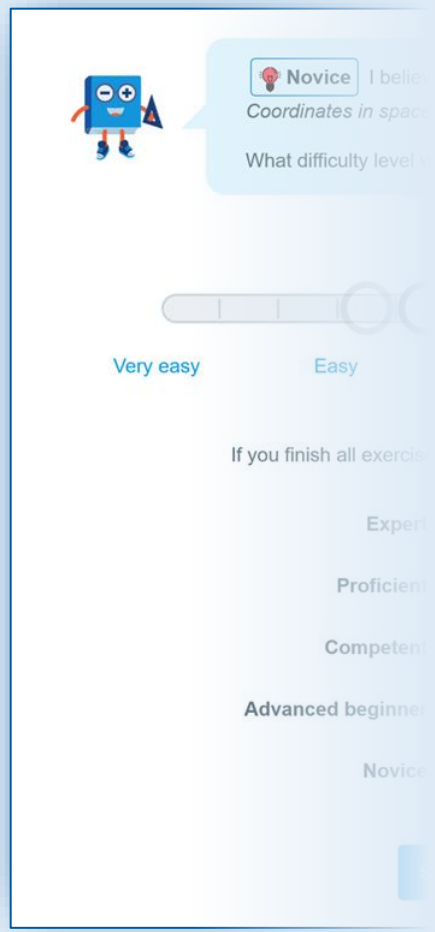
- 6 adolescents
- Collect explainability and control needs; test understandability and usability

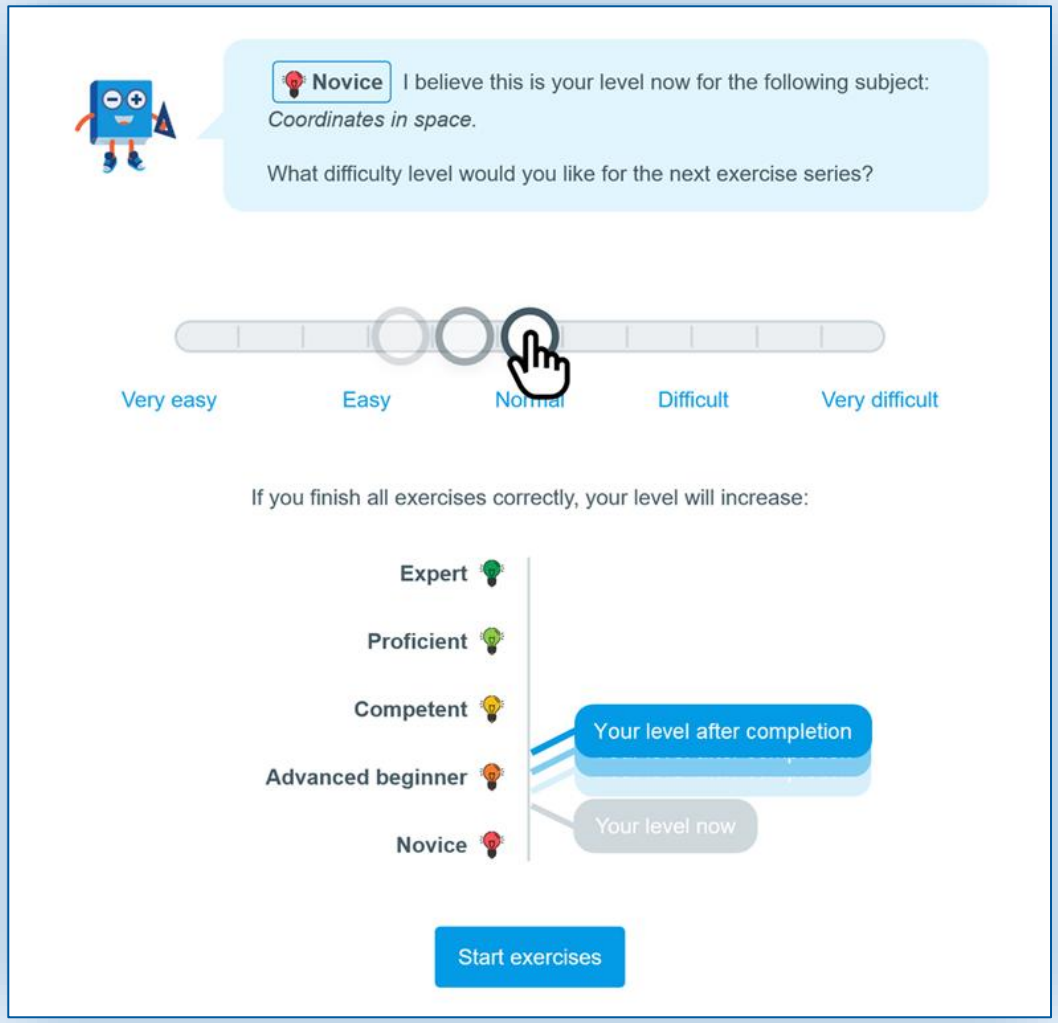
Control stimulates self-reflection

What-if explanations clarify progress





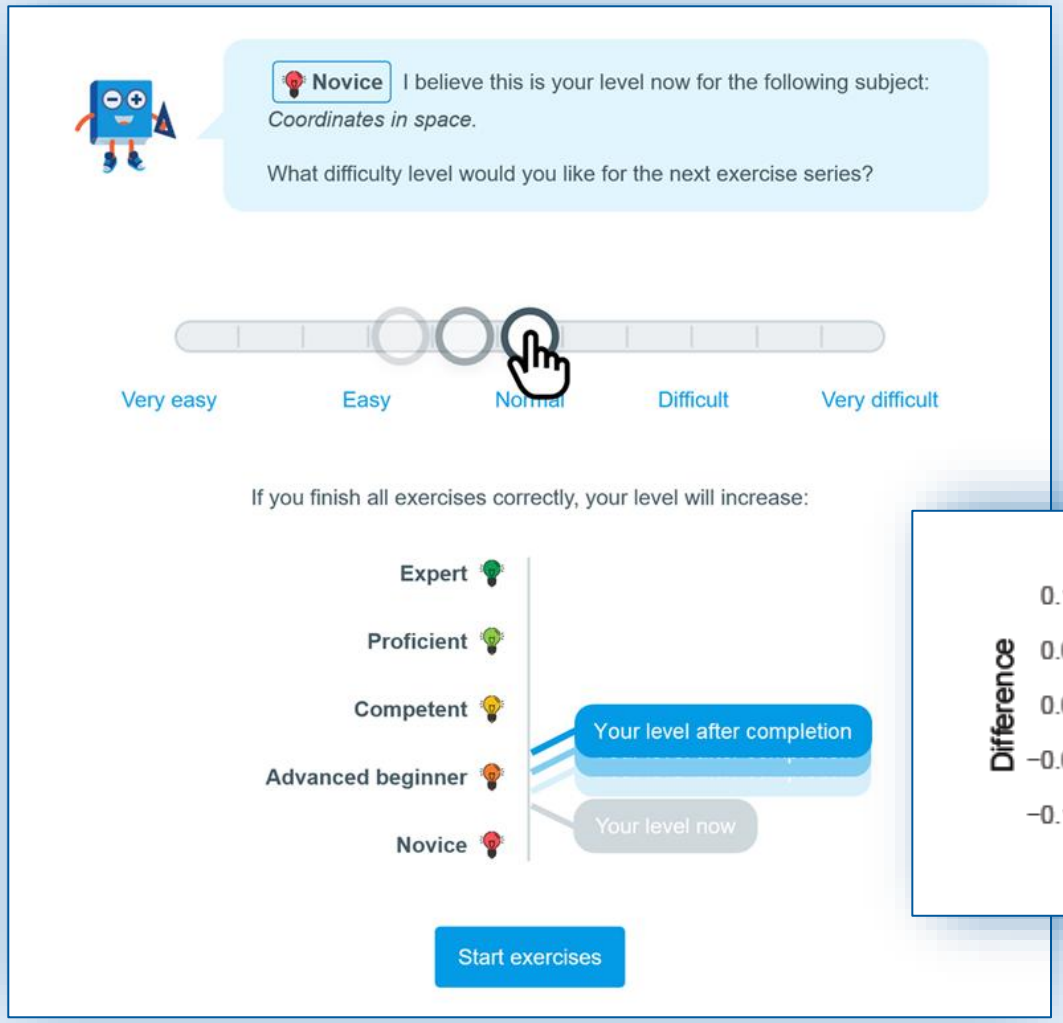




Why explanations desirable for teachers, not for adolescents

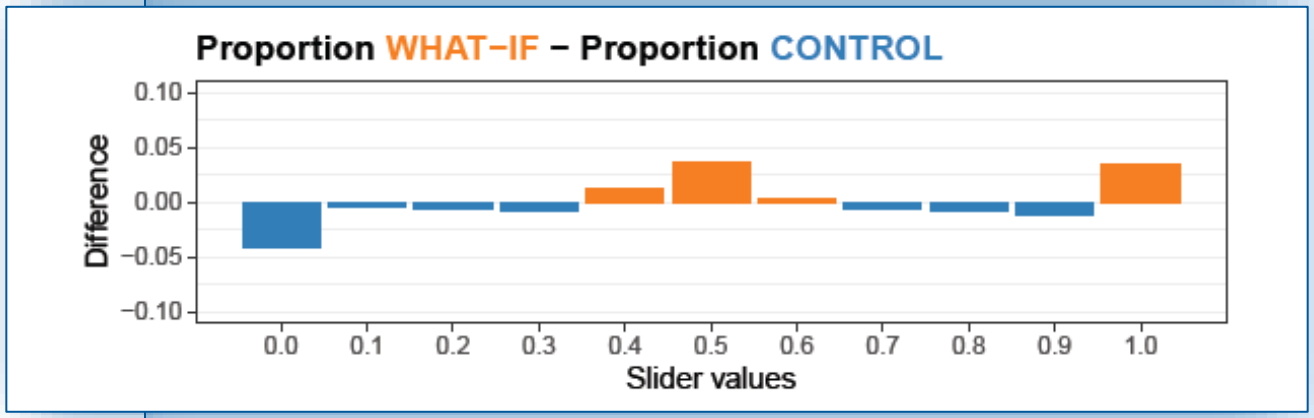
What-if explanations and learner control might **motivate and engage**

Jeroen Ooge, Arno Vanneste, Maxwell Szymanski, and Katrien Verbert. Designing Visual Explanations and Learner Controls to Engage Adolescents in AI-Supported Exercise Selection. In *Proceedings of the 15th Learning Analytics and Knowledge Conference*, March 2025. https://arxiv.org/abs/2412.16034



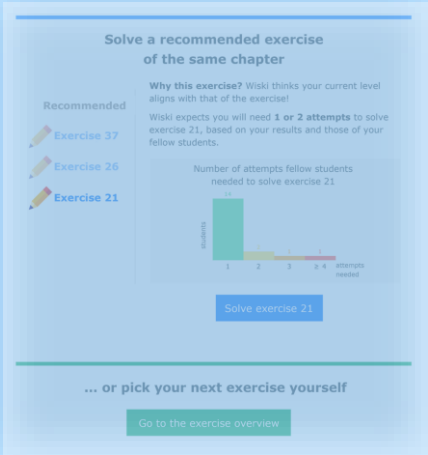
PRELIMINARY RESULTS!

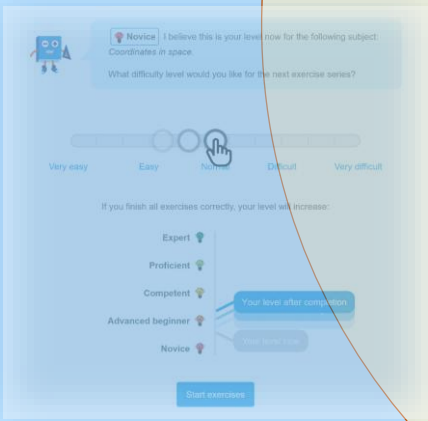
***What-if* explanations can encourage teenagers to try harder exercises**, but do not necessarily affect initial trust, metacognition, motivation, or performance



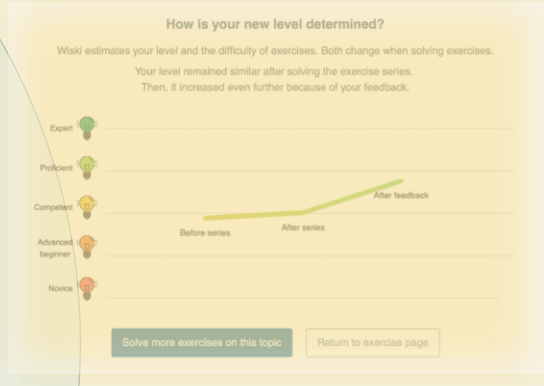
Jeroen Ooge*, Maxwell Szymanski*, and Katrien Verbert. Work in progress.

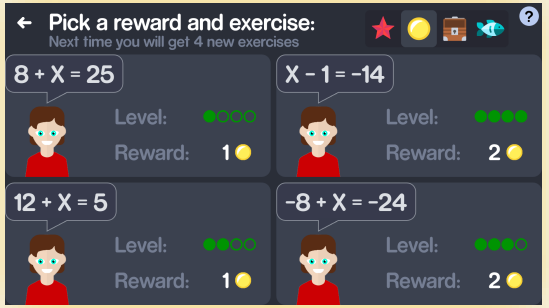
Explanations



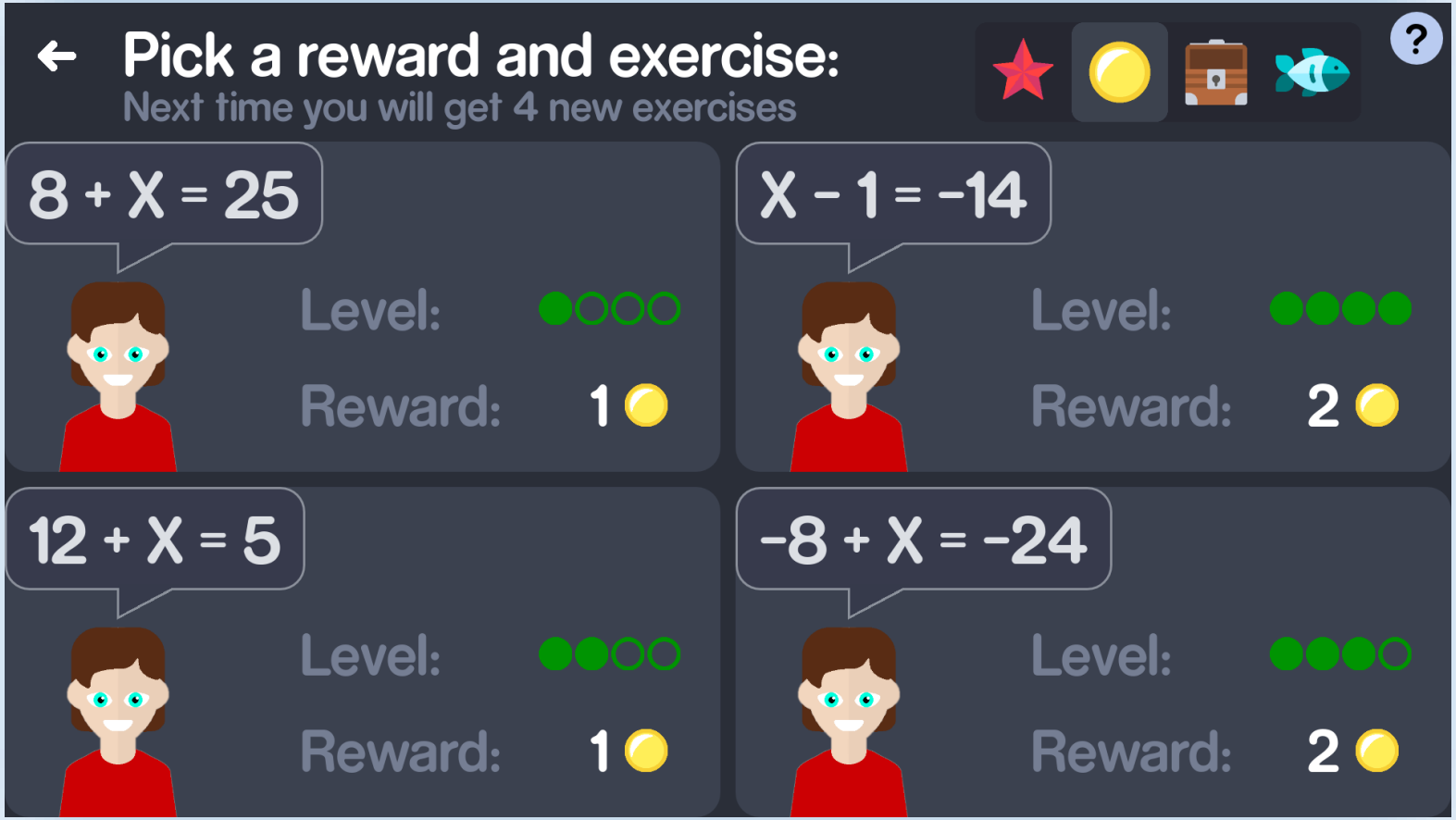


Control





Jeroen Ooge*, Joran De Braekeleer*, and Katrien Verbert. 2024. Nudging Adolescents Towards Recommended Maths Exercises with Gameful Rewards. In: Artificial Intelligence in Education. AIED 2024. Lecture Notes in Computer Science, vol 14830. Springer, Cham. https://youtu.be/12bH2HZdf1Q



Difficulty for the learner

Reward for a correct answer

Transparency: difficulty labels

Control: choose next exercise while being nudged

Jeroen Ooge*, Joran De Braekeleer*, and Katrien Verbert. 2024. Nudging Adolescents Towards Recommended Maths Exercises with Gameful Rewards. In: Artificial Intelligence in Education. AIED 2024. Lecture Notes in Computer Science, vol 14830. Springer, Cham. https://doi.org/10.1007/978-3-031-64299-9_28


TIME FOR
QUESTIONS

I How to adapt education?

Examples of adaptation in education

II What is my research about?

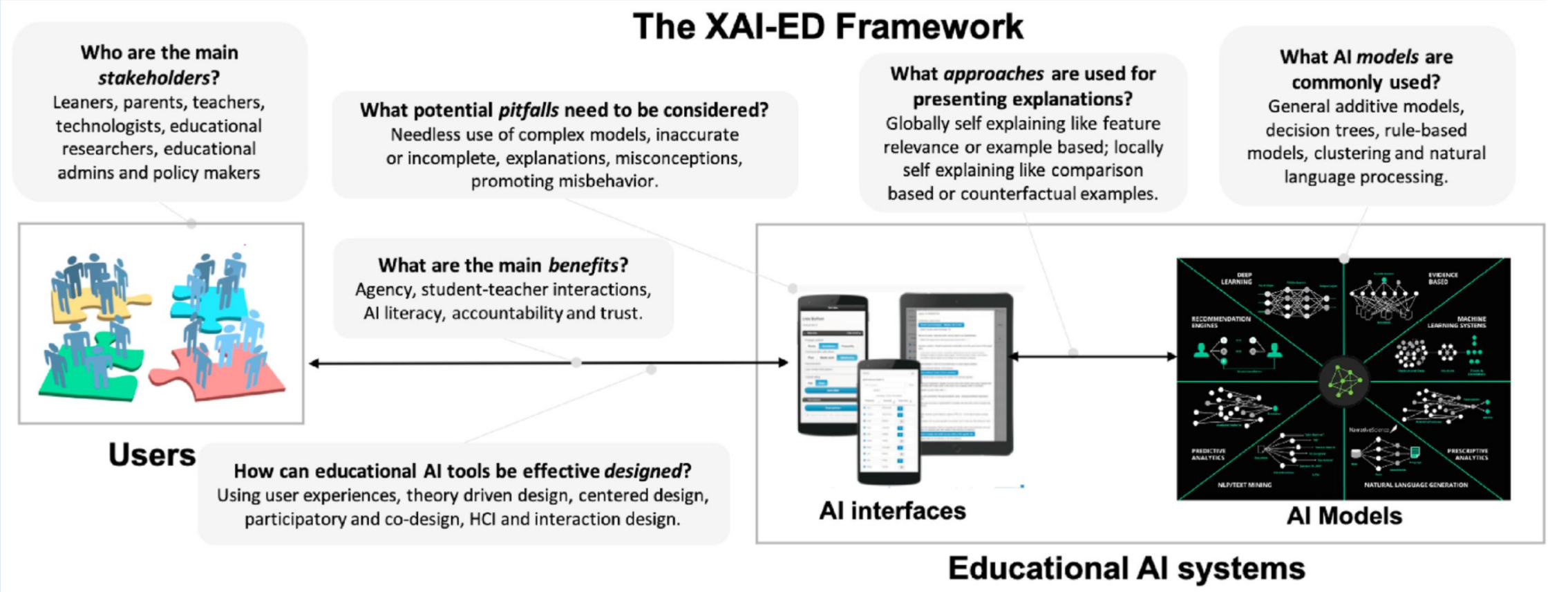
Transparent and controllable

AI systems for education

III How can you contribute?

Exercise & ideas for master’s theses

Exercise: Transparent and controllable adaptive systems at Utrecht University

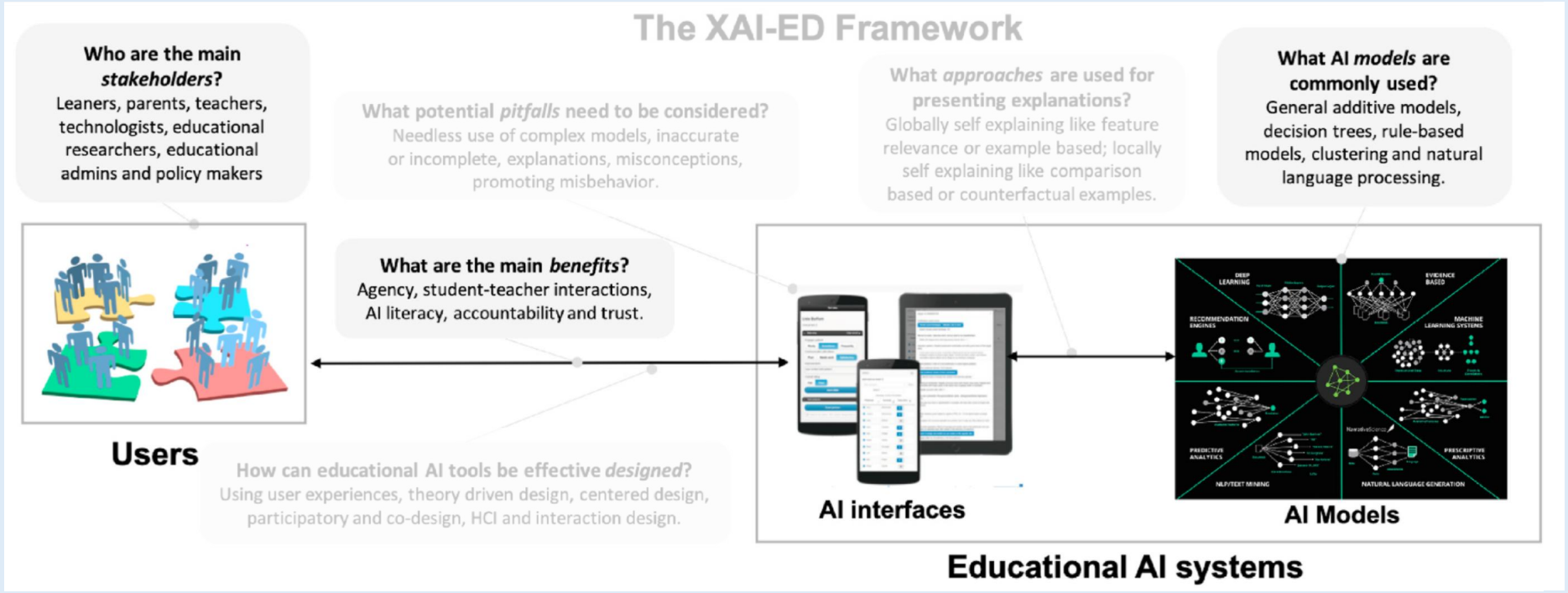


Hassan Khosravi, Simon Buckingham Shum, Guanliang Chen, Cristina Conati, Yi-Shan Tsai, Judy Kay, Simon Knight, Roberto Martinez-Maldonado, Shazia Sadiq, and Dragan Gašević. 2022. Explainable Artificial Intelligence in education. Computers and Education: Artificial Intelligence 3: 100074. https://doi.org/10.1016/j.caeai.2022.100074

Step 1: Describe an adaptive system for UU

1 **Who** is the target audience?

3 **Which** adaptive techniques are used?

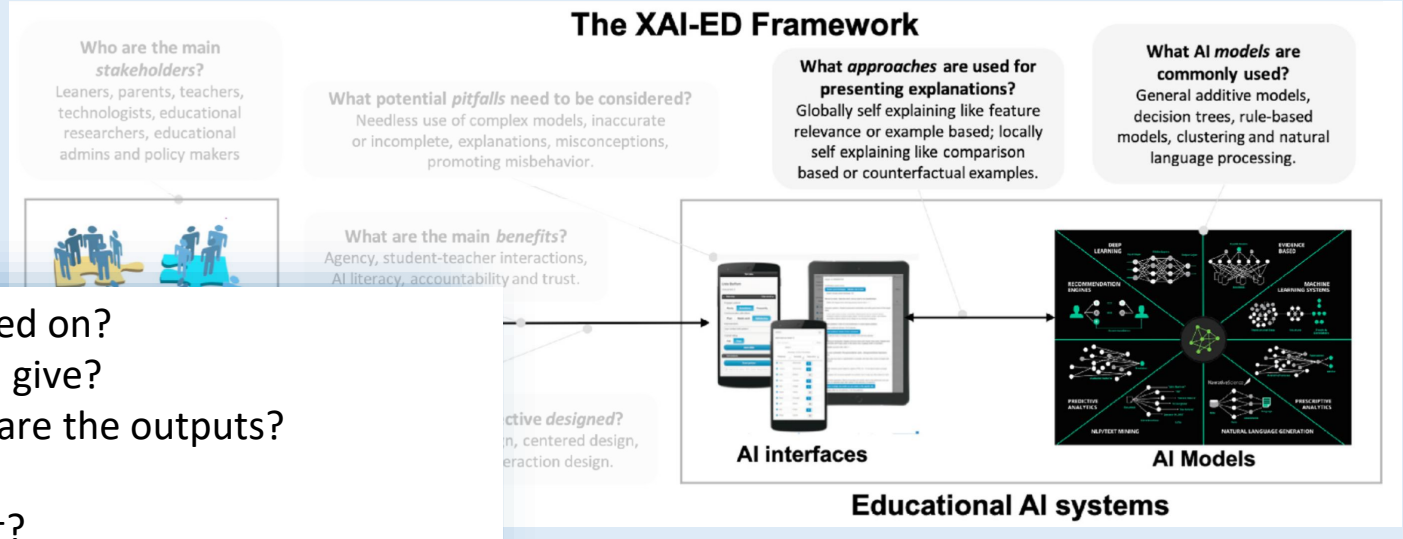


2 **How** does the system support education?

Hassan Khosravi, Simon Buckingham Shum, Guanliang Chen, Cristina Conati, Yi-Shan Tsai, Judy Kay, Simon Knight, Roberto Martinez-Maldonado, Shazia Sadiq, and Dragan Gašević. 2022. Explainable Artificial Intelligence in education. Computers and Education: Artificial Intelligence 3: 100074. https://doi.org/10.1016/j.caeai.2022.100074

Step 2: Add transparency and control

4 How to integrate explanations and control into the system?



Data: What kind of data was the system trained on?
Output: What kind of output does the system give?
Performance: How accurate/precise/reliable are the outputs?
How: How does the system obtain outputs?
Why: Why/how is this input giving this output?
Why not: Why does this input not have a different output?
How to be that: How should this input change to get a different output?
How to still be this: What is the change permitted for this input to still get the same output?
What if: What would the system predict if this input changes to...?

Q. Vera Liao, Milena Pribić, Jaesik Han, Sarah Miller, and Daby Sow. 2021. Question-Driven Design Process for Explainable AI User Experiences. *arXiv:2104.03483 [cs]*. Retrieved March 29, 2022 from http://arxiv.org/abs/2104.03483

I How to adapt education?

Examples of adaptation in education

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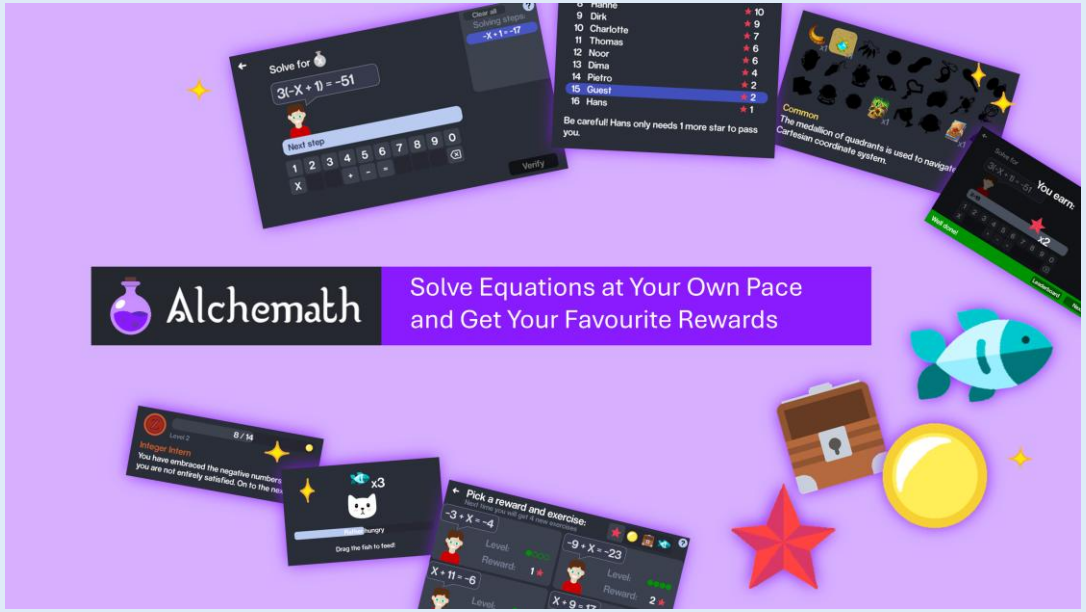
Exercise & ideas for master’s theses

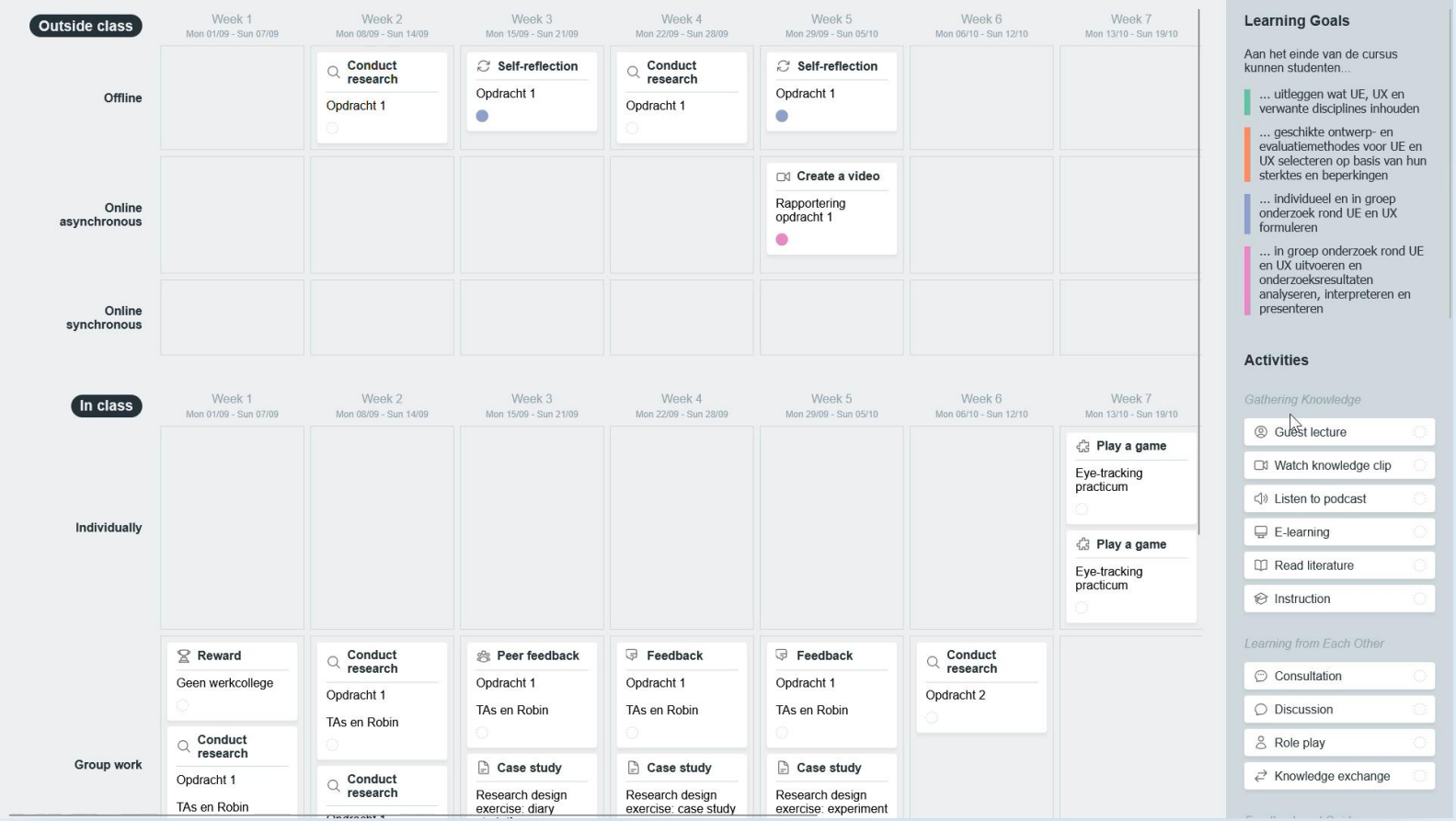
Idea 1: alternative operationalisations



Extend existing adaptive applications with cognitively engaging explanations and control mechanisms

e.g., can teachers create content more efficiently with AI?

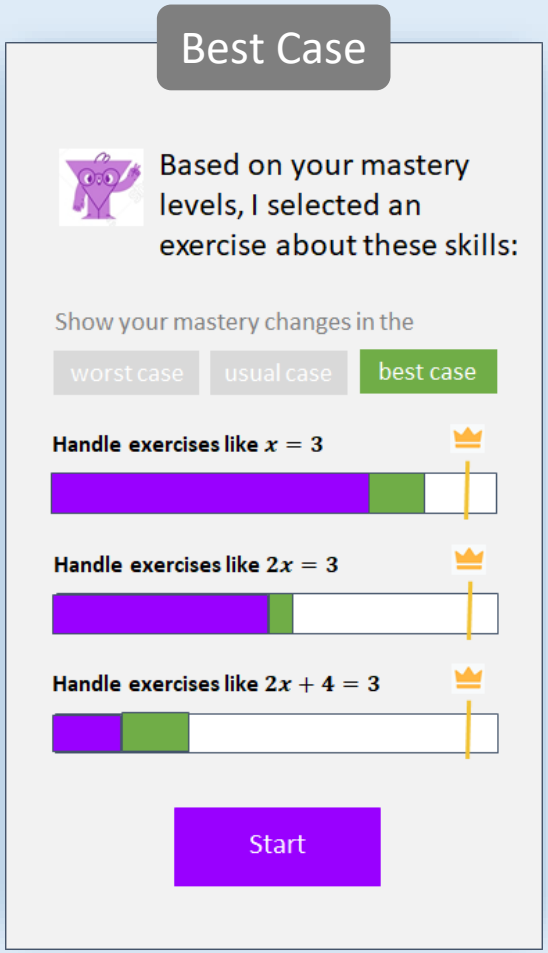
Idea 2: adaptive planning

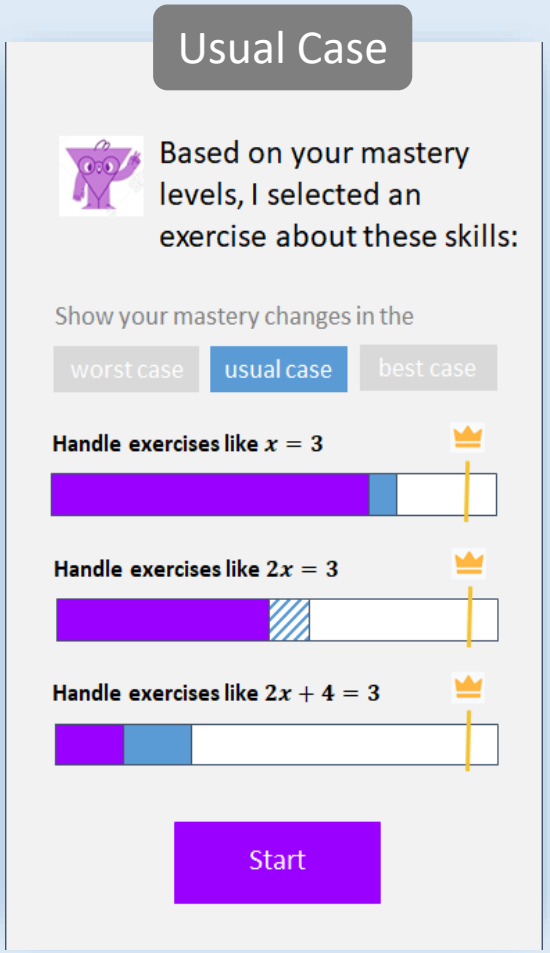


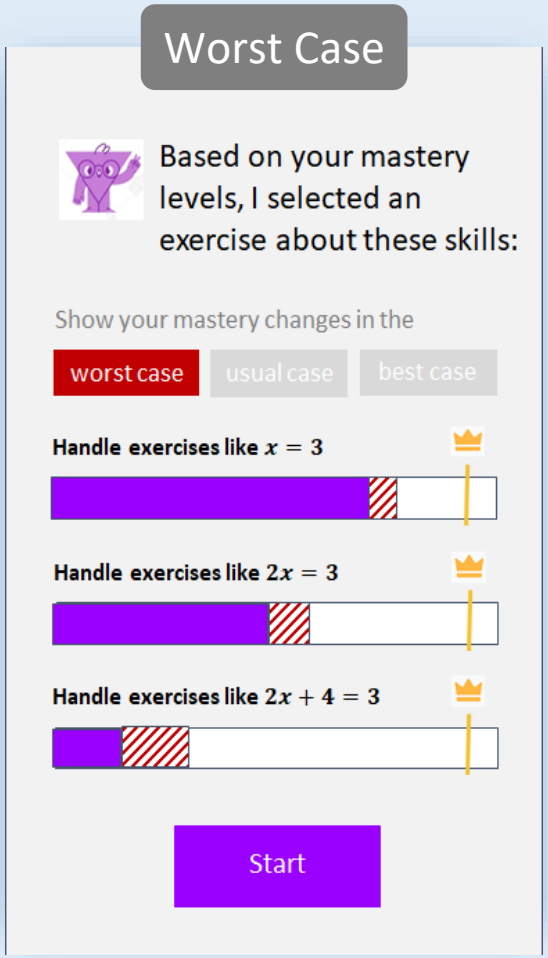
Add explainable recommendations based on blended learning theory to a planner tool

e.g., can teachers more efficiently plan blended courses?

Idea 3: generalise *what-if* explanations

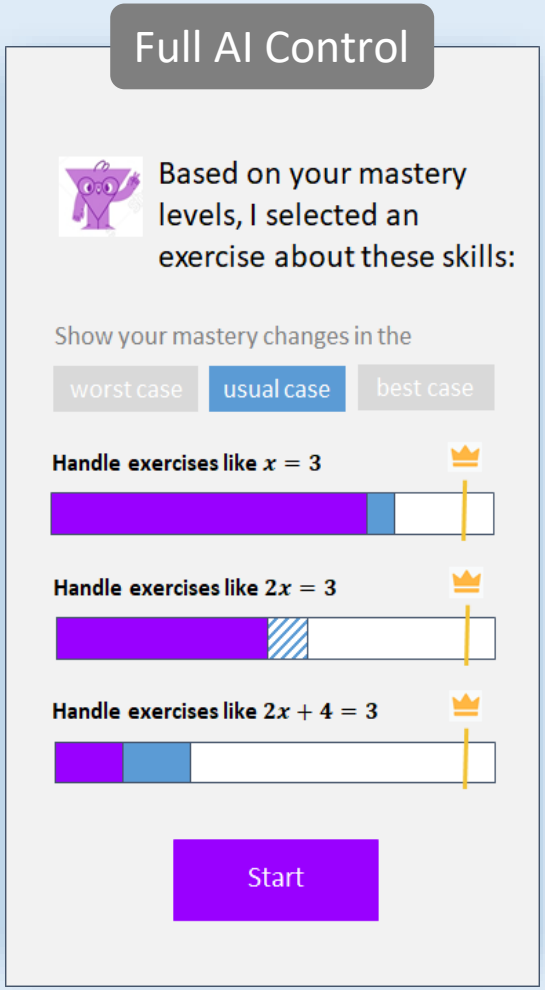


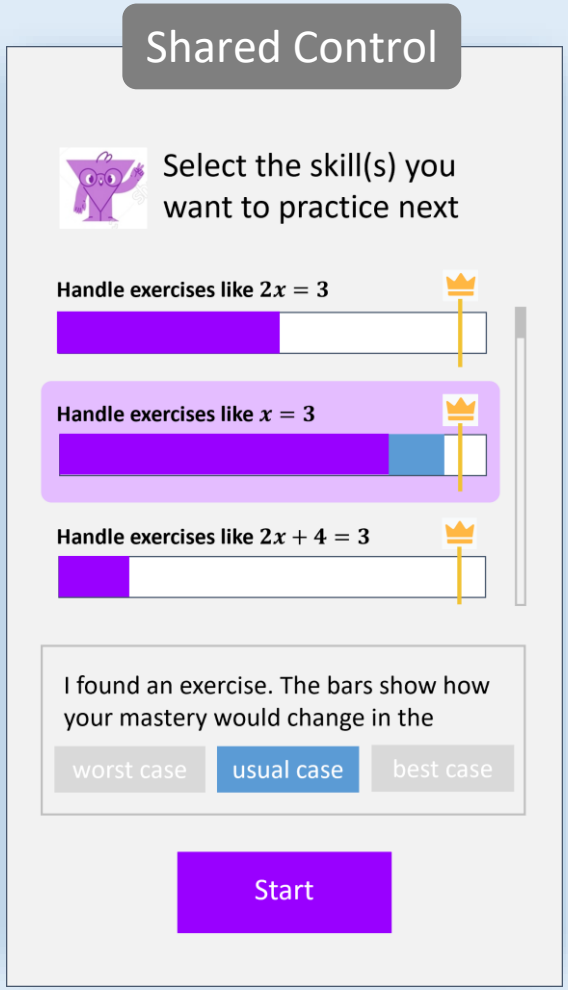


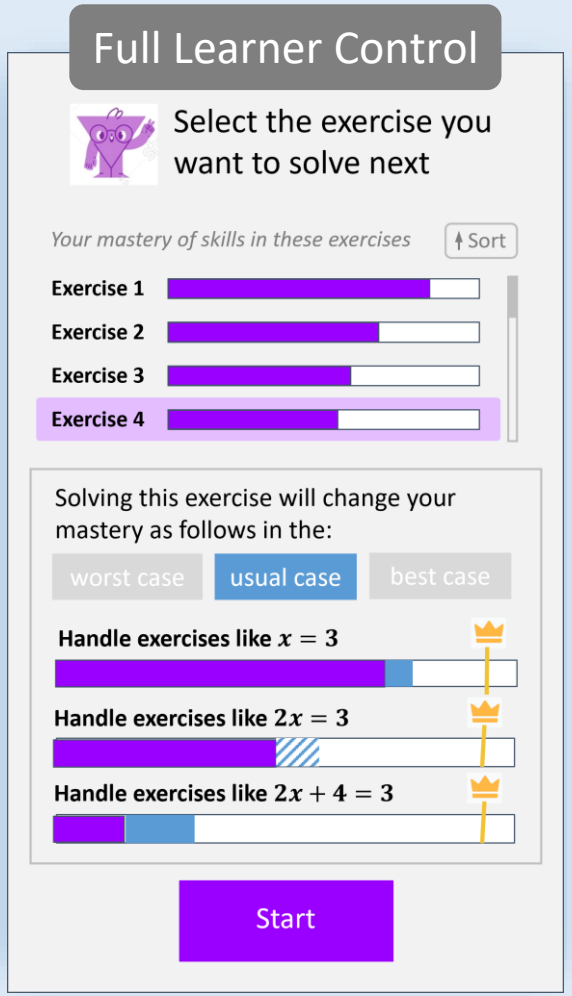


Conrad Borchers*, Jeroen Ooge*, Cindy Peng, and Vincent Aleven. 2025. How Learner Control and Explainable Learning Analytics About Skill Mastery Shape Student Desires to Finish and Avoid Loss in Tutored Practice. In *Proceedings of LAK '25*, 810–816. https://arxiv.org/abs/2412.10568

Idea 4a: explore the control spectrum







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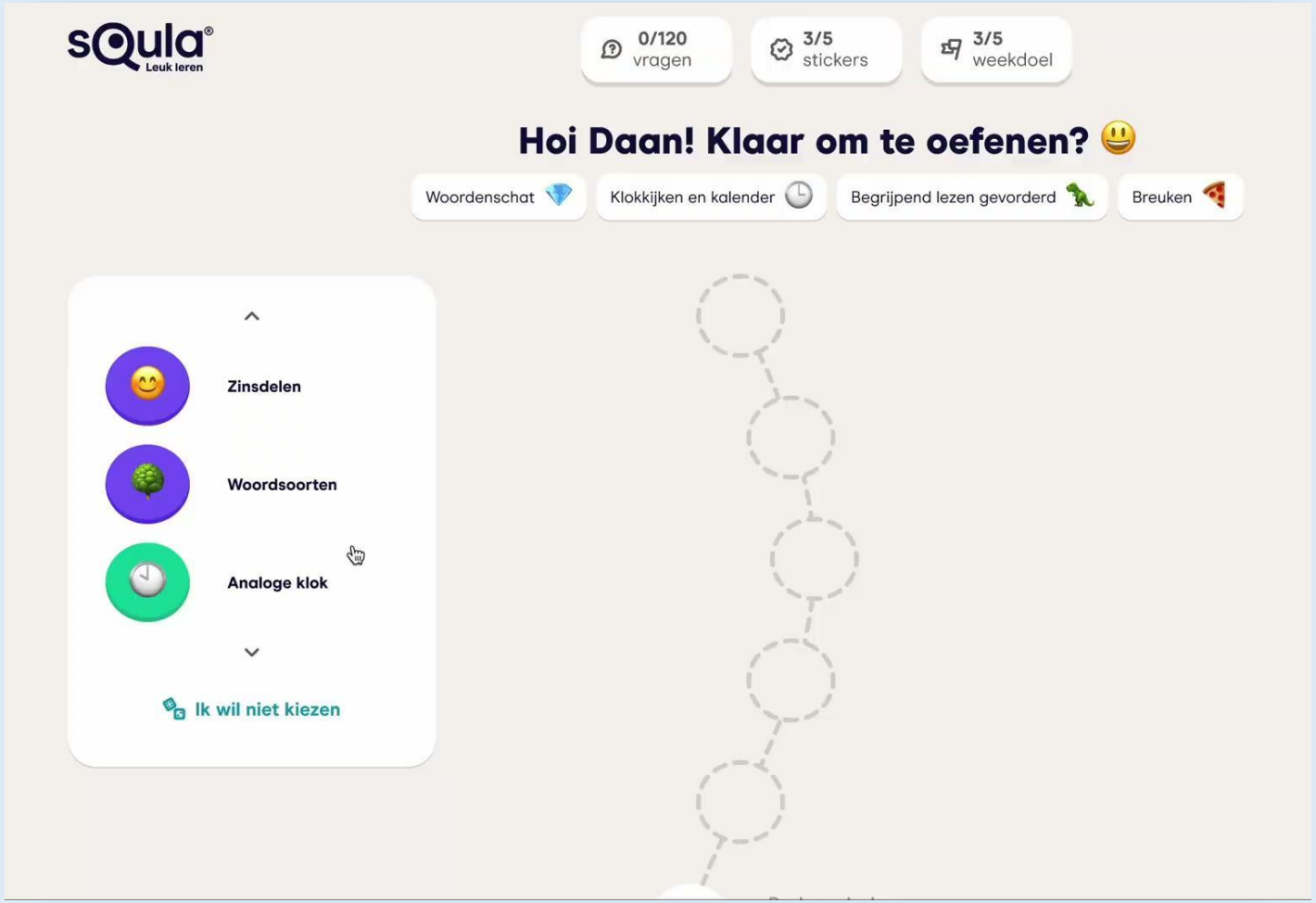
Idea 4b: explore the control spectrum

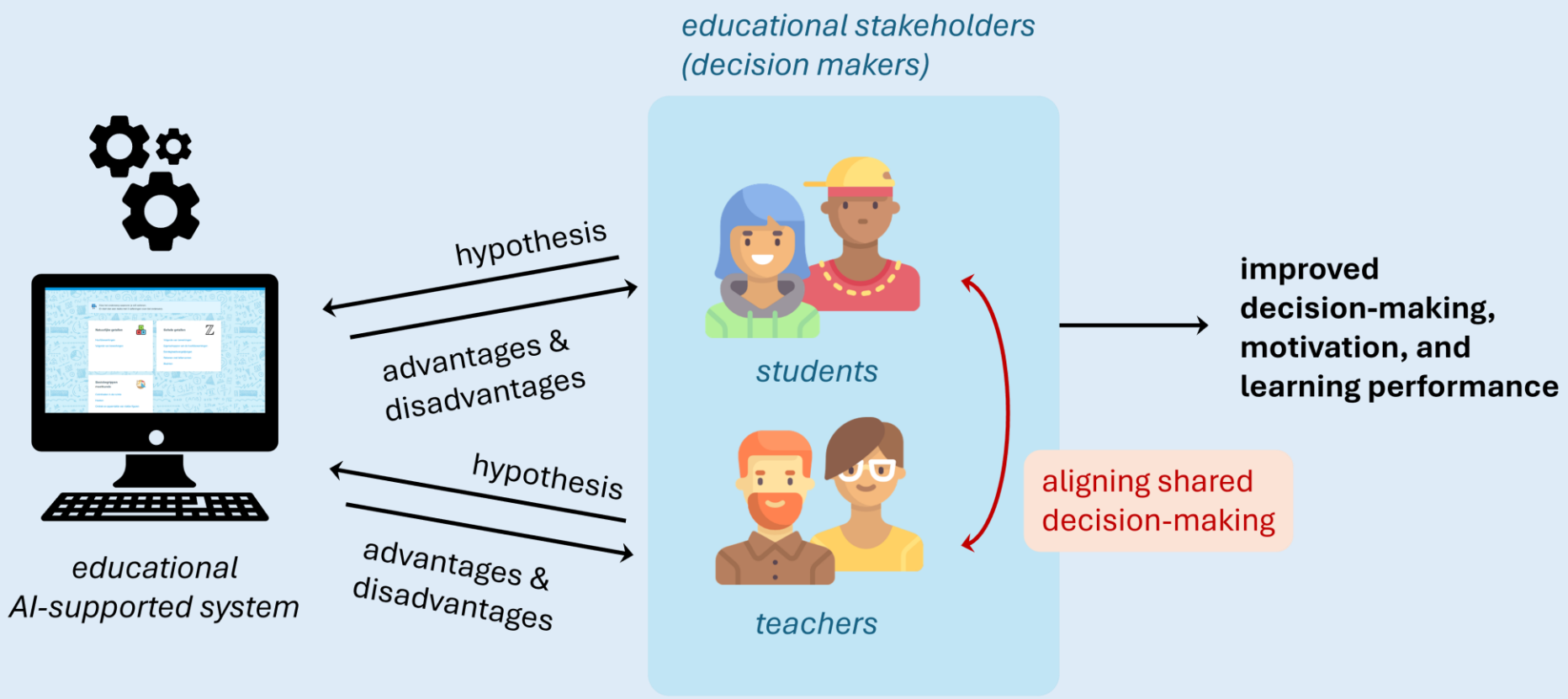


Learners have decision power about how their learning path is composed

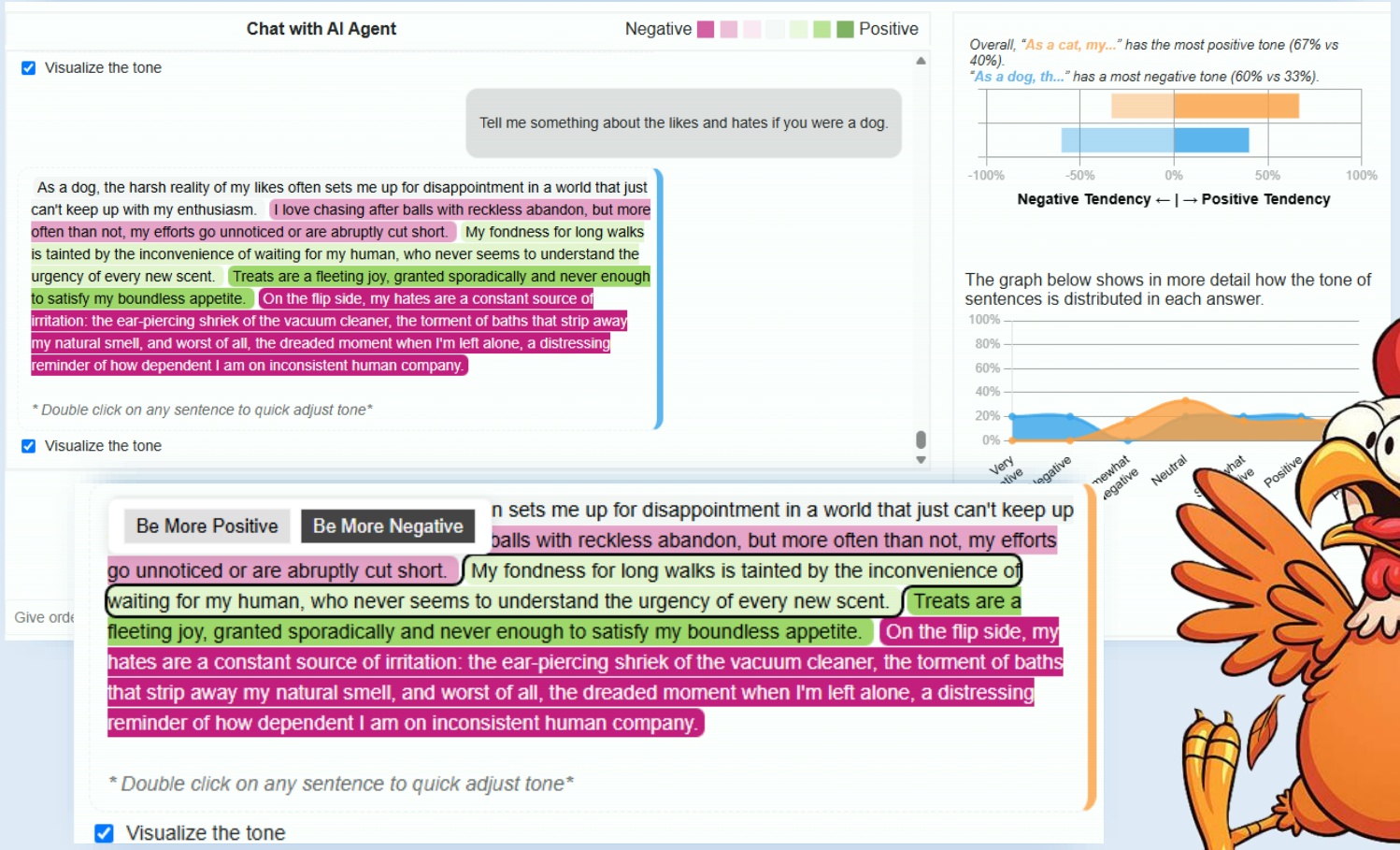
e.g., how much control is appropriate for which learners? how does it affect intrinsic motivation?

Alexis Ganciu. Learn your way: How User Autonomy Shapes Intrinsic Motivation in Gamified Learning. Master's thesis, 2025.

Idea 5: align multiple stakeholders



Idea 6: applications for LLMs



Explain and control LLM outcomes

e.g., how to visualise bias? how is writing affected?

Don’t miss the LLM hype!

Hairuo Liu. Sentiment Bias in Large Language Models: How Visualization Tools Help Users Recognize and Mitigate Bias During Interactions. Master’s thesis, 2025.


TIME FOR
QUESTIONS

How to Design Educational AI Systems With Transparency and Control

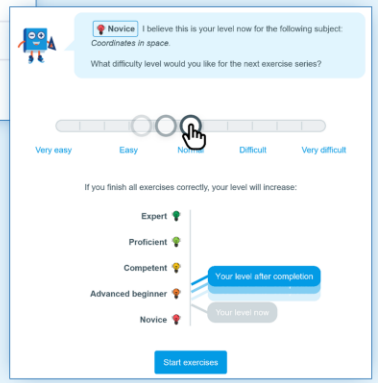
6 Examples of Experiments in Real Learning Contexts

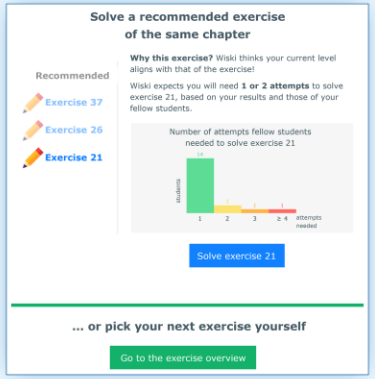
Iterative human-centred design with stakeholders involved

Ensure utility and usability, and collect valuable qualitative feedback

Steer mastery level and see the **impact visualised**

Seeing the impact of control can increase initial trust, but having control alone may not



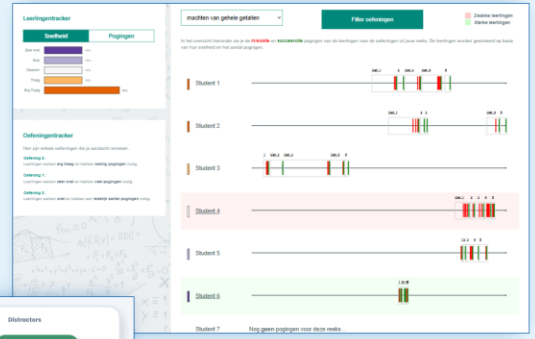


Choose difficulty of recommendations and get real-time ***what-if* explanations**

Explanations can encourage to try harder exercises, but may not affect initial trust, metacognition, motivation, or performance

Visualise time and performance data used for student outlier detection

Data-centric explanations allow teachers to calibrate their trust and perceived accuracy



Visualise similarity scores for proposed distractors and **change model parameters**

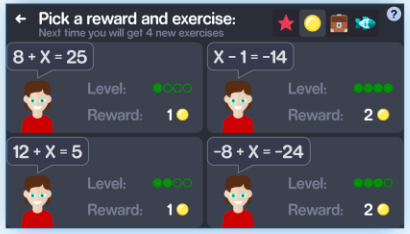
The utility of explanations and control can depend on model performance

Choose next exercises and get ***why* explanations** for recommendations

Explanations can increase initial trust but may not be the most important factor

Choose among recommendations with **difficulty labels** and **nudges**

Reward-based nudging can be effective without harming performance or self-reported competence



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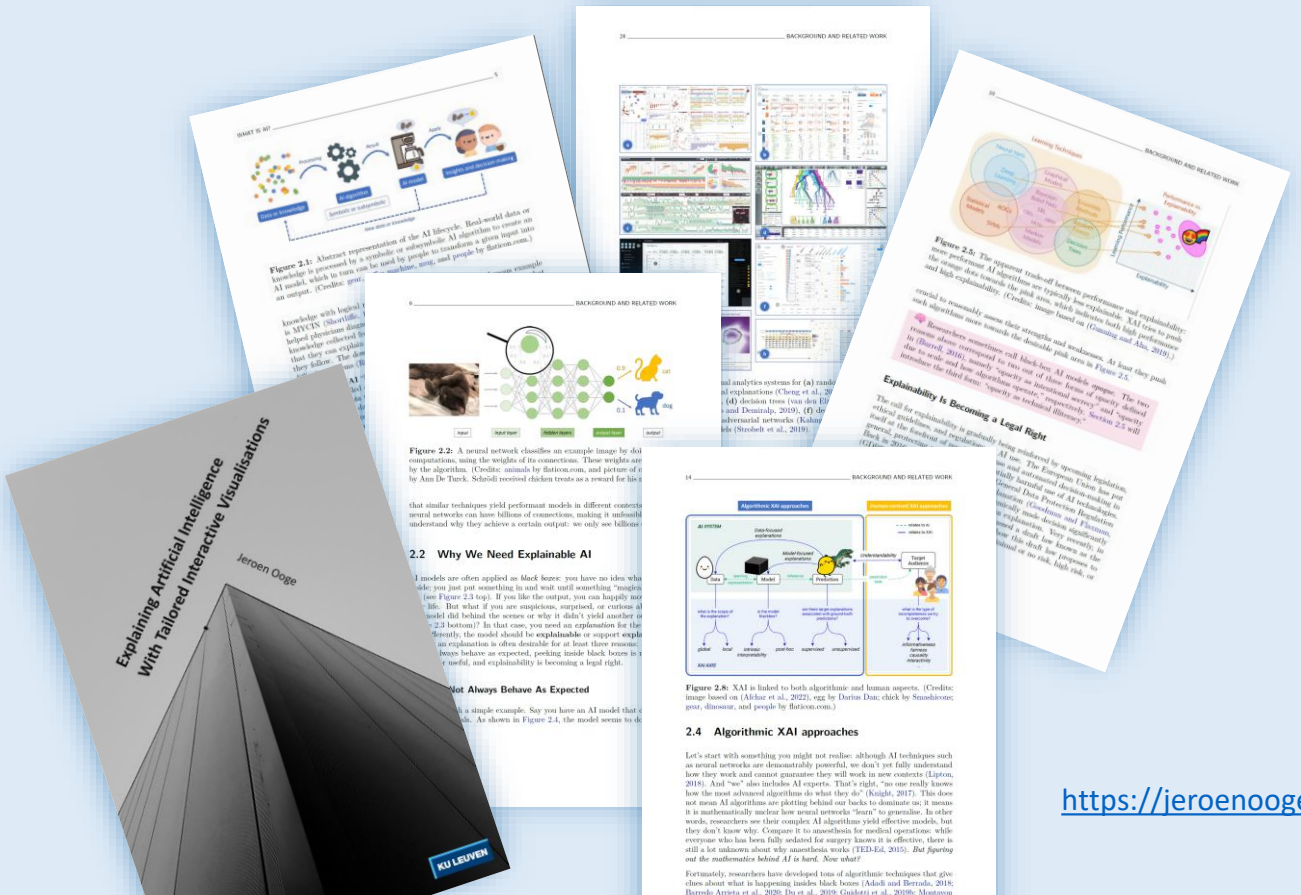
Poster at BBG 4.21

Check out **jeroenooge.be** and reach out to collaborate!



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