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Making sense of learner behavioral, cognitive and demographic characteristics to improve learner modeling

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Context

- Learner modeling techniques are crucial for providing a personalized and efficient adaptive instruction to learners [3]
- Learning management systems (LMS) automatically record online log-file data : e.g. number of clicks or minutes learners spent on a certain task
- Research in the field of educational data mining used log-files to identify learning strategies and classify learners with respect to their strategy use

→ **Log data are objective information on the use of learning strategies [1].**

For example, Fang et al., 2018 [2] used log-file data to improve adaptivity in CSAL AutoTutor thanks to a better characterization of the students' learning behaviors. They used cluster analysis (k-means + HCA) to create clusters of learners based on interaction logs (**253** learners) from CSAL AutoTutor.

→ **They distinguished 4 clusters of learners : “proficient readers”, “struggling readers”, “conscientious readers”, “disengaged readers”.**

The present study

Objectives

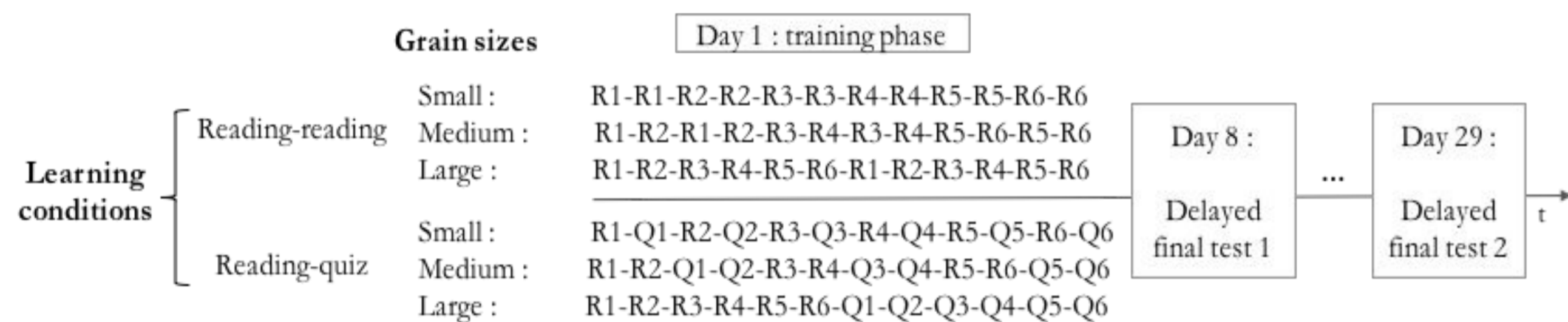
- 1) **Shedding light on underlying behavioral learner patterns**
- 2) **Improving learner predictive modeling to better tailor adaptive online tutoring systems**

Main research questions

- How do learners interact with a digital learning platform when they are assigned to specific learning strategies?
- Do learning outcomes depend on learners' interactions with the platform (training performances, times on contents...)?
- Do learning outcomes depend on learners' individual features (socio-demographic data)? And to what extent?
- Are the learning strategies effects/results driven by these predictors, variables? What are the interactions?

Methods

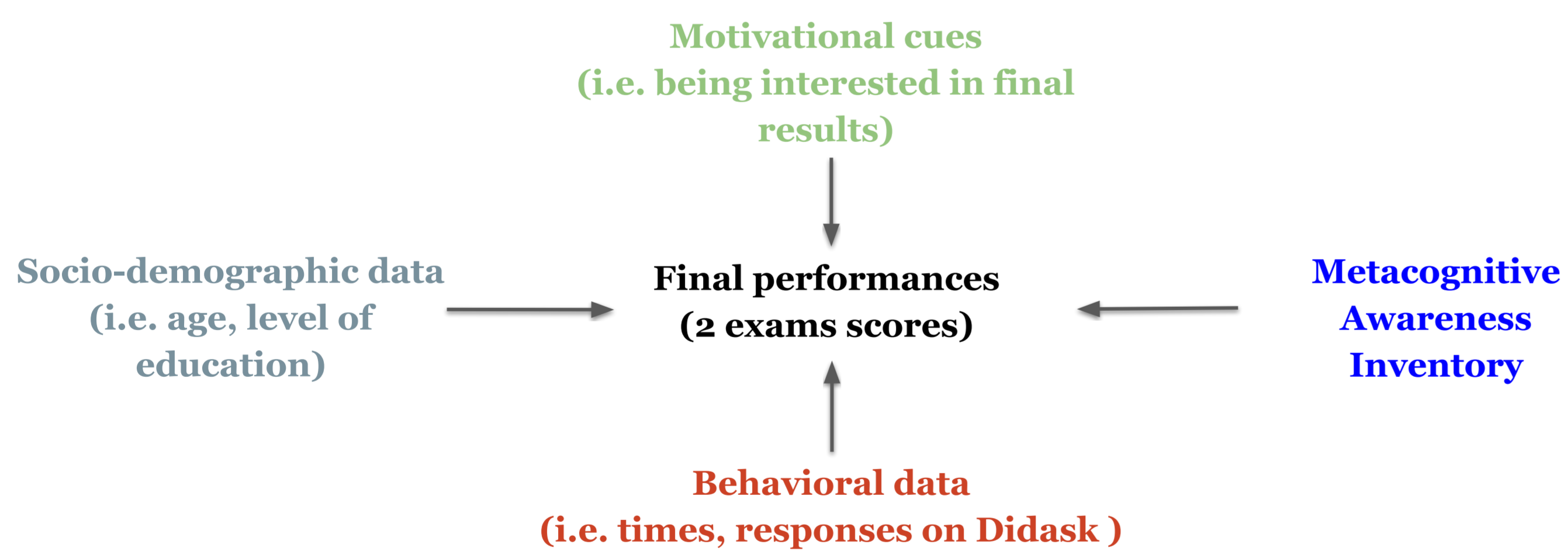
- We used log data from a **learning experiment** conducted with the digital platform Didask. It aimed at comparing **different grain sizes** of learning contents (small/medium/large) and **reviewing strategies** (retrieval practice/reading) on students' performance at two delayed tests.



DESIGN: 2 between-subjects variables and 2 within-subjects variables:

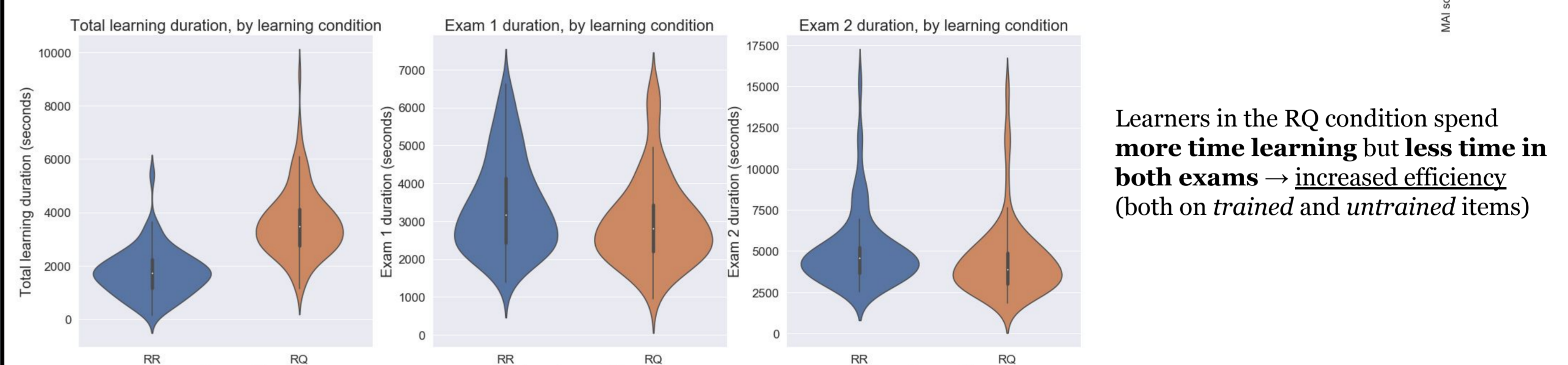
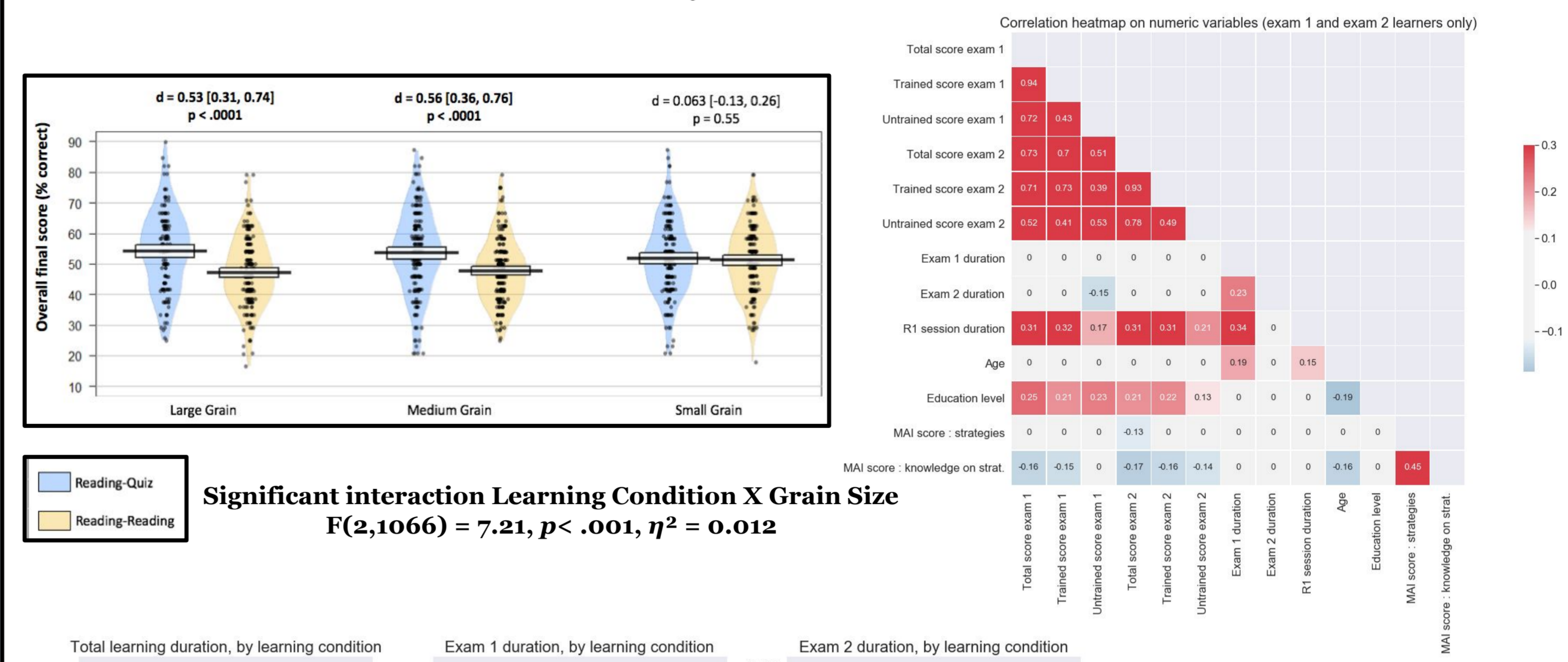
2 Learning Conditions X 3 Grain Sizes X 2 Question Types X 2 Retention Intervals

- After aggregation, four types of variables were considered in our analysis:



- Data preprocessing:
 - Data cleansing and variables aggregation (e.g. sum of durations, mean of quiz scores);
 - Specific attention to *duration data*: presence of outliers → replaced by *mean* (over chapter unit if relevant) when above a threshold (determined after histogram screening);
- After preprocessing: **251 students** who passed both exams and **294 students** who passed only exam 1
 - Balanced across learning conditions and grain sizes: RR (52%) vs RQ (48%), SGS (34%) vs MGS (35%) vs LGS (31%)
- Metacognitive Awareness Inventory (MAI) → **validated** in our population
 - 10 items were kept in total
 - Factor analysis → 2 *dimensions* (strategies and general knowledge on metacognition)

Data analysis: main results

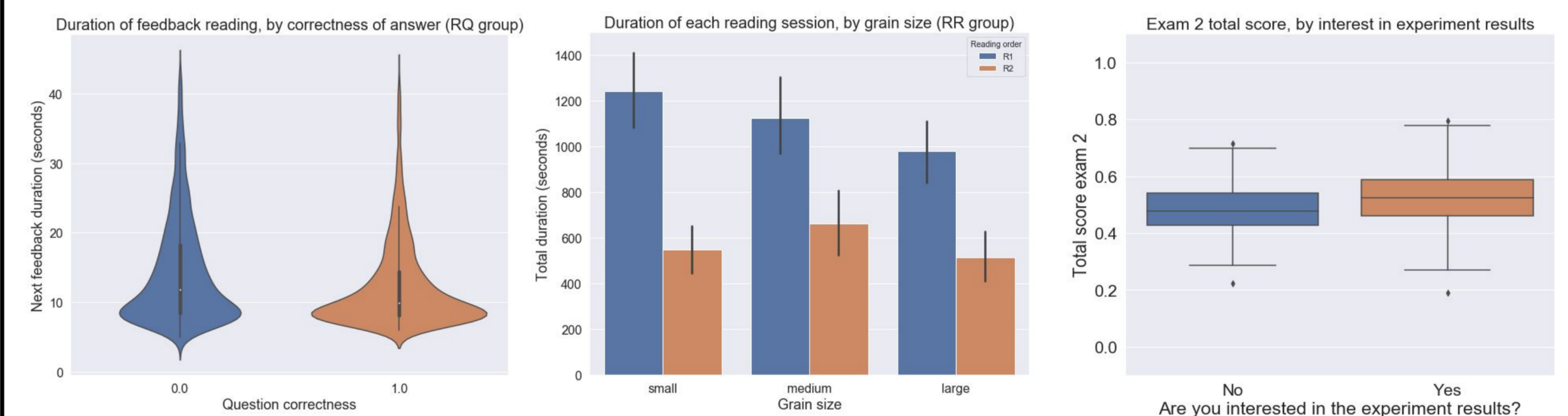


When RQ learners answer an item *correctly* during the learning phase, they tend to spend **less time reading the feedback**, even though it can be beneficial to them.
→ after incorrect: **14.43 seconds** on avg.
→ after correct: **12.34 seconds** on avg.

Illusion of mastery: RR learners spend less time on R2 than on R1.
Progressive disengagement: as the grain size increases, time spent on R1 decreases (possibly due to motivation loss).

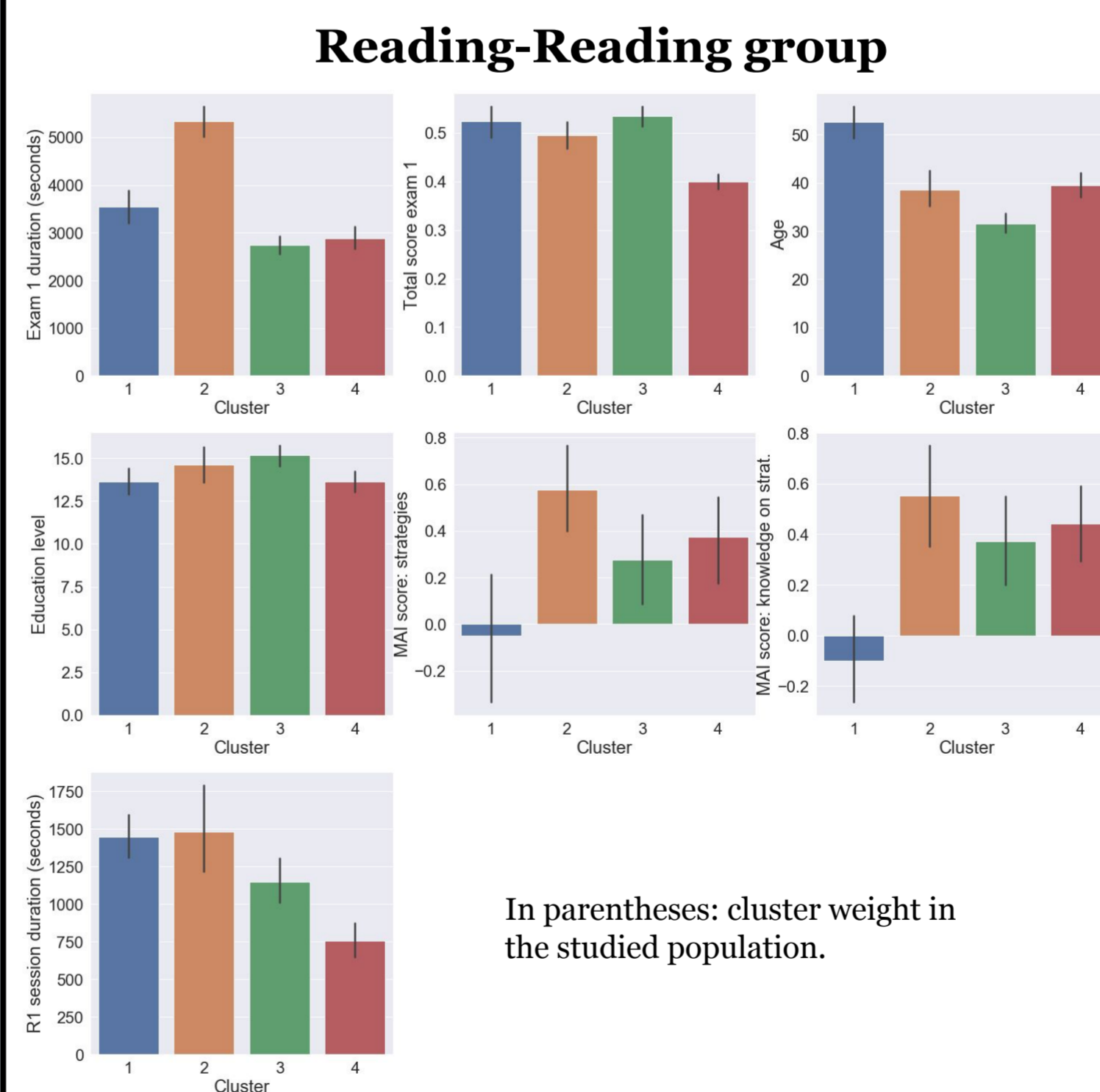
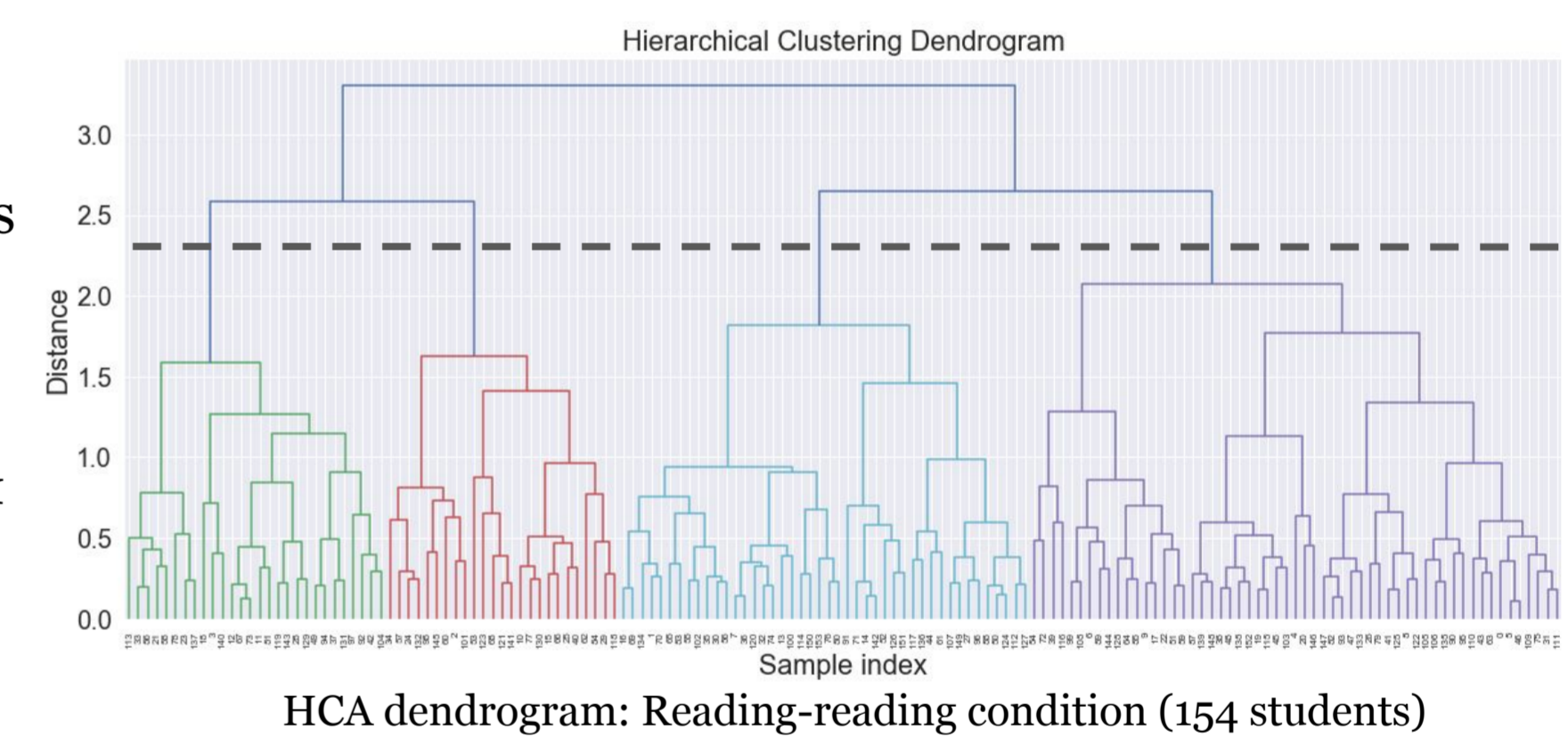
Note: 95% CI (bootstrap) are displayed.

Motivational cue: students interested in the results of the experiment have higher scores on both exams than uninterested students (*intrinsic motivation*).

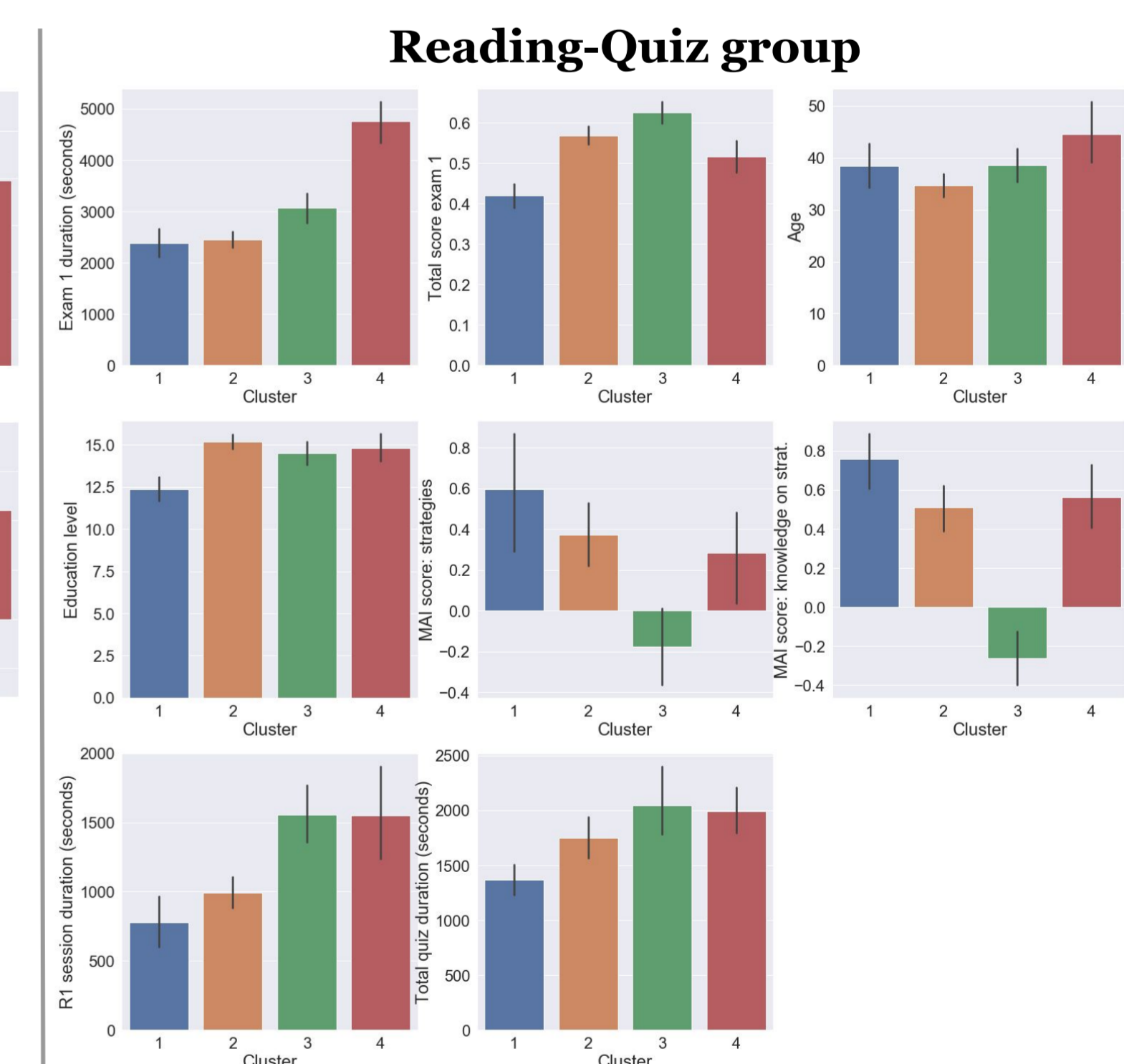


Clustering: method and results

- **Method: Hierarchical Cluster Analysis (HCA)** → partitions the population of students into homogeneous groups (based on their characteristics)
- Learners in a given cluster have **similar features and behavioral patterns**
- Performed on the 251 students (exam 1 & 2), separately on each learning condition (RR/RQ) → allows to compare clusters between conditions



- 4 clusters:
1. **The skilled learners (18%)**
 2. **The conscientious learners (16%)**
 3. **The efficient learners (29%)**
 4. **The disengaged learners (37%)**



- 4 clusters:
1. **The illusioned learners (21%)**
 2. **The efficient and confident learners (38%)**
 3. **The conscientious but under-confident learners (25%)**
 4. **The struggling learners (16%)**

Highlights & Perspectives

- Possible to use data from an e-learning platform to do post hoc analyses (could be interesting to use log file from a real learning context) → good support for **formulating new hypotheses** and **guiding future experiments**
- The IV (learning conditions and grain size) are not the only variables that explained the results, **effects are modulated by uncontrolled variables**

- Integrating both numeric and categorical variables inside the cluster analysis (e.g. *AFDM*)
- Using a *mediation model* to look at direct and indirect effects of the covariates on the exam grades
- More complex modelling: *Bayesian network* (uncover more complex dependencies)

References

1. Theobald, M., Bellhauser, H., & Imhof, M. (2018). Identifying individual differences using log-file analysis: Distributed learning as mediator between conscientiousness and exam grades. *Learning and Individual Differences*, 65, 112-122.
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