Digital Learning Forum

Data Analytics and Online Learning

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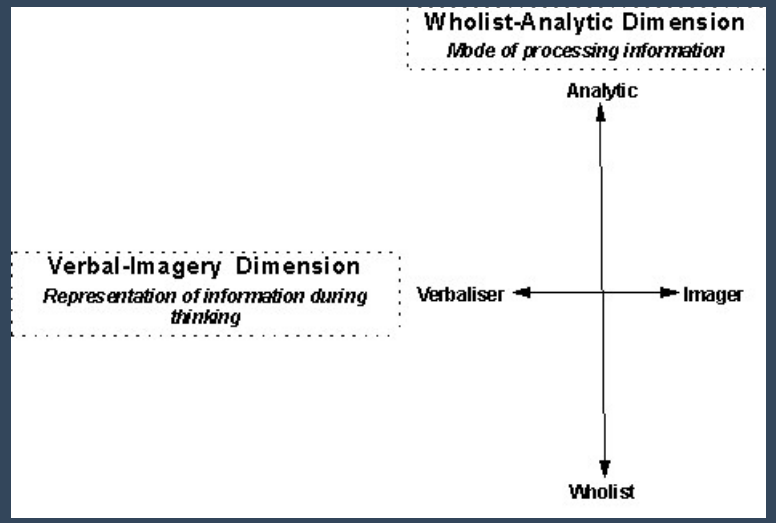
Data Analytics and Online Learning

- Relationship between Data Analytics and Online Learning
- Psychometric Testing
- Overview of a Research Project
- Methodology
- Analysis and Results
- Conclusions

Important Relationship

- **Data Analytics**



Riding & Cheema, 1991)

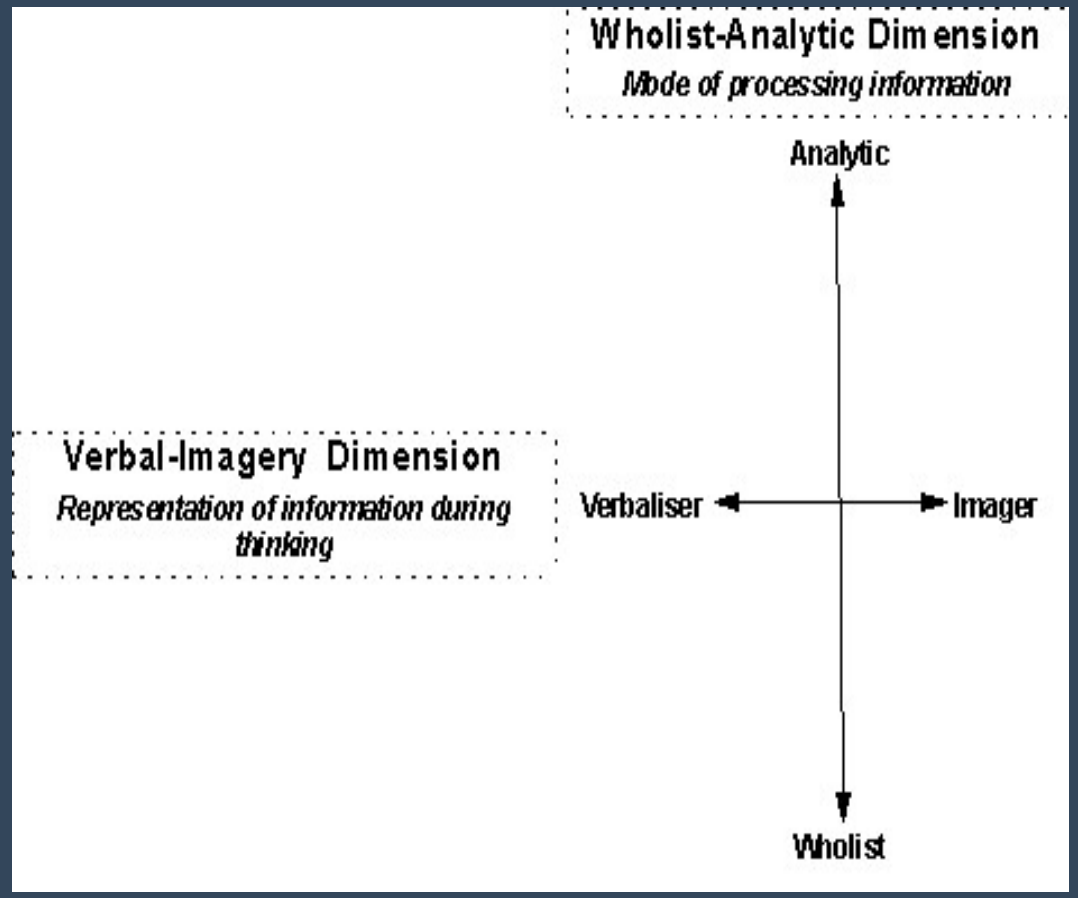
- **Online Learning**

Woerner, 2019

Important Relationship

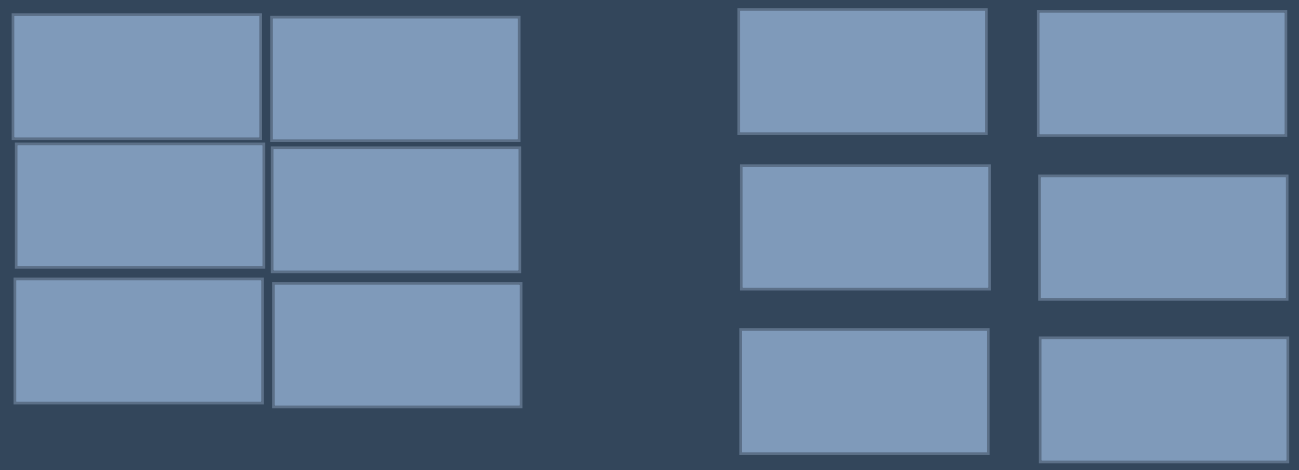
- **Data Analytics** (also known as ‘data analysis’)

Complex intellectual capabilities and personality traits



Important Relationship

- **Data Analytics**



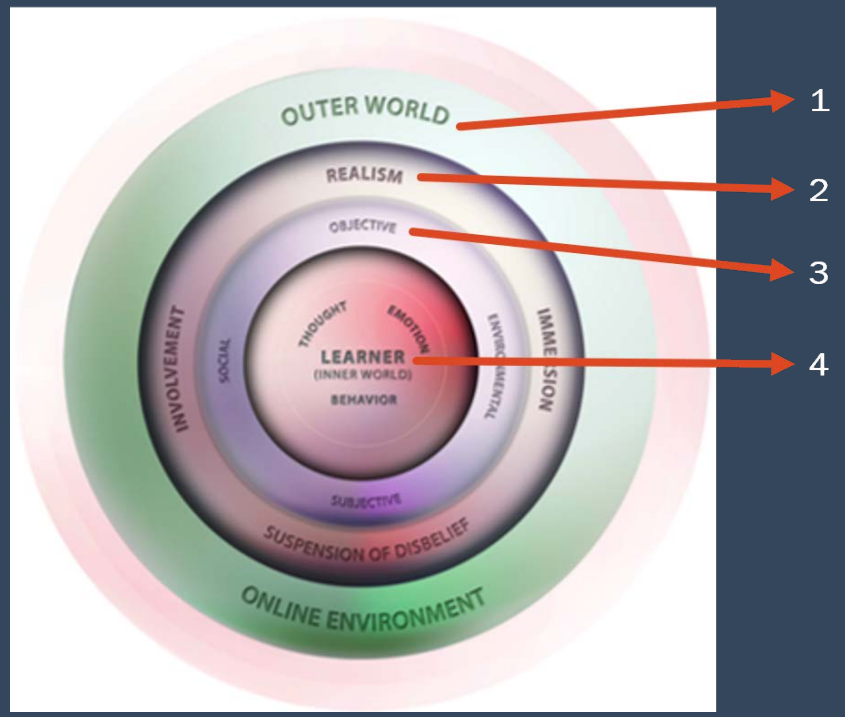
Wholist view

Analytic view

Riding and Cheema, 1991

Important Relationship

- **Online Learning**



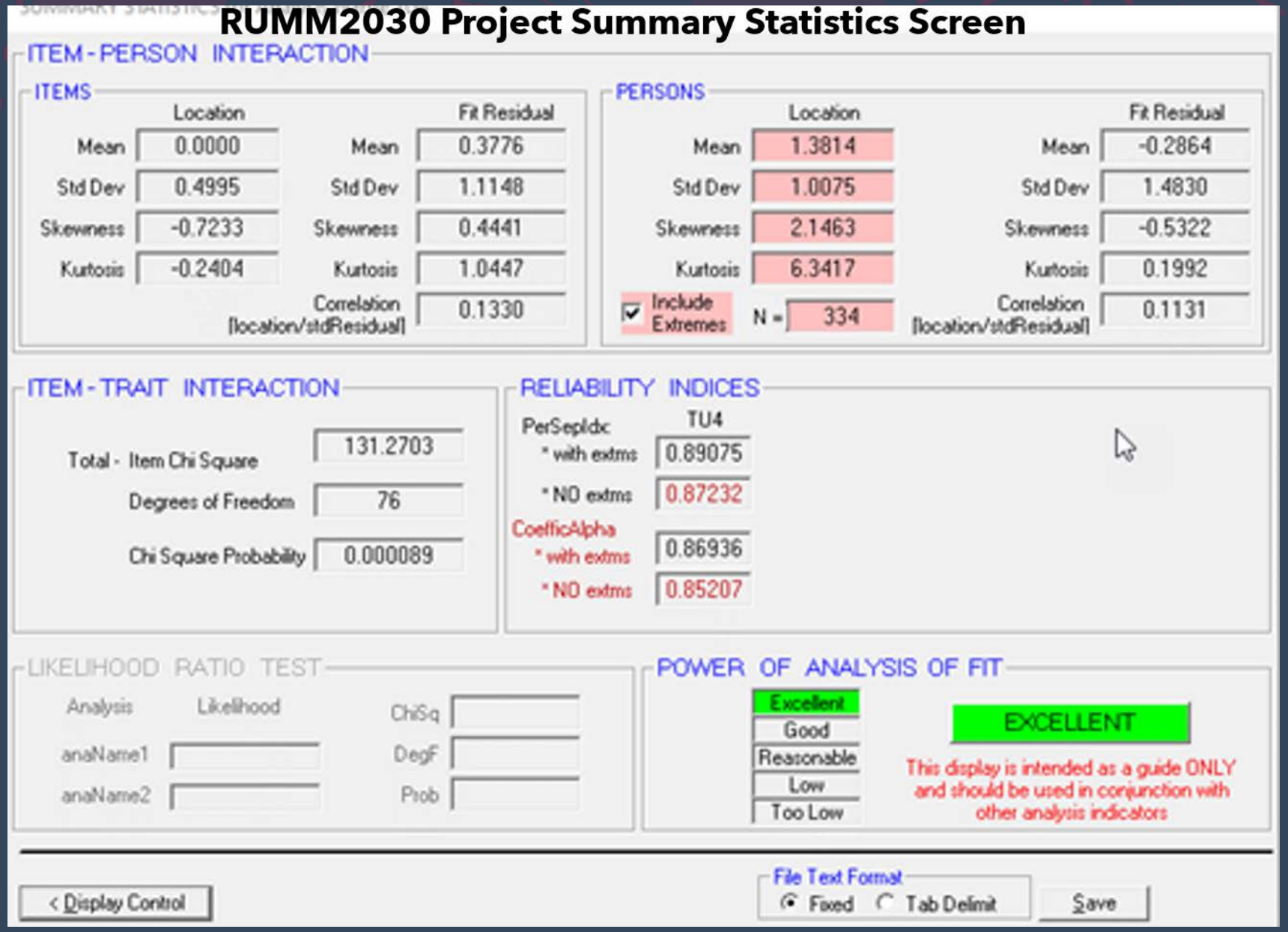
Woerner, 2019

Psychometric Testing

Measures a person's suitability for a role based on their intellectual capabilities and personality traits.

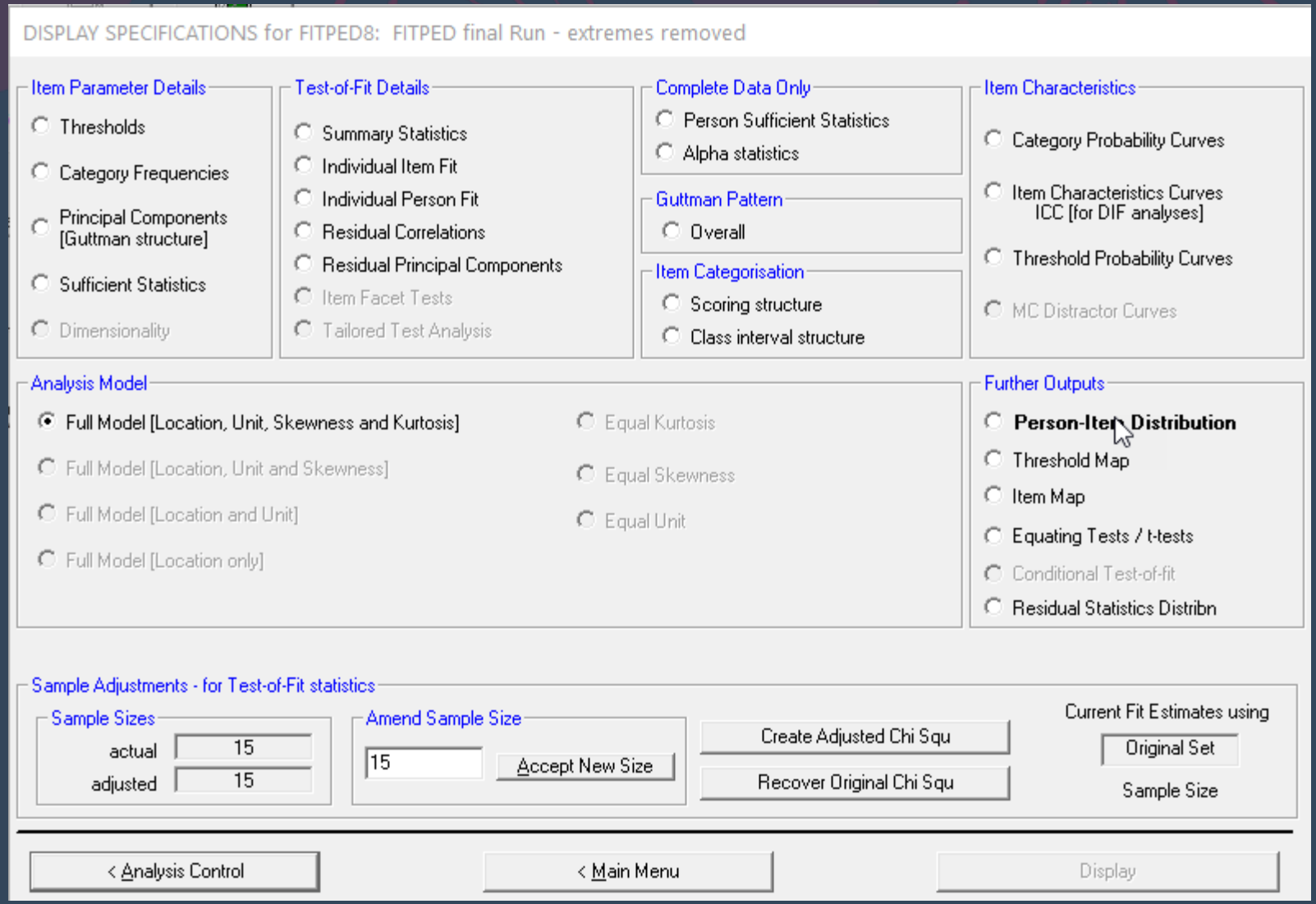
Social Sciences refers to these properties as constructs, attributes and traits.

This methodology offers an effective tool for understanding individual of differences in digital skill development.



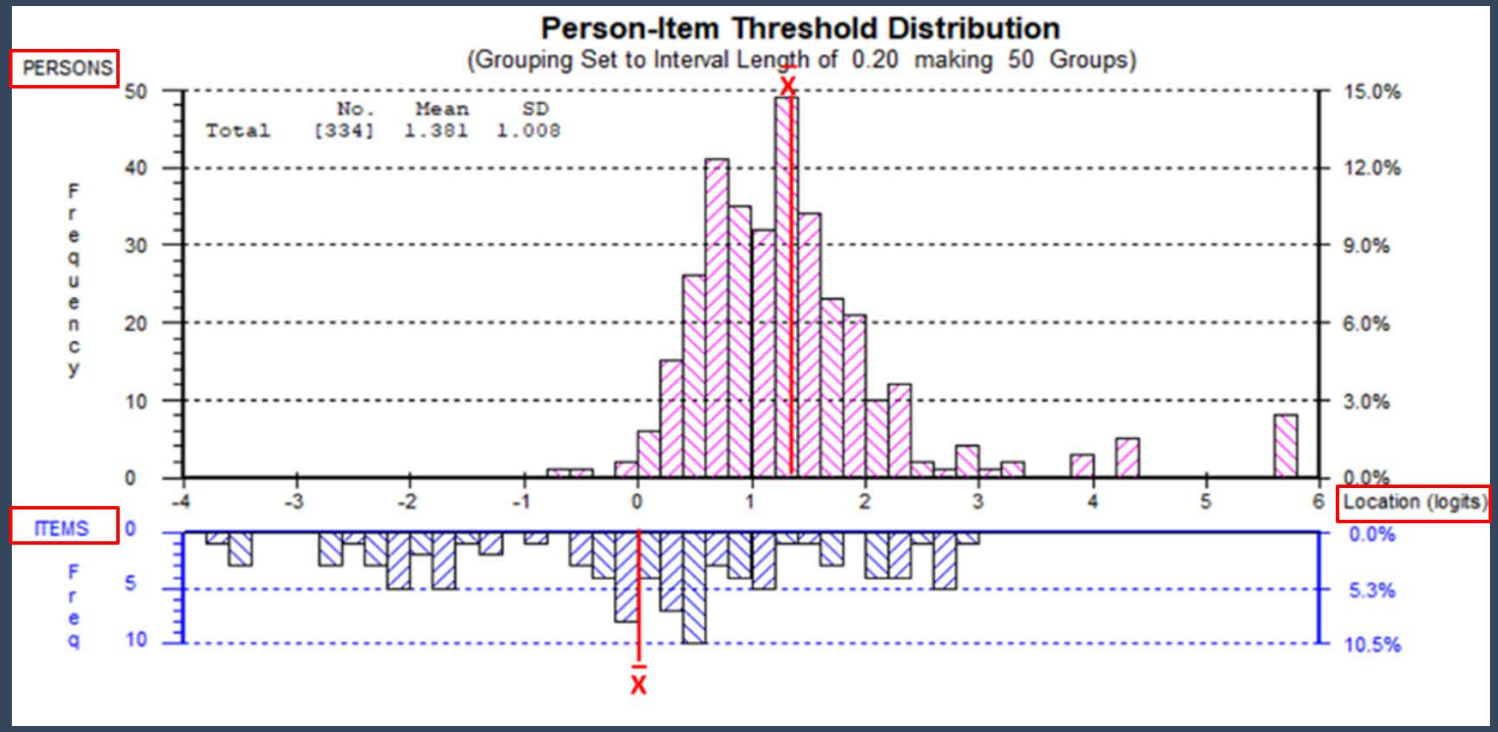
Psychometric Testing

Output display specifications



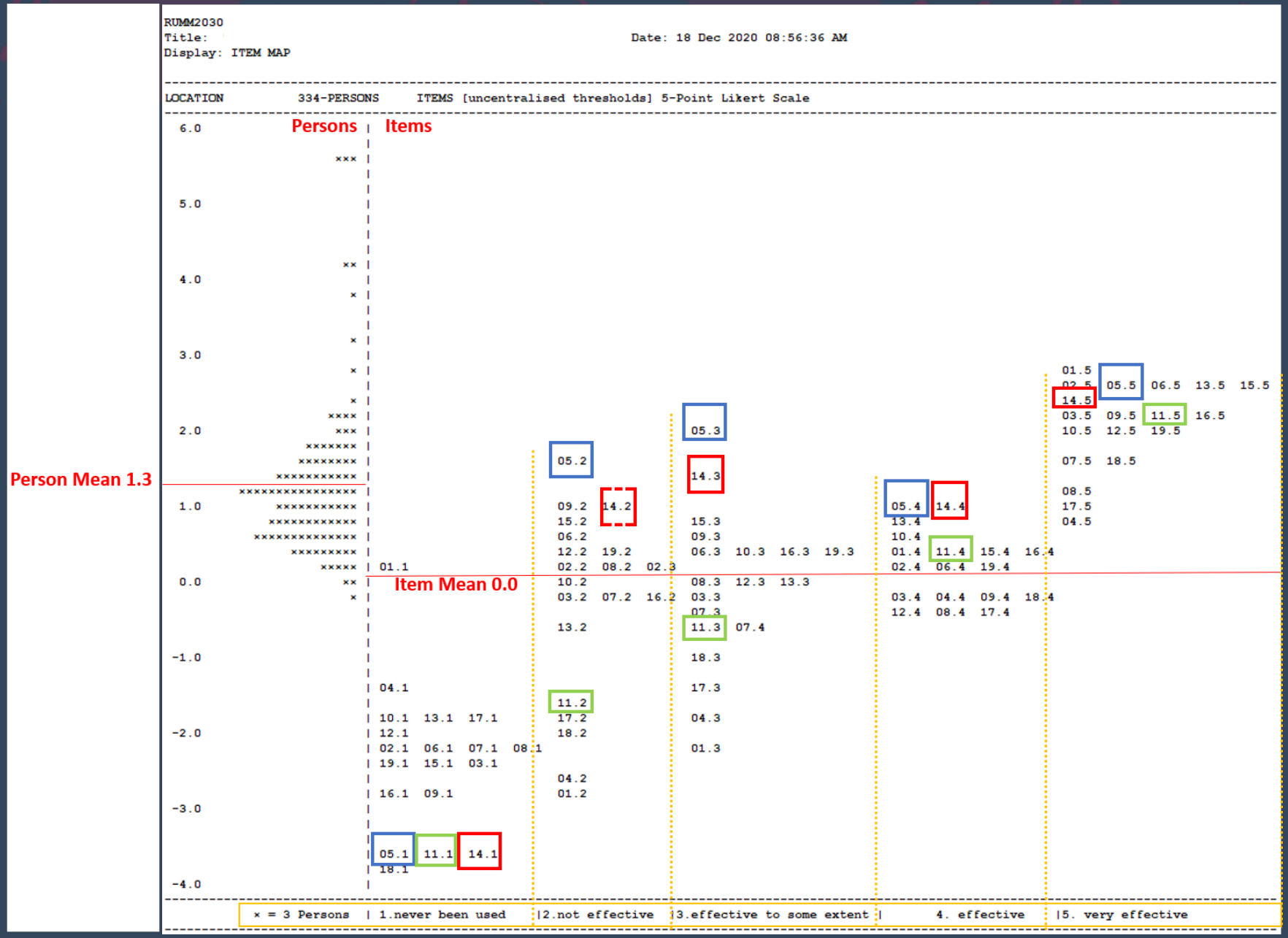
Psychometric Testing

The proverb that a picture speaks a thousand words is used here to communicate the initial research results.

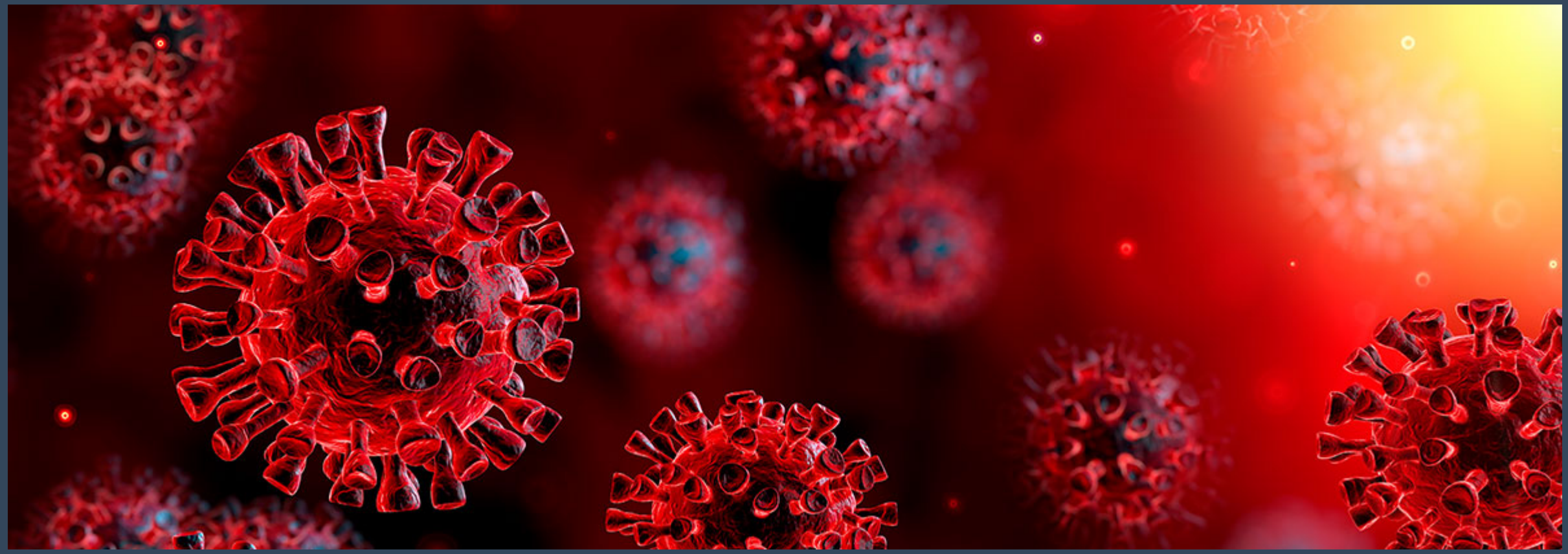


Psychometric Testing

Both people and test-items displayed along the Logit-Scale.



Overview of Research Project



Method

A two staged approach

Semi-structured interviews (qualitative)

Questionnaire/Survey (quantitative)

Participants

higher education instructors and students working or enrolled at a higher education institution

Analysis and Results - participants

- College/School Distribution

Group	# Partic	Mean	SD	Skew
4	12	0.939	0.551	-0.112
5	8	0.849	0.724	-1.095
9	289	1.438	1.011	2.112
10	9	0.875	0.636	0.514
11	6	0.899	0.385	2.363
Total Sample	**334**	**1.381**	**1.0075**	**2.146**

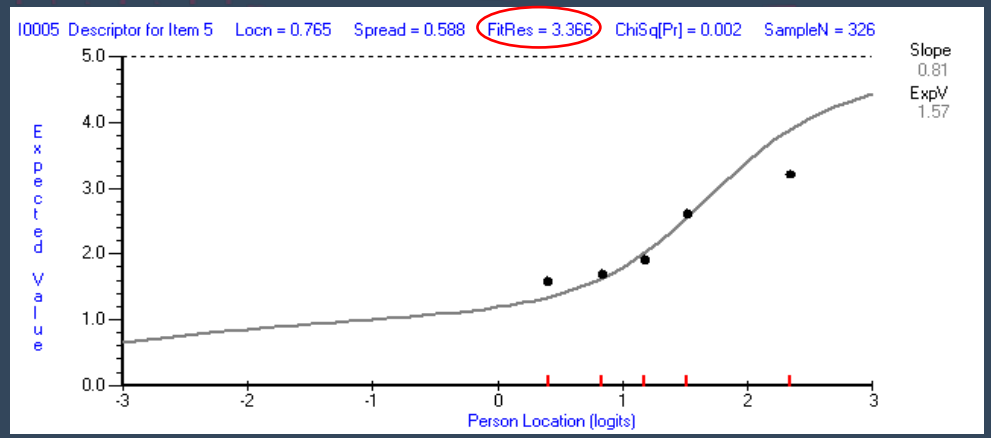
- Variation between Gender

Group	# Partic	Mean	SD	Skew
Males	127	1.426	0.921	1.074
Females	199	1.184	0.633	1.096
Total Sample	**334**	**1.381**	**1.0075**	**2.146**

Analysis and Results – Test-items

- Test-item characteristic curves

The Rasch item characteristic curves identify class intervals that show the relative ability of an item to discriminate among adjoining knowledge constructs (traits) along a liner scale. Rather than compare individual participant scores against the expected model curve, the Rasch Model divides the sample into quartiles, or in this case quintiles. So it determines the mean logit score of each 20% of the participant sample. These means are 0.402, 0.835, 1.175, 1.518 and 2.344. As you will see in the expected value plots for individual questions, these red marks on the person logit scale do not change. However the observed value of the group (see the black dots within the plot) does change for each question.

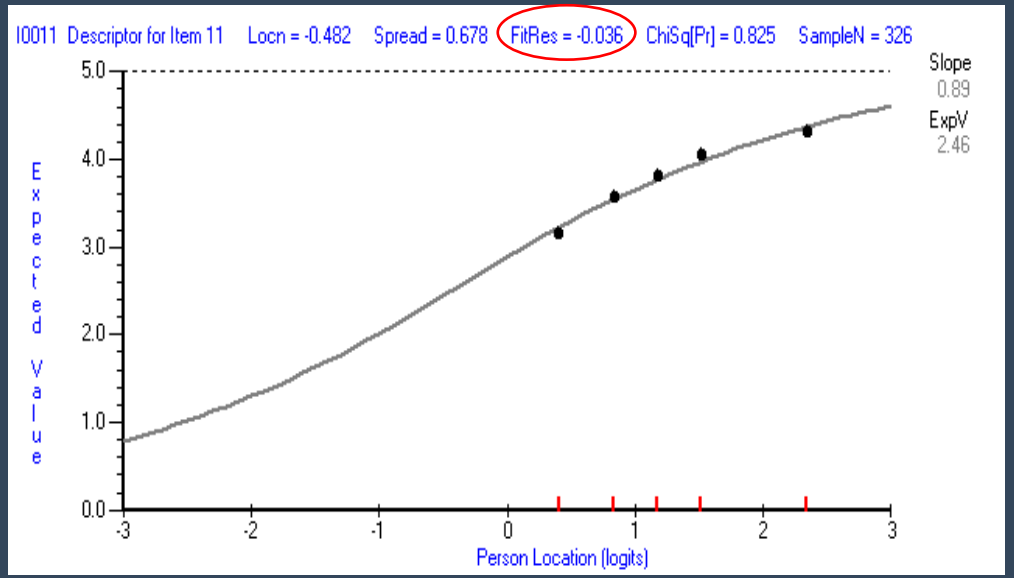


- Some items have irregular distributions and poor correlation to the model's expected curve. Item-5 for instance, (seeking agreement on *the use of cameras in online communications*) showed a relatively poor correlation with a fit-residual of 3.366, with the lowest quintile scoring above the model curve and the highest quintile scoring well below the expected curve.

Analysis and Results – Test-items

- Test-item characteristic curves

- Item-11, which asked the participants for agreement on *the strategy of allowing direct questions during virtual lectures*, illustrates that the observed score for each quintile very closely matches the expected value from the model's distribution (i.e. all black dots are very close to the expected value curve). Note, the fit-residual is very low at only -0.036 indicating a strong correlation between the observed scores and the model's expected values.

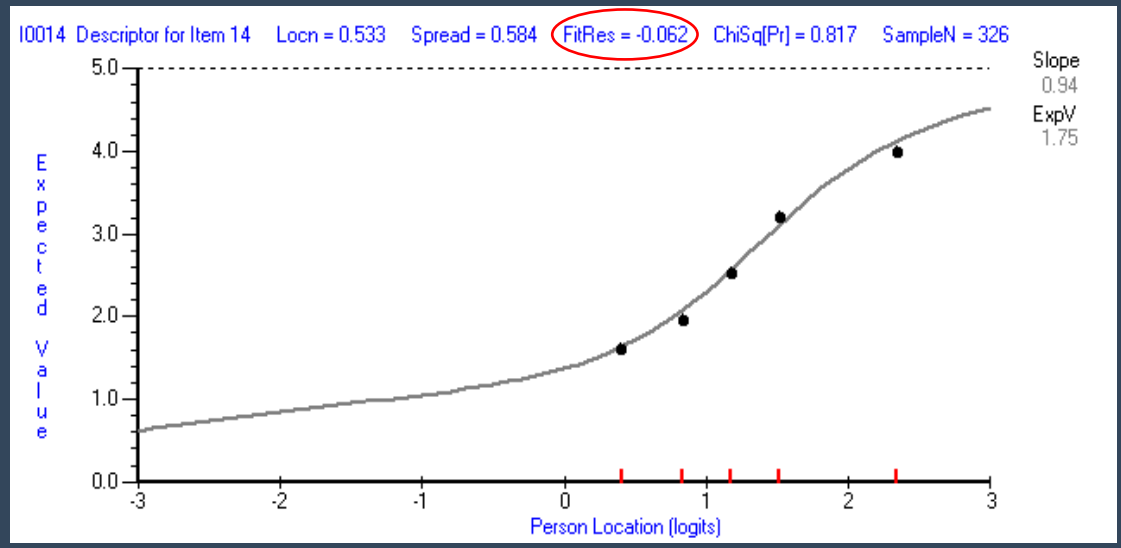


Analysis and Results – Test-items

- Test-item characteristic curves

The item characteristic curve for item-14 also illustrates a relatively good correlation to the model's expected value curve, with a small fit-residual of -0.062. This illustrates the need for the researcher to evaluate all the available data.

This item was seeking agreement on *additional lectures (unscheduled).*



Conclusions

Always strive for an understanding of the importance of the interactive relationship between data analytics and online learning.

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