

Data Analytics and Quality Assurance in K-12 Online Learning Programs

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QUALITY MATTERS

QM



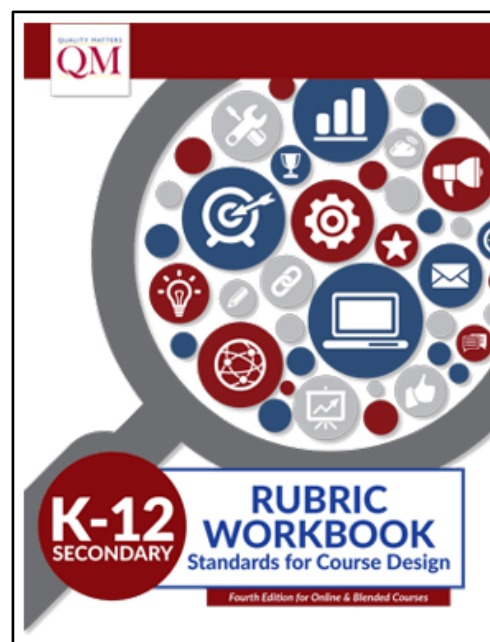
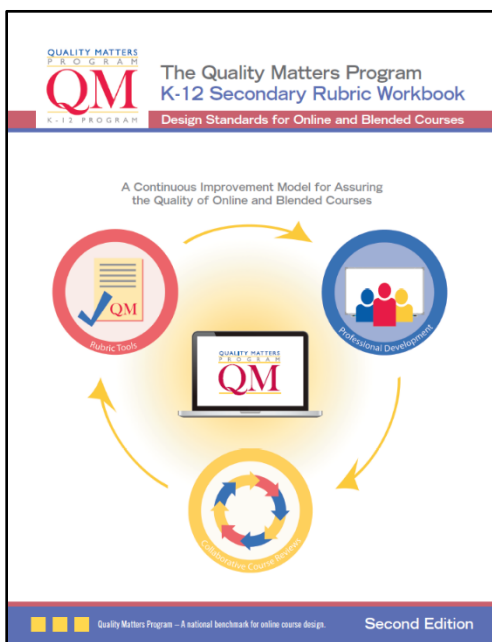
Data Analytics & Quality Assurance

OLC Accelerate 2016

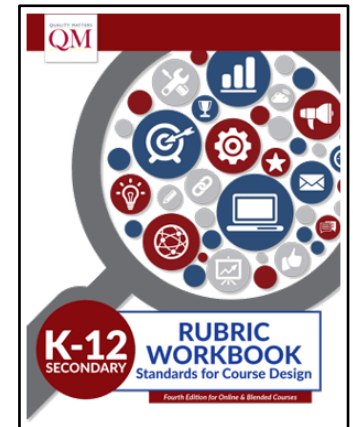
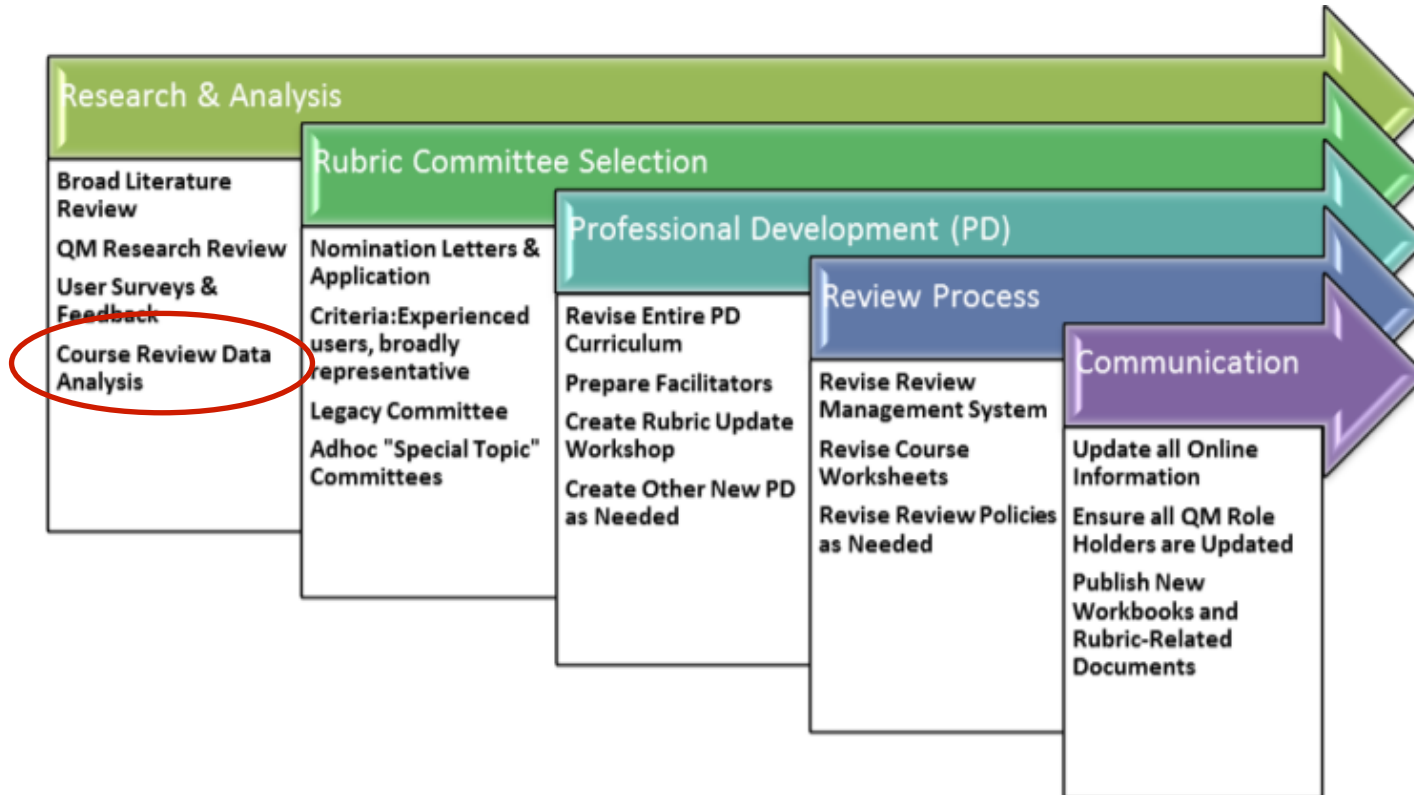
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Data Analytics & QA: Rubric Revision



Data Analytics & QA: Rubric Revision





Data Analytics & QA: Rubric Revision

Review outcomes by Standard – K-12 Secondary Reviews

Filter on 1 Rubric Title

Rubric Title	
K-12 Secondary Rubric, Second Edition	▲
Quality Matters Grades 6 – 12 Publisher Rubric	
Quality Matters Grades 6-12 Publisher Rubric - 2013 Edit...	
The Quality Matters K-12 Publisher Rubric. Third Edition	▼

Review Type	
QM-Managed K-12 Secondary	▲
QM-Managed - Content Publisher Rub...	
QM-Managed - Template Publisher Ru...	
QM-Managed HE	▼



Data Analytics & QA: Rubric Revision

Review outcomes by Standard – K-12 Publisher Reviews

Filter on 1 Rubric Title

Rubric Title	
The Quality Matters K-12 Publisher Rubric, Third Edition	▲
K-12 Secondary Rubric, Second Edition	
Quality Matters Grades 6 – 12 Publisher Rubric	▼

Review Type	
QM-Managed - Content Publisher Rub...	▲
QM-Managed - Template Publisher Ru...	
QM-Managed HE	
QM-Managed K-12 Secondary	▼



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K-12 Secondary Reviews

Percentage Met by Standard

Standard	▼↑	% Met
4.7		64%
7.3		73%
1.7		82%
7.1		82%
8.1		82%
8.4		91%
5.4		91%
3.1		91%
6.1		91%
3.3		91%
6.6		91%
4.1		91%
2.1		91%

K-12 Publisher Reviews

Percentage Met by Standard

Standard	▼↑	% Met
4.7 C		77%
8.2 C		83%
1.3 T		83%
2.3 C		90%
1.2 C		94%
4.5 C		94%
3.5 C		96%
4.4 C		96%
2.1 C		96%
4.2 C		96%
4.6 C		96%
3.1 C		98%
2.2.C		98%



Data Analytics & QA: Rubric Revision



K-12 Secondary Reviews

Percentage Met by Standard

Standard	% Met
4.7	64%
7.3	73%
1.7	82%
7.1	82%
8.1	82%
8.4	91%
5.4	91%
3.1	91%
6.1	91%
3.3	91%
6.6	91%
4.1	91%
2.1	91%

Percentage Non-Unanimous Vote

Standard	% Non-Unanimous	Non-Unanimous: Met	Non-Unanimous: Not Met
8.1	36%	50%	50%
7.3	27%	33%	67%
4.7	27%	33%	67%
1.7	18%	0%	100%

Percentage Unanimous Vote

Standard	% Unanimous	Unanimous: Met	Unanimous: Not Met
8.1	64%	100%	0%
4.7	73%	75%	25%
7.3	73%	88%	13%
1.7	82%	100%	0%



Data Analytics & QA: Rubric Revision

1.7 Prerequisite knowledge in the discipline and/or required competencies are clearly stated.



1.7 Annotation small revision defining a prerequisite:
Information such as minimum academic requirements (GPA, admission tests, etc.), previous courses completed are considered prerequisites.



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4.7 All resources and materials used in the course are appropriately cited.



Annotations revised to be more robust and to include directions to reviewers around Creative Commons Licensing, and how to handle the inclusion of third-party content.



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7.1 The course identifies policies and services for all students.



7.1 Course instructions outline and direct student access to available institutional accessibility support services and comply with special education policies and procedures.

7.3 Course instructions outline how the organization helps students reach educational goals.



7.3 Course instructions outline and direct student access to institutional academic support services.



Data Analytics & QA: Rubric Revision

8.1 Course accessibility information is provided along with guidance for obtaining student accommodations.



8.2 Information is provided about the accessibility of all technologies required in the course.

Annotations include examples of technologies in which accessibility needs to be considered.



Data Analytics & QA: Rubric Revision



K-12 Publisher Reviews

Percentage Met by Standard

Standard	% Met
4.7 C	77%
8.2 C	83%
1.3 T	83%
2.3 C	90%
1.2 C	94%
4.5 C	94%
3.5 C	96%
4.4 C	96%
2.1 C	96%
4.2 C	96%
4.6 C	96%
3.1 C	98%
2.2.C	98%

Percentage Non-Unanimous Vote

Standard	% Non-Unanimous	Non-Unanimous: Met	Non-Unanimous: Not Met
8.2 C	21%	64%	36%
4.7 C	27%	57%	43%
1.3 T	33%	50%	50%

Percentage Unanimous Vote

Standard	% Unanimous	Unanimous: Met	Unanimous: Not Met
1.3 T	67%	100%	0%
4.7 C	73%	84%	16%
8.2 C	79%	88%	12%



Data Analytics & QA: Rubric Revision

Rubric

The Quality Matters ... ▼

Standard	Met %
1.3 T	50%
6.7 T	50%
7.1 T	50%
8.1 T	50%
4.7 C	61%
8.2 C	73%
2.3 C	90%
2.1 C	92%
2.2.C	92%
1.2 C	94%
2.4 C	94%
3.1 C	94%
4.1 C	94%



Data Analytics & QA: Member Data

Rubric

The Quality Matters ... ▼

Standard	Met %
1.3 T	50%
6.7 T	50%
7.1 T	50%
8.1 T	50%
4.7 C	61%
8.2 C	73%
2.3 C	90%
2.1 C	92%
2.2.C	92%
1.2 C	94%
2.4 C	94%
3.1 C	94%
4.1 C	94%



Data Analytics & QA: Peer course Review



Anecdotal Evidence

- Collegial interaction leads to greater knowledge on improving online learning
- Review team chairs gain valuable leadership experience
- Peer reviewers make changes to their own courses through idea shopping and by doing a parallel review on their own courses by participating in a formal review of a peer's course.

Exit Survey Data:

- Consistent application of the QM Process
- Experiences for the Peer Reviewer



Data Analytics & QA: Peer course Review

Exit Surveys

1. Was this course informally reviewed before it was officially reviewed by QM?

This course went through an internal review. - (255)

I reviewed this course myself using the Self-Review Tool. - (58)

I reviewed this course myself using the QM Rubric documents or workbook. - (86)

This course was not reviewed prior to the official QM Review. - (73)

Don't know or none of the above. - (28)

Please explain if your selection was "none of the above".

No summary available for this data type.

Survey Responses



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Data Analytics & QA: Peer course Review

Exit Surveys

The feedback provided by the Peer Reviewers in the Final Report

a) Was constructive and useful

Strongly Agree - (359)
 Agree - (128)
 Disagree - (7)
 Strongly Disagree - (4)

d) Met professional standards of writing

Strongly Agree - (345)
 Agree - (143)
 Disagree - (3)
 Strongly Disagree - (4)

b) Was not prescriptive

Strongly Agree - (223)
 Agree - (142)
 Disagree - (69)
 Strongly Disagree - (58)

e) Reflected appropriate subject-matter expertise

Strongly Agree - (313)
 Agree - (165)
 Disagree - (12)
 Strongly Disagree - (4)

c) Referenced Standards or Annotations from the Rubric and included evidence from the course

Strongly Agree - (336)
 Agree - (154)
 Disagree - (5)
 Strongly Disagree - (4)



Data Analytics & QA: Peer course Review

Exit Surveys

5. The reviewers showed respect for individuals and institutions in all review interactions

Strongly Agree - (397)

Agree - (96)

Disagree - (5)

Strongly Disagree - (0)

Comments:

No summary available for this data type.

[Survey Responses](#)

6. The Pre-review conference call was helpful.

Strongly Agree - (273)

Agree - (189)

Disagree - (29)

Strongly Disagree - (5)

Comments:

No summary available for this data type.

[Survey Responses](#)



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Data Analytics & QA: Peer course Review

Exit Surveys

7. As a result of your participation as the Course Representative in QM course reviews, have you or do you intend to make changes in your other online courses?

I have made changes - (132)

I plan to make changes - (303)

I have not and do not plan to make changes - (21)

N/A - (43)

Comments:

No summary available for this data type.

[Survey Responses](#)

6. As a result of your participation as a Peer Reviewer in QM course reviews, have you or do you intend to make changes in your online courses?

I have made changes - (722)

I plan to make changes - (1145)

I have not and do not plan to make changes - (452)

N/A - (391)

Comments:

No summary available for this data type.

[Survey Responses](#)





Data Analytics & QA: Peer course Review



Exit Surveys

9. How many hours, including communications, did you spend on the course review process?

Course Representatives

3-5 hours - (203)
6-8 hours - (95)
9-11 hours - (51)
12+ hours - (149)

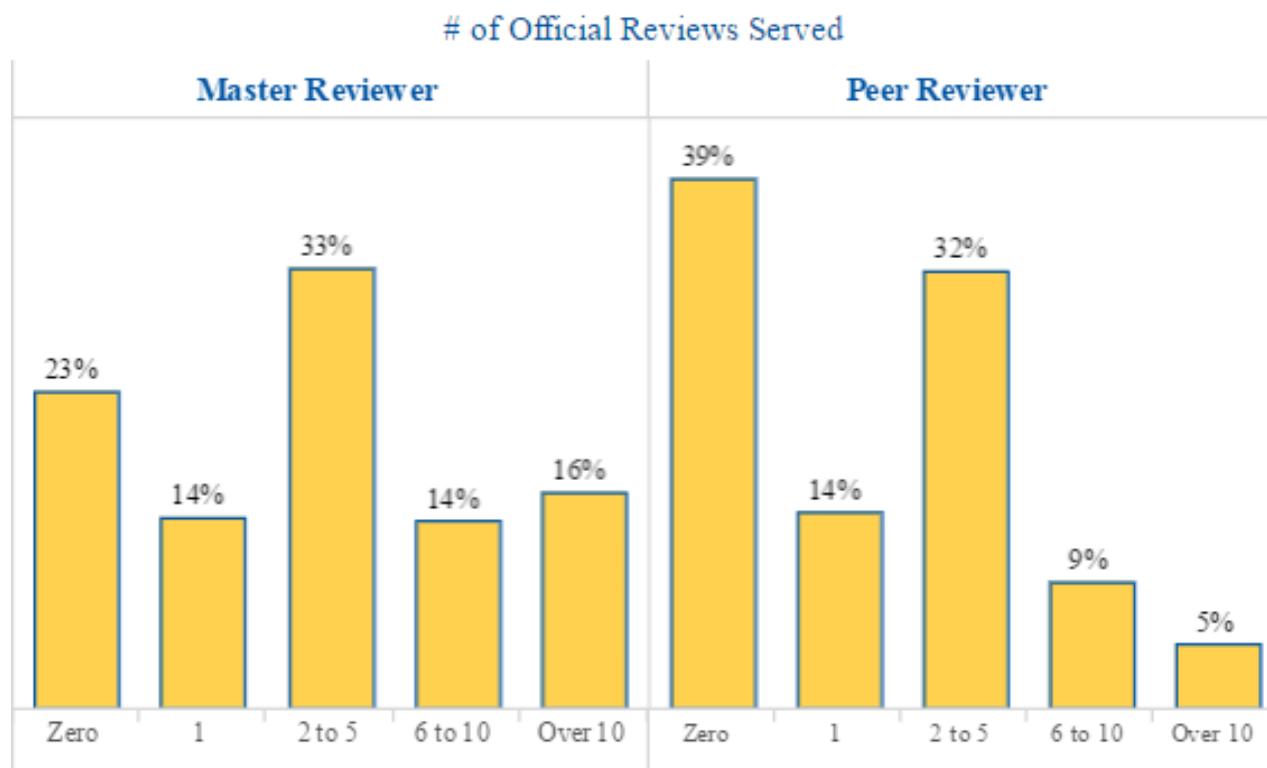
Course Reviewers

3-5 hours - (98)
6-8 hours - (743)
9-11 hours - (941)
12+ hours - (929)

Data Analytics & QA: Peer course Review



Reviewer Data

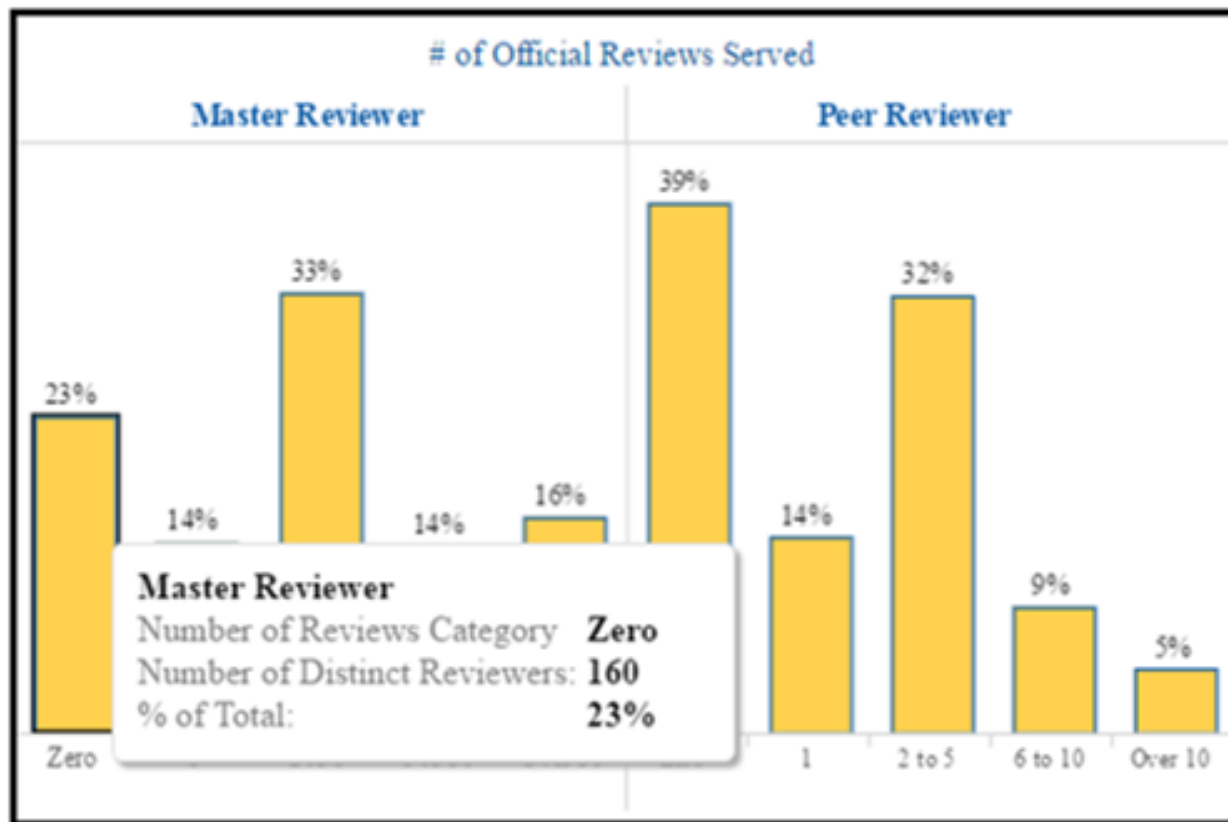


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Reviewer Data

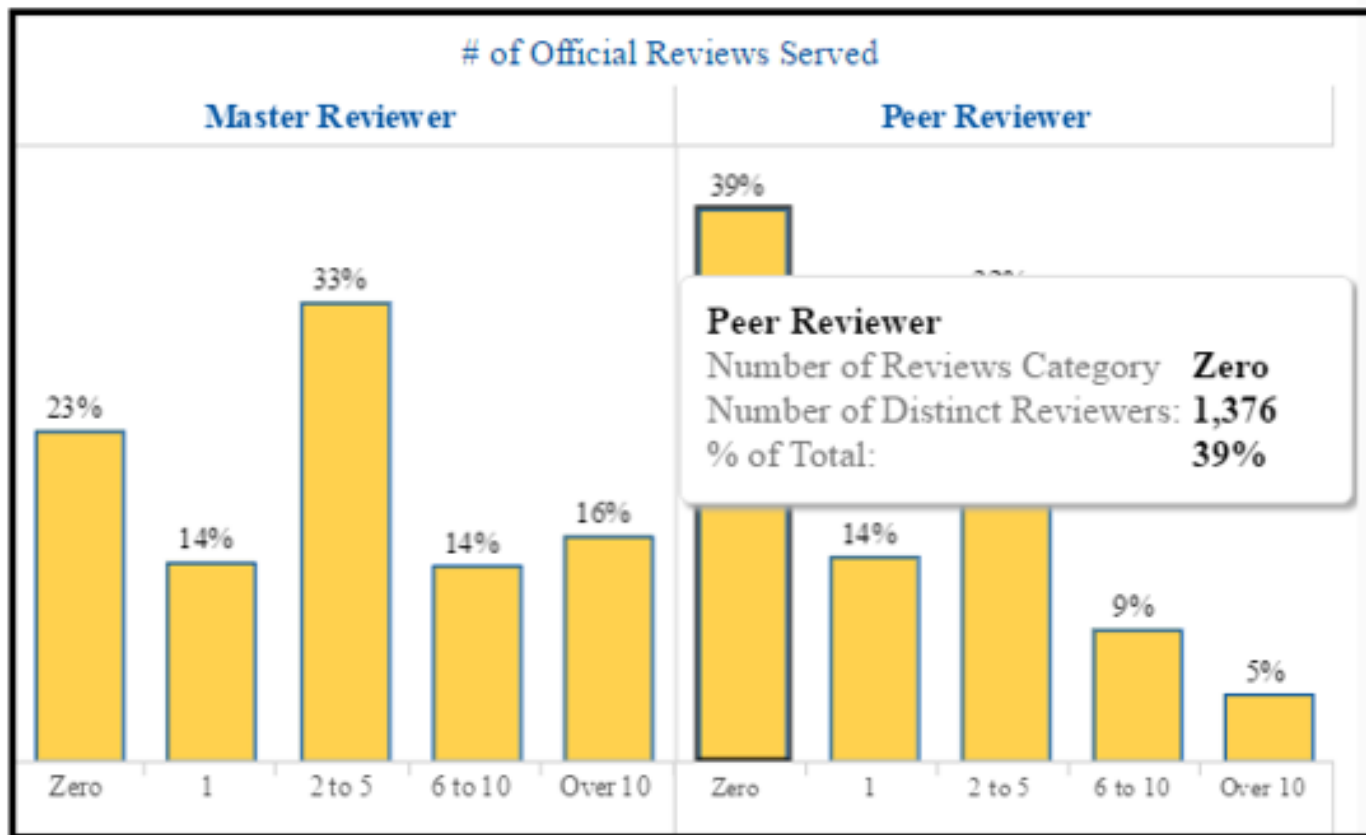


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Reviewer Data

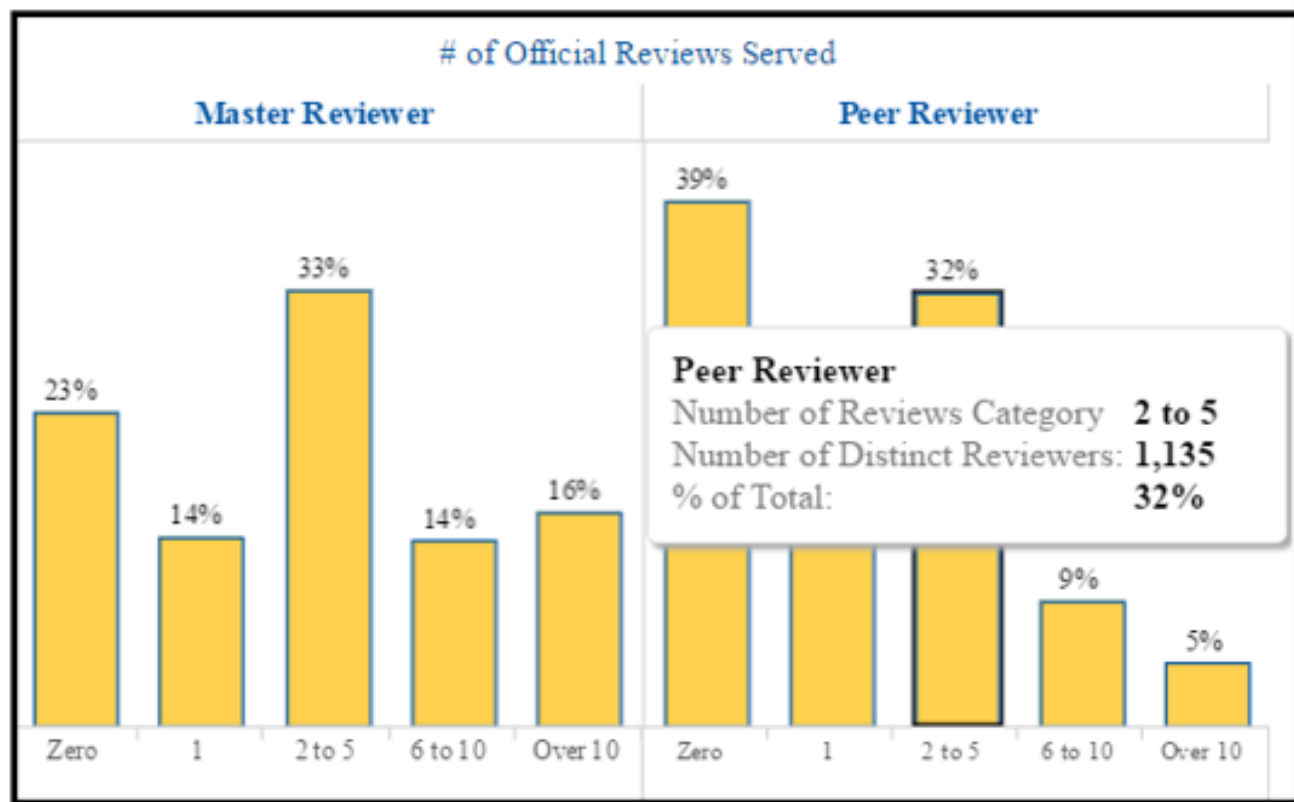


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Data Analytics & QA: Peer course Review



Reviewer Data



QUALITY MATTERS

QM



Data Analytics & Quality Assurance

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STUDENT PATHWAYS THROUGH AN ONLINE ALGEBRA 1 COURSE

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ALGEBRA 1 AT MVS

In collaboration with MVLRI, we have been analyzing LMS output data (logins, session duration, cumulative grades) from a “gatekeeper” Algebra 1 course offered through Michigan Virtual School.

We began with data from 2013. For the results reported here, we had data for 2014 and 2015.

STRUCTURE OF THE COURSE

The Algebra 1 course content is scheduled over 18 weeks, with a window before the final exam, scheduled for week 21.

The course is self-paced, and has multiple assessments throughout, as well as a midterm and final exam.

The course pacing guide lays out the week that each lesson and assessment is expected to be completed.

Students are only able to move forward if they receive at least 60% on each assessment.

STRUCTURE OF THE DATA SET

We have time-stamped web log data for Fall 2014 and Fall 2015

- Fall 2014 had 46 students who completed at least the first quiz (scheduled for Week 1)
- Fall 2015 had 52 students who completed at least the first quiz (scheduled for Week 1)

Data was organized by student, by week, by session, by time of access, and by type of page visited

This gave a total of 73,000 rows of data for 2014 and 69,000 rows for 2015

RAW DATA

fx 12/15/2014 8:58:12 PM			
C	I	J	M
user pk	data	timestamp	session
71862	Midterm Exam	12/15/14 8:58 PM	4210121
71862	Lessons	12/15/14 9:03 PM	4210121
71862	Unit 3: Linear Functions	12/15/14 9:08 PM	4210121
71862	Checkpoint: Lessons 3.5 - 3.8	12/15/14 9:09 PM	4210121
71862	Unit 3: Linear Functions	12/15/14 9:09 PM	4210121
71862	Unit 3: Linear Functions	12/15/14 9:21 PM	4210121
71862	Announcements	12/15/14 9:38 PM	4210804
71862	Lessons	12/15/14 9:39 PM	4210804
71862	Unit 4: Systems of Equations & Inequalities	12/15/14 9:39 PM	4210804
71862	Lessons	12/15/14 9:39 PM	4210804
71862	Midterm Exam	12/15/14 9:39 PM	4210804
71862	Lesson 1.8 Introduction to Functions	12/15/14 9:39 PM	4210804
71862	Midterm Exam	12/15/14 9:40 PM	4210804
71862	Lessons	12/15/14 9:40 PM	4210804
71862	Unit 3: Linear Functions	12/15/14 9:40 PM	4210804
71862	Unit 3 Test	12/15/14 9:40 PM	4210804
71862	My Grades	12/15/14 9:42 PM	4210804
71862	My Grades	12/15/14 9:42 PM	4210804
71310	Announcements	12/16/14 9:30 AM	4217889
71310	My Grades	12/16/14 9:30 AM	4217889
71310	My Grades	12/16/14 9:30 AM	4217889
71310	Getting Help	12/16/14 9:30 AM	4217889

PACING

In our first study, a qualitative examination of a few selected cases suggested that passing students tended work steadily through the semester while failing students tended to work erratically, jamming the work into a few weeks.

In other words, passing students seemed to have better pacing than less successful students.

3 selected students, 2013

Week	Pacing guide Algebra 1a	Excellent (95.2)	Just failing (52.8)	Failing (31.6)
1	Check01	Check01	Check01 + Check02 + Check03	Check01
2	Check02		Check04	Check02
3	Check03	Check02 + Check03	Check05	Check03
4	Check04		Check06 + Unit 2 Test	
5	Check05	Check04 + Check05	Check07	
6	Check06	Check06		
7	Unit 2 Test	Unit 2 Test	Check08	
8		Check07	Check09	
9	Check07			
10	Check08			
11	Check09	Check08		Check04 + Check05+ Check06 + Unit 2 test + Check07
12	Check10 + Unit 3 Test	Check09 + Check10	Check10+ Unit 3 test	
13	Midterm exam	Unit 3 Test + Midterm exam	Check11	
14	Check11		Check12	Check08
15		Check11	Unit 4 Test	Check09
16	Check12 + Unit 4 Test		Check13 + Unit 5 Test + Final Exam	
17	Check13 + Unit 5 Test	Check12 + Unit 4 Test + Check13+ Unit 5 Test		
18	Final exam	Final exam		

HYPOTHESIS

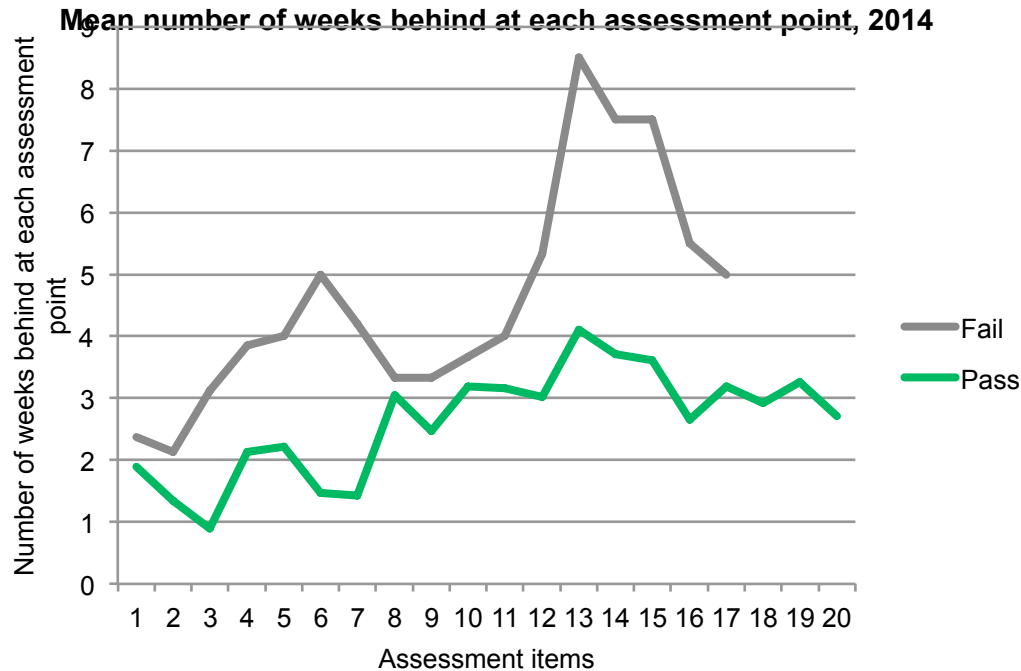
We wanted to see if this was true for an entire cohort of students.

We had this hypothesis:

Passing students stay closer to the pacing guide while failing students fall behind.

RESULTS

In both years, we found that failing students were always behind the pacing guide while passing students stayed closer to the schedule.



BUT there was also a great deal of variation, especially for the middle range students.

2014
Weeks
behind
pacing
guide

[illegible]

2015
Weeks
behind
pacing
guide

[illegible]

HYPOTHESIS REVISITED

The hypothesis:

Passing students stay closer to the pacing guide while failing students fall behind.

Yes, this seems to be true, but within each group there is great variability.

So perhaps there are other ways to group the students.

PERFORMANCE

In our previous study, we only had cumulative points earned at any one point in time.

For 2014 and 2015, we had points earned for each assessment and the date on which the assessment was taken.

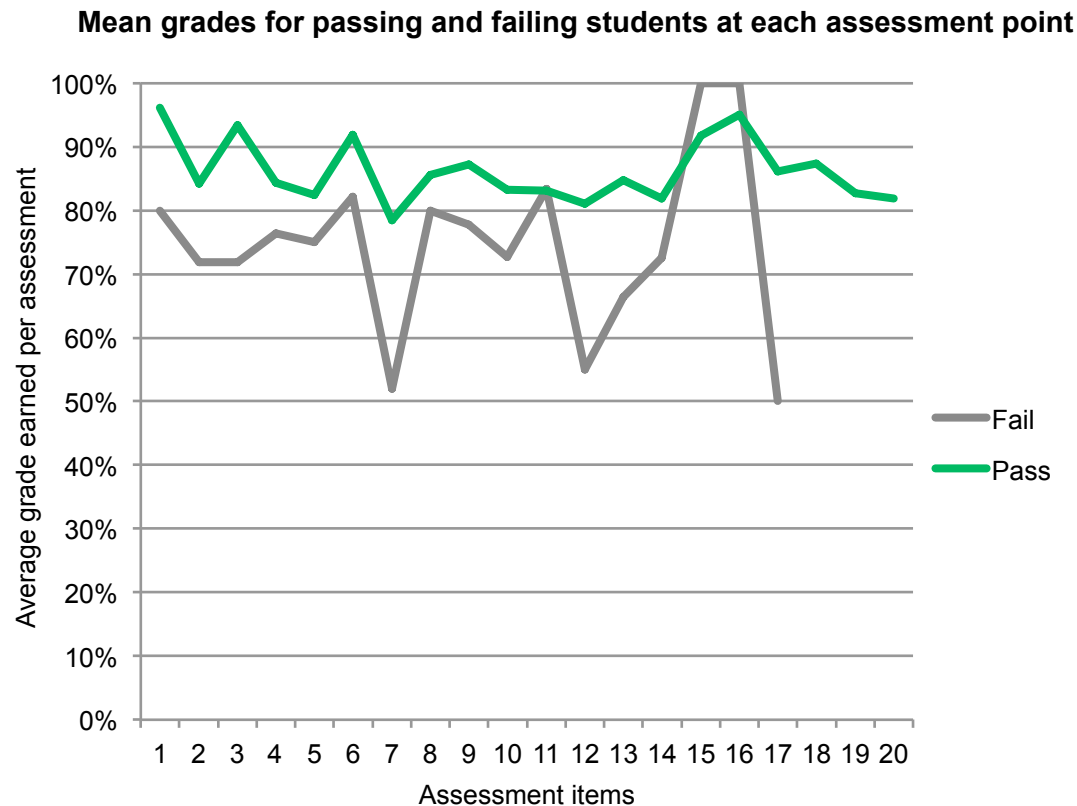
HYPOTHESIS

Our hypothesis was:

Using points earned for each assessment will provide us with additional information about student pathways.

RESULTS

Failing students earn lower grades on almost all assessment items over the entire semester.



BUT we also found that these means by group obscure a lot of variation, especially for the middle range achievers.

2014
Points
earned by
assessment

[illegible]

2015
Points
earned by
assessment

[illegible]

HYPOTHESIS REVISITED

The hypothesis:

Using points earned for each assessment will provide us with additional information about student pathways.

It does, somewhat, but this is accompanied by enormous variation.

PACING AND PERFORMANCE

Since there was variability in both pacing and performance, we wanted to see if combining them would give us better profiles of student learners.

PACING AND PERFORMANCE

We therefore created two new variables, one for pacing over time and one for performance over time.

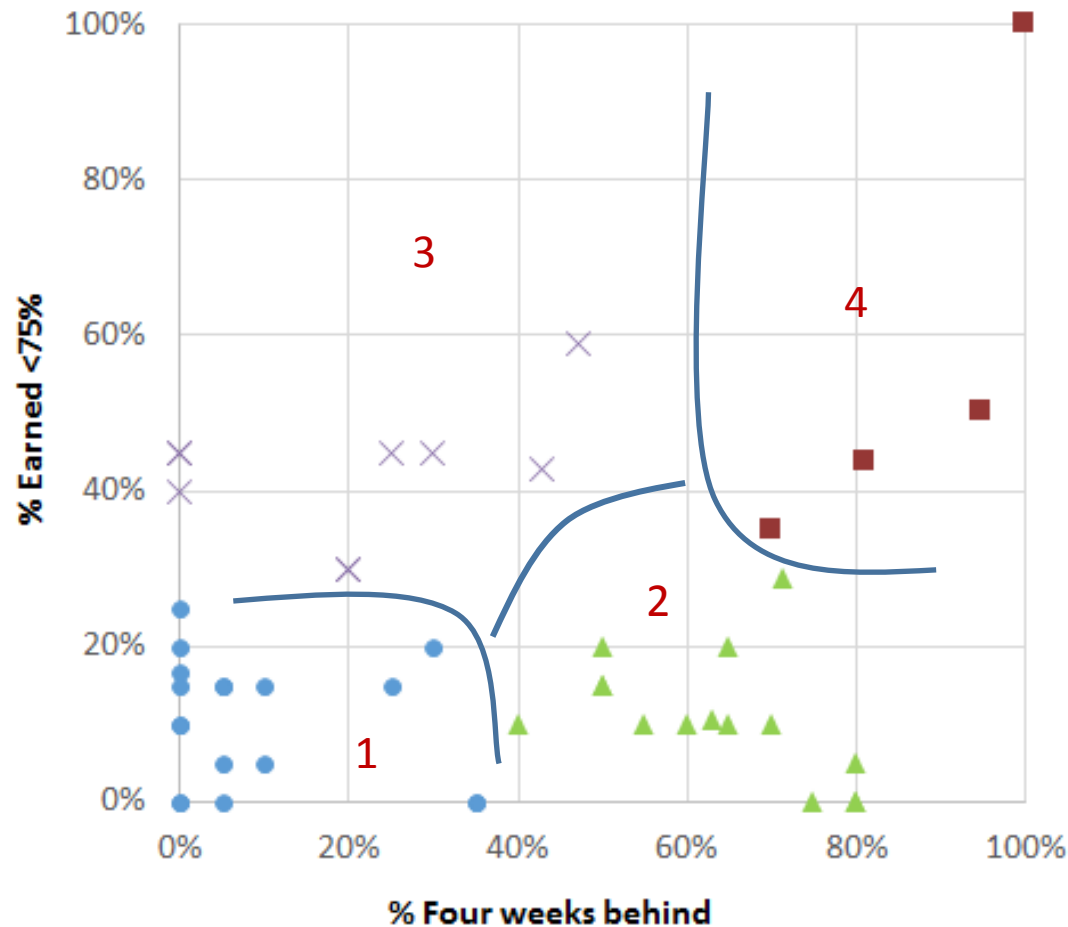
- (1) Pacing: The percentage of weeks in which a student fell four or more weeks behind, based on the pacing guide.**
- (2) Performance: The percentage of assessments completed in which a student earned less than 75% on each assessment.**

Hypothesis:

Using variables for both pacing and performance over time would better differentiate student learners than either one separately.

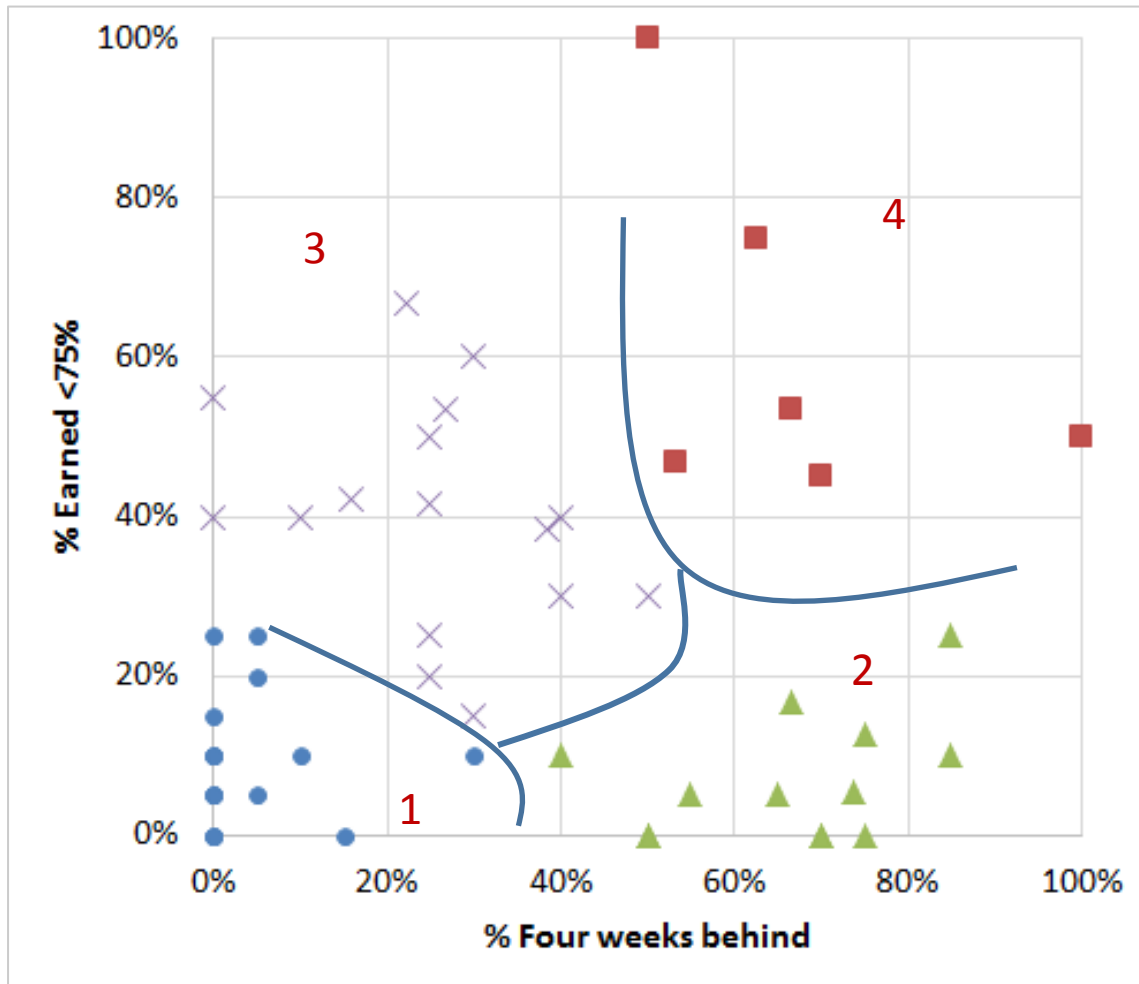
RESULTS: FOUR CLUSTERS

2014



	ACADEMIC STRENGTH	PACING
Group 1	Good	Good
Group 2	Good	Not good
Group 3	Not good	Good
Group 4	Not good	Not good

2015



	ACADEMIC STRENGTH	PACING
Group 1	Good	Good
Group 2	Good	Not good
Group 3	Not good	Good
Group 4	Not good	Not good

HYPOTHESIS REVISITED

The hypothesis:

Using variables for both pacing and performance over time would better differentiate student learners than either one separately.

Yes, this is true. And the results of cluster analysis showed that four groups was the best model fit in both years.

	2014	2015
Good performance: Good pacing	39%	33%
Good performance: Poor pacing	33%	25%
Poor performance: Good pacing	20%	31%
Poor performance: Poor pacing	9%	12%

PATHWAYS THROUGH THE COURSE

It seemed possible that students who had poor pacing also did not work through the course material systematically.

To look at this, we needed to examine the sequences of LMS page clicks by course area visited (e.g., lessons, assessments, etc.).

SEQUENCING

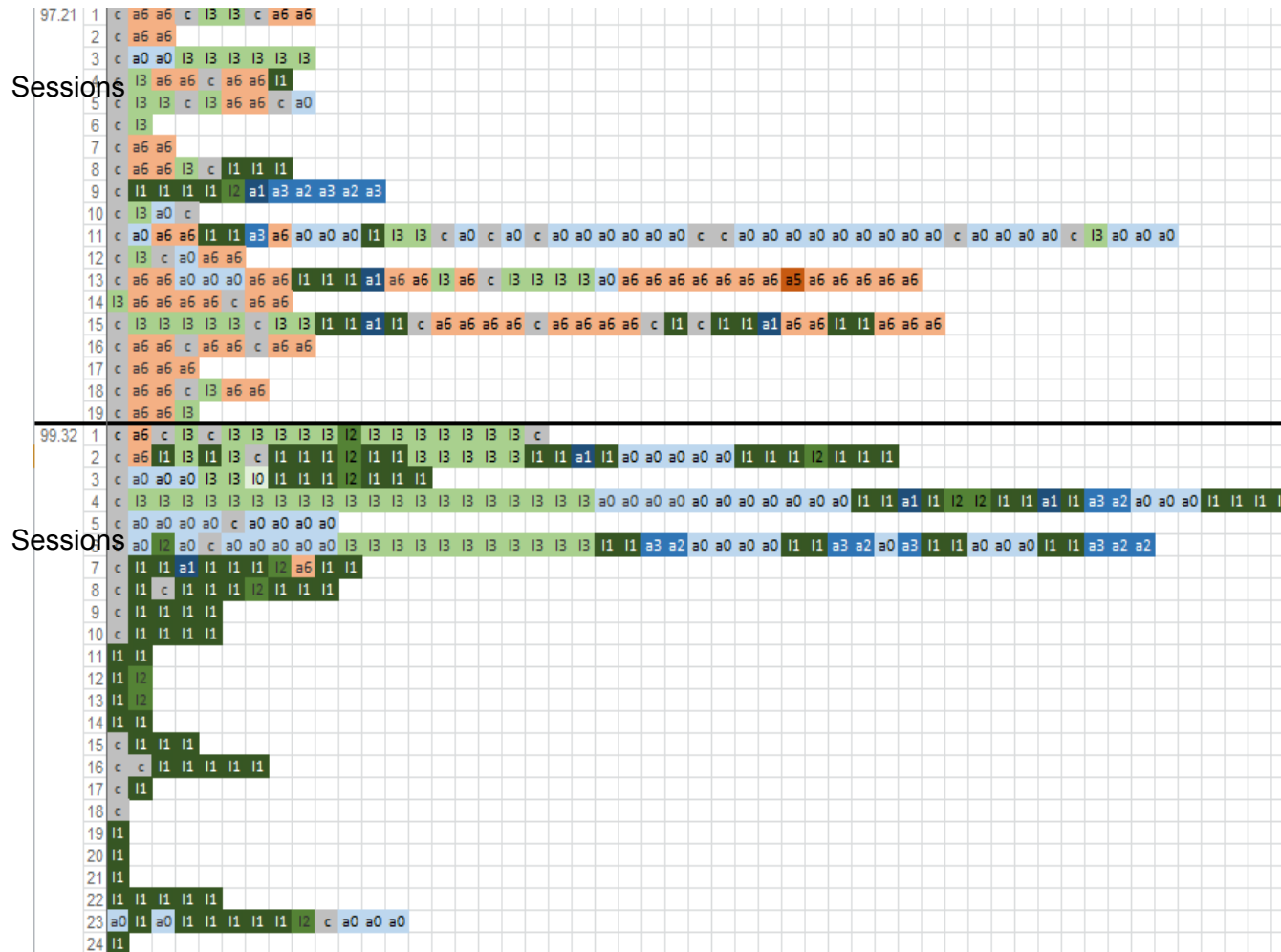
We used differential sequential pattern mining to see if we could find different patterns for our four clusters.

Our hypothesis was:

Students pathways will vary between clusters, with the poor performance/poor pacing group accessing the non-lesson-related items repeatedly.

DATA SET: LMS VISITS BY CONTENT ACCESSED

Two students with similar final grades, all sessions, week 3



HYPOTHESIS REVISITED

Our hypothesis was:

Students pathways, as seen in sequences of LMS course visits, will vary between clusters, with the poor performance/poor pacing group accessing the non-lesson-related items repeatedly.

No, a preliminary analysis suggests that all students access non-lesson-related items repeatedly.

But the poor performance/poor pacing students are less likely to access assessment-related pages immediately before and after lessons.

We are still struggling with how best to analyze sequential data.

CHALLENGES

Using this type of data poses big challenges.

MANY DIFFERENT TYPES OF CHALLENGES

Some challenges come from the small sample size of a normal class:

- Variability from student to student.
- Anomalous data points that skew the data.
- Using big data approaches with not-so-big data.

Some come from the structure of this kind of self-paced course:

- The week the data comes from is not necessarily the week the student is in the course.

Some come from the fact that the algorithms currently available are not created with online courses in mind:

- R packages, RapidMiner, and SAS Enterprise Miner only allow one time variable (in this case, the sequence of hits), and you cannot break them into the time periods that rule students' lives—such as sessions or even weeks.

Making the data usable takes massive amounts of time:

- Data restructuring is needed every time you change your mind about what variables to look at and in what order.
- Running these data sets through RapidMiner takes many hours—possibly due the variability.

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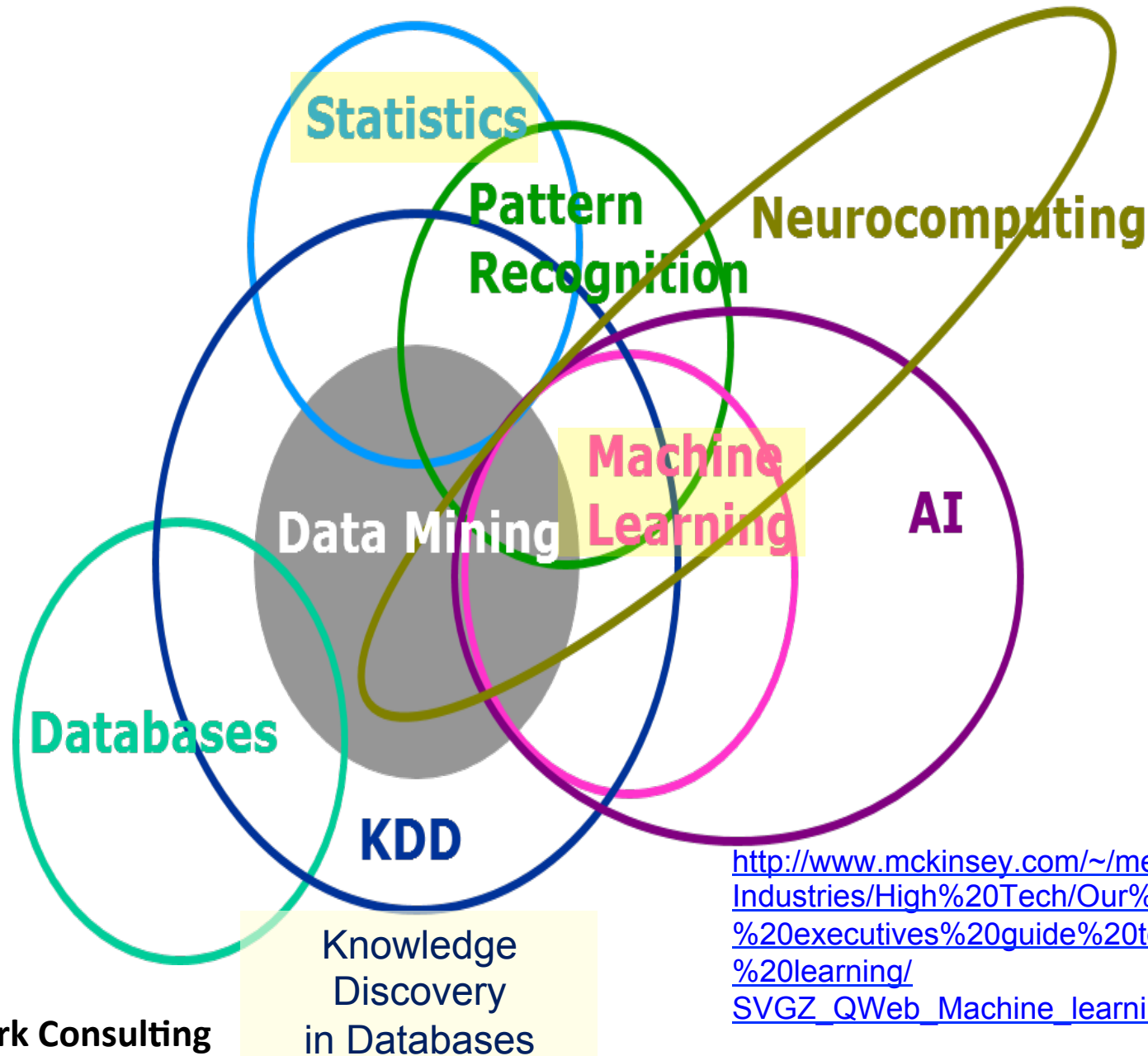
Data Analytics in a Virtual School: Then and Now

Tom Clark
Clark Consulting

Learning from Data

- Data analytics methods all focus on ***learning from data***
- **Statistic modeling:** uses math equations to find relationships between variables in data
- **Machine learning:** uses algorithms to learn from data without relying on rules-based programming.
- **Predictive analytics:** Uses these and other data analytics tools - mainly to predict future outcomes & trends

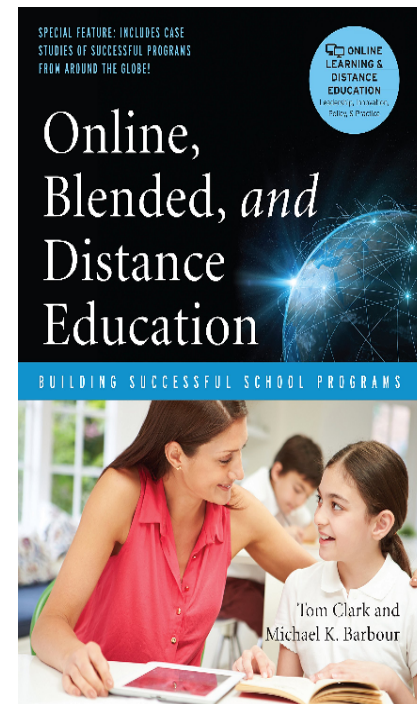
Lies, Damn Lies, and



http://www.mckinsey.com/~media/McKinsey/Industries/High%20Tech/Our%20Insights/An%20executives%20guide%20to%20machine%20learning/SVGZ_QWeb_Machine_learning_ex1.ashx

The Research Project

- 2008-09 evaluation of virtual school in a Midwestern state
- Research by **Cathy Cavanaugh & Feng Liu**, funded via the evaluation, to identify success factors and how they impact student performance
- Data source: 15 high-enrollment one-semester HS courses with 1,794 total enrollments from districts statewide



Stylus (2015) Microsoft (co-publisher)

Tom Clark & Michael Barbour (Eds..) Foreword by **Cathy Cavanaugh** - *Led to data re-analysis*

Clark

Tom Clark Consulting

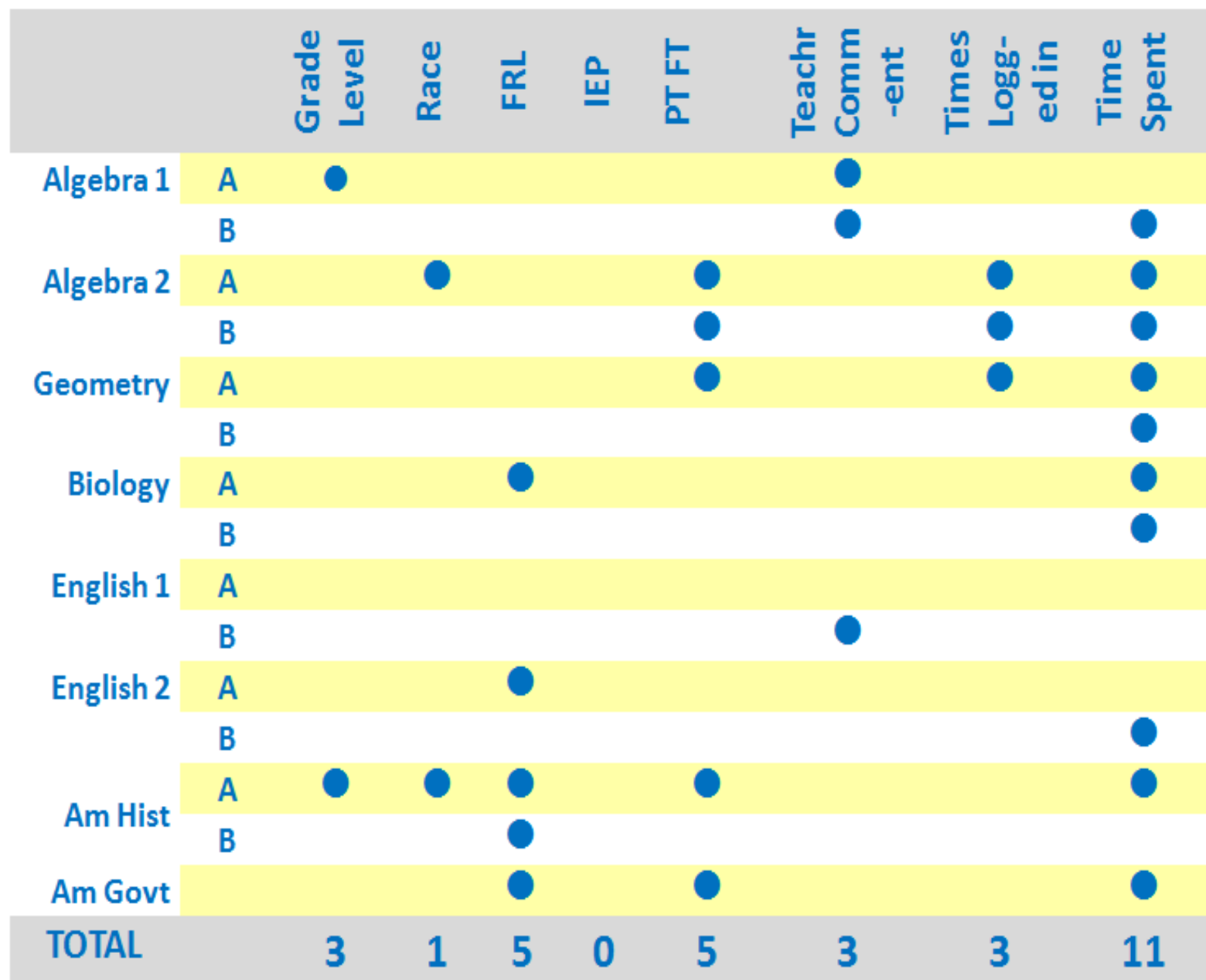
Data Analytics & Quality Assurance in K-12: Data Analytics in a Virtual School

OLC Accelerate 2016

Data Analytics 1.0 –Then (2009)

- Comparison group analysis not seen as a viable option
- Extant student record and performance data and LMS activity in all courses was available for analysis (*unusual at the time!*)
- Months spent on exploratory data analysis by UF researchers
- HLM / Random Anova model selected to study influence of 8 specific factors on student performance (final course score)

Factors with Significant Effect on Course Score



Data Analytics 1.0: Key Findings*

Factors that influenced learning outcomes positively in 15 high enrollment courses

- **Spending more time in LMS** (11 of 15 courses)
 - In 3 Math courses, students who logged in more OFTEN scored lower; students who logged in less, spent more TIME scored higher
- **Full-time student status** rather than part-time (5 courses)
- Demographics: **Students not economically disadvantaged** (5 courses), non-minority (1 course), non-IEP (0 courses)

* Liu, F. & Cavanaugh, C. (2011). Online Core Course Success Factors in Virtual School.
International Journal of E-Learning 10(4)43-65.

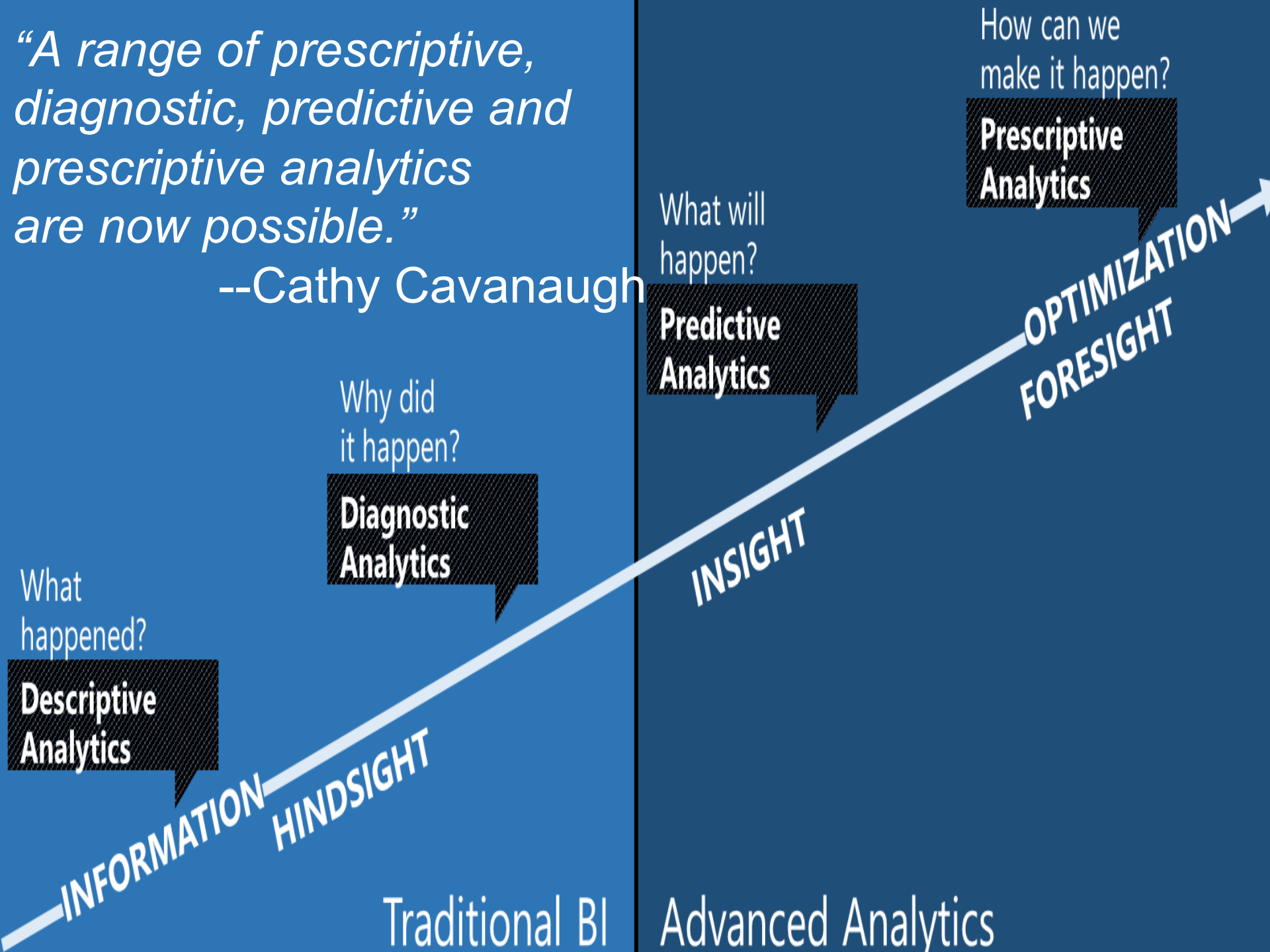
Data Analytics 2.0—Now (2015)

- Azure Machine learning (Microsoft/ Evans Analytics)
- New analysis of same dataset; basically a training exercise for new cloud-based analytics solution
- Predicts individual student pathways and likelihood of failure based on static and real-time dynamic data
 - Predictions available immediately to school leaders
- Prescribes potential interventions and gives cost-effectiveness

Source: Cavanaugh, C. (personal communication, October 31, 2016)

“A range of prescriptive, diagnostic, predictive and prescriptive analytics are now possible.”

--Cathy Cavanaugh



Teacher View

Step 2: View Lesson Progress

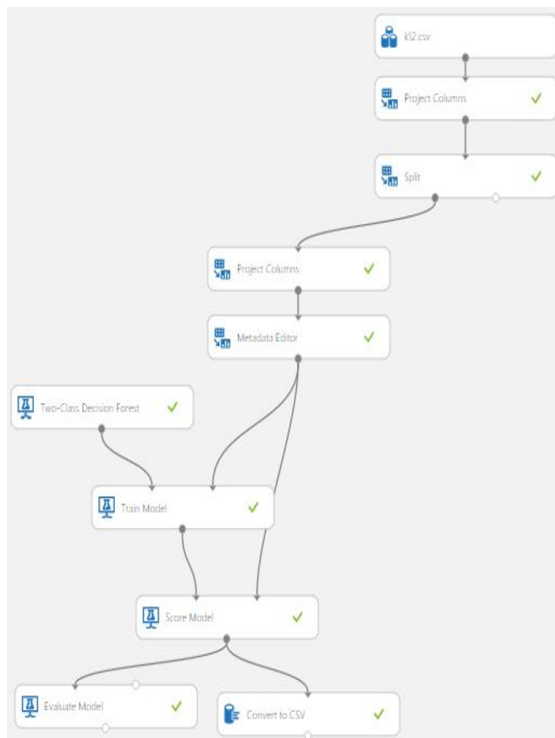
Step 1: Select Student



Source: Cavanaugh, C. (personal communication, October 31, 2016)
Tom Clark Consulting

Data Analytics 2.0: Prediction

- PREDICTION: At-risk model 80% accurate in predicting which students would fail.
- School leaders can view students at risk by school, subject, and teacher.



0.28
Average of Probability of Dropout
78.30
Average of Final Grade

ADELLE	DELANEY	True
First Name	Last Name	Predicted to Dropout
5011	0.50	ISAAC WOODSON
StudentID	Probability of Dropout	Teacher Name

AGNES	ELDRIDGE	True
First Name	Last Name	Predicted to Dropout
663	0.98	PHILLIP AGUILAR
StudentID	Probability of Dropout	Teacher Name

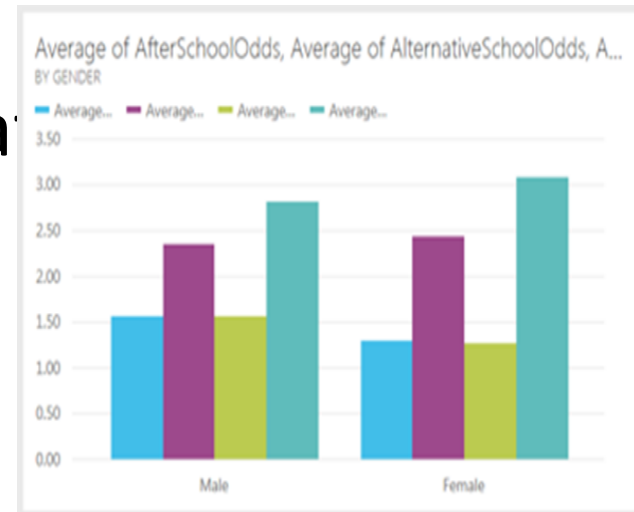
AGUSTINA	PACHECO	True
First Name	Last Name	Predicted to Dropout
1891	0.51	NATALIA GARVIN
StudentID	Probability of Dropout	Teacher Name

Source: Cavanaugh, C. (personal communication, October 31, 2016)

Data Analytics 2.0: Prescription

- Each student flagged as at risk receives a personalized ranking of effective interventions *

Row Labels	BestInterventionCost	BestInterventionCost%
Elementary	\$53,352	17.83%
AfterSchool	\$0	0.00%
ServiceLearning	\$53,352	17.83%
Middle	\$59,743	19.96%
AfterSchool	\$14,336	4.79%
AlternativeSchool	\$9,688	3.24%
MentoringTutoring	\$853	0.29%
ServiceLearning	\$34,866	11.65%
High	\$186,163	62.21%
AfterSchool	\$32,768	10.95%
AlternativeSchool	\$15,916	5.32%
MentoringTutoring	\$5,971	2.00%
ServiceLearning	\$131,508	43.94%
Grand Total	\$299,258	100.00%



- School leaders get ranking and cost modeling of suggested interventions

* www.dropoutprevention.org/meta-analysis-dropout-prevention-outcome-strategies

Affordances and Challenges

Perennial Challenges

- Getting data access
- And the right data points
- Getting the OK to share what you've learned through data

Perennial Affordances

- Client sees value in research and evaluation
- Latitude to conduct non-goal-focused research)

New Challenges

- Stats: research Qs -> Azure ML: SIP needs
- What roles do researchers play in new “flattened” learning analytics using ML?
- Cathy C suggests:

New Affordances

- New ops for research-practice partnership
- *A Call to Action for Research in Digital Learning* bit.ly/RDLcall Cavanaugh, Sessums & Drexler (2016)
- Tacoma Schools Case Study bit.ly/TPSazure

Waving a magic wand ..

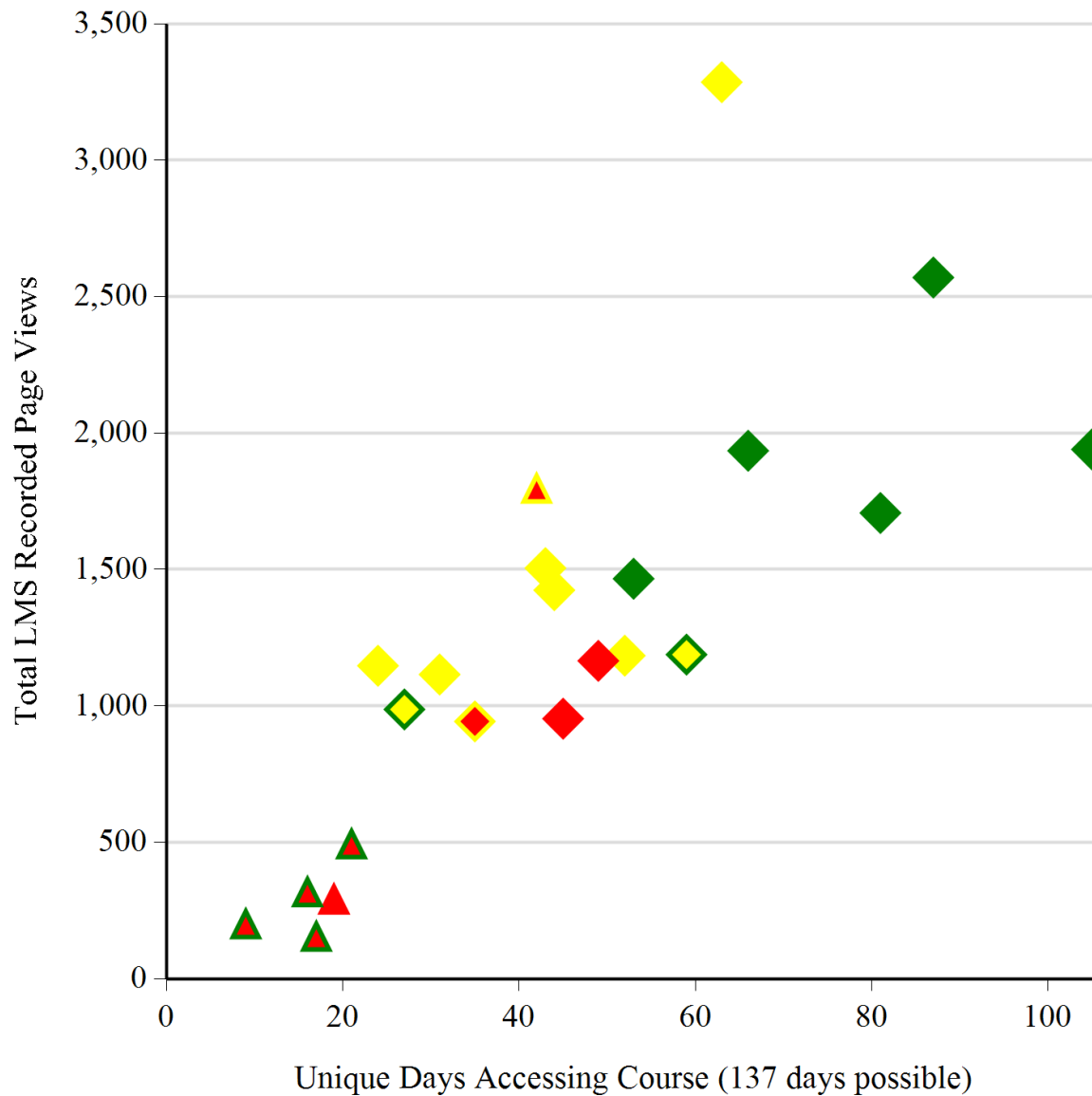
- I'd like to see Data Analytics used more to connect **research and practice**. For example:
 - Focus on a ***problem of practice*** of mutual interest
 - **Rapid cycle evaluation** that helps researchers & educators quickly identify intervention impact
 - **Design-based research** – ***tinkering with the affordances and observing the effect***, to individualize interventions to the local setting



Data Analytics for Practitioners and Policy Implications

Dr. Joe Freidhoff
Vice President
MVU





▲ Triangles: < 50% of Assignments Completed

◆ Diamonds: >= 50% of Assignments Completed

◊ Border Color: Work Quality (Pts Earned / Pts Attempted)

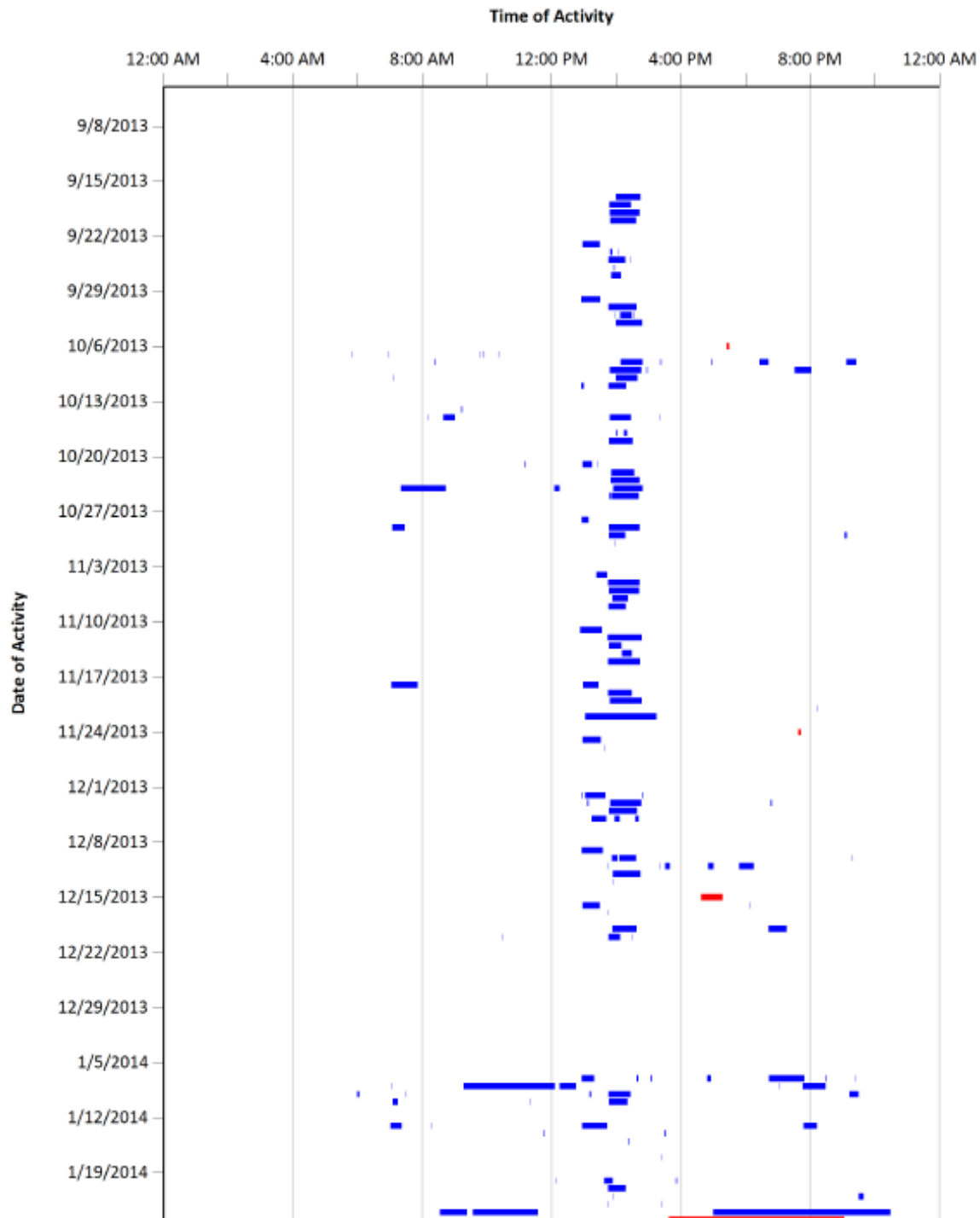
▲ Core Color: Overall Quality (Pts Earned / Total Course Pts)

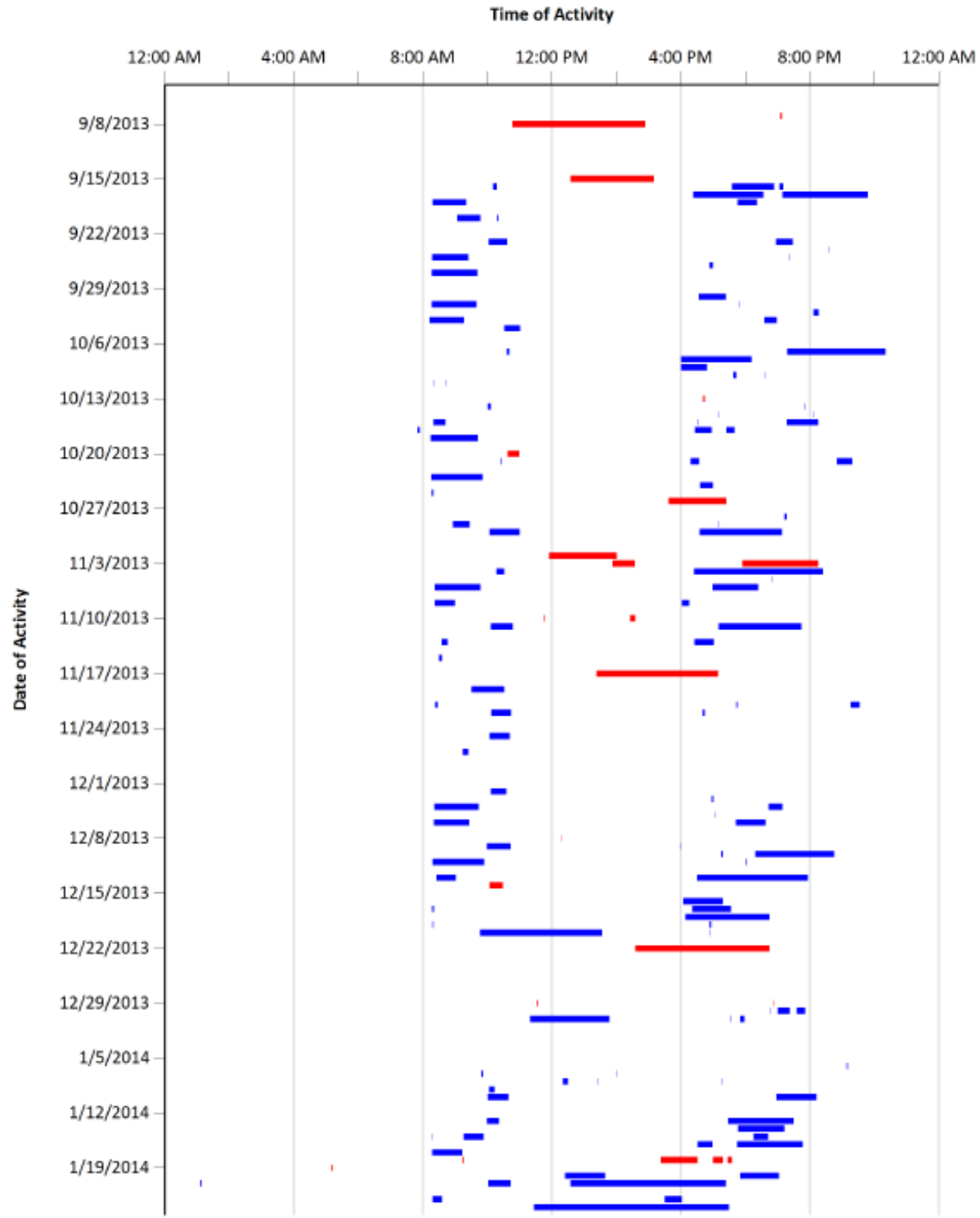
Color Explanation

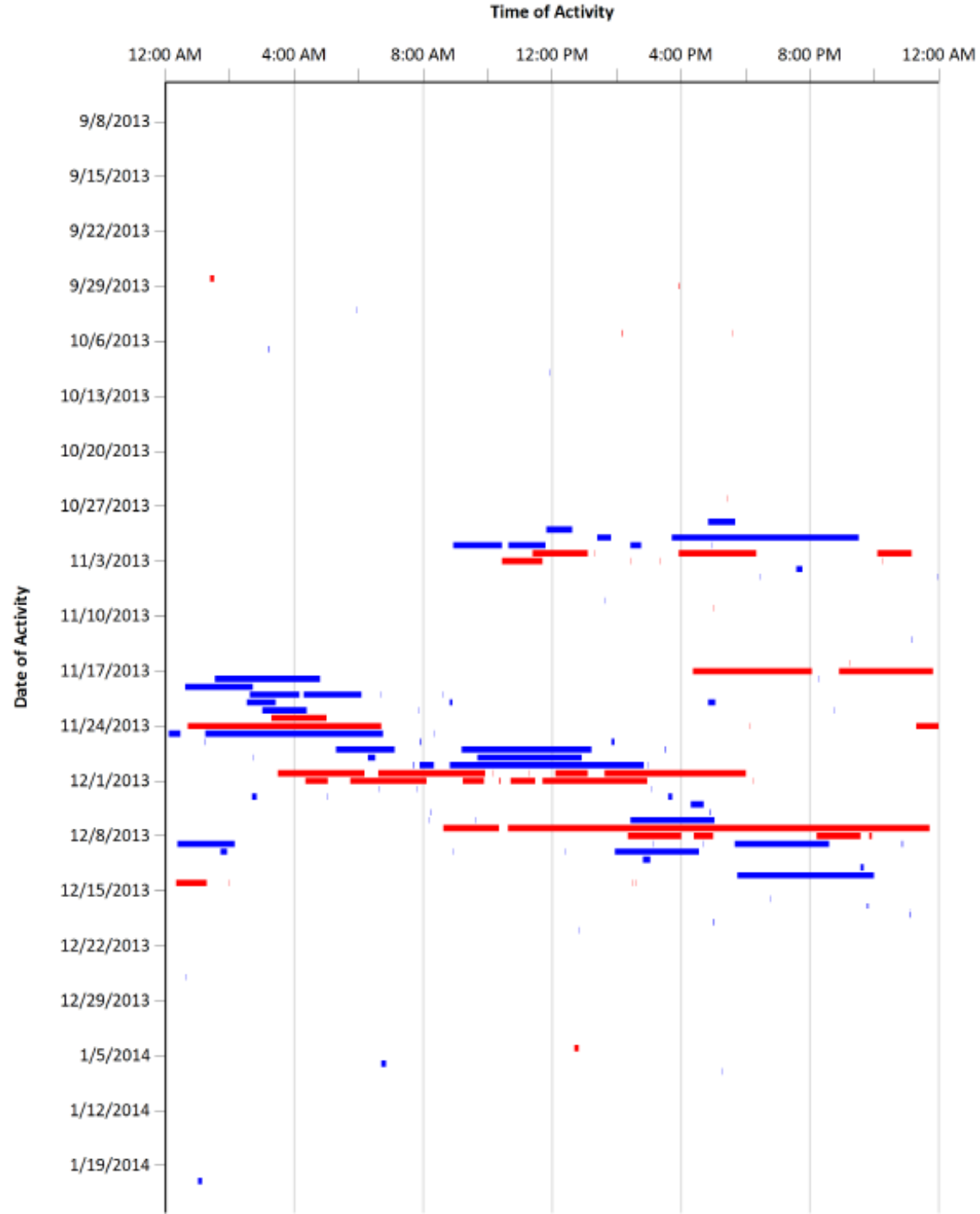
■ = Scores of 0 to < 60%

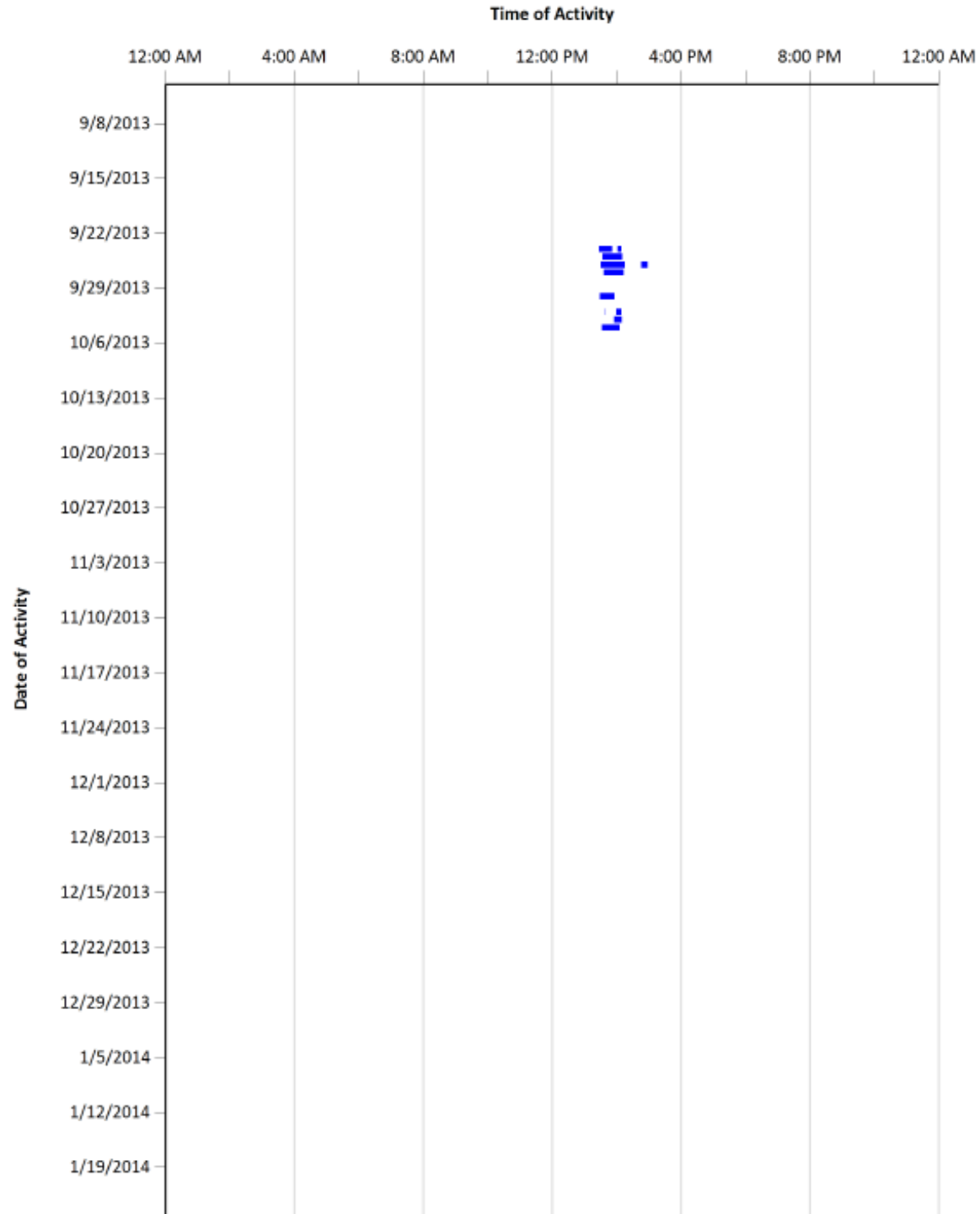
■ = Scores of 60% to < 80%

■ = Scores of >= 80%









Economics Lesson Structure

Economics - MSTR
(Econ-MSTR-16)

Start Here

Welcome
Announcements
Course Info
Instructor Info
MVS Policies
Getting Help

Student Orientation
Unit 0 - Course Introduction
Unit 1 - Economic Choices

Unit 2 - Understanding
Markets, Prices, Supply &
Demand
Unit 3 - Government & the
Economy

Unit 4 - Understanding the
American National Market
Unit 5 - Role of Government
in the U.S. Economy

Unit 6 - Types of Economic
Systems
Unit 7 - Economic
Interdependence: Trade
Unit 8 - Understanding
Personal Finance

Final Exam

Discussion Board

Message Instructor

My Grades

1.1 What is Economics?



1.1 What is Economics?



In this lesson you will become familiar with thinking in an economic manner, and we will begin to introduce key economic concepts. We will begin to explore the rational decisions that people, businesses, and governments must make in a world with limited resources.

At the conclusion of this lesson you should be able to:

- Identify the key concepts of economics.
- Demonstrate an understanding of the relationship between the study of economics and real life decision making.

Click the link above to begin your study of this lesson.



1.1 Practice Quiz

This is an opportunity to practice answering questions on the information from this lesson. This practice quiz can be accessed multiple times, and is not worth points. The five questions you see will be drawn from a larger pool. So, attempting the practice quiz multiple times will better prepare you for the unit test. Remember, the goal here is to do well on the practice opportunity before proceeding. If you have taken this quiz multiple times and you are struggling with a question, please use the "Message Instructor" link in the left margin to ask your instructor for help. Remember, that is what I am here for!



1.1 Studying Economics Discussion Board

Discussion Forum

For this discussion forum, begin by reading the following statement and decide whether you agree or disagree with the statement:

"The study of economics is really boring, and it has little to do with my daily life."

In a post of several paragraphs, discuss the reasons why you agree or disagree with the above statement. What evidence from the lesson or outside research can you find that supports your stand? How can you connect your argument with the terms and ideas we have studied in this lesson?

After you have posted your position, you will be able to see what your classmates have written. At that point, you will need to critique the content of at least two of your classmates' postings. For the purpose of this lesson, critiquing means that you will be reading your classmates' posts with an eye for accuracy. You will be looking specifically for places where you can apply supporting evidence from the lesson material or additional sources. It is not enough to simply make a statement regarding your classmates' work. For example, "Nice job, I like your post" or "I don't agree with what you are saying" are not sufficient. You are expected to provide the supporting evidence. It is fine to identify inaccuracies in your classmates' ideas as long as you provide the evidence that supports your point of view. Your response must include more information and critical thought than, "I like your posting," or "I agree." Remember to support your ideas with details, examples, and/or explanations. If you are having some difficulty generating a thoughtful reply, consider the following sentence starters:

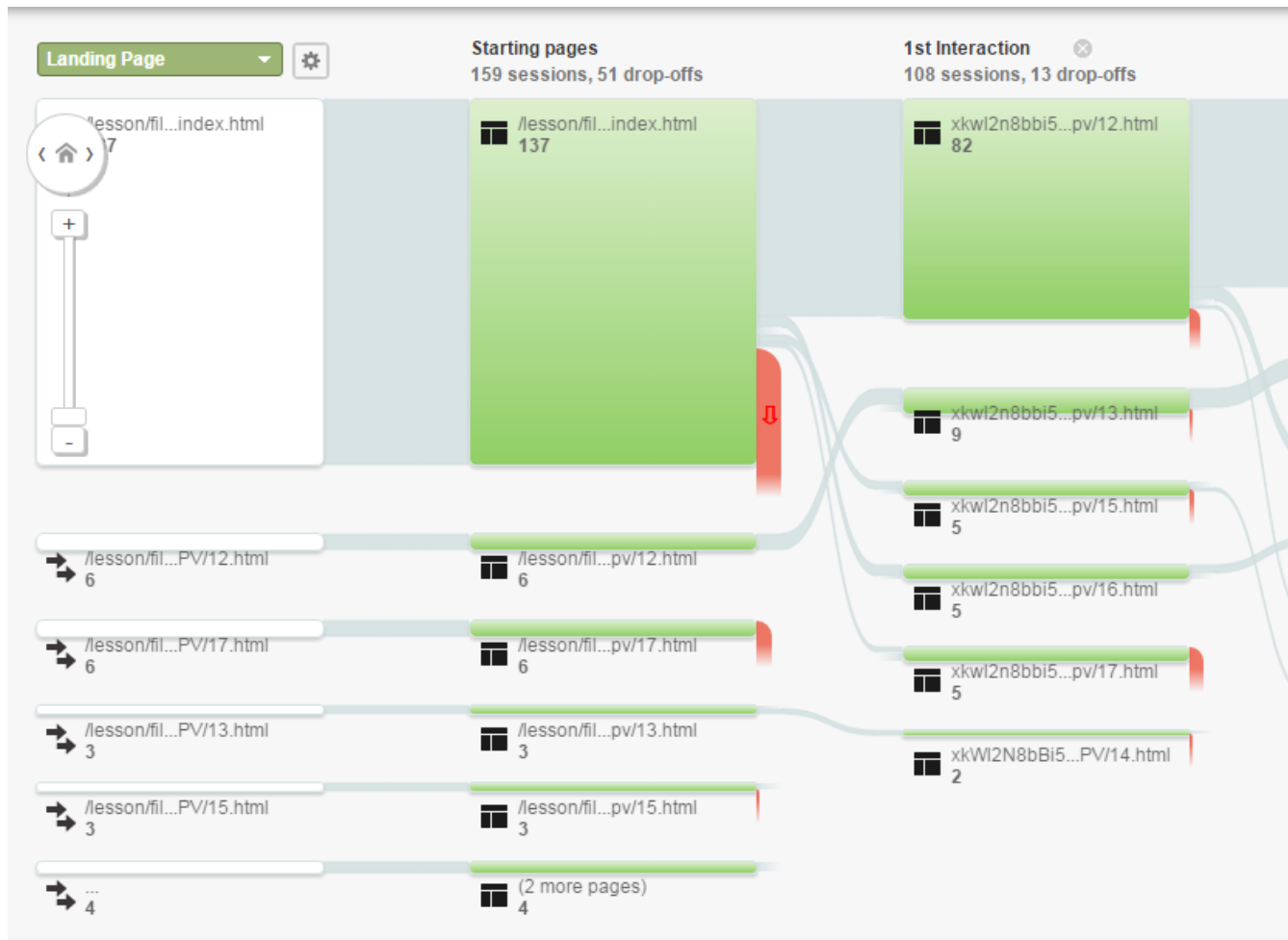
- One thing that you said that I hadn't thought about was...
- I feel this is important because... It made me think about...
- A piece of information that I would like to add is...
- A question I have is...

Kristi Peacock kpeacock@mivu.org

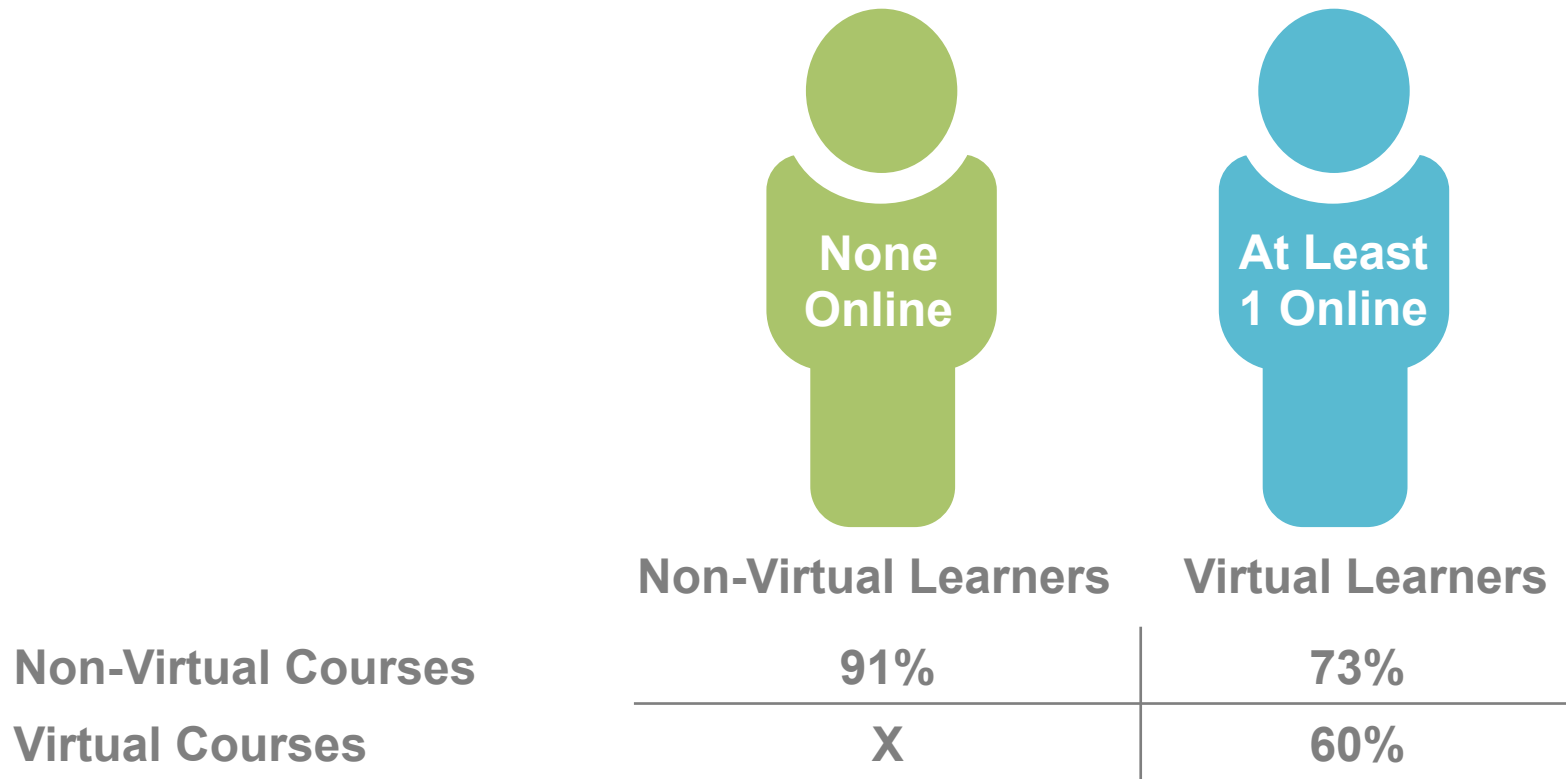
Google Analytics Lesson Structure

	Sessions	Avg. Session Duration	Bounce Rate
☆ Anatomy & Physiology A - Part 1			
☆ Anatomy & Physiology A - Part 2			
☆ Economics			
☆ Lesson 1.1 (UA-82331589-2)			
☆ All Web Site Data	159	00:09:57	28.30%
☆ Lesson 1.2 (UA-82331589-3)			
☆ All Web Site Data	158	00:09:43	36.08%
☆ Lesson 1.3 (UA-82331589-4)			
☆ All Web Site Data	112	00:10:57	27.68%
☆ Lesson 1.4 (UA-82331589-5)			
☆ All Web Site Data	57	00:10:29	24.56%

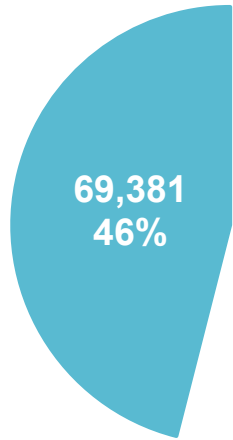
Google Analytics – Behavior Flow Detail



VIRTUAL LEARNERS PASSED THEIR VIRTUAL COURSES 60% OF THE TIME



THE LOW PASS RATE FOR VIRTUAL STUDENTS IS OFTEN AN IMPROVEMENT, RIGHT?

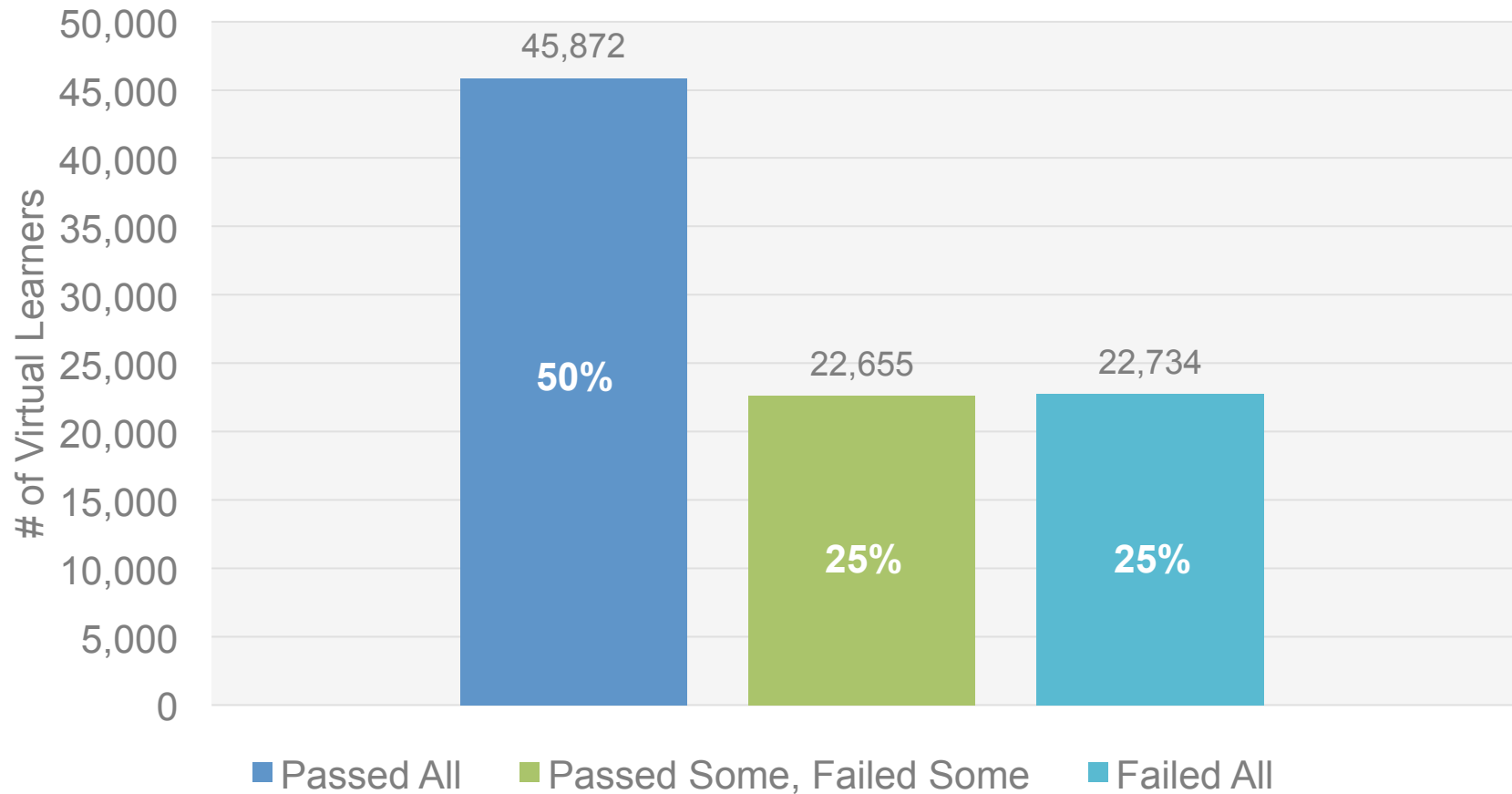


For Virtual Learners who Failed 3+ NV Courses

- 41% had higher pass rates in their virtual courses
- 14% had the same pass rates
- 45% had lower pass rates in their virtual courses

■ Failed 3+ NV Courses

HALF OF THE VIRTUAL LEARNERS PASSED EVERY VIRTUAL COURSE THEY TOOK



Count and Percentage of Students by Virtual Course Performance

STUDENTS IN POVERTY DID WORSE ACROSS THE BOARD THAN STUDENTS NOT IN POVERTY

- 64% of Virtual Enrollments Came from Students Living in Poverty
- 47% of Michigan students lived in poverty for that year

“Completed/Passed” Rates

Poverty Status	Virtual Learners Virtual Courses	Virtual Learners Non-Virtual Courses	Non-Virtual Learners Non-Virtual Courses
In Poverty	55%	64%	87%
Not in Poverty	67%	83%	95%
Difference	-12%	-19%	-8%

“Completed/Passed” Rates for Poverty Status

Thank you!

Questions?

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Dr. Tom Clark – *Tom Clark Consulting*
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Dr. Joe Freidhoff – *Michigan Virtual University*
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