PREDICTING STUDENT SOCIAL AND EMOTIONAL SKILLS USING LEARNING ANALYTICS.

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Agenda

1. Introduction
   • Problem, Research Context & Methods

2. Findings
   • Correlations
   • Predictive Models
   • Subpopulation Analysis

3. Conclusion, Limitations & Future Work


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Learning Analytics

At its core, learning analytics (LA) is the collection and analysis of usage data associated with student learning. The purpose of LA is to observe and understand learning behaviors in order to enable appropriate interventions.

~Educause Learning Initiative (ELI), 2011
Social and Emotional (SE) skills strongly predict academic achievement, career success and lifelong well-being.

Many studies find that these attributes contribute as much or more than academic skills in helping students succeed.

MULTIDIMENSIONAL, COMPREHENSIVE, AND RESEARCH-DRIVEN

Tessera is based on the research-validated and widely adopted Big Five personality factors. The broad, multidimensional Big Five framework encompasses attributes related to successful performance across different ages, contexts, and cultures.

Tessera measures six areas of Social and Emotional Learning Skills:

- Grit
- Teamwork
- Resilience
- Curiosity
- Leadership
- School Climate
<table>
<thead>
<tr>
<th>Skill</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grit</td>
<td>Grit reflects the extent to which a student’s actions demonstrate persistence, goal striving, reliability, dependability, and attention to detail at school.</td>
</tr>
<tr>
<td>Teamwork</td>
<td>Teamwork reflects the extent to which a student’s actions demonstrate collaboration, empathy, helpfulness, trust, and trustworthiness.</td>
</tr>
<tr>
<td>Resilience</td>
<td>Resilience reflects the extent to which a student’s actions demonstrate stress management, emotional regulation, a positive response to setbacks, and poise.</td>
</tr>
<tr>
<td>Curiosity</td>
<td>Curiosity reflects the extent to which a student’s actions demonstrate creativity, inquisitiveness, flexibility, open-mindedness, and embracing diversity.</td>
</tr>
<tr>
<td>Leadership</td>
<td>Leadership reflects the extent to which a student’s actions demonstrate assertiveness, influence, optimism, and enthusiasm.</td>
</tr>
</tbody>
</table>
Need for a Stealth Assessment of Socio-Emotional (SE) Skills

- Blackboard LMS Data and LA can predict course grade and risk of failing a course, but does not tell us **WHY** students are more or less active in a course (or what they can do about it).
- SE skill assessments also predict course outcomes, but **don’t reveal how these skills are related to day-to-day student activity**.
- What if we could **observe** students’ SE skills through their interactions in educational technologies in authentic learning contexts?

**Identify students at risk AND understand WHY**

**Design effective interventions**
Research Context

- Introduction to Chemistry (Chem 102)
- 492 (406 w/Tessera scores) students from diverse backgrounds
- History of pedagogical innovation by instructor
- Extensive use of LMS: ~700k log entries
  - Weekly online reading quizzes, test preparation, learning objectives, discussion forum
- Challenging course with substantial number of students not passing.

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enrolled with Final Grade</td>
<td>492</td>
<td>97%</td>
</tr>
<tr>
<td>Tessera Participant (Y)</td>
<td>406</td>
<td>83%</td>
</tr>
<tr>
<td>Female</td>
<td>242</td>
<td>50%</td>
</tr>
<tr>
<td>Race / Ethnicity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td>141</td>
<td>29%</td>
</tr>
<tr>
<td>Black/African American</td>
<td>84</td>
<td>17%</td>
</tr>
<tr>
<td>Hispanic/Latino</td>
<td>43</td>
<td>9%</td>
</tr>
<tr>
<td>White</td>
<td>189</td>
<td>39%</td>
</tr>
<tr>
<td>Two or More</td>
<td>29</td>
<td>6%</td>
</tr>
<tr>
<td>Not specified</td>
<td>3</td>
<td>1%</td>
</tr>
<tr>
<td>First Generation College Student (Y)</td>
<td>119</td>
<td>24%</td>
</tr>
<tr>
<td>Transfer Student (Y)</td>
<td>53</td>
<td>11%</td>
</tr>
</tbody>
</table>
### Social and Emotional Skill Scores and Course Grade

<table>
<thead>
<tr>
<th>Variable</th>
<th>N*</th>
<th>Min</th>
<th>Mean</th>
<th>Median</th>
<th>SD</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Student Course Grade</td>
<td>489</td>
<td>0</td>
<td>2.78</td>
<td>3.00</td>
<td>1.07</td>
<td>4</td>
</tr>
<tr>
<td>SE Skill Scores</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grit</td>
<td>406</td>
<td>-2.65</td>
<td>-0.01</td>
<td>-0.09</td>
<td>0.95</td>
<td>2.58</td>
</tr>
<tr>
<td>Teamwork</td>
<td>406</td>
<td>-2.61</td>
<td>-0.19</td>
<td>-0.19</td>
<td>0.93</td>
<td>2.72</td>
</tr>
<tr>
<td>Resilience</td>
<td>406</td>
<td>-2.48</td>
<td>-0.07</td>
<td>-0.07</td>
<td>0.88</td>
<td>2.88</td>
</tr>
<tr>
<td>Curiosity</td>
<td>406</td>
<td>-2.88</td>
<td>-0.22</td>
<td>-0.24</td>
<td>0.92</td>
<td>3.45</td>
</tr>
<tr>
<td>Leadership</td>
<td>406</td>
<td>-2.64</td>
<td>-0.18</td>
<td>-0.21</td>
<td>0.89</td>
<td>3.43</td>
</tr>
</tbody>
</table>
Research Questions

• RQ1: Can we observe student social and emotional skills (SE skills) from behaviors recorded in online learning environments?
• RQ2: How do predictions of SE skills compare to predictions of student course grade using these behaviors?
• RQ3: How does sequential data mining affect predictive model accuracy and interpretability compared to individual LMS features?
Data Sources

- Student information system (e.g. race/ethnicity, family college history, ACT/SAT scores, college GPA & history)
- Scores on Tessera constructs
- LMS clickstream data
- eTextbook clickstream data (not used in Psych)
Research Process

1. Recruit faculty; student opt-in Tessera participation

2. Review syllabus; create design map to identify potential features

3. Interview faculty & confirm design map

4. Merge SIS & Tessera data; preliminary analysis

5. Main analysis: extract features, examine relationships between LMS data, SE skills & grade.
Research Method Summary

LMS Feature Extraction

1. Manually map clickstream data [Action + Title] to categories [110 -> 21]
2. Calculate counts, SD, length for each item [21 -> 64]
3. Factor loading using Varimax orthogonal rotation [64 -> 16]
4. Sequential data mining (‘learning tactics’) using Markov transition matrices [64 -> 5]

Statistics Analysis

1. Correlational analysis (Spearman Rho) between [#2 - #4] and SE skills & student grade
2. Predictive models using gradient boosted machines between [#2 - #4] and SE skills & student grade. Create baseline model with SiS only and consolidated models
3. Subpopulation analysis of predictive models [remove criteria of interest, split into groups] use T-test and visual inspection of bias distributions
Results

Correlational Analyses
Process Mining for “Learning Tactics”

Group activity sessions into clusters using finite mixtures of Markov transition matrices. Each session is generated from one of the $K$ transition probability matrices (TPM)

- First randomly selecting an initial activity and a TPM according to a mixing probability distribution.
- The rest of the activities in the sequence can be generated iteratively using the chosen TPM.
- Sequences using the same TPM can be grouped together
Learning Tactics

Five Learning Tactics

- Study and Assignment
- Assignment and Reading Quiz
- Exam-related Activities
- Gradebook and Discussion
- Announcement
Learning Tactics vs. Grit

Predict the results!
Learning Tactics vs. Grit

Averaged Frequency of Each Learning Tactic

Relative Frequency of Each Learning Tactic

Grit
- Low
- Med
- High
Learning Tactics vs. Grade

Averaged Frequency of Each Learning Tactic

Relative Frequency of Each Learning Tactic

Grade
- low
- med
- high

Learning Tactic

Study and Assignment
Reading Quiz
Exam Related Activity
Gradebook and Discussion
Announcement

Relative Frequency
- 0.058
- 0.058
- 0.064
- 0.046
- 0.066
- 0.066
- 0.055
- 0.046
- 0.084
- 0.066

Figure Source: ActNext
Correlational Analyses
Learning Tactics vs. Outcomes

"Study and Assignment" (count) was significantly correlated with grade \( (r = 0.341) \) and grit \( (r = 0.152) \)

"Reading Quiz" (relative frequency) was negatively correlated with grade \( (r = -0.158) \)

"Exam-related" (count) was correlated with grade \( (r = 0.402) \), grit \( (r = 0.211) \)

"Gradebook and Discussion" (frequency) was correlated with grade \( (r = 0.242) \), grit \( (r = 0.189) \), teamwork \( (r = 0.146) \), and curiosity \( (r = 0.112) \)
Results

Predictive Models
Types of Predictors

1. Background Variables (BV)
   - Gender, Ethnicity, First Generation Indicator, Transferred Student Indicator.
   - Number of Credits Attempted, Number of Credits Completed, Current College GPA

2. All five SE Skill scores (TES)

3. LMS Activity Features (ACTV)

4. Learning Tactic Sequence Features (SEQ)

Gradient boosted machines used; linear regression tested and found to be lower accuracy, especially at early weeks of the term.
RMSE Values of Predicting Grade with Different Predictor Sets

![Bar chart showing RMSE values for different predictor sets.](chart.png)
RMSE Values of Predicting Six Outcomes with Different Predictor Sets

<table>
<thead>
<tr>
<th>Predictor Set</th>
<th>grade</th>
<th>grit</th>
<th>leadership</th>
<th>teamwork</th>
<th>resilience</th>
<th>curiosity</th>
</tr>
</thead>
<tbody>
<tr>
<td>BV</td>
<td>0.692</td>
<td>0.899</td>
<td>0.895</td>
<td>0.933</td>
<td>0.971</td>
<td>0.951</td>
</tr>
<tr>
<td>SEQ</td>
<td>0.813</td>
<td>0.911</td>
<td>0.897</td>
<td>0.926</td>
<td>0.956</td>
<td>0.940</td>
</tr>
<tr>
<td>ACTV</td>
<td>0.703</td>
<td>0.881</td>
<td>0.871</td>
<td>0.914</td>
<td>0.829</td>
<td>0.923</td>
</tr>
<tr>
<td>SEQ + ACTV</td>
<td>0.768</td>
<td>0.873</td>
<td>0.873</td>
<td>0.911</td>
<td>0.823</td>
<td>0.919</td>
</tr>
<tr>
<td>SEQ + BV</td>
<td>0.683</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SEQ + BV + SEQ + ACTV</td>
<td>0.691</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SEQ + BV + SEQ + ACTV</td>
<td>0.677</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Results
Subpopulation Analyses of Predictive Models
Are our predictive models biased?

- Comparisons conducted: Gender, race/ethnicity, underserved minority, transfer student, first in family college student.
- Two-sided T-tests & visual inspection: no significant (nor substantive) differences
- Predictive models equally apply to students from all subgroups
Key Takeaways

1. Tessera SE skills are systematically represented in LMS data, whether viewed through individual activity correlations or consolidated models.

2. Predictions through behavioral data outperform (slightly) background data and could be much more useful in helping students improve learning.

3. Course grade stronger relationship with LMS activity than Tessera SE skills.

4. Sequential data mining identifies meaningful patterns that appear to represent higher-level learning tactics.

5. No evidence of bias was found; predictions apply to all students, independent of background or educational experience.
Limitations and Future Work

1. **Generalizability.** Findings are from a single course; we are currently replicating with 4 additional course subjects from UMBC.

2. **Impact of interventions.** Do interventions based on these findings improve student outcomes?

3. **Automation of feature creation.** Principled design is time-consuming; can we automate feature extraction with fidelity to pedagogical intent?

Image credit: Font Awesome by Dave Gandy
Thank you!

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Acknowledgements

John Whitmer¹, Ruitao Liu¹, Sweet San Pedro, Kate Walton¹, Joann Moore¹, Alejandro Andrade¹, John Fritz², Tom Penniston², David Evans³ & Benny Johnson⁴


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Additional Resources about Learning Analytics

1. Check out “Society for Learning Analytics Research”, with conferences (regional, live streamed) and an open access journal. [http://solaresearch.org/](http://solaresearch.org/)


3. Educause has a section of their website dedicated to Learning Analytics. [https://library.educause.edu/topics/teaching-and-learning/learning-analytics](https://library.educause.edu/topics/teaching-and-learning/learning-analytics)


Weekly Predictive Models

- **grade**
- **grit**
- **leadership**
- **teamwork**
- **resilience**
- **curiosity**

Cross-validated RMSE measurements for each model over 20 weeks, comparing GBM model performance.
# Model Comparison: LR vs. GBM

<table>
<thead>
<tr>
<th>Grade</th>
<th>Grit</th>
<th>Leadership</th>
<th>Teamwork</th>
<th>Resilience</th>
<th>Curiosity</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model</strong></td>
<td><strong>LR</strong></td>
<td><strong>GBM</strong></td>
<td><strong>LR</strong></td>
<td><strong>GBM</strong></td>
<td><strong>LR</strong></td>
</tr>
<tr>
<td>BV</td>
<td>0.69</td>
<td>0.90</td>
<td>0.91</td>
<td>0.88</td>
<td>0.90</td>
</tr>
<tr>
<td>SEQ</td>
<td>0.90</td>
<td>0.91</td>
<td>0.91</td>
<td>0.95</td>
<td>0.90</td>
</tr>
<tr>
<td>ACTV</td>
<td>0.90</td>
<td>0.91</td>
<td>0.91</td>
<td>0.95</td>
<td>0.90</td>
</tr>
<tr>
<td>SEQ+ACTV</td>
<td>0.90</td>
<td>0.91</td>
<td>0.91</td>
<td>0.95</td>
<td>0.90</td>
</tr>
</tbody>
</table>

**Cross-Validated RMSE**
Predicting Student Social and Emotional Skills using Learning Analytics

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