Master of Education in Learning

Design and Technology

Learning Analytics

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EDLD 607

Assessment 3

Ethical Learning Analytics Dashboard for Enhancing Learner Engagement and Academic Performance

Submitted To

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Analytics Dashboard on Ethics of Improving Learner

Engagement and Academic Performance.

1. overview of the Dashboard and Dataset.

This online lab introduces an analytics learning dashboard that is intended to track and optimize the interaction and academic success of students in an online learning setting in a systematic manner. The dashboard is established on a dataset of 25 learners, including major behavioral and academic indicators, including:• LM logins frequency.• Mean time spent on the LMS (hours/week)• *\ 5.50 academic performance score.

- Frequency of LMS logins
- Average time spent on the LMS (hours per week)
- Overall academic performance scores

In order to provide clarity in analysis, the dashboard is organized into three interconnected parts:• Engagement Analysis• Performance Analysis• Analytical Classification (Summary Insights)

- Engagement Analysis
- Performance Analysis
- Analytical Classification (Summary Insights)

The design facilitates the transition by educators between descriptive observation and interpretation and informed intervention, which is a key objective of learning analytics (Siemens and Baker, 2012).

2. Engagement Analysis

Engagement component gives a descriptive account of the interactions of students with LMS by:• A bar graph of the number of times each student logs in.• A visual representation on the average weekly time spent on the platform.

- A bar chart illustrating login frequency per student

- A visualization of average weekly time spent on the platform

These charts enable the teacher to see the patterns of participation and differentiate between very active and the ones showing minimal interaction.

Key Insight

Engagement profiles of students who show regular behavior in logging in and maintaining time-on-task are more likely to be associated with better learning outcomes (Zimmerman, 2000).

This part is a form of early diagnostic tool, which helps in determining disengagement prior to its adverse effect on performance.

3. Performance Analysis

Performance section measures student achievement by use of:A bar chart with average scores in performance.•´ □ówniec 3. A scatter plot of engagement versus performance.

- A bar chart displaying average performance scores
- A scatter plot illustrating the relationship between engagement and performance

The scatter plot demonstrates that there is a positive relationship, which implies that the higher a student engages, the better academic performance is expected.

This result is in line with studies that have indicated that engagement and engagement with learning environments are the major predictors of academic achievement (Siemens and Baker, 2012).

4. Analytical Classification and Dashboard Summary.

The dashboard incorporates classification analytics in order to give a succinct view of the student distribution in terms of performance and engagement.

4.1 Student Performance Distribution• Pass: 48%• Borderline: 20%• At Risk: 32%

- Pass: 48%
- Borderline: 20%

- At Risk: 32%

This distribution means that although some of the students are up to the expected standards, a considerable percentage (52%) needs further academic support or attention.

4.2 Student Engagement Distribution• High Engagement: 40%• Moderate Engagement: 32%• Low Engagement: 28%

- High Engagement: 40%
- Moderate Engagement: 32%
- Low Engagement: 28%

These results indicate that despite the existence of a core group of learners who are actively engaged, a large number of them are not exhibiting the best engagement behaviors at all times.

Integrated Interpretation

In the combination of the two distributions:Students who have low engagement rates have a higher chance of being At Risk.• HIGH ENGAGED students have a higher chance of passing.

- Students with low engagement levels are more likely to be categorized as At Risk
- Students with high engagement levels are more likely to achieve passing outcomes

This supports the finding that engagement is a vital source of academic achievement, which is in line with self-regulated learning theories (Zimmerman, 2000).

5. Learning Analytics and AI-Based Solutions.

The dashboard uses several learning analytical methods to enable informed, data-driven decision-making:

Descriptive Analytics

Generalises learner behavior and performance by visualising.

Diagnostic Analytics

The scatter plot allows to investigate the correlation between engagement and performance.

Predictive Analytics

Categories of classification (At Risk, Borderline, Pass) give prior signs of future academic performance.

Prescriptive Analytics

The information collected in the dashboard can be used to create relevant interventions, including personalized feedback and engagement strategies.

Though automated categorization is applied, the decision-making is still human-oriented meaning that analytics does not displace professionals but only supplements professional judgement (Slade and Prinsloo, 2013).

6. Major Results and Theoretical Implication.

6.1 Engagement as a Determinant of Performance.

The dashboard shows that a positive relationship between engagement and academic achievement is strong, which supports the fact that active participation can greatly improve the learning outcomes.

The school has at-risk learners as students.

The results indicate the importance of implementing intervention strategies promptly and selectively, with 32% of students being At Risk.

6.3 Theoretical Alignment

The trends identified are consistent with the known learning theories:Self-Regulated Learning Theory (Zimmerman, 2000)

- Self-Regulated Learning Theory (Zimmerman, 2000)

→ Students who are proactive in regulating their activities are likely to perform well.• Constructivist Theory (Vygotsky, 1978)

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Active participation and meaningful interaction facilitates learning.Social Learning Theory (Bandura, 1977)

- Social Learning Theory (Bandura, 1977)

→ Communication and interaction lead to better learning results.

7. Actionable Recommendations

According to the dashboard insights, the following interventions are suggested:

At-Risk Students (32%)• Immediate academic intervention• Personalized feedback• One-on-one support sessions

- Immediate academic intervention
- Personalized feedback
- One-on-one support sessions

Borderline Students (20%)• Structured learning activities• Regular progress monitoring• Continuous feedback

- Structured learning activities
- Regular progress monitoring
- Continuous feedback

Low Engagement Students (28%)• Motivational strategies• Greater LMS contact demands.• Collaborative activities promoted.

- Motivational strategies
- Increased LMS interaction requirements
- Encouragement of collaborative activities

These suggestions indicate the value of interaction and engagement to support the learning outcomes (Bandura, 1977).

8. Governance and Ethical Iss considerations.

Application of learning analytics should be based on major ethical principles:

Privacy

The data of students needs to be safely stored and controlled.

Fairness

Classification labels are meant to be taken as indications and not as definite judgments.

Transparency

The students are supposed to know how their data is gathered, analyzed and utilized.

Human Oversight

Teachers have the duty of interpretation and finalisation of results, which must be ethically and pedagogically correct (Slade and Prinsloo, 2013).

9. Ethical Reflection

Two main ethical risks are observed:

Over-surveillance

Students might have a sense that they are under constant surveillance.

Mitigation:

Minimize data gathering to key measures and explicitly convey intent.

Misclassification

There is a possibility of incorrect classification of students.

Mitigation:

Integrate data knowledge and human intuition and understanding.

Notwithstanding these actions, there are still limitations, especially, the inability of the dashboard to consider external factors: personal or environmental influence.

10. Conclusion

This dashboard illustrates how learning analytics can convert raw data into valuable and actionable insights that can be used in educational decision-making. With the combination of engagement, performance, and classification information, educators can have a global view of learner behavior.

Descriptive, diagnostic, predictive, and prescriptive analytics can be used to deal proactively and selectively with improving student outcomes. Notably, the design is at the level of balancing the analytical ability and ethical accountability, such that data-driven practices are also human-centric and context-sensitive.

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