Educational Data Mining: Student Learning Behavior Analysis using Apriori Algorithm for the EDM Cup 2023 Dataset

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BSCS-4

The Problem

Educational institutions often struggle to understand which specific learning behaviors and help-seeking patterns contribute to student success or failure on assessments. While online learning platforms capture vast amounts of clickstream data, extracting actionable insights that can guide instructional interventions remains challenging.

Dataset

Source: EDM Cup 2023 - Kaggle Competition

Used Dataset Files

File	Rows	Columns	Size	Description
action_logs.csv	23,932,276	10	1.37 GB	Timestamped student actions
assignment_details.csv	9,319,676	9	921 MB	Assignment metadata
problem_details.csv	132,738	10	59 MB	Problem characteristics
training_unit_test_scores.csv	452,439	3	10 MB	Unit test outcomes
assignment_relationships.csv	702,887	2	14 MB	Unit test <-> in-unit links
sequence_details.csv	10,774	8	3.8 MB	Curriculum structure

Conducted Analysis

1. Behavioral Co-occurrence: What problem-solving behaviors (hints, wrong attempts, time spent) naturally occur together during student work sessions?
2. Performance Prediction: Which combinations of aggregated behaviors across multiple assignments predict success or failure on unit tests?
3. Mastery Patterns: What help-seeking patterns distinguish students who achieve mastery from those who continue to struggle?

Data Cleaning

Column	Type	Description	Example Values
`action`	categorical	Student interaction type	`problem_started`, `wrong_response`, `correct_response`, `hint_requested`, `explanation_requested`, `answer_requested`, `problem_finished`
`timestamp`	float	Unix epoch time	`1599150990.0`
`problem_id`	string	Unique problem identifier	`I2GX4OQIE`
`problem_type`	categorical	Question format	`Multiple Choice`, `Numeric`, `Algebraic Expression`
`problem_skill_code`	string	Common Core standard	`6.RP.A.3b`, `8.EE.A.1-1`
`score`	binary	Unit test outcome	`0` (fail), `1` (pass)

Methods

Each analysis required different aggregation and feature engineering to acquire the nessesary categories as shown below:

```
def aggregate_attempts(group, assignment_log_id, problem_id):
    if not (group['action'] == 'problem_finished').any():
        return None
    started = group.loc[group['action'] == 'problem_started', 'timestamp'].min()
    finished = group.loc[group['action'] == 'problem_finished', 'timestamp'].max()
    if pd.isna(started) or pd.isna(finished):
        return None
    time_spent = finished - started
    hint_count = (group['action'] == 'hint_requested').sum()
    wrong_count = (group['action'] == 'wrong_response').sum()
    correct_count = (group['action'] == 'correct_response').sum()
    answer_requested = (group['action'] == 'answer_requested').any()
    explanation_requested = (group['action'] == 'explanation_requested').any()
    ...
```

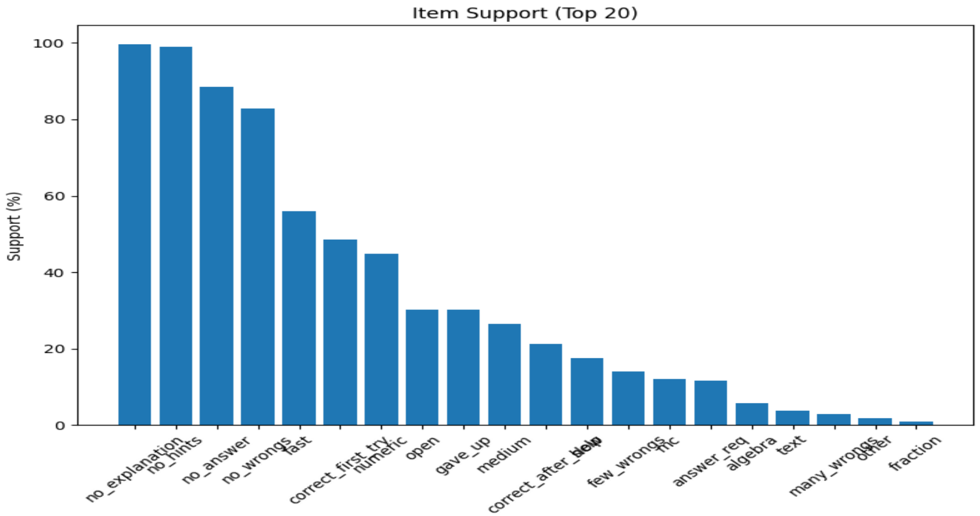
```python
def action_problem_transactions(transactions):
    transactions = transactions.copy()
    transactions['hints'] = pd.cut(
        transactions['hint_count'],
        bins=[-0.1, 0, 2, np.inf],
        labels=['no_hints', 'few_hints', 'many_hints']
    )
    transactions['wrongs'] = pd.cut(
        transactions['wrong_count'],
        bins=[-0.1, 0, 2, np.inf],
        labels=['no_wrongs', 'few_wrongs', 'many_wrongs']
    )
    ...
```

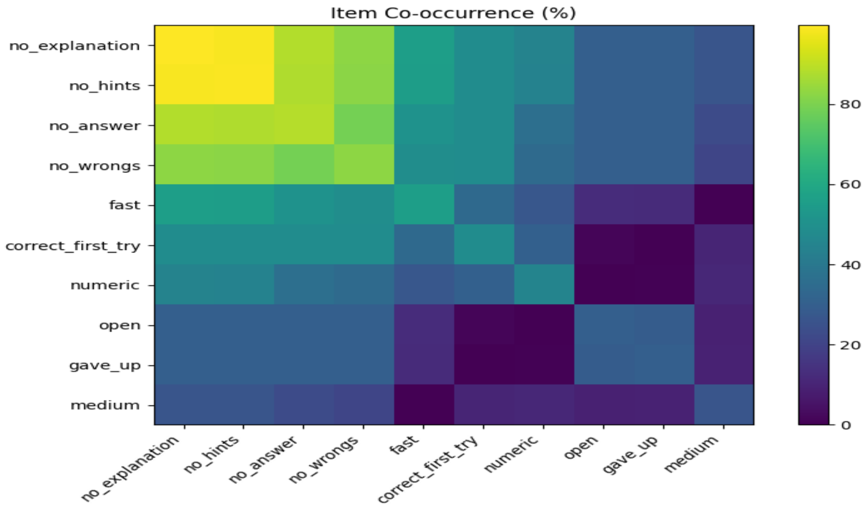
Apriori Configuration

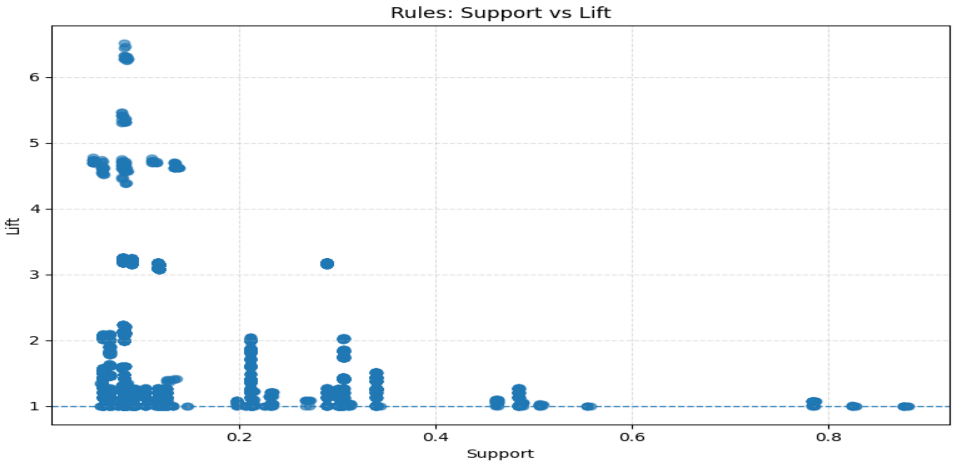
```
@dataclass
class AnalysisConfig:
    """Apriori analysis parameters"""
    min_support: float = 0.05
    min_confidence: float = 0.6
    min_lift: float = 1.0
    top_n_rules: int = 10
```

Results (Student-Problem Interactions)

Visualization







Top 5 Itemsets

Rank	Itemset	Support	Interpretation
1	{no_explanation}	0.996	Nearly all avoid explanations
2	{no_hints}	0.990	Hints rarely used
3	{no_explanation, no_hints}	0.986	Minimal help-seeking
4	{no_answer}	0.884	Answer key rarely viewed
5	{no_answer, no_explanation}	0.881	Help resources ignored

Top 5 Association Rules:

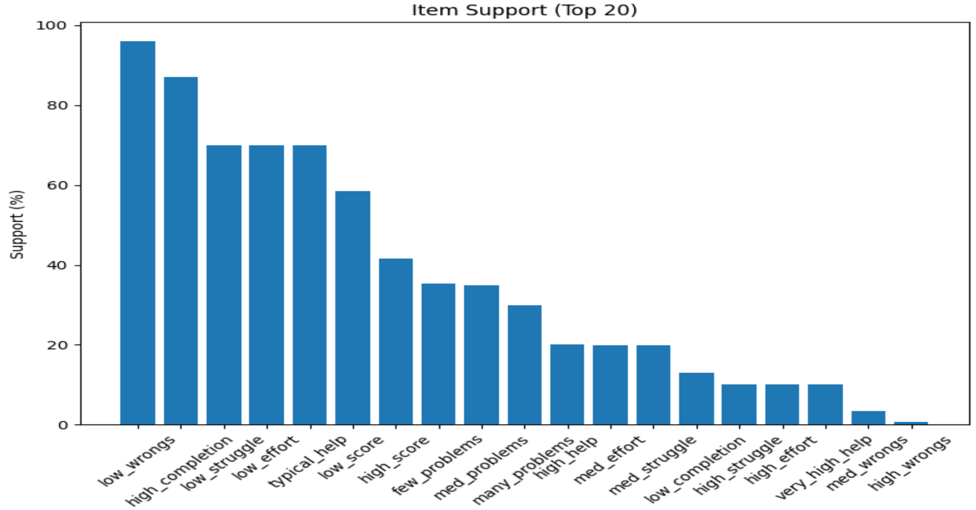
Rank	Rule	Support	Confidence	Lift	Interpretation
1	{correct_after_help, no_hints, no_answer, no_explanation} → {few_wrongs}	0.083	0.919	6.509	Students who succeed with no help had few errors
2	{correct_after_help, no_hints, no_answer} → {few_wrongs}	0.084	0.913	6.467	Same pattern without explanation filter
3	{correct_after_help, no_hints, no_answer} → {no_explanation, few_wrongs}	0.083	0.899	6.442	Reinforces explanation avoidance
4	{correct_after_help, no_answer, no_explanation} → {no_hints, few_wrongs}	0.083	0.867	6.323	Hints unnecessary when successful
5	{no_hints, few_wrongs} → {correct_after_help, no_answer, no_explanation}	0.083	0.602	6.323	Reverse: few errors predict success

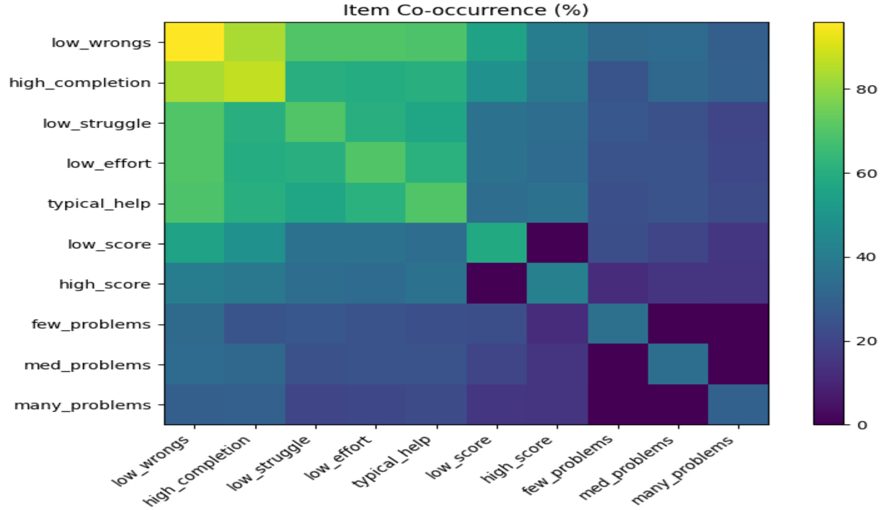
Analysis 1 Key Findings

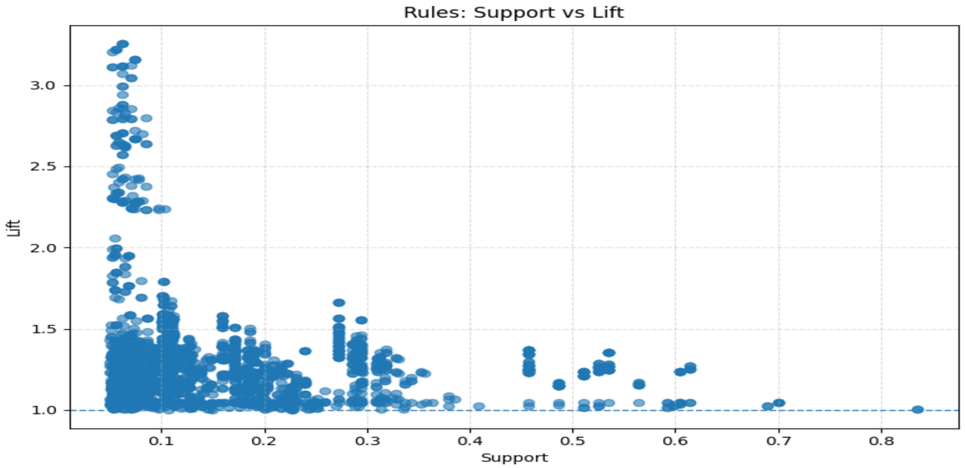
- Self-directed success: Students who eventually succeed (correct_after_help) overwhelmingly avoid hints, answers, and explanations (lift 6.3-6.5×)
- Few errors matter: Rules consistently highlight few_wrongs (0-2 errors) as a strong predictor of eventual correctness
- Help paradox: The strongest associations involve not using help resources, suggesting either:
    i. Successful students don't need help
    ii. Help-seeking occurs only when deeply struggling (not captured in "correct_after_help" outcome)
- Problem type irrelevance: No strong rules involve problem_type, suggesting behavior patterns transcend question format

Results (Student-Unit Aggregations)

Visualization







Top 5 Itemsets

Rank	Itemset	Support	Interpretation
1	{low_wrongs}	0.959	Nearly all have minimal errors
2	{high_completion}	0.869	Most complete assigned work
3	{high_completion, low_wrongs}	0.836	Success duo: completion + accuracy
4	{low_effort, low_wrongs}	0.700	Minimal interactions with few errors
5	{low_effort}	0.700	Standard effort level

Top 5 Association Rules:

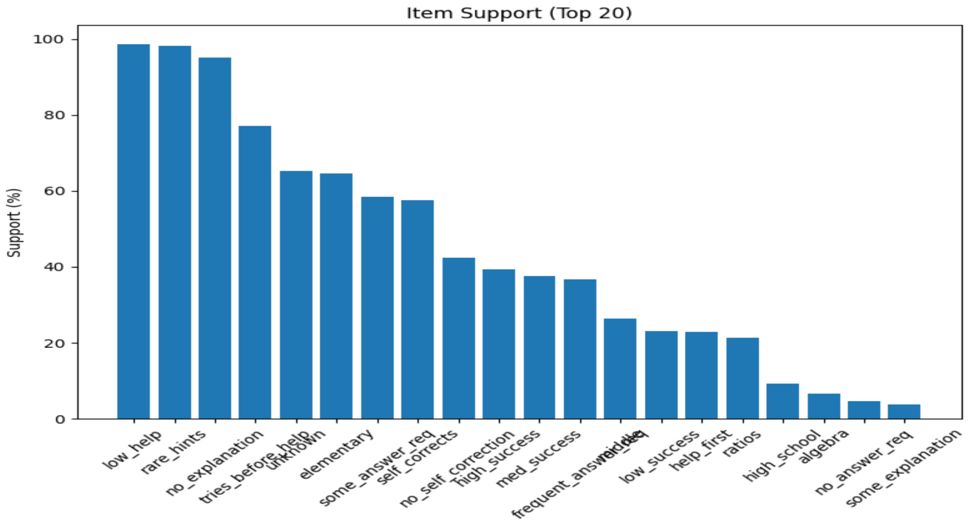
Rank	Rule	Support	Confidence	Lift	Interpretation
1	{low_wrongs, low_struggle, typical_help, low_completion} → {low_effort, few_problems}	0.062	0.803	3.258	Low completion + typical help → low effort on few problems
2	{low_struggle, typical_help, low_completion} → {low_effort, low_wrongs, few_problems}	0.062	0.803	3.258	Same pattern emphasizing accuracy
3	{low_struggle, typical_help, low_completion} → {low_effort, few_problems}	0.062	0.803	3.258	Core low-completion pattern
4	{low_completion, low_struggle, low_score} → {low_effort, few_problems}	0.056	0.794	3.221	Low score adds to pattern
5	{low_struggle, low_wrongs, low_completion, low_score} → {low_effort, few_problems}	0.056	0.794	3.221	Full struggling student profile

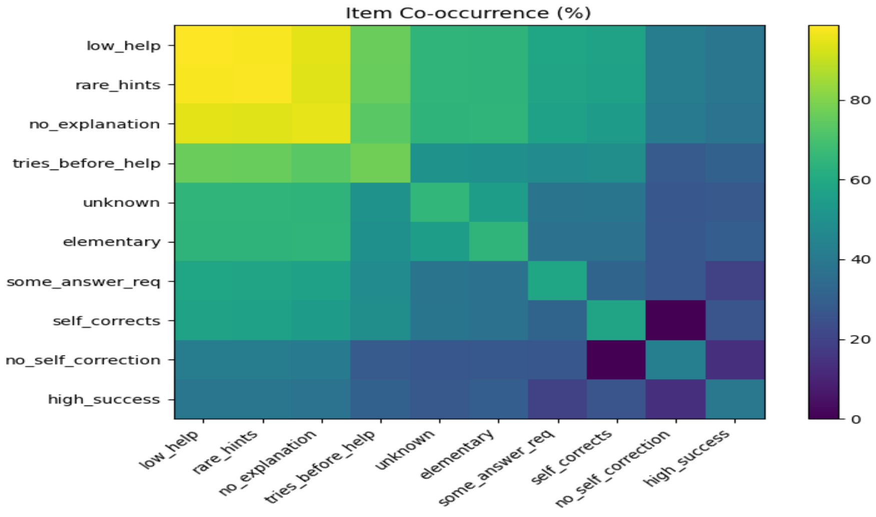
Analysis 2 Key Findings

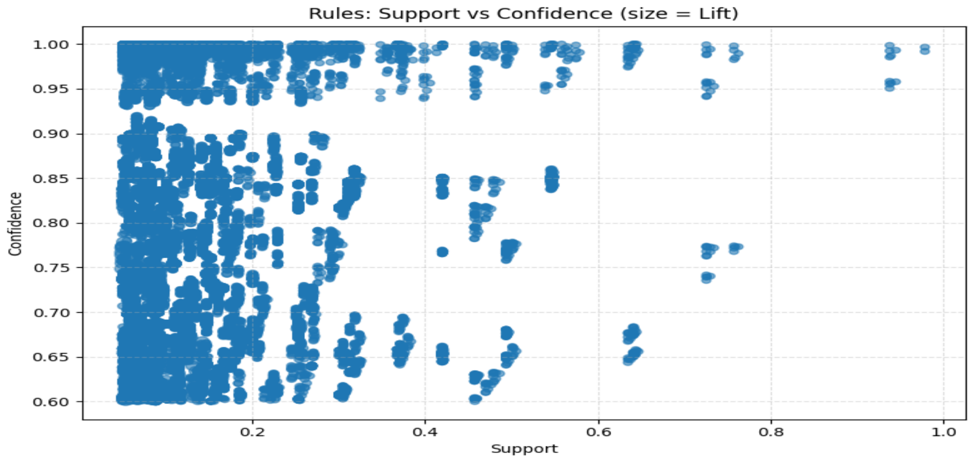
- Low completion trap: Students with low_completion (<70% finished) strongly associate with few_problems and low_effort (lift ~3.2×), forming a disengagement profile
- Score paradox: Rules emphasize low_score patterns, but lack symmetric high_score rules due to balanced dataset (50/50 split)
- Help-seeking neutrality: typical_help appears in rules without strong directional effect on outcomes
- Effort-completion link: High completion_rate breaks the low_effort → few_problems cycle, suggesting completion as a key intervention target

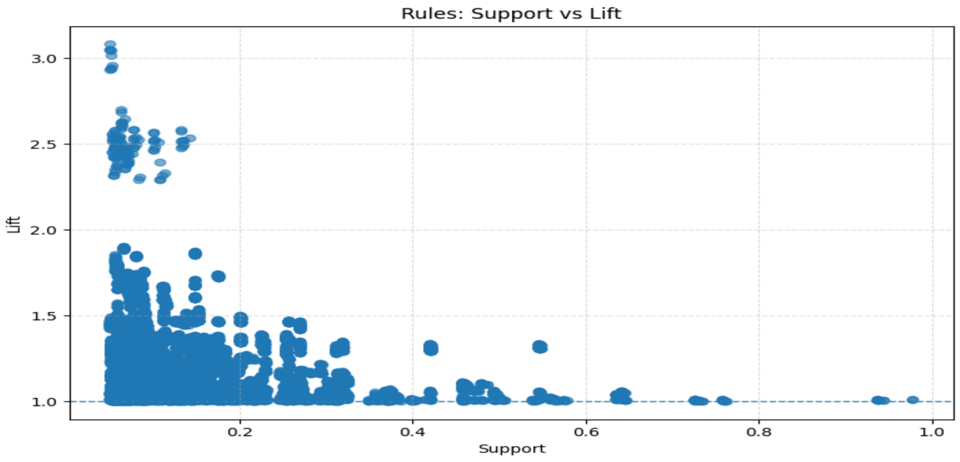
Results (Help-Seeking Patterns)

Visualization









Top 5 Itemsets

Rank	Itemset	Support	Interpretation
1	{low_help}	0.986	Help-seekers still use minimal resources
2	{rare_hints}	0.982	<0.5 hints per problem
3	{low_help, rare_hints}	0.978	Double minimal-use pattern
4	{no_explanation}	0.951	Explanations almost never used
5	{low_help, no_explanation}	0.945	Help comes from hints/answers, not explanations

Top 5 Association Rules:

Rank	Rule	Support	Confidence	Lift	Interpretation
1	{algebra, low_help} → {middle, rare_hints}	0.050	0.764	3.082	Middle school algebra uses minimal hints
2	{algebra, rare_hints} → {middle, low_help}	0.050	0.767	3.050	Algebra students avoid help
3	{algebra} → {middle, rare_hints, low_help}	0.050	0.748	3.049	Core algebra-middle school pattern
4	{algebra} → {middle, rare_hints}	0.051	0.755	3.045	Algebra = rare hints
5	{algebra} → {middle, low_help}	0.051	0.758	3.016	Algebra = low help

Analysis 3 Key Findings

- Curriculum dominance: Strongest rules involve subject-grade associations (algebra→middle school) rather than help-seeking→success patterns
- Elementary-middle divide: Rules cluster by grade level, suggesting different help-seeking cultures:
    - Elementary: More help_first behavior
    - Middle school: More tries_before_help + algebra
- Success pattern absence: No strong rules linking help strategies to high_success outcome, possibly due to:
    1. Selection bias (analysis only includes help-seekers, excluding successful non-help-seekers)
    2. Help-seeking as a distress signal rather than strategy
- Self-correction irrelevance: self_corrects appears in few rules, suggesting

Educational Insights

The Apriori analysis reveals a dominant “silent majority” pattern in which students overwhelmingly avoid platform-provided help. Across all analyses, most problem attempts involve no hints, answers, or explanations, and even designated help-seekers typically use minimal assistance. Notably, some of the strongest associations show that students who eventually succeed appear to do so while avoiding in-platform help altogether, suggesting that effective support may occur outside the learning system (e.g., peers, parents, or external resources). This highlights a key limitation of clickstream data: platform logs capture only one channel of a broader, multi-channel learning ecosystem.

More critically, the analysis identifies completion rate as a stronger and more actionable predictor of academic outcomes than help-seeking behavior. Low completion is tightly linked to low effort, fewer attempted problems, and poor unit test performance, forming a self-reinforcing disengagement cycle. Effort alone is ambiguous—low effort can signal mastery when paired with high completion, or disengagement when paired with low completion—underscoring the need for contextual interpretation. Additionally, help-seeking behaviors vary by subject and grade level, indicating that effective interventions must be developmentally and curriculum-specific. Overall, these findings suggest that early completion monitoring and contextualized behavioral metrics are more effective intervention targets than simply encouraging increased help usage.