

Article

One Classroom, Multiple Paths: How Work Habits Predict Academic Achievement of Differently Paced Seventh-Grade Students

Maria Kosogorova ^{1,*}, Oksana Ilina ¹, Sona Antonyan ¹, Manasi Singhal ¹, Jenya Brodskaja ¹, Anna Mirny ¹, Anjie Chen ¹, Matthew Chen ¹, Rohan Danda ¹, Samuel Gurevich ¹, Anran Liu ¹, Alice Ma ¹, Matthew Macera ¹, Lielle Rifkin ¹, Chiara Sardi Rogines ¹, Tarun Venkatesh ¹ and Larry Ludlow ²

¹ Russian School of Mathematics, Newton, MA 02459, USA; oksana.ilina@russianschool.com (O.I.); sona.antonyan@russianschool.com (S.A.); manasi.singhal@russianschool.com (M.S.); anna.mirny@mathschool.com (A.M.)

² Department of Measurement, Evaluation, Statistics & Assessment, Lynch School of Education and Human Development, Boston College, Boston, MA 02467, USA; ludlow@bc.edu

* Correspondence: maria.kosogorova@mathschool.com

Abstract

This study examines behavioral predictors of academic success among seventh graders enrolled in the Russian School of Mathematics, a rigorous extracurricular mathematics program. Using a comprehensive set of engagement and homework indicators available for the online portion of our classes, multiple regression models were applied to explore how persistence, time management, and participation predicted performance across three curriculum levels, namely Accelerated, Advanced, and Honors. Accelerated and Honors students exhibited similarly strong work habits but required different types of instructional support. Advanced-level students were further distinguished into “progressing” and “plateaued” groups, each with unique behavioral profiles. Across levels, several habits such as starting homework promptly, revisiting unsolved problems, and providing detailed work were consistently associated with higher achievement. These findings highlight the value of differentiated instruction and targeted feedback, particularly in mixed-ability classrooms. By identifying the behaviors most closely linked to success, this work offers actionable insights for fostering self-regulated learning in middle school mathematics.

Keywords: student work habits; academic performance; curriculum-level analysis; online math education; predictive modeling; middle school



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1. Introduction

Students approach learning in diverse ways, yet consistent behavioral patterns often emerge in relation to academic success, particularly for homework performance. The present study seeks to identify such patterns and develop predictive models for seventh-grade students' average homework scores using a range of indicators collected both during class and within the homework process itself.

Data were drawn from the Russian School of Mathematics (RSM), an extracurricular program serving grades K–12 since 1997. It draws on the Soviet tradition of mathematics instruction, adapting principles associated with Lev Vygotsky, such as the zone of proximal development and instructional scaffolding, to the U.S. educational context by integrating a rigorous, conceptually driven approach to mathematical thinking with the practical

demands of American schooling. RSM provides mathematics enrichment in over 90 in-person school locations across the United States and abroad, and in an online school catering to students across the globe.

For Grade 7, instruction is organized into three curriculum levels—Accelerated, Advanced, and Honors—progressively increasing in pace, content depth, and cognitive demand. For instance, in Grade 7 Accelerated, students become familiarized with the equation of a line in its slope-intercept form and learn to use it for graphing and problem-solving. In Grade 7 Advanced, in addition to what has been mentioned, students are introduced to the world of linear functions, including function notation and the definition of domain and range. In Grade 7 Honors, in addition to all the above, students are taught point-slope and standard forms of an equation of a line and various ways to define linear functions (table, graph, verbal or formula).

In addition to traditional on-site classes, RSM offers online instruction via its proprietary Virtual Classroom (VCR) platform, which replicates in-person features while capturing detailed engagement metrics. Combined with data from the RSM homework and teacher portals, these systems yield a uniquely rich dataset for examining the behavioral correlates of mathematics achievement.

Context

This study examines a broad spectrum of predictors, ranging from attendance and participation to homework practices and private teacher interactions, to better understand drivers of academic success. While prior research has often centered on test scores (Osmanbegovic & Suljic, 2012), time-on-task (Bowman et al., 2014), or home environment (Cortez & Silva, 2008; Hellas et al., 2018; Ramesh et al., 2013), our approach integrates fine-grained behavioral and engagement data. This enables a more comprehensive portrait of student performance, capturing not only outcomes but also the daily habits and attitudes that sustain achievement in a demanding academic environment.

Unlike many studies of college populations (Dollinger et al., 2008; Chen & Ward, 2021), this research focuses specifically on seventh-grade students, an underexamined age group compared to others, while also leveraging data from RSM's VCR system and homework portal. This online learning context offers an instructive contrast to prior work on in-person courses (Bekkering & Ward, 2021). Moreover, RSM's placement system provides a distinctive opportunity to examine how curriculum level influences behavioral predictors, even when the underlying content is held constant and differences lie primarily in pacing, difficulty, and scope.

Three research questions guide this work:

- (a) Can the proposed indicators predict homework performance among Grade 7 students?
- (b) Do predictors differ significantly across the three curriculum levels?
- (c) Can model accuracy be improved by subdividing Advanced-level students into distinct progression groups?

Our null hypothesis is that the chosen set of predictors has no effect on the mean homework success of students in Grade 7 Accelerated and Honors online courses at RSM. Our alternative hypothesis is that the chosen set of predictors can be used to predict the mean homework success of students in Grade 7 Accelerated and Honors online courses at RSM.

Ultimately, this research stretches far beyond the scope of just the seventh-grade RSM online curriculum. By learning more about how seventh graders are influenced by various ways of academic reinforcement, teachers can tailor lessons to help each student learn more. Additionally, students can benefit by improving the areas of their learning habits that proved to be significant, and thus improve their predicted performance. In the end,

this research will assist teachers in helping every student make the most of their education, especially in their 7th-grade year, as they begin preparing for high school and college.

2. Methods

2.1. Sample

RSM maintains an extensive database of student activity that supports the extraction and analysis of behavioral indicators. For this study, we focused on Grade 7 students—a cohort with a stable curriculum that undergoes minimal annual revision, allowing for potential replication with data from subsequent years. Only students enrolled exclusively in VCR-mode classes were included, ensuring access to both in-class behavioral measures and homework portal metrics.

VCR is a synchronous online learning environment designed to replicate the structure of a traditional in-person lesson. Students and the teacher participate via live video and audio, while instruction is supported through a shared interactive whiteboard on which the teacher can present material, display curriculum problems, and grant students editing access when appropriate. During class, students may complete individual assignments on a personal digital workspace; responses are automatically submitted and graded by the system, with results recorded in the database and made available immediately after the lesson. In addition to whole-class instruction, the teacher can engage students through a private chat channel to collect responses and provide individualized feedback or points for correct answers, which are visible only to the teacher and the respective student. Teachers may also award public “stickers,” displayed on a student’s video tile and visible to the entire class, as a form of immediate reinforcement. Instruction can be further differentiated through a “private talk” feature, allowing the teacher’s audio to be directed to selected students only. The platform also includes gamified elements such as timers and interactive tasks to structure engagement. All instructional actions, interactions, and time-stamped events within the session are automatically logged in the RSM database, forming the basis for behavioral and engagement measures used in this study.

The dataset for the 2023–24 academic year encompassed data from 36 online lessons and 35 homework assignments.

After class, all students, regardless of the class mode (both online and offline), are assigned homework. To complete assignments, all students log into the same homework portal, where they are presented with a sequence of problems. Each problem appears on a separate screen, allowing the student to input an answer and submit it before proceeding to the next item (non-restricted order). Upon submission, the system provides immediate feedback indicating whether the response is correct or incorrect. The correctness and timestamp of each response, along with additional metadata, are automatically recorded in the database for every attempt and made accessible to the teacher for review.

Active engagement time is approximated using the intervals between successive attempts within a homework assignment. Specifically, time spent on assignment is computed as the duration between recorded submissions, excluding extended inactivity gaps. Consistent with prior research on online learning behavior (Ilina et al., 2025; Kovanović et al., 2016), intervals shorter than 12 min are heuristically treated as continuous, uninterrupted engagement with the task, whereas longer gaps are interpreted as breaks between work sessions.

Several exclusion criteria were applied. Students were removed if they withdrew before the first report card (thus lacking behavior or participation scores), if they attended classes that did not use chatscore or stickers (eliminating zero activity scores), or if they participated in fewer than 10 lessons. Additional exclusions targeted test accounts, special cases flagged in the database, and records reflecting implausible behavioral patterns (e.g.,

excessively long attempt times or unusually high talk counts). Finally, observations identified as outliers by the DFBETAs algorithm on three or more parameters (predictors or outcomes) were excluded. The resulting sample distribution is presented in Table 1.

Table 1. Sample distribution of Grade 7 students delineated by curriculum level.

7_1 Accelerated	7_2 Advanced	7_3 Honors	Total
153	206	226	585

2.2. Data

From our extensive array of process data, we identified twelve data-driven predictors for inclusion in our analytic models. These predictors were selected based on three criteria: (a) their frequent use in the educational research literature, (b) their conceptual relevance as derived from adjacent research domains, and (c) their novelty and unique contribution to this particular context, despite their limited representation in the prior literature.

The first subset of predictors has established precedent in educational research. For example, fraction of lessons attended was calculated by dividing the number of attended lessons by the total number of sessions in the curriculum for that student (maximum 36 lessons). This measure is commonly utilized due to the routine availability of attendance data in educational databases and has been validated across both postsecondary (Dollinger et al., 2008; Ancheta et al., 2021) and K–12 contexts (Klein & Sosu, 2023).

Average participation, operationalized as the mean of teacher-assigned participation scores across one or two semesters, was scored on a 1–5 scale (1 = low, 5 = high). This metric builds on prior work that considers participation as a proxy for student engagement, albeit through diverse operationalizations (Razaque et al., 2018). Similarly, average behavior, also scored from 1 to 5 (1 = low, 5 = high) based on teacher evaluations, aligns with research linking classroom behavior to academic outcomes (e.g., Kremer et al., 2016; Dollinger et al., 2008; Wagner & Ruch, 2015), although our measure reflects general classroom conduct rather than diagnostic behavioral indicators.

Average days before first attempt captures the average number of days between the conclusion of a class session and the student’s initial homework submission. This measure, which was bounded between 0 and 7 days, builds upon temporal homework engagement metrics introduced in studies such as Raff and Matuszek (2023), albeit reoriented to measure proactive engagement from the time of assignment.

Fraction late quantifies the proportion of classes for which a student arrived more than ten minutes late. This metric aligns with prior research examining tardiness and academic success (Zerbini et al., 2017). Average revisits per homework captures the mean number of 12+ hour breaks between homework sessions. This measure echoes studies examining homework frequency and engagement as shown by Akram et al. (2019) and Smith et al. (2021), though our approach emphasizes temporal breaks rather than raw frequency.

Average time spent on homework was computed as the mean number of minutes students spent on each assignment. This aligns with measures used by Rohani et al. (2024) to examine student activity via assignment-level analytics. Likewise, average attempts per problem as the average number of submissions per individual problem has been employed in prior online learning research by Bowman et al. (2014).

The second subset of predictors, though less frequently cited in the literature, provides potentially valuable insight into behavioral dimensions not traditionally captured. Fraction of homework uploaded reflects the proportion of completed written homework submissions. Unlike auto-graded portal submissions, paper homework offers insight into students’ problem-solving logic and reasoning. Fraction of private talk captures the ratio of minutes a student spent in private communication with the instructor relative to the instructor’s total

spoken time during the year. While initially conceived as an index of need-based support or misbehavior, it may also reflect differential reinforcement strategies for high-achieving students. Fraction of activity measures the proportion of class-wide positive reinforcement (stickers, reactions, or private praise) that a student received. This multidimensional metric captures both public engagement and private academic validation.

Finally, average number of revisits per unsolved problem represents the frequency with which a student returns to problems initially left unsolved. A student who never abandons problems would register a value of 1. This predictor thus reflects both perseverance and problem-solving diligence.

All predictors, with the exception of behavior and participation, are derived directly from system-generated logs. In contrast, behavior and participation are based on teacher evaluations and therefore reflect instructor interpretations rather than automatically recorded system activity. A summary of all twelve predictors, their operational definitions, and conceptual domains is presented in Table 2.

Table 2. Operational definitions and theoretical dimensions of selected predictors.

Predictor	Operational Definition	Conceptual Indicators
Fraction of lessons attended	Number of attended lessons $\div$ total number of lessons	Activity, diligence
Average participation	Mean teacher-evaluated participation score	Engagement
Average behavior	Mean teacher-evaluated behavior score	Willingness to learn, classroom climate
Average days before first attempt	Average days (0–7) between class and first homework submission	Diligence, proactivity
Fraction of homework uploaded	Number of written homework submissions $\div$ total homework assignments	Diligence, commitment
Fraction of activity	Student's received positive reinforcements $\div$ total class reinforcements	Participation, independent work
Fraction late	Number of late arrivals (10+ min) $\div$ total number of lessons	Diligence, willingness to learn, participation
Fraction of private talk	Minutes of private teacher–student talk $\div$ total teacher talk minutes for the class	Proactivity
Average revisits per homework	Mean number of 12+ h breaks before returning to incomplete homework	Diligence
Average attempts per problem	Mean number of submissions per problem	Diligence, perseverance
Average revisits per unsolved problem	Mean number of returns to problems not solved on first attempt	Perseverance
Average time spent on homework	Mean number of minutes per homework assignment	Diligence, effort

2.3. Outcome Variable

The outcome was defined as the average fraction of homework solved, calculated as the average number of correctly solved problems divided by the total number of problems assigned per assignment. This outcome was chosen over a calculated performance score to ensure inclusion of bonus assignments, which we consider an important indicator of academic performance and engagement within the RSM framework.

The descriptive statistics for the selected predictors and the outcome—non-standardized but without outliers—can be found in Table 3.

Table 3. Descriptive statistics for predictors and outcome.

Predictor	Mean	Median	StDev	Min	Max
Fraction of lessons attended	0.91	0.95	0.09	0.52	1
Average participation	4.03	4	0.89	1	5
Average behavior	4.60	5	0.52	2	5
Average days before first attempt	2.56	2.5	1.34	0	5.86
Fraction of homework uploaded	0.59	0.69	0.35	0	1
Fraction of activity	0.12	0.12	0.07	<0.01	0.47
Fraction late	0.09	0.04	0.14	0	0.83
Fraction of private talk	0.09	0.06	0.10	0	1
Average revisits per homework	1.53	1.42	0.81	0.15	4.6
Average attempts per problem	1.6	1.56	0.23	1.10	3.84
Average revisits per unsolved problem	0.72	0.74	0.17	0.15	1.23
Average time spent on homework	74.5	72.1	25.53	16.43	174.19
Average fraction of homework solved	0.75	0.88	0.11	0.31	1

2.4. Statistical Model

To investigate the association between student process indicators and homework performance, we employed a multiple linear regression framework. This approach assumes that the outcome can be represented as a linear function of one or more predictor variables, plus a stochastic error term (Belsley et al., 1980). When multiple predictors are incorporated, the model generalizes to: $y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + \varepsilon$. Here, y denotes the outcome variable (i.e., the average fraction of homework problems completed by a student), X_i represents the i th predictor, β_i is the corresponding regression coefficient, and ε is the random error term. Coefficient estimation was conducted via the method of least squares, which minimizes the sum of squared differences between observed and model-predicted outcomes. When estimates are reported we use the standard notation of “a” for the intercept and “b” for the regression coefficients.

This modeling strategy is valued for its parsimony, interpretability, and statistical rigor. Multiple linear regression is particularly appropriate when the objective is to quantify and test the linear association between several predictors and a continuous outcome. In educational research, its utility is well documented; the approach yields directly interpretable parameter estimates while maintaining modest assumptions about the underlying data-generating process. For instance, Chen and Ward (2021) applied this method to predict exam performance from measures of prior task accuracy and temporal engagement variables, while Bekkering and Ward (2021) used it to model achievement based on online participation metrics, including join time, leave time, and attentiveness.

Model Evaluation Criteria

Model performance was evaluated using two primary diagnostics: the coefficient of determination (R^2) and the statistical significance of individual predictors, indicated by p-values. The R^2 statistic represents the proportion of variance in the outcome variable accounted for by the set of predictors, ranging from 0 (no explanatory capacity) to 1 (perfect fit). Higher R^2 values signal greater explanatory adequacy.

The significance of individual predictors was assessed through t -tests on each regression coefficient, with p-values compared against the conventional $\alpha = 0.05$ threshold (Montgomery et al., 2012). Predictors with p-values below this threshold were considered to contribute meaningfully to the prediction of homework performance. Conversely, predictors with larger p-values were interpreted with caution, as their apparent effects could plausibly arise from sampling variability rather than substantive relationships.

3. Research Design

Following a review of the literature to identify relevant predictors, we examined the alignment of these variables with those available in the RSM database. During this alignment process, we identified predictors that were available, measurable and reflective of student work habits, without directly encoding the outcome variable. A final set of 12 such predictors was selected. These variables, along with the outcome measure, were extracted from the database, cleaned of outliers, and prepared for analysis. Each predictor was evaluated individually to assess distributional characteristics and determine the need for transformation. The only transformation applied was standardization, which facilitated comparison across variables.

The analysis began with relational plots of each predictor disaggregated by curriculum level. These plots illustrated the degree of association between each predictor and the outcome variable. A representative example is provided in Figure 1, which displays the relationship between the average number of days before the first attempt and the outcome variable.

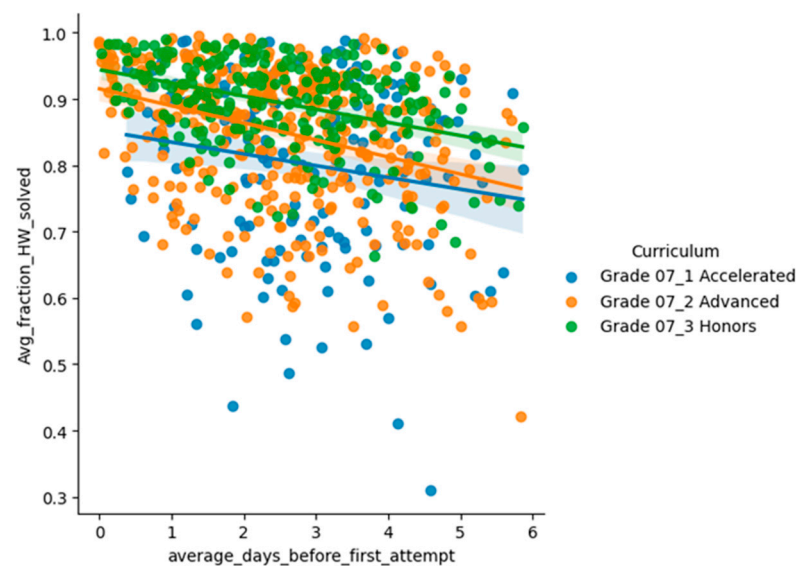


Figure 1. Relationship between average days before first homework attempt and average fraction of homework solved, delineated by curriculum level.

When linear associations were weak but conceptually plausible, we investigated curvilinear relationships using quadratic transformations (Kutner et al., 2005). For instance, Figure 2 shows a curvilinear association in the Advanced group, where students revisiting problems more than 0.6 times showed markedly improved outcomes, suggesting persistence plays a key role in this subgroup. The Accelerated group, in contrast, exhibited no such pattern.

To formally test these observations, both linear (X) and quadratic (X^2) regression models were estimated for each predictor–outcome pair. Statistical significance of model coefficients was used to classify predictors as linear or curvilinear within each curriculum group. Results from one such analysis are presented in Table 4.

Next, multivariate regression models incorporating all predictors (in linear or curvilinear form as appropriate) were estimated separately for each curriculum level. This stratified modeling approach was justified by the distinct academic backgrounds and learning behaviors of students in each curriculum group. For example, the Accelerated group, comprising primarily new students ($n = 153$) entering to build foundational skills, yielded robust model performance. The Honors group ($n = 226$), consisting of high-achieving students with traits such as rapid mental calculation or prior advanced training, exhibited less predictable

outcomes, likely due to latent variables not captured in the model. Surprisingly, the model for the Advanced group ($n = 206$) underperformed despite this being the dominant cohort of Grade 7 students. Further inspection revealed internal heterogeneity in student work habits, prompting a secondary segmentation.

Table 4. Regression results for average fraction of homework solved on average revisits per unsolved problem.

Curriculum Level	7_1 Accelerated	7_2 Advanced	7_3 Honors
n	153	362	226
R^2	0.558	0.462	0.355
RMS	0.010	0.010	0.000
a	0.359	0.658	0.728
$b_1 X$	0.732	0.106	0.141
$b_2 X^2$	−0.126	0.225	0.092
t_{b_1}	3.177	0.724	0.984
t_{b_2}	−0.741	2.084	0.933
$P > t _{b_1}$	0.002	0.470	0.326
$P > t _{b_2}$	0.460	0.038	0.352

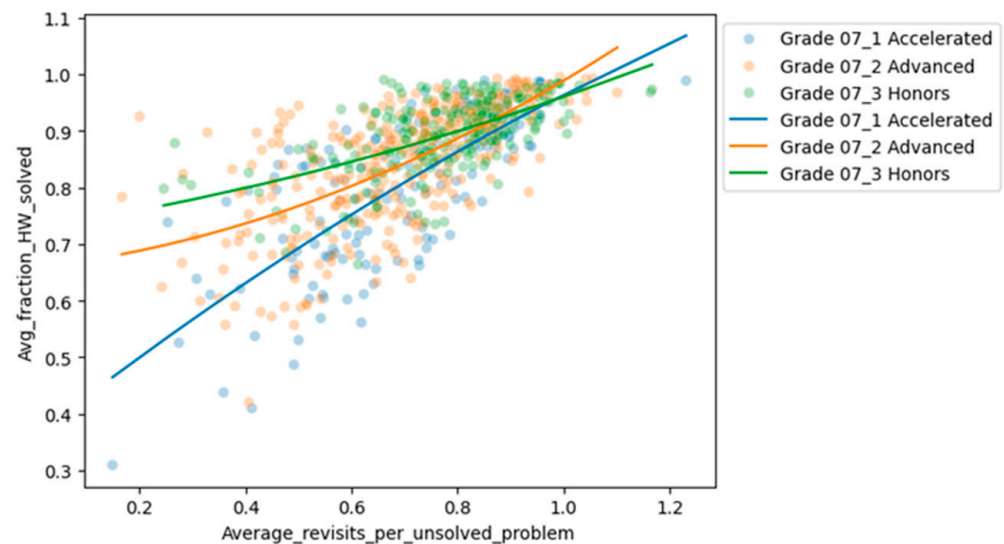


Figure 2. Curvilinear relationship between average revisits per unsolved problem and homework performance in advanced-level students.

Two subgroups were delineated within the Advanced cohort. The Advanced Progressing (ADV-PR) group ($n = 127$) included students who progressed from Grade 6 Accelerated to Grade 7 Advanced and were projected to continue to Grade 8 Honors. These students typically followed the trajectory $6_1 \rightarrow 7_2 \rightarrow 8_3$ and occasionally included exceptionally gifted students who skipped grades or advanced rapidly. In contrast, the Advanced Plateaued (ADV-PL) group ($n = 79$) included students who remained in Advanced across grades or were demoted from Honors. These students demonstrated plateaued academic progression within the RSM system. As shown in Figure 3, these two groups exhibited differential correlations between time spent on homework and the outcome variable. While ADV-PL showed a consistent positive linear relationship, the ADV-PR group exhibited diminishing returns after 90 min of homework effort. This divergence indicates that time spent on homework reflects different underlying processes across subgroups—productive engagement for progressing students and inefficiency or unresolved difficulty for plateaued students.

This subgroup analysis substantially enhanced model performance and revealed meaningful differences in learning behavior at the same curriculum level.

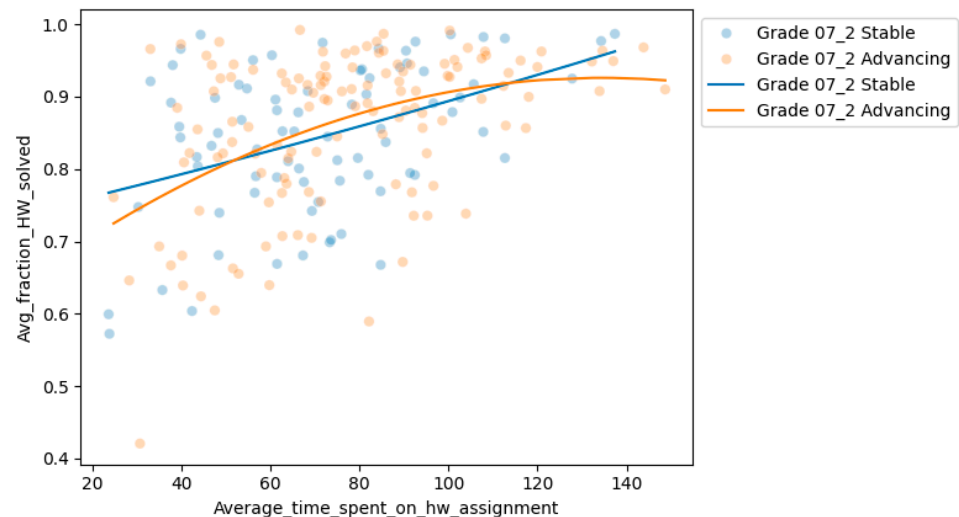


Figure 3. Relationship between homework completion and time spent for advanced–progressing and advanced–plateaued students.

4. Results

The results of the predictive modeling analysis are organized by curriculum level, as distinct patterns emerged for Accelerated and Honors students. Each model was evaluated for overall predictive strength, key contributing predictors, and interpretation of statistically significant effects.

4.1. Comparison of Accelerated and Honors Models

The predictive model for Accelerated students demonstrated the strongest performance, with a coefficient of determination (R^2) of 0.81 and a mean squared error (MSE) of 0.33. The residuals, not shown, were narrowly distributed around zero with few significant outliers, indicating a reliable fit between observed and predicted values.

By contrast, the model for Honors students exhibited a lower R^2 of 0.60 but a smaller MSE of 0.156, suggesting that although the model captured less variance overall, its predictions were more precise in absolute terms. These contrasting performance metrics underscore important differences in model dynamics across curriculum levels.

4.1.1. Shared Statistically Significant Predictors

Several predictors emerged as statistically significant across both levels. These included the following:

- Average behavior;
- Attempts per problem;
- Fraction of homework uploaded;
- Average revisits per homework;
- Average revisits per unsolved problem;
- Average time spent on each homework assignment.

A summary of statistically significant coefficients and associated p -values is presented in Table 5.

4.1.2. Common Predictors Across Both Curriculum Levels

ATTEMPTS PER PROBLEM was negatively associated with homework performance in both models. Students requiring multiple attempts may lack conceptual clarity or problem-solving strategies. Bowman et al. (2014) found similar results, concluding that frequent, unguided attempts were associated with reduced learning gains.

Table 5. Statistically significant predictors for the accelerated and honors levels.

Predictor	7_1 Accelerated		7_3 Honors	
	Coefficient	P > t	Coefficient	P > t
Average_Participation	−0.02	0.72	0.15	<0.01
Average_Behavior	0.14	0.02	0.06	0.28
np.power (Average_Behavior, 2)	n/a	n/a	0.09	<0.01
Average_days_before_first_attempt	0.08	0.20	−0.15	<0.01
Avg_attempts_per_problem	−0.15	<0.01	−0.12	<0.01
Fraction_HW_uploaded	0.35	<0.01	0.10	<0.01
Fraction_late	−0.24	0.01	−0.01	0.87
Avg_revisits_per_HW	−0.14	0.03	−0.13	<0.01
Average_revisits_per_unsolved_problem	0.66	<0.01	0.34	<0.01
Average_time_spent_on_hw_assignment	0.23	<0.01	0.12	<0.01

FRACTION OF HOMEWORK UPLOADED was positively associated with performance. This likely reflects deeper engagement, as students who document their work are more deliberate in their problem-solving processes. [Rawson and Stahovich \(2013\)](#) similarly found that visible effort measured by ink usage predicted academic success. The effect was more pronounced in the Accelerated group, where foundational mastery is especially dependent on showing full mathematical reasoning.

AVERAGE REVISITS PER HOMEWORK was negatively correlated with performance for both groups, suggesting that students who repeatedly revisit homework may lack efficiency or fluency in solving problems. In contrast, average revisits per unsolved problem had a strong positive effect, particularly for Accelerated students, highlighting the benefits of targeted persistence. These findings align with [Brown et al. \(2015\)](#), who showed that students improve when encouraged to correct mistakes on past assessments.

TIME SPENT ON HOMEWORK was positively associated with performance in some groups; however, this relationship was not uniform across the sample. As shown in subsequent subgroup analyses, the effect of time depends on the efficiency and structure of engagement, with evidence of diminishing returns and attenuation in certain student groups. [Bowman et al. \(2014\)](#) reported similar findings in their study of charter schools, noting that extended homework engagement contributed to academic improvement beyond selection effects.

4.1.3. Behavioral Effects and Nonlinearities

AVERAGE BEHAVIOR was predictive of homework performance in both models (which is supported by previous studies, such as [Wagner and Ruch \(2015\)](#)) but operated differently across levels. For Accelerated students, the relationship was linear: better behavior was consistently associated with higher scores. For Honors students, the relationship was curvilinear. As illustrated in Figure 4, some students with below-average behavior still performed above average academically, possibly due to higher intrinsic motivation or content familiarity.

4.1.4. Curriculum-Specific Effects

LATE ARRIVAL TO CLASS was a significant negative predictor for Accelerated students only. Missing early instructional time, which is often used for homework review, may have directly affected performance. For Honors students, tardiness was not predictive, likely due to broader academic maturity or scheduling conflicts unrelated to engagement. These results are consistent with [Serut et al. \(2023\)](#), who reported that tardiness hindered academic success among first-year college students.

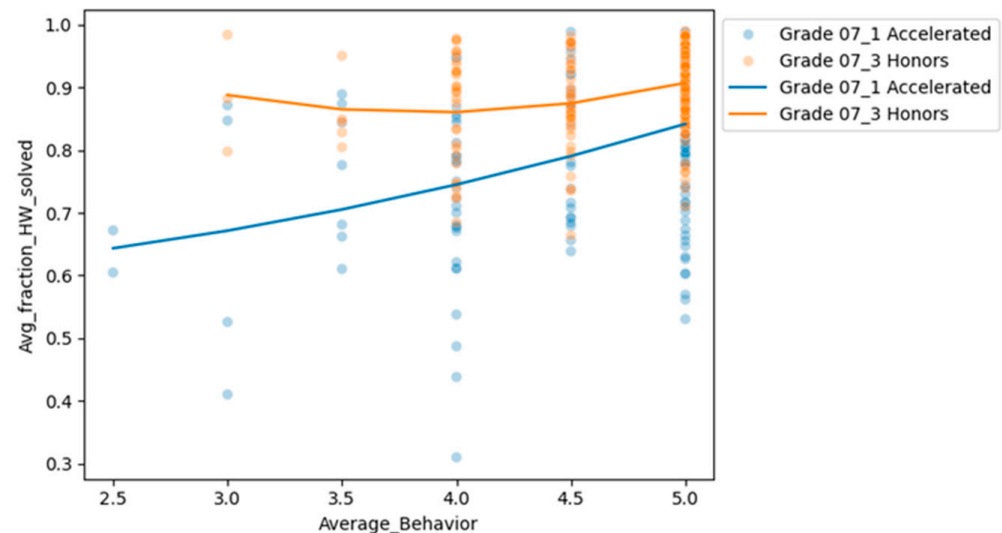


Figure 4. Scatterplots of homework score by average behavior for accelerated and honors students.

DAYS BEFORE FIRST ATTEMPT was negatively associated with performance for Honors students, suggesting that early engagement is critical for navigating more challenging material. Accelerated students did not show a significant relationship on this variable. These findings align with Nieberding and Heckler (2021), who found that procrastination was linked to lower academic outcomes.

PARTICIPATION was a marginally significant predictor for Honors students, implying that classroom engagement is more essential in cognitively demanding contexts. The same was not observed for Accelerated students, where success may be attainable through independent work. Kim and Ketenci (2019) likewise found that active engagement, such as moderating discussions, was positively associated with learning outcomes.

4.1.5. Nonsignificant Predictors

Some predictors were not statistically significant for either group. These included the following:

- Fraction of lessons attended;
- Fraction of classroom activity;
- Fraction of private teacher–student talk.

The absence of a significant ATTENDANCE effect may be due to students accessing learning materials outside class.

A key limitation of the other two predictors is related to implementation fidelity in the use of the VCR platform. The variables examined (classroom activity, private teacher–student interactions) may not represent uniform constructs across classrooms, as instructors differ in how they employ these tools. For example, PRIVATE CONVERSATIONS may be used for remediation, enrichment, or non-academic purposes, while measures of classroom ACTIVITY may depend on teacher-specific practices. This variability reduces the interpretability of these predictors and may attenuate their observed statistical significance.

4.2. Advanced Level Split

Unlike the Accelerated and Honors levels, the Advanced curriculum encompasses a broader and more heterogeneous student population. This group includes students who are continuing to make measurable academic progress, as well as those whose performance appears to have plateaued. While both Honors and Advanced classrooms contain students with varied profiles, the key distinction is that all Honors students demonstrate academic

strength, albeit for different reasons, whereas Advanced students vary more widely in their performance trajectories.

To address this heterogeneity, we developed a quantitative method for dividing Advanced students into two subgroups based on their previous academic path: those who are progressing and those who are plateaued. This segmentation yielded more homogeneous groups and allowed for more accurate modeling and interpretation of performance indicators.

The original (undivided) Advanced model demonstrated an R^2 of 0.62—higher than that of the Honors model—but a comparatively high mean squared error (MSE) of 0.49 raised concerns regarding precision. After splitting the Advanced group, both resulting models improved substantially. The Advanced–Plateaued model achieved an R^2 of 0.67 with an MSE of 0.30, while the Advanced–Progressing model achieved an R^2 of 0.70 and an MSE of 0.31. These results indicate that disaggregating the Advanced group improved model fit and reduced prediction error.

4.2.1. Comparison of Predictors Across Advanced Subgroups

Although the Advanced–Plateaued (ADV-PL) and Advanced–Progressing (ADV-PR) students share the same curriculum and classroom setting, the characteristics of their predictive models differ substantially. As shown in Table 6, only three predictors were statistically significant in both models:

- Average attempts per problem;
- Fraction of homework uploaded;
- Average revisits per unsolved problem.

Table 6. Model coefficients for advanced–progressing and advanced–plateaued levels.

Predictor	7_2 Advanced Plateaued		7_2 Advanced Progressing	
	Coefficient	P > t	Coefficient	P > t
Fraction_lessons_attended	0.27	<0.01	0.11	0.07
Average_Participation	−0.21	0.04	0.09	0.40
Average_days_before_first_attempt	0.03	0.77	−0.16	0.03
Avg_attempts_per_problem	−0.17	0.10	−0.15	0.11
Fraction_HW_uploaded	0.29	0.01	0.28	<0.01
Avg_revisits_per_HW	−0.07	0.53	−0.28	<0.01
Average_revisits_per_unsolved_problem	0.60	<0.01	0.23	<0.01
Average_time_spent_on_HW_assignment	−0.02	0.83	0.23	<0.01

The three shared predictors—AVERAGE ATTEMPTS PER PROBLEM, PAPER HOMEWORK SUBMISSION, and REVISITS TO UNSOLVED PROBLEMS—demonstrate consistent directionality and, in most cases, similar magnitudes within a predictor across both groups. These predictors appear to be universal indicators of homework performance across all Grade 7 curriculum levels. While the p -values for the AVERAGE ATTEMPTS predictor exceed conventional thresholds for significance, the consistency and strength of their negative relationships across models support the decision to retain this predictor in both models. Additionally, although Figure 5 shows a slight curvilinear relationship, this curve is mainly due to few outlying observations; they are also the main source of loss of the linear model’s statistical significance.

4.2.2. Importance of Revisits to Unsolved Problems

Among the three shared predictors, AVERAGE REVISITS PER UNSOLVED PROBLEM emerged as the most significant and impactful, particularly for the ADV-PL and Accelerated groups. As shown in Figure 6, the magnitude of this coefficient is highest for students in

lower-performing cohorts, underscoring the critical role of persistence in this population. In contrast, for ADV-PR and Honors students, the effect is more modest since these students tend to solve problems successfully on the first attempt and, thus, have fewer revisits.

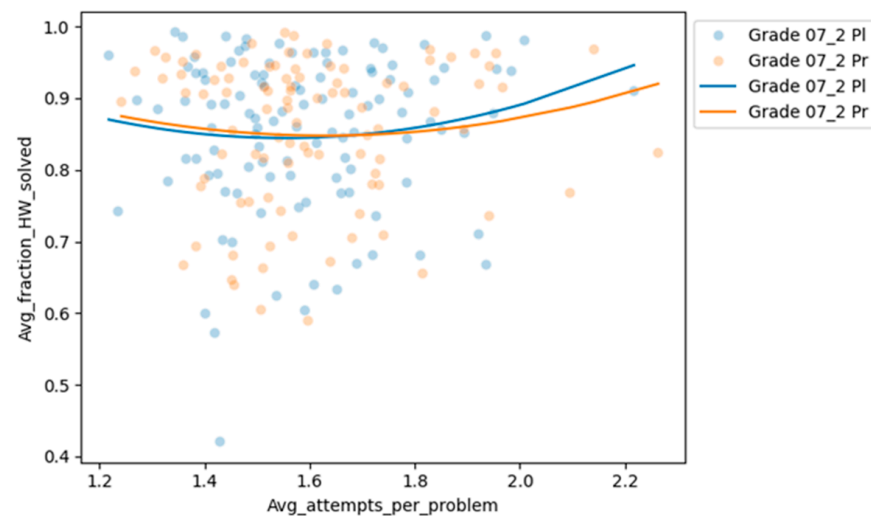


Figure 5. Correlation between average attempts per problem and homework performance for advanced–progressing and advanced–plateaued students.

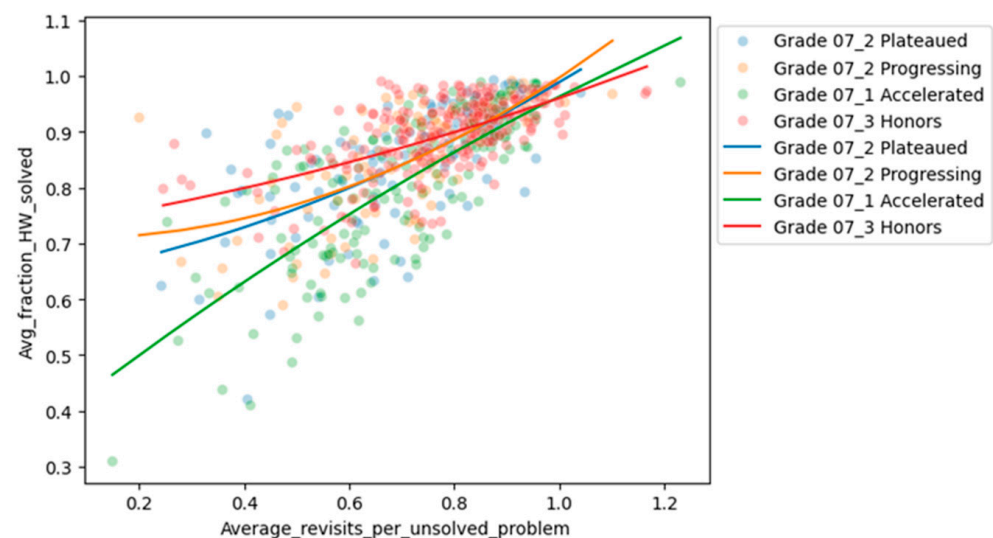


Figure 6. Effect of average revisits per unsolved problem on homework performance across all Grade 7 curriculum levels.

This pattern suggests that among lower-performing students, success is more likely when they either solve all problems on the first attempt or make a deliberate effort to return to those initially left incomplete. The greater regression coefficient magnitudes for these groups underscores how essential persistence is for foundational mastery.

4.2.3. Group-Specific Predictors

ATTENDANCE was a statistically significant predictor only for the Advanced–Plateaued group, likely reflecting the group’s overall slower academic pace. For these students, each class session may provide essential instruction that cannot be easily recovered through independent work. These findings are consistent with the broader literature, which identifies class attendance as one of the strongest predictors of academic performance—often more predictive than standardized test scores, GPA, or study habits (Kassarnig et al., 2017).

Interestingly, PARTICIPATION was also significant for the ADV-PL group, but with a negative association. Unlike the positive relationship observed in Honors students, increased participation among plateaued students may signal confusion, frequent guessing, or increased reliance on teacher prompts. It is possible that higher participation in this context reflects struggle rather than engagement.

For the Advanced–Progressing group, several predictors linked their profile to both the Accelerated and Honors levels. These students, like Accelerated students, appear to benefit from a relatively less complex curriculum and demonstrate strong growth trajectories. At the same time, their pace of progress and responsiveness to time-based predictors—such as fewer days before first attempt and more time spent on homework—align them with the faster-paced Honors group. These patterns support the classification of ADV-PR students as a high-potential cohort that benefits from both deliberately more difficult progression of tasks and early engagement.

4.3. Model Testing

To assess the generalizability of the predictive models developed for the 2023–2024 academic year, we conducted a longitudinal validation using an independent dataset from the 2024–2025 school year for Grade 7 students.

The Accelerated model, originally yielding an R^2 of 0.81, produced a reduced predictive R^2 of 0.44 and a mean squared error (MSE) of 0.56 on the independent dataset. The Honors model, which had an R^2 of 0.60 on the training data, showed relatively stable predictive accuracy on the test data ($R^2 = 0.52$), with a low MSE of 0.25, indicating stable performance. The Advanced–Plateaued model, which initially yielded an R^2 of 0.67, achieved an R^2 of 0.57 and MSE = 0.46 when applied to the new data. Similarly, the Advanced–Progressing model, originally with an R^2 of 0.70, retained reasonable accuracy with an R^2 of 0.57 and MSE = 0.50 in the independent sample. The progression of R^2 and MSE from 2023 to 2024 to 2024–2025 can be observed in Table 7.

Table 7. Train and test results for different curriculum levels.

	Accelerated		Advanced–Plateaued		Advanced–Progressing		Honors	
	R^2	MSE	R^2	MSE	R^2	MSE	R^2	MSE
Training set 2023–2024	0.81	0.33	0.67	0.30	0.70	0.31	0.6	0.156
Testing set 2024–2025	0.44	0.56	0.57	0.46	0.57	0.50	0.52	0.25

Although there was a decline in performance metrics across all models, the degradation was modest and acceptable within the context of educational research. These results demonstrate that the models and their derived conclusions are valid across academic years, supporting their robustness and longitudinal applicability.

5. Discussion

5.1. Developmental Trajectories Across Levels

5.1.1. Accelerated Level

Students typically begin their RSM journey at the Accelerated level, where the curriculum is foundational and the emphasis is on filling knowledge gaps, reinforcing basic skills, and practicing procedural fluency. While students at this level demonstrate a range of academic ability and pace, this level is marked by quick progress due to the clarity of instructional goals. Students who exhibit diligence, time management, and persistence also tend to progress quicker.

Our analyses suggest that the most academically successful Accelerated students shared several behavioral characteristics:

- They attempted to solve every problem and returned to any that remained unsolved;
- They consistently showed their work in detail;
- They worked at a measured pace, dedicating sufficient time per problem;
- They arrived at class on time, maximizing instruction and demonstrating time management;
- Students who averaged fewer attempts per problem¹ tended to outperform peers with higher attempt counts by as much as 20% of the homework score;
- They completed homework in as few sessions as possible, associating with higher efficiency, possibly due to minimizing warm-up time;
- They maintained classroom focus and a respectful atmosphere.

These patterns outline the directionality of habits that are correlated with stronger academic outcomes, suggesting potential areas for instructional focus.

5.1.2. Promotion Criteria and Habits of Successful Honors Students

At the end of the Accelerated year, most students are promoted to the Advanced level. Retention in Accelerated is reserved for students with persistent gaps in understanding. A prior study by Kosogorova et al. (2025) identified the key work habits that are associated with teacher promotion decisions. These include average attempts per problem, frequency of homework uploads, and revisits to unsolved problems—many of which are also indicators of academic success.

Promotion from Advanced to Honors, however, is more selective. In contrast to the baseline skills required for Accelerated-to-Advanced promotion, movement into Honors demands consistent demonstration of advanced work habits and mindset. As a result, many students remain in Advanced, which functions as RSM's core academic level.

Successful Honors students were distinguished by the following behaviors, in order of significance:

- Consistent problem completion, with no unsolved items or timely revisits;
- Proactive participation in classroom discussions;
- Homework completed in minimal sessions;
- Early initiation of homework (e.g., students starting one day after class tended to outperform those starting six days later by over 10%);
- Steady pacing and time management;
- Precision and low average attempts per problem;
- Full solution uploads for teacher feedback;
- Positive classroom behavior and, when distracted, compensatory learning strategies.

The similarities in successful student habits between Accelerated and Honors levels are not coincidental. In both cases, students tend to show rapid progress and strong commitment, often supported by parental involvement and motivation (help at home and external motivation for class) in the case of new Accelerated students, and by the intrinsic drive of math-minded Honors students. Differences in observed behaviors may be related to differences in instructional emphasis: while guided discussion and review are important across all levels, Honors classes seem to place more focus on independent work and active participation of the students whereas Accelerated students benefit most from consistent punctuality and more structured guided practice.

5.1.3. Differentiation Within the Advanced Level

The Advanced level includes two distinct groups, namely Advanced–Progressing and Advanced–Plateaued students, who share a classroom and curriculum but diverge in work habits, mindset, and academic readiness.

5.1.4. Advanced–Progressing Students

Most of the time the successful students in the progressing subgroup stay in the Advanced level for one year only on their way to Honors. Their behavioral patterns align closely with those of successful Accelerated and Honors students:

- Returning to unsolved problems shows an even stronger association with success here than in Honors;
- Completing homework in fewer sessions is moderately associated with higher performance, more so than in Accelerated, but less than in Honors;
- Uploading solutions is highly valued, more than in Honors, but less than in Accelerated;
- Taking sufficient time on homework is strongly associated with better outcomes, with importance similar to Accelerated and slightly less than Honors;
- Early homework initiation is strongly associated with performance, mirroring patterns observed in Honors students;
- Fewer attempts per problem correlate with better scores across all levels;
- Class attendance is especially important in Advanced, even more so than in other levels.

These shared habits are consistent with patterns observed among students who later reach Honors-level readiness.

5.1.5. Advanced–Plateaued Students

Students in the plateaued group typically lack one or more of the qualities needed for Honors advancement. They may be affected by a variety of challenges, including lack of time, motivation, ability, or external constraints (e.g., health, family obligations). As such, this group is more heterogeneous and harder to predict.

Nonetheless, successful students in this group shared key behaviors:

- Consistent class attendance was essential, highlighting the demanding nature of the Advanced curriculum.
- They demonstrated self-reliance, often working independently before seeking help. Less successful students who most likely try to obtain hints from the teacher during class, thus increasing their participation score, cannot obtain them during homework (hints are not available for every problem). This pattern resulted in a unique negative relationship between participation and performance in this group.

The nuanced behavior of this subgroup suggests that high participation does not always reflect comprehension; in fact, it may indicate confusion or over-reliance on guessing—distinguishing them from their Advanced–Progressing peers.

Furthermore, we note that time spent on homework is often modeled as a nonlinear predictor, reflecting diminishing returns. Our findings are consistent with this general expectation, but indicate that the form of the relationship varies across subgroups. Specifically, the Advanced–Progressing group exhibits a curvilinear pattern, with positive effects at lower levels of time and diminishing returns at higher levels, whereas the Advanced–Plateaued group shows little or no benefit from additional time, suggesting inefficiency or unresolved difficulty. When these groups are combined, the aggregate effect is attenuated and may appear negative under a linear specification. Thus, the negative coefficient does not contradict the broader literature but reflects heterogeneity in the underlying relationship. Nonlinear forms were examined and retained where supported; the linear specification for time is therefore interpreted conditionally, in light of subgroup differences and the inclusion of other engagement variables.

5.2. Cross-Level and Longitudinal Comparisons

Across all Grade 7 curriculum levels, three universal predictors consistently emerged:

- Number of attempts per problem;
- Fraction of homework uploaded;
- Revisits per unsolved problem.

It is important to note that given that the predictors represent behavioral process variables drawn from a common instructional context, some degree of intercorrelation was theoretically expected; participation, behavior, attendance, and engagement are not necessarily independent constructs. Multicollinearity diagnostics, however, were uniformly modest. Variance inflation factors (VIFs), for example, ranged from 1.03 to 2.32 across models. These values fall well below conventional thresholds for concern (e.g., $VIF > 5$, [Menard, 2001](#)), and VIFs below approximately 3 are typically regarded as benign in applied settings. Accordingly, the observed diagnostics do not indicate a level of inflated standard errors that materially affected the statistical significance of the estimated regression coefficients.

These findings align with a three-year longitudinal study conducted by [Ilina et al. \(2025\)](#) using Grade 4 RSM data. That study identified a similar set of predictors as critical to elementary-level homework success. The regression coefficients from their analysis are summarized in Table 8.

Table 8. Predictor coefficients from a multi-year Grade 4 student efficiency study ([Ilina et al., 2025](#)).

Outcome	Homework (HW) Score					
Predictor	All Predictors					
Curriculum	4_1 Accelerated		4_2 Advanced		4_3 Honors	
	b	p	b	p	b	p
Intercept	−10.180	0.001	0.140	0.001	0.303	0.000
attendance	0.140	0.000	0.216	0.000	0.187	0.000
attendance_squared	−0.042	0.011	0.003	0.879	0.038	0.066
hw_revisits	−0.201	0.000	−0.170	0.000	−0.2289	0.000
problem_attempts	0.267	0.000	0.449	0.000	0.123	0.057
problem_attempts_squared	−0.060	0.000	−0.136	0.000	−0.070	0.009
picture_upload	0.466	0.000	0.390	0.000	0.355	0.000
unsolved_problem_revisits	−0.094	0.002	−0.183	0.000	−0.062	0.237
unsolved_problem_revisits_squared	0.051	0.002	0.048	0.003	0.068	0.014
time_spent_on_hw	0.018	0.563	−0.063	0.065	0.090	0.093
time_spent_on_hw_squared	−0.023	0.216	0.021	0.318	−0.002	0.957
days_first_attempt	−0.149	0.000	−0.181	0.000	−0.140	0.002

5.3. Implications and Developmental Considerations

While core predictors remain consistent across elementary and middle school, the relative importance of some variables shifts developmentally. In elementary grades, parental oversight increases the impact of classroom-based behaviors like attendance. As students mature, cognitive development extends memory span, thereby reducing the importance of session count and time lag before beginning homework.

Taken together, these findings suggest that reinforcing a foundational set of habits across grades and levels can significantly enhance academic performance. At the same time, level-specific behaviors must be understood and addressed to meet students where they are developmentally and academically ([Pozas & Schneider, 2020](#); [Smale-Jacobse et al., 2019](#)).

6. Conclusions

This study demonstrates that for Grade 7 students, certain behavioral habits, such as showing one's work, persisting with unfinished tasks, minimizing repeated attempts, and starting assignments early, serve as reliable predictors of academic success across

different levels of curriculum rigor. These findings emphasize that while cognitive ability and curriculum placement matter, the everyday learning behaviors students adopt are equally critical for long-term achievement.

Despite the differing cognitive demands of the Accelerated and Honors curricula, both models exhibited a surprising number of similarities. These stem from the fact that students at both levels tend to progress rapidly, Accelerated students due to the review-oriented nature of the curriculum, and Honors students due to their advanced placement and academic disposition. Beyond the universal behaviors, successful students at both levels demonstrated key habits such as starting homework early in the week and maintaining a positive learning environment by avoiding distractions, both for themselves and their peers. That said, the models also revealed important level-specific differences: while Honors students benefit most from active participation in class discussions, Accelerated students rely more heavily on timely attendance to capitalize on instructional homework and previous material review and introduction to the topic at the start of the lesson.

For students in the intermediate Advanced level, the findings point to the importance of differentiating between two subgroups (admittedly, although it is hard to bifurcate the student body at the Accelerated level due to the nature of the curriculum, where everyone learns basic skills and covers gaps, the Accelerated level students may also have two different subgroups):

- Advanced–Progressing students, who exhibit strong potential for continued academic growth, and
- Advanced–Plateaued students, whose performance appears to have stabilized, which may be influenced by a variety of factors such as prior learning gaps, a slower work pace, less effective learning strategies, or external considerations like class scheduling or strong commitments to other activities.

The Advanced–Progressing subgroup aligns closely with the behavioral patterns of successful Honors and Accelerated students. Their most effective strategies include beginning assignments promptly, avoiding excessive fragmentation of study sessions, and engaging with homework tasks deliberately rather than rushing through them. Though the Accelerated curriculum tends to mask subgroup differences due to its focus on foundational review, there is evidence to suggest that even within Accelerated cohorts, a distinction can be made between students progressing rapidly and those still consolidating basic skills.

In contrast, the Advanced–Plateaued subgroup demonstrated a narrower set of success indicators. In addition to the core behaviors noted above, only two additional behaviors were statistically significant: consistent class attendance and attempting to solve problems in class independently before seeking help. The absence of a more consistent behavioral pattern is likely due to the wide range of personal, cognitive, and situational factors contributing to a plateau in this group, highlighting the importance of individualized instructional approaches to reignite academic momentum.

For educators, our results point to the value of teaching and reinforcing these habits explicitly, alongside content instruction. Structured opportunities for persistence, deliberate practice, and reflection should be built into classroom routines, while teachers remain attentive to subgroup differences. Students whose progress has plateaued may require individualized support, whether through targeted scaffolding, alternative strategies for problem-solving, or adjustments that address external challenges such as scheduling and competing extracurricular demands.

Concretely, these findings translate into several actionable classroom practices that are transferable beyond the RSM context. For example, teachers can encourage early task initiation by assigning short, low-stakes “start-up” problems within 24 h of instruction, rather than concentrating all work closer to the next class meeting. Persistence can be

reinforced by building structured opportunities for revisiting unfinished problems, such as requiring students to resubmit at least one previously unsolved item with a revised solution. To promote deliberate practice and reduce unproductive guessing, teachers can emphasize solution completeness by requiring students to show all steps for selected problems and incorporating brief feedback cycles focused on reasoning rather than final answers. Additionally, minimizing fragmentation of work sessions can be supported by setting expectations for completing assignments in one or two sittings, coupled with guidance on time management strategies. Finally, simple participation structure, such as rotating responsibility for explaining solutions or using think–pair–share routines, can increase active engagement without relying on program-specific tools.

For parents, the study underscores the importance of cultivating a positive home learning environment by reducing distractions, encouraging steady work habits, and helping students start tasks early rather than delaying them. Even modest changes in routine, such as establishing regular homework time or prompting students to return to unfinished problems, can significantly impact learning outcomes.

Specifically, these findings can be translated into a set of practical routines that support effective learning habits at home. For example, encouraging students to begin homework soon after it is assigned, rather than the day before it is due, can be reinforced by establishing a consistent weekly schedule with designated start times. Persistence can be supported by asking students to revisit at least one unfinished or challenging problem after a break, rather than moving on entirely. Parents can also promote deliberate practice by prompting students to explain their reasoning aloud or to write out full solutions, even when they believe they have the correct answer. To reduce fragmented work patterns, families can encourage completing assignments in one or two focused sessions, minimizing distractions such as phones or multitasking. Finally, maintaining a structured and distraction-limited environment (such as a regular workspace and predictable routine) can help students sustain attention and develop the consistency associated with stronger academic outcomes.

Taken together, the findings affirm that academic progress in middle school is not only shaped by ability or placement but also by consistent behaviors and supportive contexts. By fostering these practices both at home and in school, educators and families can better equip students to sustain growth and overcome periods of stagnation, making success more attainable for a wider range of learners.

A key consideration in interpreting these findings is their generalizability. All participants were drawn from RSM, an extracurricular program that families actively choose, and thus represent a population that is, on average, more motivated and academically oriented than the general middle school population. As a result, the strength and consistency of the observed behavioral patterns may not fully extend to less self-selected or less academically engaged settings. At the same time, the underlying learning behaviors identified, such as persistence, early task initiation, and precision, are not unique to this context and align with broader educational research. Thus, while the magnitude of effects may differ, the general patterns are likely applicable to other academically engaged student populations and can inform instructional practices in more heterogeneous settings when adapted appropriately.

Ultimately, the study underscores the need for instructionally responsive strategies that are tailored to both the student's level and their stage of academic development. In many K–12 educational environments where full classroom differentiation is not always possible teachers must be able to identify subgroups within their classrooms and adapt their strategies accordingly. These findings are not only relevant to the specific context of the Russian School of Mathematics but also extend to a broader range of middle school settings, offering insight into scalable behavioral practices that foster academic success in heterogeneous learning environments.

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Abbreviations

The following abbreviations are used in this manuscript:

ADV-PL	Advanced–Plateaued group of students
ADV-PR	Advanced–Progressing group of students
RSM	Russian School of Mathematics
VCR	Virtual Classroom

Note

- ¹ This pattern should not be interpreted as suggesting that limiting attempts improves performance; rather, it likely reflects differences in initial accuracy and conceptual understanding. Consistent with existing literature on persistence, productive re-attempts remain an important component of the learning process, but only if effort is effectively directed (Goh, 2025).

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