

The Impact of Personal Student Characteristics on Mathematics Achievement for Nontraditional Students in an Online Charter High School

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In online virtual-based learning, combining more adaptive personal student characteristics with risk factors, the purpose of this study was to examine the relationship between student at-risk factors and mathematics achievement. Further, the study examined how personal student characteristics, which are sometimes amenable to change and intervention, impact the relationship between risk and mathematics achievement. Sixty-three Algebra 1 students in one online charter school were surveyed about perceptions of their self-efficacy and study management. Using multiple linear regression, results show that students' age, likely coinciding with the grade level at which they took the courses, negatively and significantly predicted course grades. Additionally, domain-specific self-efficacy in mathematics contributed most to course grades among the hypothesized moderators. Finally, results show that when students have more adaptive self-efficacy or study behavior profile, impacts of prior family-based academic risk factors on achievement are lessened or positively strengthened. Virtual school teachers and administrators should consider ways to strengthen students' self-efficacy and build programs to teach students about important study habits, such as time management.

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Education among K-12 students has exhibited a significant shift within the past two decades. According to the National Center for Education Statistics (2018), the number of schools offering alternative, nontraditional educational opportunities has more than tripled from the start of the century and is partly responsible for the rise in the popularity of non-traditional educational options. Since the early 1990s, traditional, in-person charter schools have expanded to address the needs of nontraditional students, increase access to credit recovery programs, and promote educational choice amid diverse educational options (Ahn, 2011). More recently, K-12 online learning has expanded to offer additional educational programming for nontraditional students (Ahn, 2011; Waters et al., 2014), offering a wider population of students access to alternative, flexible educational opportunities. The continued growth of K-12 online learning has led to a rich, diverse, and multifaceted approach to alternative education. One of these alternatives, an online charter school (OCS), has been formed recently. OCSs are public schools of choice operating statewide and governed by a charter approved by the state (Waters et al. 2014; Ahn 2011).

Two noteworthy research strands have targeted OCSs. First, one line of inquiry has focused on tracing academic achievement in OCSs through large-scale national studies. In particular, this research has examined the intersection of the student population attending OCSs and indicators of school achievement. For instance, a national analysis of OCSs (Woodworth et al., 2015) discovered their students do not exhibit the same success level as traditional public school counterparts. Specific subgroups are significantly underperforming in OCSs. That is, regardless of racial identity, being in poverty, an English Language Learner or a special education student negatively impacts growth while enrolled in an OCS versus a traditional public school (Woodworth et al., 2015), particularly in secondary mathematics. Second, another body of work has focused on a deficit approach, identifying potential risk factors (or root causes) that predict school dropout or relate to mathematics achievement. These root causes are prior educational or social risk factors that positively or negatively impact future academic achievement (Bowers et al., 2013; Gleason & Dynarski, 2002). Despite this body of work, while these research strands have examined what types of students are at-risk and how risk broadly influences mathematics achievement (Bowers et al., 2013; Croninger & Lee, 2001; Kaufman & Bradbury, 1992; Woodworth et al., 2015), what remains absent is a narrower and more positive approach to exploring how context-specific, student self-beliefs may relate to these risk factors and mathematics achievement in a virtual learning setting.

Set within the domain of high school mathematics, the purpose of this study was to examine the relationship between academic risk factors and Algebra 1 achievement outcomes in an online charter high school. The study explored how personal student characteristics, such as self-beliefs, impacted the relationship between these academic risk factors and Algebra 1 achievement. This research may help explain vital mechanisms that improve algebra learning outcomes for nontraditional students in online learning. While extending these findings to an online school environment, this study will add to the existing literature on risk factors among high school students and how these self-beliefs may mitigate the relationship between primary risk factors and mathematics achievement.

In the current study, we refer to nontraditional students, both in the literature review as well as participants of the study. We define nontraditional students as students who enroll in an online charter school. Online charter schools often serve students who, for various reasons, have withdrawn from their traditional local public school to the online charter school. Because this represents the minority of the school population (i.e., approximately 6% of the school population

attends charter schools; National Center for Education Statistics, 2019) and students may trend older for the typical grade level, we term these students *nontraditional*.

In the next section, we introduce key variables and provide a theoretical foundation guiding the current study. Then, we propose our methodological plan, including data analysis procedures, and provide our key findings and results. Finally, we contextualize our results to the prior literature while offering scholarly and practical significance alongside study limitations.

Literature Review

Academic Risk Factors

The term *at-risk* is a complex, ambiguous, and multifaceted concept. For instance, Croninger and Lee (2001) argued that risk represents a “probability of future difficulties and not an explanation” for why some of these factors occur, and difficulties ensue, such as academic underperformance (p. 552). On the other hand, Placier (1993) emphasized that “Dropout focuses attention on the end of a student’s school career. At-risk focuses on an early stage in this chain of events, in which educators might be able to address the precursors of dropping out at a relatively low cost” (p. 386). As such, identifying risk factors early in a child’s education may mitigate later academic difficulties.

Within the literature, the term at-risk has often been viewed through a deficit approach, including a focus on how salient risk factors impact the likelihood of students dropping out of school (e.g., Bowers et al., 2013; Croninger & Lee, 2001). Among students who typically enroll in OCSs, several student academic variables often associated with dropout status (e.g. prior achievement, prior attendance, or family socioeconomic status (SES)), herein labeled *academic risk factors*, have been readily studied alongside mathematics and school achievement (Ahn, 2011; Bowers et al., 2013; Kaufman & Bradbury, 1992; Woodworth et al., 2015). Although past literature has considered dropout as a key outcome variable when relating these different variables, the goal of this study is to examine how academic risk factors present among the school population predict mathematics achievement. Below, we discuss highly impactful academic risk factors noted in the literature and appropriate to the virtual learning context.

Parental Involvement

Parental involvement is the support and control exerted by parents as facilitators of students’ education. Previous studies have differed on the impact of parental involvement in various educational settings. In traditional learning environments, for instance, researchers have hypothesized parental involvement or parental expectations as predictors of achievement among students (e.g. Anderson & Keith, 1997; Battin-Pearson et al., 2000). Despite this prediction, according to Anderson and Keith (1997), parental involvement, among other variables, was the only factor that did not significantly predict achievement in traditional in-person settings, contrary to other findings (Johnson, 1997, 1998; Somers et al., 2009). Additionally, Núñez et al. (2015) found less significant effects of parental involvement for secondary grades than primary grades. Thus, parental involvement at the high school level may be more limited and less influential than at younger grade levels, noting that, among older learners, student autonomy may diminish as parents provide less academic or emotional support (Anderson & Keith, 1997).

Despite the findings presented in the previous paragraph, both anecdotal and empirical evidence suggests, and we hypothesize, that parental involvement may play an even more critical role among online learning students because students are expected to bear more responsibility for their learning, and parents are typically called upon to transition to some level of an instructional role (Gill et al., 2015; Waters et al., 2014; Woodworth et al., 2015). Further, prior research has shown the importance of parents/guardians in online learning environments, both in achievement and in student engagement (Borup, 2016; Curtis & Werth, 2015; Hawk & Xie, 2022; Somers et al., 2009). This prior research has generally determined that parents or guardians, as they play multiple roles, highly impact student engagement, assist in student homework completion, and may impact student achievement. Despite this awareness, parent-school interaction is typically limited among these nontraditional students, specifically among online learning students where the parental role is less defined (Gill et al., 2015; Woodworth et al., 2015).

SES

Economic disadvantage is consistently labeled as one of the most widely used academic risk factors (e.g., Anderson & Keith, 1997; Kaufman & Bradbury, 1992; Suh et al., 2007). Data included in a family's Free and Reduced-Price Lunch (FRL) application are a widely used variable to measure SES (Battin-Pearson et al., 2000; Downing & Vette, 1994). Because FRL application information on family SES is easily accessible and calculable, it has often been used as a risk factor variable.

Harwell and LeBeau (2010) note that SES is an easily accessible statistic to obtain when researching students; however, FRL status leaves out other indicators such as social resources that are part of SES, including parent education or number of books in the household. Despite these shortcomings, across the literature, students living in low SES households are consistently measured as most at risk of school failure and low academic achievement (Anderson & Keith, 1997; Kaufman & Bradbury, 1992; Suh et al., 2007). Across studies, when controlling for SES, other social and academic factors consistently associated with academic risk typically persist, such as race/ethnicity or prior achievement, suggesting that the effect of SES is independent of other factors, at least descriptively speaking (Kaufman & Bradbury, 1992).

From a review of the relevant research literature and positioned within this study, academic risk factors are often characterized as more stable. Because these risk factors are evidence of family-focused variables not within the direct control of students, these risk factors are often static and more resistant to intervention and change. In the current study, we examine the relationship between academic risk factors and mathematics achievement in a virtual learning environment.

Importance of Malleable Student Characteristics

Alongside our examination of academic risk factors, we also focus on two variables important to the online learning environment (i.e., students' self-efficacy and time management), which are adaptable, learned, and within control by students (Bandura, 1977; Pintrich, 1995; Zimmerman, 2000), highlighted further below, called *personal student characteristics* in this study. We believe that further attention should explore these other more adaptive personal student characteristics, especially the ones that are subject to intervention and change. Because the instructional environment differs across online and traditional face-to-face classrooms, personal

student characteristics are often more associated with online mathematics achievement (Dray et al., 2011; Roblyer & Marshall, 2002; Ronsisvalle & Watkins, 2005).

Central to social cognitive theory, one motivational aspect that students can control is their self-efficacy which refers to one's perceived capability to accomplish tasks (Bandura, 1977). Usher and Pajares (2008) noted that Bandura hypothesized that a student's prior successes affect current efficacy perceptions. Success encourages future confidence, whereas failure, especially after making a great effort, might negatively impact future efficacy judgments.

Self-efficacy is best operationalized as a domain-specific measure (Usher & Pajares, 2008). Notably, self-efficacy may be particularly important for online nontraditional students because of the lack of direct teacher support typified across online learning environments. According to social cognitive theory (Bandura, 1977), efficacy judgments are informed by the environment, the self, and behavior. A potential reason for the potent relationship of teacher caring and student-teacher interactions with at-risk students may be that encouragement and feedback from others (environment) translate to improved self-efficacy, enhancing performance and engagement (Lehman et al., 2001; Muller, 2001; Usher & Pajares, 2008). These findings have important implications for online learning students, where parents are increasingly expected to assume the teacher role, suggesting a positive and persistent parental support and involvement system is necessary for students in online learning environments (Gill et al., 2015; Waters et al., 2014; Woodworth et al., 2015). Because the current study takes place among students taking a mathematics course in an online learning environment, two pertinent dimensions of self-efficacy include mathematics self-efficacy and technology efficacy for online learning.

Mathematics Self-efficacy

In mathematics education, mathematics self-efficacy has been described as one's perceived capacity to attain acceptable course grades, complete content-specific problems, or accomplish some other math-related task (May, 2009). Prior achievement has been shown to be an essential predictor for current mathematics self-efficacy; students who have a history of low achievement are less likely to be confident in their future success (Grigg et al., 2018).

In literature, mathematics self-efficacy consistently predicts mathematics achievement, beyond other factors such as teacher influences, attitudes, self-concept, and other control variables such as gender or ethnicity (Fast et al., 2010; Parr & Bonitz, 2015; Randhawa et al., 1993; Wu, 2016). Parr and Bonitz (2015), relying on a structural equation model, aimed to predict school dropout. In their work, self-efficacy did not predict dropout, but it was the most salient predictor of achievement outcomes (Parr & Bonitz, 2015). Mathematics self-efficacy was more strongly correlated with achievement than one's value for engaging in a task, provided greater predictive power than one's prior performance, and mathematics anxiety on current and future mathematics achievement (Fast et al., 2010).

Technology Efficacy for Online Learning

Throughout the prior literature, various scholars have used distinct terms to describe one's self-efficacy in a technology-mediated environment. Computer self-efficacy is the "perceived competence to perform specific computer tasks and to the extent to which individuals perceive themselves capable of using computers for diverse applications" (Malliari, 2012, p. 610). Computer self-measures are often one-dimensional; they consider one aspect of technology use,

such as the capability to use some type of software or hardware (Malliari, 2012; Spence & Usher, 2007).

Research studies report on how key antecedent variables impact self-efficacy for various technology-mediated environments. For example, family support structure impacted students' information technology self-efficacy, defined as general Internet self-efficacy for performing basic web tasks, and communication Internet self-efficacy, or confidence in communicating online (Chu, 2010). Across the full sample, both efficacy dimensions influenced students' perceptions of the learning environment. However, emotional support was a more salient predictor of both efficacy dimensions. Thus, for online learners, close relationships (e.g., parents of K-12 learners) likely impact their degree of self-efficacy, consistent with one of the four primary sources of self-efficacy: verbal and social persuasion (Usher & Pajares, 2008).

The relationship between technology efficacy and academic achievement has been mixed. Contributing to part of these mixed findings may be how technology efficacy is measured. For instance, Zimmerman and Kulikowich (2016) noted that most correlational results have been weak, although technology self-efficacy has significantly influenced achievement across various studies. Zimmerman and Kulikowich (2016) reported that despite examining technology use in online learning contexts, other important online learning factors have not been included in these scales, such as navigating the technology-enabled learning environment and using various digital tools in the online environment.

A recent systematic review of over 25 studies revealed that online learning self-efficacy had a significant positive relationship with achievement (Peechapol et al., 2018). Further, in several of the studies included in the review, prior achievement and prior experiences were antecedent variables of motivation and online learning self-efficacy. Other research supports the changing nature of Internet self-efficacy over time, suggesting that as students become more comfortable with technology, beliefs in their confidence increase (Lee, 2015).

As expressed above, the extant literature has utilized numerous terms to describe similar, but with some minor differences, self-efficacy measures within the domain of technology. In this study, however, we define technology efficacy for online learning somewhat differently. Because students are often experiencing full-time online learning environments for the first time and may only indirectly interact with teachers, we focus on a student's self-efficacy for engaging within an online learning environment. To accomplish this, we examine students' self-efficacy for navigating or using technology in the learning process and use the phrase *technology efficacy for online learning*.

Time Management

Students' success in OCSs heavily relies on their self-regulation of learning, as typical external supports (e.g., teachers' monitoring) are less available for students in OCSs. According to models of self-regulated learning (SRL), managing one's time, resources, and environment is one crucial aspect that must be planned, monitored, and reflected on (Pintrich & Zusho, 2007). Managing time may be particularly critical for students in OCSs because effectively managing time may promote the use of other strategies, reciprocally influence self-efficacy, and act as an outcome to measure overall learning performance (Zimmerman et al., 1994).

Within this study, student time management is essential for two primary reasons. First, time management is relevant for students most at-risk academically. For instance, Lewis et al. (2014) reported that at-risk alternative high school students list time management as a critical

challenge to online learning success along with self-responsibility. Second, other research suggests that SRL variables' (e.g. time management) impact may be particularly significant for online learners (Lewis et al., 2014; Roblyer & Marshall, 2002).

Time management has predicted academic performance across various contexts. For instance, in evaluating time spent on homework, the amount of homework completed, and general homework time management, Núñez et al. (2015) found that time management positively related to achievement, especially among older students. This relationship was substantiated by findings of other researchers. For instance, while including various personal student characteristics, Bender and Garner (2010) show, particularly among college students, a significant relationship between time management, attitudes, test strategies, and first-year college GPA. In sum, these findings provide evidence that time management, particularly from a goal-setting perspective, influences students' academic performance at the college level. Further analysis with younger learners and exploring other prior factors would be essential to understand in what manner time management relates to achievement.

Considering this review, in this study, we hypothesize that at-risk factors significantly predict Algebra 1 course grades. Additionally, we hypothesize that personal student characteristics (e.g. mathematics self-efficacy, technology efficacy, and time management) are causally related to mathematics achievement and that the impact of academic risk factors on achievement is conditioned by both domain-specific self-beliefs (mathematics self-efficacy and technology efficacy for online learning) and time management. As a result, the following research questions guide the current exploration:

1. After controlling for gender and age, to what degree do academic risk factors significantly predict mathematics achievement in Algebra 1?
2. Controlling for student gender, student age, and academic risk factors, to what extent do personal student characteristics significantly predict Algebra 1 achievement in a virtual learning setting?
3. How do personal student characteristics interact with the relationship between these academic risk factors and Algebra 1 achievement?

Setting the Context within Urban (Mathematics) Education

The current study takes place in one online charter school. This school primarily operates in an emerging midsize metropolitan city in the Midwest; however, students reside across a wide variety of geographic settings and demographic groups (Ohio Department of Education, 2019, 2021). The present study is situated in what could be considered an urban emergent setting (Milner, 2012), in this type of setting, schools are typically located in larger cities but not among the largest cities across the country; albeit to a smaller degree, these cities face similar resource challenges as the largest cities.

We believe that three key aspects of urban education, as conceptualized by Milner (2012) and Martin and Larnell (2013), are evident in this online charter school. First, according to Martin and Larnell (2013), an emerging aspect throughout the evolution of urban education has, at times, characterized students using a “deficit-focused, failure-focused master narrative” (Martin & Larnell, 2013, p. 981). This viewpoint is also evident in research on school dropout (e.g. Bowers et al., 2013; Croninger & Lee, 2001). More recently, Martin and Larnell (2013) recommended moving away from that approach, contending that research focused on mathematics success or excellence may not be as visible in the urban context. They suggest focusing on positive-minded

aspects, “based on robust, nondeficit significations of urban” (Martin & Larnell, 2013, p. 1009). Aligned with this view, the current study considers how various academic risk factors may be mitigated to positively impact mathematics achievement, de-emphasizing a deficit-minded approach (i.e. likelihood to dropout). Our study focuses on student-focused assets that may positively predict mathematics achievement (e.g., mathematics self-efficacy, technology self-efficacy, and time management skills). Second, urban education’s focus on equity and access through historical development is notable. Historically, issues of educational equity either have not appeared in reform work (upon the advent of NCTM Standards, for example) or these concerns “have been transformed into other kinds of issues” (Martin & Larnell, 2013, p. 1000). In part to address equity, access, and new opportunities for students, charter schools (and later online charter schools) evolved to provide academic programming for underserved populations from a variety of demographic and academic backgrounds. Charter schools promoted new educational initiatives and instructional approaches, like the online charter school in this study (Ahn, 2011; Waters et al., 2014). Third, Milner (2012) proposes three key geographic areas for how we might frame urban education. According to these conceptions, this study adds elements of both urban characteristics and urban emergence. According to the characterizations of these typologies, this school also faces similar challenges as other urban areas, such as an increase in diverse populations and socioeconomic diversity. Most recent data show that overall, as a state, charter schools serve lower-income, more demographically diverse, and higher percentages of students with disabilities (Ohio Department of Education, 2019). More directly, at the school level, this online charter school includes students of similar demography (81% economically disadvantaged, 64% minority students, and 18% students with disabilities).

We believe that the current study can extend the knowledge base of urban mathematics education in two key areas. First, the study can provide support for research that targets an asset-minded focus. We focus on factors that positively impact achievement and might mitigate the effects of risk factors on academic achievement, particularly considering student beliefs about learning. Second, this study can provide support for how charter schools in general, and online charter schools more directly, might address educational equity and access.

Methodology

Participants and Procedures

The current study included a sample of 93 Algebra 1 students from one online charter high school in a midwestern state in the United States. Students were enrolled in an online Algebra 1 course, primarily conducted asynchronously, with regular weekly opportunities for synchronous tutoring sessions with teachers. Of these students, 63 included complete survey responses used for analysis. Approximately 71% ($n=45$) of the sample is female, and 38% qualified for Free and Reduced-Price Lunch. Additionally, about 7% of the sample had taken the course previously. Finally, about half of the students (52%) were 14 years of age, the typical age for Algebra 1 students in 9th grade. Data collection occurred across one semester in the fall of 2020. During the semester, students completed one combined survey requesting demographic and self-report items of four separate adapted scales outlined in the following section and surveyed in the following order: parental involvement, technology efficacy for online learning, mathematics self-efficacy, and time management. After the semester, we requested from the school data on prior academic, demographic, and outcome variables, of which a subset was retained for the current study.

In making these methodological choices, our research design is informed by our research purpose. Through our design and to conduct primarily associative and predictive analysis techniques, we utilized quantitative techniques in a survey research design. Our data collected further supported this research design by the nature and scope of the data. When examining similar variables, other prior studies have used similar procedures and analysis techniques when examining associations with achievement, such as with at-risk factors (Ahn, 2011; Bowers et al., 2013; Kaufman & Bradbury, 1992; Woodworth et al., 2015); with mathematics self-efficacy (Fast et al., 2010; Parr & Bonitz, 2015; Randhawa et al., 1993; Wu, 2016); and technology efficacy (Zimmerman & Kulikowich, 2016). Thus, our design is also influenced by these prior studies.

Measurement Instruments

Data collection included both school-provided (*) and self-reported (#) items (demographic and self-report items on one survey). First, both gender* and age* were collected as demographic variables from school-provided data.

The reliability of the instruments can be found as Cronbach's alpha coefficient in Table 1 within the Results section. Prior to examining reliability, we conducted a factor analysis on each of the four existing survey scales. For parental involvement, technology efficacy for online learning, mathematics self-efficacy, and time management, we utilized factor analysis to examine the feasibility of a one or two-factor variable, in alignment with the prior research studies from which they were adapted. To conduct factor analysis, the study used principal components analysis (PCA). The primary assumptions of PCA were checked, and only minimal outliers were detected; however, because all other assumptions were met, analysis was conducted while acknowledging this limitation. The goal of PCA is to examine patterns of correlations across observed variables to reduce the data to a smaller subset of factors or components (Tabachnick & Fidell, 2013). Using PCA, there was strong support for a one-component solution for each of the four pairs of subscales included in the analysis, except for Grade Anxiety, which was dropped from final analyses. Additionally, Cronbach's alpha examined internal consistency, and data supported strong scale reliability. Thus, composite scores were used for this analysis.

Academic Risk Factors

Two variables are included as academic risk factors. SES* was measured using Free and Reduced Priced Lunch Application status. Parental involvement[#] was measured using an original scale which "was developed to assess mothers' and fathers' educational involvement in the home." (Rogers et al., 2014, p. 173). Original scale reliability range was .6 -.89 (Cronbach's alpha). This study's scale was adapted to read "parent/primary guardian" instead of "mother or father" For this study, parental involvement was modified to a 13-item self-report measure, rated on a 5-point Likert scale, ranging from strongly disagree to strongly agree. An adapted sample item includes *Most of the time, my parent/primary guardian looks at my homework*. Past studies have used this scale in its original form with acceptable validity (Campbell, 1994; Mboya, 1993 as cited in Rogers et al., 2014).

Personal Student Characteristics

Three variables are included to measure personal student characteristics: technology efficacy for online learning, mathematics self-efficacy, and time management. Technology self-efficacy for online learning (TE-OL)[#]: the Online Learning Self-Efficacy Scale (Zimmerman & Kulikowich, 2016) included three factors representing online learning: self-efficacy for navigating technology, self-efficacy for using technology in learning, and time management (original scale reliability range Cronbach's alpha: .843-.890). For the current study, the survey was adapted to a 17-item scale utilizing the first two factors, measured on a 6-point Likert scale, ranging from "performing task poorly" to "perform at an expert level." A sample item asks for student perceptions of their ability to perform certain tasks, such as searching the Internet to find the answer to a course-related question. In the validation study, utilizing the original items, validity was acceptable across their factor analysis (Zimmerman & Kulikowich, 2016), particularly noting a multiple-scale instrument as a better indicator.

Mathematics self-efficacy (MSE): an adapted version of the Mathematics Self-Efficacy and Anxiety Questionnaire (May, 2009) was used. MSE (original scale reliability range Cronbach's alpha: .92-.96) is a 15-item scale utilizing the first two factors (General Mathematics Self-Efficacy, Grade Anxiety factor), measured on a 5-point Likert scale, ranging from never to usually. A sample item asks for student perceptions of confidence across several components, such as *I believe I can do well on a mathematics test.*

Time management (TM)[#]: the time management scale (Won & Yu, 2018) included three latent factors: planning time, monitoring time, and procrastination (original scale reliability range Cronbach's alpha: .8-.89). For the current study, TM is an adapted 9-item survey utilizing these first two factors, measured on a 7-point Likert scale, ranging from strongly disagree to strongly agree. A sample item asks for student perceptions of their ability to manage time, such as setting goals or making lists regarding what I need to get done each day. Regarding validity, past research and analysis completed in the original source, who conducted exploratory factor analysis (Won & Yu, 2018), indicated support for three subscales, of which the current study used two of those subscales.

Outcome Variables

The academic outcome variable included in this study is Mathematics course grade* using the final semester grade in Algebra 1.

Data Analysis

For all analyses, we used SPSS version 27. Regarding assumptions of statistical tests for PCA, there were some minor deviations in assumptions of multiple linear regression, such as marginal errors between observed and predicted outcome values, and in homoscedasticity with some marginal uneven patterns. All other assumptions were met.

First, descriptive statistics and bivariate correlation coefficients of all continuous variables are presented. Next, in seeking responses to research questions 1-3, we used sequential multiple linear regression to examine whether different groups of variables predicted mathematics achievement. Three separate models were examined when analyzing research questions two and three. All three models started with and controlled for student demographics, including age and

gender. Further analytical procedures are outlined below. For research question one, we developed one statistical model. After controlling for student gender and age in our statistical model, we added each of the academic risk factors (parental involvement and SES) as the second set of predictor variables of Algebra 1 semester grade in our sequential multiple regression model. We sought to examine both the regression coefficients and change in explained variance obtained by adding academic risk factors to our model.

For research question two, we added an additional variable in step three of our sequential multiple regression model. For this research question, we created three different statistical models: a model for mathematics self-efficacy (Model 1); technology efficacy for online learning (Model 2); and time management (Model 3). We analyzed these three models separately and examined both regression coefficient and changes in variance explained while adding the personal student characteristics. Finally, for research question three, we added two interaction terms to each of the three models in step four of our sequential multiple regression analysis. A multiplicative interaction term combining one of the personal student characteristics with each academic risk factor separately was calculated and included in each of the three models. We analyzed these three models separately and examined both regression coefficient and changes in variance explained while adding these interaction terms. Along with this analysis, conditional effects were examined, centering the referenced personal student characteristic at one SD below the mean, one SD above the mean, and at the mean.

Results

Table 1 presents descriptive statistics for the continuous variables, and bivariate correlations were also examined (Table 2).

Table 1

Descriptive Statistics of Continuous Variables

Variable	Minimum	Maximum	Mean	SD	Alpha reliability
Semester Grade	7.00	102.00	82.70	18.06	-
Age	11	16	13.89	.88	-
GPA	.24	4.5	3.08	1.00	-
Parental Involvement	1.62	4.92	3.65	.79	.885
Technology Efficacy	2.50	5.76	4.79	.73	.890
Mathematics Self-efficacy	1.00	5.00	3.76	1.18	.97
Time Management	1.56	7.00	4.58	1.56	.919

Students performed at an above-average level during the semester (83%); however, individual grades varied considerably, with a standard deviation of 18.06. Additionally, slightly under 50% qualify for free- and reduced-price lunch. Although this is high according to the state average across all schools (Ohio Department of Education, 2019), it is relatively low compared to

similar schools. Most of the students in this study sample are of traditional 9th grade age (14-15 years old), however a small percentage differs. Limited to one course (Algebra 1), the use of age in this study may be more meaningful given that students typically take Algebra 1 for the first time in 9th grade. Further triangulation of other data would be needed to verify this claim. Finally, students perceive that they are fairly capable of doing well in mathematics class and using technology to attend and engage in class.

There were small to moderate significant correlations among several of the variables with Semester Grade, including age, technology efficacy for online learning and mathematics self-efficacy; personal student characteristics were moderately correlated with each other; but the family-based academic risk factors were not significantly correlated with each other or any of the personal student characteristics. Age and grade level were negatively correlated. Because most students take Algebra 1 near the ninth grade in Ohio, it is likely older students either took Algebra 1 more than once or were enrolled in remedial courses, and more likely to earn a lower grade although this is only speculative.

Table 2

Correlation Table of Study Variables

Variable	1	2	3	4	5	6
1. Grade	1					
2. Age	-.458**	1				
3. Parental Involvement	.037	.019	1			
4. Technology Efficacy	.273*	-.07	.233	1		
5. Mathematics Self-efficacy	.593**	-.269*	.14	.384**	1	
6. Time Management	.234	-.032	.349**	.508**	.435**	1

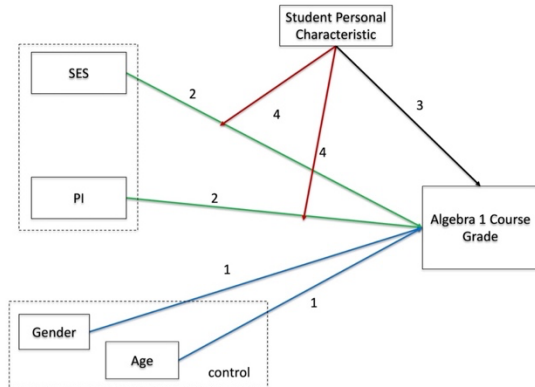
* $p < .05$. ** $p < .01$.

Multiple Linear Regression

The analyses considered four groups of predictors: 1) control variables (gender and age); 2) family-based academic risk factors; 3) one of three of the personal student characteristics (Model 1: mathematics self-efficacy; Model 2: technology efficacy, and Model 3: time management); and 4) interaction terms between the personal student characteristics and each family-based risk factor, as depicted in Figure 1.

Figure 1

Proposed Conceptual Model of Academic Risk Factors, Personal student Characteristics and Mathematics Achievement



Impact of Demographics and Family-based Factors

Two family-based academic risk factors were included in this study: parental involvement and family SES. Controlling for student gender and age, family-based academic risk factors added no additional significant variance, F change(2,45) = 1.341, $p = .272$, R^2 Change = .044. However, the overall model was significant, $F(4,45) = 4.054$, $p = .007$. Controlling for gender, parental involvement, and SES, student age significantly predicted Semester Grade, suggesting the importance of accounting for when students enroll into Algebra 1 ($Age: B = -8.54$, $p < .001$), according to Step 2 in Table 3. See Table 3 for the results of all models. This result is, at least, somewhat surprising, given past research that suggests a strong influence of family and social influences on achievement (e.g. Anderson & Keith, 1997; Croninger & Lee, 2001; Kaufman & Bradbury, 1992; Suh et al., 2007). The current study focused on a single measure of SES, potentially impacting this relationship.

Table 3*All Model Results*

Variable	Standardized Coefficient <i>B</i> (SE)			
	Step 1	Step 2	Step 3	Step 4
<i>(Models for mathematics self-efficacy)</i>				
Constant	78.46** (3.04)	82.4** (3.92)	83.21** (3.23)	83.76** (3.02)
Gender	4.63 (5.43)	5.37 (5.54)	3.98 (4.57)	6.32 (4.36)
Age	-9.32** (2.64)	-8.49** (2.67)	-4.99* (2.32)	-5.66* (2.18)
SES		-7.14 (4.96)	-8.01 (4.16)	-9.7* (3.95)
Parental involvement		-0.17 (3.23)	-0.63 (2.66)	0.5 (2.52)
Mathematics Self-efficacy			9.27** (1.96)	2.67 (3.13)
MSExSES				9.62* (3.76)
MSExPI				-3.74 (2.2)
<i>R</i> ² Change:		.04	.25**	.08*
<i>R</i> ² Cumulative:	.22**	.26	.51**	.59*
<i>(Models for technology self-efficacy)</i>				
Constant	78.46** (3.04)	82.4** (3.92)	80.73** (3.78)	82.03** (3.75)
Gender	4.63 (5.43)	5.37 (5.54)	7.91 (5.49)	7.86 (5.3)
Age	-9.32** (2.64)	-8.49** (2.67)	-8.36** (2.58)	-8.9** (2.5)
SES		-7.14 (4.96)	-7.16 (4.85)	-7.71 (4.69)
Parental involvement		-0.17 (3.23)	-1.69 (3.21)	-0.29 (3.29)
Technology Efficacy			6.25 (3.31)	-1.58 (4.63)
TE-OLxSES				12.9* (6.05)
TE-OLxPI				-3.91 (4.36)
<i>R</i> ² Change:		.04	.05	.08
<i>R</i> ² Cumulative:	.22**	.26	.31	.39
<i>(Models for time management)</i>				
Constant	78.46** (3.04)	82.4** (3.92)	81.38** (3.85)	82.04** (3.98)
Gender	4.63 (5.43)	5.37 (5.54)	7.23 (5.49)	7.65 (5.42)
Age	-9.32** (2.64)	-8.49** (2.67)	-8.54** (2.6)	-9.35** (2.63)
SES		-7.14 (4.96)	-7.14 (4.96)	-6.93 (5)
Parental involvement		-0.17 (3.23)	-2.21 (3.33)	-1.29 (3.32)
Time Management			3.05 (1.64)	0.47 (2.17)
TMxSES				5.82 (3.25)
TMxPI				-1.31 (2.27)
<i>R</i> ² Change:		.04	.05	.05
<i>R</i> ² Cumulative:	.22**	.26	.31	.36

Note. Gender reference group is female. SES reference group represents students who do not qualify for free- or reduced-price lunch.

* $p < .05$, ** $p < .001$

Direct and Moderating Influence of Personal Student Characteristics

Research question two examined the relationship between personal student characteristics with Algebra 1 course grades. Model 1 added mathematics self-efficacy. Model 2 added technology efficacy for online learning. Model 3 added time management. Research question three explored the interaction of personal student characteristics and family-based academic risk factors on Algebra 1 achievement.

Mathematics Self-Efficacy (MSE). MSE added approximately 25% additional variance explained to Semester Grade, F change (1,44) = 22.47, $p < .001$, R^2 Change = .248, and the overall model was significant, $F(5,44) = 9.284$, $p < .001$. Controlling for other variables, students' mathematics self-efficacy significantly predicted Semester Grade ($B = 9.27$, $p < .001$; Table 3). Additionally, a student's age is significantly predictive of Semester Grade, controlling for other factors. Together, these results suggest that content-specific perceptions of capability influence how well students achieve in the course. MSE has been shown to be a relatively consistent predictor of mathematics achievement, and these results mirror those from other studies (Fast et al., 2010; Grigg et al., 2018; Parr & Bonitz, 2015). Further, domain-specific self-efficacy measures more often predict achievement (i.e. mathematics self-efficacy, rather than general self-efficacy; Compeau & Higgins, 1995; Wang et al., 2013; Zimmerman & Kulikowich, 2016).

Interaction Effects. Adding two interaction terms significantly added to the explained variance in Semester Grade: by approximately 8%, $F(2,42) = 4.251$, R^2 Change = .082, $p = .02$. Results show that the interaction of mathematics self-efficacy with SES is significant ($B = 9.623$, $p < .05$). These results suggest that the association of mathematics self-efficacy on Semester Grade strengthens as SES increases. Additionally, the relationship of parental involvement on Semester grades weakens as mathematics self-efficacy increases, although this effect is not significant.

Conditional Effects. Regarding the effect of SES on Semester Grade, conditioned on various levels of mathematics self-efficacy, the effects at both low and average mathematics self-efficacy were statistically significant (Low: $B = -19.5$, $p < .001$; Average: $B = -9.73$, $p < .05$). Results suggest that as perceived mathematics self-efficacy decreases, the impact of SES on Semester Grade is stronger and more pronounced. Although not significant, the impact of SES on Semester Grade nearly disappears for students with high mathematics self-efficacy ($B = -.39$, $p > .05$). Regardless of the level of mathematics self-efficacy, the impact of SES on Semester Grade appears more positive or stronger for those who qualify for free- or reduced-price lunch.

Next, when students reported lower or average mathematics self-efficacy, the relationship between parents' involvement in their course grades was slightly negative in contrast to those with higher mathematics self-efficacy. Students with higher mathematics self-efficacy may more likely experience benefits from parental involvement in their schooling, while parental involvement had a somewhat negative relationship on Semester Grade for those with average or low mathematics self-efficacy. Clarifying these results, it is possible that students might succeed regardless of other extenuating or negative factors such as SES. For instance, Spence and Usher (2007) determined that mathematics self-efficacy within a virtual learning environment may promote change in the risk to achievement relationship.

Technology Efficacy for Online Learning. Technology efficacy added approximately 5% additional variance explained to Semester Grade, a nonsignificant increase, F change(1,45) = 3.562, $p = .066$, R^2 Change = .054. However, the overall model was significant, $F(5,45) = 4.184$, $p = .003$. Despite an overall significant model, controlling for other variables, students' technology efficacy for online learning did not significantly predict Semester Grade ($B = 6.248$, $p = .066$).

Age was significantly and negatively predictive of Semester Grade, controlling for other variables ($B = -8.36, p = .002$). These results differ from Model 1, which included a more domain-specific measure of self-efficacy. Other research has generally supported some of these results, suggesting that technology self-efficacy most likely relates to motivational characteristics (Malliari, 2012; Spence & Usher, 2007). The current study may help to support those prior claims. Additionally, a more general self-efficacy (technology self-efficacy predicting mathematics achievement) also may be another explanation for the weak association, noted in the above results regarding MSE. Despite this, other research does support its relationship to other outcome variables, such as achievement (Bates & Khasawneh, 2007; Wang et al., 2013).

Interaction Effects. Model 2 added technology efficacy as a moderator which did not significantly add to the explained variance in Semester Grade, $F(2,43) = 2.717, R^2 \text{ Change} = .077, p = .077$. Results show that the interaction of technology efficacy with SES was significant ($B = 12.9, p = .039$).

Conditional Effects. The effects at both low and average technology efficacy were statistically significant (Low: $B = -16.51, p < .05$; Average: $B = -9.39, p < .05$). Results suggest that as perceived technology efficacy decreases, the relationship of SES on Semester Grade is stronger or more pronounced. Although not significant, the impact of SES on Semester Grade is reduced for students with high technology efficacy ($B = -2.27, p > .05$), suggesting that for students with higher perceived self-efficacy for learning in online environments, SES had minimal impact on Semester Grade.

Time Management. Similar to technology efficacy, when interpreting the model that included time management, this variable also added approximately 5% additional variance explained to Semester Grade; however, this additional variance was nonsignificant, $F \text{ change}(1,44) = 3.457, p = .07, R^2 \text{ Change} = .054$. The overall model was significant, $F(4,45) = 4.112, p < .004$. Controlling for other variables, students' planning and monitoring of time management did not significantly predict Semester Grade ($B = 3.048, p = .07$), while age was significantly and negatively predictive of Semester Grade, controlling for other variables ($B = -8.54, p = .002$). Past research has shown the importance of time management in online learning (Lewis et al., 2014; Whipp & Chiarelli, 2004) and for at-risk learners (Archambault et al., 2010; Lewis et al., 2014), however, our results contradict these past findings, such as in Núñez et al., (2015).

Interaction Effects. Model 3 added time management as a moderator which did not significantly add to the explained variance in Semester Grade, $F(2,42) = 1.631, R^2 \text{ Change} = .049, p = .208$. Results show that the interactions of time management with both SES ($B = 5.821, p = .08$) and parental involvement ($B = -1.308, p = .375$) were not significant.

Conditional Effects. Regarding the effect of SES on Semester Grade, conditioned on various levels of time management, the conditional effects for low time management were statistically significant (Low: $B = -14.78, p < .05$). These results suggest that as perceived time management decreases or for students with lower levels of time management skills, the impact of SES on Semester Grade is stronger or more pronounced. No other conditional effects were significant.

Error! No text of specified style in document.1Error! No text of specified style in document.2 **Discussion**

Set within the domain of high school mathematics, the study explored how personal student characteristics, including mathematics self-efficacy, online learning self-efficacy, and time

management planning and monitoring, and family-based at-risk factors impacted mathematics achievement in an online charter school among Algebra 1 students.

Three key findings were identified from the analysis, highlighted in the following sections.

1. Family-based academic factors did not significantly account for additional variance in Semester Grade. However, student demographics, including gender and age, significantly explained variance in mathematics achievement.
2. Personal student characteristics did not consistently predict mathematics achievement. While mathematics self-efficacy significantly predicted Semester Grade, a student's self-efficacy for online learning and time management did not predict mathematics achievement.
3. Personal student characteristics interacted with family-based factors, and mathematics self-efficacy was the strongest moderator. Additionally, while the moderators significantly interacted with SES, other important though insignificant trends were observed with the interaction of parental involvement.

Family-Based Academic Factors and Mathematics Achievement

Together both family SES and a student's perception of parental involvement did not significantly explain additional variance or predict Semester Grade. This result contrasts findings from other studies that emphasized a strong influence of family or social factors on student achievement and motivation (e.g. Croninger & Lee, 2001).

Unlike other studies that have shown a consistent and notable relationship among SES and achievement (Anderson & Keith, 1997; Kaufman & Bradbury, 1992; Suh et al., 2007), this study situated SES as a single variable, self-reported by families. This measurement choice, in combination with a more narrowed focus on Algebra 1 achievement, rather than more general achievement likely impacted the strength of this relationship.

Parental involvement also did not predict Semester Grade. This finding aligns with other research; however, the impact of parental involvement might be weaker across older students. For instance, Anderson and Keith (1997) and Núñez et al. (2015) found little to no effect of parental involvement on achievement, after accounting for other variables such as grade level and student homework behavior. In the current study, both the regression coefficient and the correlation between Algebra 1 grade and parental involvement support this conclusion. That is, although parental involvement was generally positive among students in this study, it had little impact on their academic achievement.

Differential Role of Personal Student Characteristics

Mathematics self-efficacy, compared to other more general academic predictors (technology efficacy, time management), was a more consistent predictor of Semester Grade, similar to other studies (Fast et al., 2010; Grigg et al., 2018; Parr & Bonitz, 2015). Further takeaways are elaborated below.

First, research across several scale validation studies has shown that more specific, rather than more general, survey scales function as a better predictor for student outcomes (Compeau & Higgins, 1995; Wang et al., 2013; Zimmerman & Kulikowich, 2016). In the current study, the scale items included a combination of both general and specific self-reported survey items. Consequently, for technology efficacy and time management, these findings from prior research provide support for their negligible influence.

Second, more recent research has shown that one's technology efficacy is most likely to be related to motivational characteristics or course satisfaction rather than achievement (Malliari, 2012; Spence & Usher, 2007) although this is not conclusive. For instance, Zimmerman and Kulikowich (2016) state that although some studies do show a significant and positive link between technology-efficacy and achievement in online learning (Peechapol et al., 2018), the relationships are often weak. Zimmerman and Kulikowich argue that this is because task-specific online learning factors are not often included in the analysis, such as using the learning management system or locating digital resources. Possibly, results from this study are more aligned to these former studies; this may help explain some of the weaker findings from this current study (Abulibdeh & Hassan, 2011; Lee, 2015; Malliari, 2012; Zimmerman & Kulikowich, 2016).

Lastly, time management, similar to technology-efficacy for online learning, was not a significant predictor of Semester Grade, controlling for student demographics and family-based academic risk factors. Although time management is considered essential for online learning students (Lewis et al., 2014; Whipp & Chiarelli, 2004) and at-risk learners (Archambault et al., 2010; Lewis et al., 2014), the results from this study show that students' time management only marginally relates to achievement. However, these findings contradict other research that shows a moderate and significant relationship between time management and achievement, especially among older students (Núñez et al., 2015). It is possible that the influence of self-efficacy was too strong to detect any influence of time management. Additionally, students responded generally about time management, and their responses might not have been directly related to their attendance in Algebra 1 class. Typically, managing time can be controlled and monitored (Bowman et al., 2019; Pintrich, 2000). Once students are effective at managing time, this promotes other strategies and attributes needed in online learning. Additionally, effectively managing time reciprocally influences positive self-efficacy (Zimmerman et al., 1994).

Personal Student Characteristics Moderated Risk and Achievement

Mathematics self-efficacy was a significant moderator variable. Across various studies, researchers found a consistent and similar pattern, where mathematics self-efficacy was one of the strongest predictors of achievement, while also being significantly related to other more personal characteristics, such as SES or prior achievement (Anderson & Keith, 1997; Parr & Bonitz, 2015). Because mathematics self-efficacy significantly predicted Semester Grade, similar to other studies (Fast et al., 2010; Parr & Bonitz, 2015; Randhawa et al., 1993), this finding is not too surprising.

Conversely, technology-efficacy for online learning and time management did not significantly predict course achievement when interacted with the family-based at-risk factors. It is plausible that these two moderator variables were not situated directly enough within the context of the course. Evidence from other research has shown that these variables are less likely to relate to achievement; rather, they relate more directly to other outcomes, such as course satisfaction, task value, or technology use (Lee, 2015; Malliari, 2012; Shen et al., 2013; Wang et al., 2013).

A second notable finding showed that across each of the moderation models, SES significantly interacted with each of the moderator variables. The effects of these moderators generally diminish the relationship of SES on Semester Grade. In the model that included mathematics self-efficacy, when the strength of SES on mathematics achievement was conditioned on specific levels of mathematics self-efficacy, as mathematics self-efficacy increased, the negative relationship of SES on Semester Grade diminished. Students who might perceive they are more self-efficacious during school in this virtual learning environment may succeed

regardless of extenuating social or familial factors. Spence and Usher (2007) determined that mathematics self-efficacy within a virtual learning environment may promote change in the risk to achievement relationship. The results from this study provide additional evidence among younger online students of the importance of mathematics self-efficacy, even when controlling for other variables.

Similar findings were observed in the model that included technology efficacy. If students feel highly efficacious in navigating the various features of the online learning platform, they are more likely to succeed in their course. Consequently, schools should consider scheduling orientation courses that promote technology-efficacy through developing technology ability because research shows a relationship between technology self-efficacy and technology ability (Bates & Khasawneh, 2007). Although much of the research has shown that technology efficacy more consistently relates to course satisfaction outcomes, evidence supports its role alongside other predictor and outcome variables (Bates & Khasawneh, 2007; Wang et al., 2013).

As levels of the moderators increase, the effect of these family-based factors on achievement becomes more positive. This suggests that virtual school students who experience higher levels of personal self-beliefs or time management could benefit from these more positive aspects, despite the presence of family-based SES. Thus, as students have more adaptive profiles of these characteristics, the relationship between family and achievement is less negative.

Scholarly and Practical Significance

The results of this study have several implications for future research and practitioners.

First, the results of this study support the critical role of student demographics. For instance, age was an important and significant predictor of Algebra 1 achievement. The results suggest that while age matters, once other more personal characteristics are added in, the effects of age are less important. As a result, even for students who might retake Algebra 1, strong or more adaptive self-beliefs or learning strategies may help to minimize the negative effects of age. Parents, as learning coaches, and school officials should have a role in building this capacity for students.

Second, this study showed how social-emotional factors such as self-efficacy were critically influential on students' success in Algebra 1. Research shows that prior mastery experiences, vicarious experiences, as well as verbal or social persuasion, such as support or encouragement, are fundamental for students to build self-efficacy. Teachers can help build students' skills, engendering higher confidence, by modeling approaches and connecting learning to real-life experiences and career-focused opportunities. Additionally, to build effectiveness and confidence within the instructional environment, increasing orientation programming to scaffold students (and parents) into the learning management system and learning environment could provide necessary positive mastery experiences to support students and their families.

Finally, the results of this study show that self-beliefs and time management act as important mechanisms for the relationship between family-based academic risk factors and Algebra 1 achievement in virtual learning environments. The results show that for students with more adaptive beliefs and better time management the effects of SES on Algebra 1 achievement diminished. If this is replicable across other research, this finding has broad implications because it shows the important contribution of deep personal beliefs and how they might change the relationship of some possible risk factors on achievement. As a result, schools should strive to

create programming that supports students' social-emotional and self-regulated learning development in addition to academic skills.

Study Limitations

The study has several key limitations. First, the sample size that was useable for analysis necessarily limited both the analytic techniques and the confidence for reliable results with the statistical power needed. A larger sample size with a more diverse sample would improve future generalizations and broader implications.

Second, the outcome variable for the current study was end-of-semester course grades. Although course grades represent an easily obtainable continuous measure for analysis, using a singular component such as a course grade may not be most effective in understanding students' actual achievement. Using targeted assessment outcomes based on a task or using more sequenced achievement measures might provide an ongoing measure of performance instead.

Third, across multiple studies and decades of at-risk research, researchers have found that adding multiple, rather than single risk factors in analysis likely captures a more holistic picture of risk. Researchers also acknowledge that adding in family-based social factors and student-based academic factors increases statistical fidelity. Due to sample size limitations, this study was unable to add additional academic risk factors, limiting this study to develop and interpret a family-based risk model instead.

Finally, the study consistently found that subject-specific mathematics self-efficacy was more predictive than the other moderator variables. The other moderators did not specifically address the subject area (mathematics) while students self-reported their responses. As such, this may have limited some takeaways and given increased relevance to mathematics self-efficacy.

Conclusion

This study provides theoretical and empirical support for the role that students' self-regulated learning strategies and beliefs have in virtual learning environments. In this study, the results showed that students with more context-specific beliefs, in this case, mathematics self-efficacy, achieve higher grades, mostly despite the influence of family-based risk factors. This study contributes to the small subset of research into important factors within high school virtual learning and calls for the field to expand knowledge of virtual learning success factors. These findings could impact how schools serve and prepare historically underrepresented and nontraditional students to succeed in high school and beyond.

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