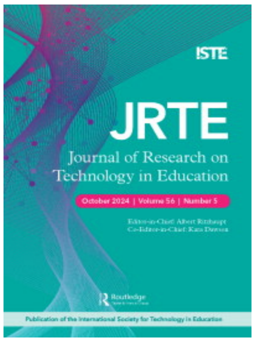

Journal of Research on Technology in Education

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ujrt20

Teacher goal setting for personalized learning software: associations with perceptions of the value of software and growth mindsets

Ellen Rydell Altermatt & Andrea K. Rorrer

JOURNAL OF RESEARCH ON TECHNOLOGY IN EDUCATION
https://doi.org/10.1080/15391523.2024.2411697

Routledge
Taylor & Francis Group

Teacher goal setting for personalized learning software: associations with perceptions of the value of software and growth mindsets

Ellen Rydell Altermatt and Andrea K. Rorrer

Utah Education Policy Center, University of Utah, Salt Lake City, Utah, USA

ABSTRACT

Although student use of personalized learning software has been linked to higher test scores and more positive achievement-related attitudes, much remains to be learned about best practices for creating strong technology-enabled learning environments. The current study examines associations between the goals teachers set for their students' use of math personalized learning software and both teacher and student attitudes. Teachers reported setting mastery-based goals for software use less frequently than time-based goals. However, mastery-based goal setting was more strongly associated with positive teacher perceptions of the value of math software and with students' endorsement of growth mindsets. Associations between goal setting and outcomes were especially strong among teachers who reported providing lower levels of support to students as they used software.

ARTICLE HISTORY
Received 4 January 2024
Revised 5 August 2024
Accepted 26 September 2024

KEYWORDS
Educational technology; K-12; mathematics; pedagogy; achievement motivation; academic performance

Introduction

Students in the United States are not performing well in mathematics (National Science Board & National Science Foundation, 2021; OECD, 2022). Although K-12 students showed modest gains in math achievement test scores over the past few decades, there have been significant drops in these scores since the pandemic. Declines in mathematics achievement since 2019 have been particularly pronounced among some groups of students, including Black students, Hispanic students, and students attending high-poverty schools (Fahle et al., 2023; Kuhfeld et al., 2022).

One approach that educational stakeholders have promoted to both improve performance and address disparities in mathematics achievement involves "personalizing" instruction to be responsive to students' individual learning needs. Proponents of this approach argue that personalized learning environments have myriad benefits for teachers and students, including improving teachers' self-efficacy for supporting struggling students (Brizard, 2023), more effectively addressing learner variability at the classroom level (Pape & Vander Ark, 2021), and increasing students' interest and confidence in mastering academic content (Reber et al., 2018; Schoenherr, 2024).

Although personalized instruction takes many forms (see Bernacki et al., 2021, for a review), advances in technology have resulted in increased uptake of digital solutions to personalization, including learning software programs that are designed to continuously adjust tasks, instructions, and feedback to help students master new skills (Baker, 2016; Bernacki et al., 2021; Gallup, 2017; Pane et al., 2015). Several recent meta-analyses have shown that K-12 students who use personalized learning software programs have higher scores on standardized mathematics

CONTACT Ellen Rydell Altermatt ellen.altermatt@utah.edu Utah Education Policy Center, 1721 Campus Center Drive, Room 1262, Salt Lake City, UT 84112, USA.

assessments than similar students who do not (e.g. Cheung & Slavin, 2013; Hillmayr et al., 2020; Ma et al., 2014; Zheng et al., 2022). Likewise, several recent studies have linked use of math learning software to positive student attitudinal outcomes including higher perceptions of competence and stronger endorsement of a growth mindset, or the belief that ability can change through hard work (e.g. Altermatt, Rorrer, et al., 2023; Rutherford et al., 2020).

Importantly, however, the effect of personalized learning software on students' motivational, affective, and learning outcomes appears to be moderated by various factors including the quality of its use (e.g. Campuzano et al., 2009; Pane et al., 2017). More research is needed to identify, understand, and address these factors, particularly given growing evidence for a "digital use divide" wherein some students use learning software in ways that enhance both their mathematics confidence and skills while others use these programs in ways that contribute to disengagement among students and dissatisfaction among educators (Ritzhaupt et al., 2020; U.S. Department of Education, 2017; Valadez & Durán, 2007). In the current study, we focus our attention on one of these factors: the goals that teachers set for their students' use of math personalized learning software.

Achievement goal orientations and achievement goal structures

Decades of research indicate that the goals students adopt for completing academic tasks can be important predictors of students' achievement-related attitudes. Students who adopt mastery goal orientations—that is, goals to develop new skills or improve competence—typically have higher self-efficacy and more positive achievement-related emotions than students who adopt other types of goal orientations, including goals to avoid appearing incompetent (i.e. performance-avoidance goals) and, in some cases, goals to outperform others (i.e. performance-approach goals) (Huang, 2011, 2016). One reason that mastery goal orientations may yield positive achievement-related attitudes is that students who adopt these goals tend to engage in effective learning strategies, including viewing errors as a normal part of learning, seeking help when necessary, deepening cognitive engagement, and persisting in the face of challenges (Diseth & Kobbeltvedt, 2010; Kaplan & Maehr, 1999).

Notably, teachers play an important role in influencing students' achievement goal orientations by fostering specific achievement goal structures in their classrooms (Bardach et al., 2020; Shim et al., 2013). Achievement goal structures are sometimes communicated directly to students. Often, however, these structures are communicated indirectly *via* grading criteria, grouping practices, or reward systems. For example, teachers can reinforce mastery goal orientations by setting clear learning objectives, using data from formative assessments to inform instruction and practice, providing feedback that focuses on improvement, encouraging students to self-assess and reflect on their learning, and allowing opportunities for revision and reassessment (Patrick et al., 2003; Shim et al., 2013; Wolters et al., 2010). Like achievement goal orientations, achievement goal structures have been linked to positive achievement-related attitudes and behaviors. For example, mastery goal structures have been linked to increased persistence, decreased procrastination, and decreased self-handicapping in students (Midgley & Urdan, 2001; Wolters, 2004) and to students' perceptions that the classroom climate is respectful and supportive (Patrick et al., 2011). Mastery goal structures have also been linked to positive teaching-related emotions among educators including greater enjoyment of teaching and increased self-efficacy (Wang et al., 2017).

The bulk of achievement goal theory and research has focused on mastery goals, performance-approach goals, and performance-avoidance goals (Bardach et al., 2020; Wolters, 2004). However, there is a growing consensus that focusing on these goals, alone, fails to capture the array of aims that govern students' behaviors in the classroom. Consistent with this perspective, researchers are increasingly attending to other types of goals (Elliot et al., 2011), including goals to minimize effort on school-related tasks (i.e. work-avoidance goals; King & McInerney, 2014) and goals to match or exceed a previous accomplishment (i.e. personal-best goals; Martin & Elliot, 2016). Researchers are not only broadening the scope of goals they examine, but also recognizing the limitations of primarily evaluating achievement goal structures at a "macro" level. This acknowledgment stems from evidence that the achievement goal structures formulated and conveyed by teachers to their students can differ across various classroom activities (Lüftenegger et al., 2017). Consistent with these trends, the current study focuses on time-based and mastery-based goals for students' software use as these are the goals most often recommended by math learning software developers (An et al., 2022).

Goal setting for personalized learning software

The use of digital learning platforms in K-12 classrooms is widespread. While their use is sometimes contested (Kerssens & van Dijck, 2022), perceptions of digital learning platforms are generally positive. For example, in a Gallup (2017) study that included a nationally representative sample, 53% of teachers reported that students in their classrooms use digital learning platforms every day to support their learning. Moreover, 81% of teachers reported that they see value in using digital learning platforms, with the majority indicating that digital learning platforms are more effective than non-digital tools for personalizing instruction and engaging students with school and with learning (Gallup, 2017). At the same time, most respondents also indicated that teachers do not have enough training on how to effectively use digital learning platforms (Gallup, 2017). To effectively respond to calls to make "more and better information and training available to teachers" (Gallup, 2017, p. 59), more empirical work is needed to understand how teachers are integrating digital learning platforms in their classrooms and which strategies are most effective in creating technology-enabled learning environments that lead to positive outcomes for both teachers and students (Brizard, 2023; Callaghan et al., 2018; Huebner & Burstein, 2023; Shabrina et al., 2020).

To date, very little attention has been paid to the goals teachers set for their students' use of personalized learning software. Some preliminary evidence suggests that teachers vary widely in their approaches to goal setting in technology-enabled learning environments, with some teachers primarily adopting time-based goals (e.g. requiring students to record 30 min of software use per week) and other teachers primarily adopting mastery-based goals (e.g. requiring students to demonstrate proficiency on two skills per week) (Altermatt et al., 2022). These different approaches may reflect differences in teachers' general achievement goal orientations for math instruction (see Retelsdorf & Günther, 2011) as well as differences in recommendations for implementation from school administrators, instructional staff, or software developers (An et al., 2022). While both goals might, ostensibly, be deployed to ensure that students stay on task and eschew work-avoidance, only mastery-based goal setting requires students to demonstrate evidence of skill development.

Much remains to be learned about associations between teachers' goal setting for students' personalized learning software use in technology-enabled learning environments and both teacher and student attitudes. One possibility is that goal setting of any kind is associated with positive attitudes. This finding would be consistent with literature indicating that students benefit when they are working toward goals that are specific, challenging, and attainable (Locke & Latham, 2002; Martin & Elliot, 2016). A second possibility is that mastery-based goal setting is associated with more positive attitudes than time-based goal setting because time-based goals do not hold students accountable for their learning. For example, a student who spends 30 min per week "engaged" with a math learning software program and who becomes proficient in few skills during that time may be fulfilling a "seat time" requirement, but learning very little (An et al., 2022). This scenario—meeting the mandated time goal but gaining minimal knowledge—may lead both teachers and students to doubt the effectiveness of math learning software and may lead students to question their ability to improve in mathematics.

Importantly, the effect of teacher goal setting for software use on teacher and student attitudes is likely to be moderated by other features of the instructional setting, including the level of support that teachers provide to students as they use the software. Again, preliminary evidence suggests that teachers vary widely in the support they provide. While some teachers are actively engaged with students as they use personalized learning software, other teachers provide only occasional support (e.g. when a student asks for assistance), and still other teachers use the time that students are engaged with the software to accomplish other tasks including lesson planning and meeting individually with students on matters unrelated to software use (Altermatt et al., 2022). Establishing goals for students' software use is one way that teachers can provide students with clear expectations for how to be autonomous and responsible learners in technology-enabled learning environments. Doing so may be especially important in cases when teachers' attention is not directly focused on students while students are using software (McCombs & Miller, 2007). Consistent with this idea, we predict that goal setting will be an especially strong predictor of teacher and student outcomes among teachers who report providing relatively low levels of support to students as they use math personalized learning software.

The current study

The key purposes of the current study are a) to explore the factors that predict teachers' use of time-based and mastery-based goals for their students' software use and b) to examine the effect of teachers' adoption of these two types of goals on both teacher attitudes (i.e. perceptions of the value of math software) and student attitudes (i.e. perceptions of the value of math software and endorsement of growth mindsets). The decision to focus on perceptions of value and growth mindsets as key outcome variables is based on evidence that perceptions of value are associated with both strong academic engagement and academic achievement (Wigfield & Eccles, 2000) and that growth mindsets and growth mindset interventions are associated with strong academic achievement, especially for students who are academically underperforming or economically disadvantaged (Macnamara & Burgoyne, 2022; Tipton et al., 2023). Importantly, relationships between attitudes and achievement appear to be reciprocal. For example, students who have confidence in their ability to improve their skills in mathematics through hard work tend to perform better over time. Improved performance, in turn, boosts perceptions of competence (Tschannen-Moran & Barr, 2004; Vu et al., 2024). This study seeks to answer four research questions: 1. How likely are teachers to set time-based and mastery-based goals for math personalized learning software use? 2. What factors are associated with teachers' adoption of time-based and mastery-based goals for math personalized learning software use? 3. What is the relationship between teachers' time-based and mastery-based goal setting and their perceptions of the value of math personalized learning software? 4. What is the relationship between teachers' time-based and mastery-based goal setting and students' perceptions of the value of math personalized learning software and endorsement of growth mindsets?

Method

Participants

In Spring 2023, the Utah Education Policy Center distributed email invitations to complete a survey on technology-enabled learning environments to 16,923 teachers in Utah.[1] Each invitation included a description of the study, a personalized link to a teacher survey, and an anonymous link to a related student survey. The teacher survey was designed to assess teachers' general instructional strategies in math, strategies for using math personalized learning software, perceptions of math personalized learning software, and self-efficacy for teaching mathematics. The student survey was designed to assess students' attitudes toward math and their use and perceptions of math personalized learning software.

The distribution list for email invitation included all K - 6th grade teachers in Utah as well as all math teachers for 7th - 12th grades in Utah. The analytic sample for the current study includes the 1,377 teachers who consented to participate, indicated that they taught math, completed the survey using a personalized survey link, and reported using math personalized learning software. The analytic sample also includes 6,920 3rd—12th grade students linked to teachers in the analytic sample. These students had teachers who completed the survey, assented to participate using an anonymized link that was personalized for each teacher, and reported using math personalized learning software. To enhance the reliability of analyses linking teacher practices to student outcomes, students were included in the analytic sample only if 10 or more students of a participating teacher completed the survey.[2] As described in an earlier report (Altermatt, Timmer, et al., 2023), the sample of teachers who responded to the survey using a personalized link was similar to the population of K-6 teachers and 7-12 grade math teachers in Utah who were invited to participate in the survey on a wide range of teacher characteristics (e.g. gender, age, and highest degree) and school characteristics (e.g. percent of students who are chronically absent, low-income, and English-language learners).

Measures

Teachers and students reported using a variety of math personalized learning software programs in their classrooms, including, most commonly, ALEKS, i-Ready, and ST Math. Text piping was used throughout the survey such that [math software] was replaced with the software program respondents reported using most frequently.

Teachers' goal setting for math personalized learning software

Teachers' goal setting was assessed with two items. First, ***time-based goal setting for software use*** was assessed by asking teachers to indicate the extent to which they "require students to spend a certain amount of time using [math software]." Second, ***mastery-based goal setting for software use*** was assessed by asking teachers to indicate the extent to which they "require students to demonstrate mastery of a certain number of concepts, topics, or skills when using [math software]." Teachers responded to both items on a four-point scale that ranged from 1 ("not at all") to 4 ("to a great extent").

Context for goal setting for math personalized learning software

Teachers were asked to respond to a variety of items designed to characterize the contexts in which math personalized learning software was being used. Following preliminary analyses, we utilized six items or sets of items in analyses for the current study. First, teachers were asked to indicate the grade levels in which they used math software. Teachers were considered to be using software at the ***secondary level*** if they reported using software in Grade 7 or above. Second, ***teaching experience*** was assessed by asking teachers to report the number of years they had taught math. Third, ***software experience*** was assessed by asking teachers to report the number of years that had used their current math software program. Fourth, ***level of software use*** was assessed by asking teachers to estimate the number of minutes students in their math class spent using math software during a typical week. Teachers who taught more than one math class were asked to provide an estimate for the math class in which they used the software the most. Estimates for use "during the regular school day" and "outside of the regular school day" were summed. Fifth, level of ***student support*** was assessed by asking teachers to indicate the extent to which, "when students use math software," their "attention is focused on students as they work." Teachers responded to this item on a four-point scale that ranged from 1 ("not at all") to 4 ("to a great extent"). Sixth, teachers' general ***mastery-based instructional practices*** were assessed with three items tapping the degree to which teachers employ a set of strategies that encourage students to achieve and demonstrate mastery of concepts (e.g. "My students have opportunities to review and practice new material in math until they fully understand it."). These items were adapted from a measure developed by the

RAND corporation to examine personalized learning strategies and their effects on student outcomes (Pane et al., 2015).

In addition to self-report data, teacher and school characteristics were obtained from the Utah State Board of Eduction. Following preliminary analyses, we utilized one school-level variable in the current study: ***percentage of low-income students*** (i.e. the percentage of students in the school who qualified for free- or reduced-price lunch).[3]

Teachers' perceptions of the value of math personalized learning software

Teachers were asked to respond to four items tapping the degree to which they find value in the math learning software their students are using (e.g. "[Math software] helps my students improve their skills in math."; "[Math software] helps my students improve their confidence in math."). Teachers responded to all four items on a five-point scale that ranged from 1 ("strongly disagree") to 5 ("strongly agree"). Analyses indicated that the four items formed a reliable scale (α = .85).

Students' perceptions of the value of math personalized learning software

Students were asked to respond to six items tapping the degree to which they perceive math software to be valuable for their learning (e.g. "[Math software] helps me improve my skills in math." "[Math software] help me improve my confidence in math."). Students responded to all items on a five-point scale that ranged from 1 ("strongly disagree") to 5 ("strongly agree"). Initial analyses indicated that the six items formed a reliable scale (α = .89).

Students' endorsement of growth mindsets in mathematics

Students were asked to respond to one item assessing their perceptions of the degree to which their ability in mathematics is malleable (i.e. "I have a certain amount of ability in math, and I can't do much to change it."). Students rated their agreement with this item on a scale that ranged from 1 ("strongly disagree") to 5 ("strongly agree"). Ratings were reverse scored so that higher numbers indicate greater endorsement of a growth mindset. Prior research indicates that a single-item measure of growth mindset has psychometric properties that are similar to a three-item measure (Rammstedt et al., 2024).

Results

RQ1. How likely are teachers to set time-based and mastery-based goals for math personalized learning software use?

Table 1 presents descriptive statistics for all teacher-level and student-level study variables. As highlighted in the table, teachers were, as a group, more likely to report setting time-based goals for students' use of software (mean = 2.81) than mastery-based goals (mean = 2.43). A dependent *t*-test indicated that this difference was statistically significant, $t(1295) = 10.46$, $p < .001$.

Figure 1 presents frequency distributions for teachers' ratings of time-based and mastery-based goal setting. As shown, although teachers were more likely to report setting time-based goals than mastery-based goals "to a great extent," there was considerable variability across teachers in goal setting.

RQ2. What factors are associated with teachers' adoption of time-based and mastery-based goals for math personalized learning software use?

To begin to explore factors that explain some of the variability in teachers' time-based and mastery-based goal setting for students' use of math personalized learning software, we calculated zero-order correlations among all teacher-level study variables. As shown in Table 2, teachers

Table 1. Descriptive statistics for teacher-level and student-level study variables.

Variable	*n*	Range	Mean or %	SD
Teacher-level study variables				
1. time-based goal setting for software use	1298	1 – 4	2.81	1.11
2. mastery-based goal setting for software use	1300	1 – 4	2.43	1.07
3. grade level (1 = secondary)	1377	0, 1	23.60%	–
4. teaching experience (# of years)	1377	0 – 45	12.23	8.76
5. software experience (# of years)	1377	0 – 15	3.08	2.40
6. level of software use (mins/wk)	1377	0 – 300	55.24	39.25
7. student support	1218	1 – 4	2.78	0.79
8. mastery-based instructional practices	1373	1 – 4	2.49	0.61
9. % low-income students	1368	1 – 100	30.00%	21.00%
10. value of software	1229	1 – 4	3.81	0.75
Student-level study variables				
1. value of software	6865	1 – 5	3.27	0.96
2. growth mindset in mathematics	6735	1 – 5	3.32	1.14

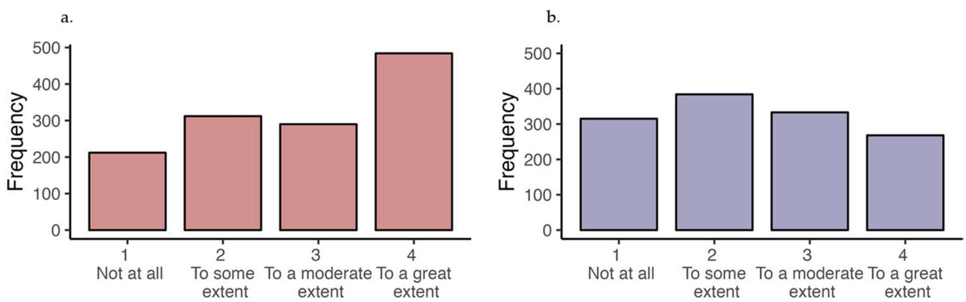

Figure 1. Frequency distributions for time-based goal setting (panel a) and mastery-based goal setting (panel b) for math personalized learning software.

Table 2. Zero-order correlations for teacher-level study variables.

Variable	1	2	3	4	5	6	7	8	9	10
1. time-based goal setting	–									
2. mastery-based goal setting	.27***	–								
3. grade level (1 = secondary)	−0.29***	.06*	–							
4. teaching experience (# of years)	.01	.01	−0.05	–						
5. software experience (# of years)	−0.03	.08**	.06*	.31***	–					
6. level of software use (mins/wk)	.14***	.27***	.15***	.05	.12***	–				
7. student support	.04	.24***	.27***	.03	.08**	.20***	–			
8. mastery-based instructional practices	.11***	.30***	.10***	−0.04	.06	.17***	.20***	–		
9. % of low-income students	.06*	−0.02	−0.04	−0.03	−0.05	−0.01	−0.05	−0.09**	–	
10. value of software	.13***	.26***	.06*	.01	.18***	.17***	.14***	.23***	−0.05	–

*$p < .05$.
**$p < .01$.
***$p < .001$.

using software at the secondary level were less likely than teachers using software at the elementary level to report setting time-based goals for their students' use of software ($r = -0.29$, $p < .001$). Teachers using software at the secondary level were, in turn, more likely than teachers using software at the elementary level to report setting mastery-based goals for their students' use of software ($r = .06$, $p < .05$), though this relationship was considerably weaker. Teachers with more experience using software and who reported providing higher levels of student support during software use were more likely to report setting mastery-based goals for software use than teachers with less experience or who reported providing lower levels of student support (*rs* = .08 and .24, *ps* < .01). Teachers whose students used software more frequently and who reported using mastery-based instructional practices in their math classrooms in general were more likely to report setting both time-based and mastery-based goals for software use, but these relationships were stronger for mastery-based goals (*rs* = .27 and .30, $p < .001$) than for time-based goals (rs = .14 and .11, $p < .001$). Finally, there was a weak, positive association between the percentage of low-income students in a school and teachers' adoption of time-based goals for software use ($r = .06$, $p < .05$).

RQ3. What is the relationship between teachers' time-based and mastery-based goal setting and their perceptions of the value of math personalized learning software?

As shown in Table 2, both time- and mastery-based goal setting were positively related to teachers' perceptions of the value of math personalized learning software. That is, as ratings for goal setting increased from 1 ("not at all") to 4 ("to a great extent"), teachers' perceptions of the value of software also increased. However, the association was stronger for mastery-based goal setting ($r = .26$, $p < .001$) than for time-based goal setting ($r = .13$, $p < .001$).

Given the positive association between teachers' ratings of time-based and mastery-based goals ($r = .27$, $p < .001$; see Table 2), we conducted a multiple regression analysis to examine the *independent* effects of these goals on teachers' perceptions of the value of math personalized learning software. Models also controlled for other potentially confounding variables, including grade level, teaching experience, software experience, level of software use, and general mastery-based instructional practices. Finally, models included interactions between goals and student support ratings to examine whether associations between goals and perceptions of value might vary by the level of support teachers provided to students during software use. Variables included in the interaction were centered. Results are summarized in Table 3. Estimated marginal means are presented in Figure 2.

As shown in Table 3 and Figure 2, both time-based goal setting (panel a) and mastery-based goal setting (panel b) were positively related to teachers' perceptions of the value of math personalized learning software. However, the effect for mastery-based goal setting, $B = .11$, $t = 4.97$, $p < .001$, was stronger than the effect for time-based goal setting, $B = .05$, $t = 2.42$, $p < .05$. A marginally significant interaction between mastery-based goal setting and student support also emerged (see Table 3 and Figure 2, panel b), indicating that the effect for mastery-based goals was moderated by the level of support teachers offered to students as they used software, $B = -0.04$, $t = -1.91$, $p < .10$. As indicated by the slopes of the lines in Figure 2 (panel b), the relationship between mastery-based goal setting and teachers' perceptions of the value of math software was especially strong for students whose teachers provide lower levels of support as students used math software (i.e. at levels equal to one standard deviation below the mean of student support). Indeed, the lowest value ratings emerged for teachers who rarely set mastery-based goals for their students' use of math software *and* who also provided relatively low levels of support to students as they used software. Importantly, these relationships held even after

Table 3. Summary of multiple regression model predicting teachers' perceptions of the value of math learning software.

Predictor	Estimate	SE	*t*
(Intercept)	3.20	.11	28.72***
1. time-based goal setting for software use	.05	.02	2.42*
2. mastery-based goal setting for software use	.11	.02	4.97***
3. grade level (1 = secondary)	.03	.06	0.59
4. teaching experience (# of years)	.00	.00	−1.15
5. software experience (# of years)	.05	.01	5.79***
6. level of software use (minutes/week)	.05	.02	2.40*
7. student support	.00	.00	1.13
8. mastery-based instructional practices	.17	.04	2.04*
9. % low-income students	−0.05	.10	−0.66
Interaction 1* 7	.02	.02	0.89
Interaction 2* 7	−0.04	.02	−1.91+

Note. Multiple $R^2 = .129$. Adjusted $R^2 = .120$. $F(11, 1122) = 15.06$, $p < .001$.
+$p < .10$.
*$p < .05$.
***$p < .001$.

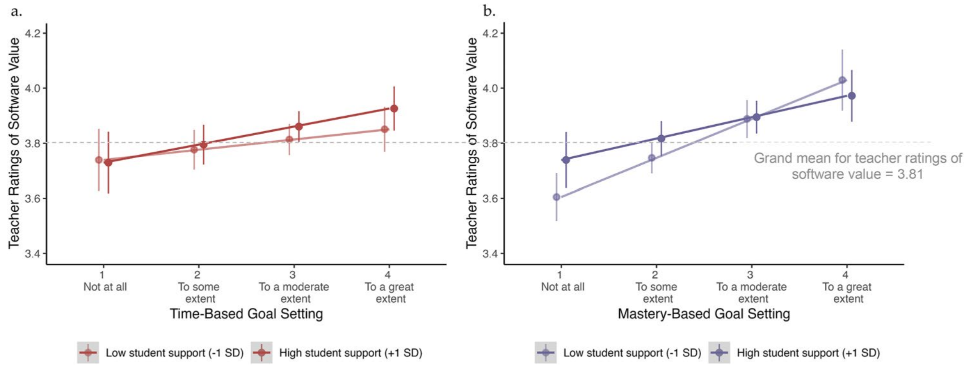

Figure 2. Estimated marginal means from regression models predicting teachers' ratings of the value of math personalized learning software from time-based goal setting (panel a) and mastery-based goal setting (panel b).
Note. Points represent estimated marginal means from regression models at each of four levels of time-based goal setting and mastery-based goal setting for math personalized learning software use. Lines emanating from these points represent 95% confidence intervals.

controlling for potentially confounding variables including teachers' general use of mastery-based instructional strategies in mathematics.

RQ4. What is the relationship between teachers' time-based and mastery-based goal setting and students' perceptions of the value of math software and endorsement of growth mindsets?

Given that students were nested within teachers, two random-intercepts multilevel models (MLMs) were used to examine associations between teachers' goal setting and both students' perceptions of the value of math personalized learning software and their endorsement of a growth mindset. As before, models controlled for potentially confounding variables, including grade level, teaching experience, software experience, level of software use, and general mastery-based instructional practices. Models also included interactions between teachers' goal setting and teachers' support ratings to examine whether associations between goal setting and perceptions of value or mindset ratings might vary by the level of support teachers provided to students during software use. Variables included in the interaction were centered.

As shown, in Table 4, neither time-based nor mastery-based goal setting predicted students' perceptions of the value of math software. However, mastery-based goal setting positively predicted students' endorsement of growth mindsets, $B = .06$, $t = 2.36$, $p < .05$. This effect was moderated by the level of support teachers offered to students as they used software as indicated by a significant mastery-based goal setting x student support interaction, $B = -0.06$, $t = -2.28$, $p < .05$.

To aid in the interpretation of this interaction, estimated marginal means are presented in Figure 3. As indicated by the slopes of the lines, while mastery-based goals were associated with stronger endorsement of growth mindsets, this relationship was especially strong for students whose teachers provided lower levels of support as students used math software. Indeed, the lowest growth mindset ratings emerged for students whose teachers never or rarely set mastery-based goals for their students' use of math software *and* who also provided relatively low levels of support to students as they used the software. Importantly, these relationships held even after controlling for potentially confounding variables including teachers' general use of mastery-based instructional practices in mathematics.

Discussion

The results of the current study suggest that while teachers, as a group, were more likely to set time-based than mastery-based goals for their students' use of math personalized learning

Table 4. Summary of multilevel models predicting students' perceptions of the value of math learning software and growth mindsets.

	Value of Software			Growth Mindsets		
Predictor	Est.	SE	*t*	Est.	SE	*t*
(Intercept)	2.37	.02	15.70***	3.70	.14	25.91***
1. time-based goal setting for software use	.01	.03	0.42	−0.02	.03	−0.73
2. mastery-based goal setting for software use	−0.03	.03	−1.02	.06	.03	2.36*
3. grade level (1 = secondary)	−0.34	.07	−4.81***	−0.05	.06	−0.76
4. teaching experience (# of years)	.01	.00	1.51	.00	.00	0.86
5. software experience (# of years)	−0.01	.01	−0.93	−0.02	.01	−1.67
6. level of software use (minutes/week)	.07	.01	14.89***	.00	.01	−0.49
7. student support	−0.01	.03	−0.45	.03	.03	0.03
8. mastery-based instructional practices	.07	.05	1.53	−0.05	.04	−1.03
9. % low-income students	.45	.19	2.50*	−0.59	.17	−3.55***
Interaction 1* 7	.00	.03	0.14	−0.01	.02	−0.51
Interaction 2* 7	.01	.03	0.49	−0.06	.03	−2.28*
Number of observations		6099			5989	
Conditional R^2		.19			.06	
ICC		.121			.044	
RMSE		0.86			1.11	

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

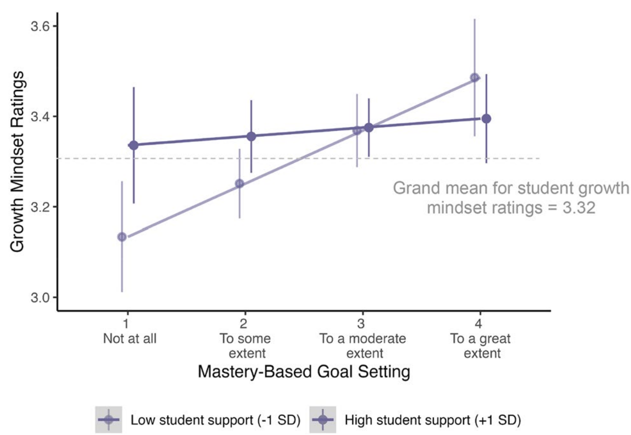

Figure 3. Estimated marginal means from multilevel model predicting students' endorsement of growth mindsets.
Note. Points represent estimated marginal means from multilevel models at each of four levels of mastery-based goal setting. Lines emanating from these points represent 95% confidence intervals.

software, teachers also varied widely in the degree to which they set these goals. Mastery-based goal setting for software use was unrelated to the number of years teachers taught math (see also Wolters & Daugherty, 2007 and Wolters et al., 2010). In contrast, mastery-based goal setting for software use was positively related to the number of years teachers used software, the number of minutes students in their classrooms used software, and the level of support that teachers provided to students as they used software. Together, this pattern of findings suggests that teachers may be more likely to adopt mastery-based goals for their students' use of software as their experience, confidence, and engagement with the software increases. This conclusion is consistent with evidence that years of teaching experience predicts teachers' general instructional self-efficacy which, in turn, predicts teachers' general adoption of mastery-based achievement goal structures (Wolters & Daugherty, 2007). The finding that secondary school teachers were slightly more likely than elementary school teachers to set mastery-based goals for their students' use of math software (and somewhat less likely than elementary school teachers to set time-based goals) is more puzzling given some evidence that mastery-based goal structures are more common at the elementary than at the secondary level (Wolters et al., 2010; Wolters & Daugherty, 2007). Notably, however, the extant literature has not examined whether the relationship between academic level and goal structures is impacted by subject area (e.g. language arts vs. math). This is important given that subject area appears to influence the likelihood that teachers will adopt mastery-based goal structures, with language arts teachers adopting mastery-based goals structures more frequently than math teachers (see Wolters et al., 2010). More work is needed to examine how academic level (elementary vs. secondary), subject area (language arts vs. math), and context (e.g. general vs. activity-specific) interact to impact teacher goal-setting.

In addition to identifying factors that impact teachers' adoption of time-based versus mastery-based goals for their students' use of math learning software, the the current study contributes to the extant literature by providing evidence to support recommendations that teachers set mastery-based goals for students' use of math learning software. Both time-based goal setting and mastery-based goal setting were associated with stronger perceptions among teachers that math software has value. However, the relationship was stronger for mastery-based goal setting such that the highest value ratings for math personalized learning software emerged for teachers who reported setting mastery-based goals "to a great extent." Moreover, only mastery-based goal setting was associated with students' beliefs that their ability in mathematics can change with hard work. Importantly, mastery-based goal setting appears to be a particularly strong predictor of positive teacher attitudes about the value of software and student growth mindsets among teachers who provide relatively low levels of support to students as they use the software. This finding is consistent with evidence that students benefit from learning environments that effectively balance students' needs for autonomy and support: when autonomy is high (as it might be when teachers allow students to work independently on the software), students may languish if teachers do not simultaneously set clear goals for learning (Johansen et al., 2023).

The findings of the current study are consistent with a large research literature indicating that student outcomes are improved when teachers work to create learning environments that foster mastery orientations (Ames & Archer, 1988; Patrick & Kaplan, 2022). In addition, the findings contribute to a still-nascent research literature on personalized learning (Bernacki et al., 2021). While there is growing evidence that personalized learning opportunities have the potential to benefit both teachers and students and growing advocacy for technology-enabled instruction (Brizard, 2023), the current study reminds us that implementation strategies for digital solutions to personalization vary widely from classroom to classroom, with clear impacts on teacher and student outcomes. Much more work is needed to build the evidence base on personalized learning to ensure that teachers have the information and professional learning they need to effectively implement both digital and traditional personalized learning strategies. In carrying out this work, researchers must draw upon prior theory and research on teaching and learning and must move beyond descriptive, exploratory research designs (Bernacki et al., 2021).

The results of the current study have practical implications insofar as they suggest that teachers need both information on "promising practices" for math learning software implementation and time to learn how to effectively implement these practices. Too often, Professional learning opportunities for math learning software focus on the mechanics of implementation, leaving little time for teachers to gain knowledge and practice skills for creating strong technology-enabled learning environments. To the degree that professional learning can bolster the confidence of both novice and experienced teachers in using evidence-based practices for math learning software implementation, teachers' adoption of mastery-based goals for their students' use of the software should follow (see also Desimone et al., 2002; Nolan & Molla, 2017). Findings from the current study suggest that adoption of mastery-based goals should, in turn, bolster teachers' perceptions of the value of math software and students' endorsement of growth mindsets.

Limitations

The findings of the current study contribute to the extant literature by identifying mastery-based goal setting for math learning software use as a "promising practice" for personalized learning software implementation. At the same time, it is important to note several important caveats that are relevant to both empirical research and professional learning efforts.

First, we cannot infer causality from the current findings. Although we were able to control for several potentially confounding variables (e.g. grade level, number of years of software use, and general mastery-oriented instructional practices) in models, we are not able to rule out the possibility that other variables might partially (or fully) explain the associations between goal-setting, perceptions of value, and growth mindsets. Likewise, we were not able to determine the directionality of the effect. It may be that mastery-based goal setting leads teachers to view math software as more valuable, or it could be that teachers who value math software are more likely to set mastery-based goals.

Second, while mastery-based goal setting was positively associated with *teachers*' perceptions of the value of math personalized learning software and students' endorsement of growth mindsets, mastery-based goal setting was unrelated to *students*' perceptions of the value of math software. Instead, students' perceptions of value were most strongly related to the number of minutes that software was used in and outside of the classroom, as reported by teachers. This finding is consistent with prior work linking high frequency of software use, as reported by students, to a range of positive outcomes including greater confidence in math and heightened perceptions of improvement in math (Altermatt, Rorrer, et al., 2023). Given a large research literature linking student perceptions of value to myriad positive achievement outcomes (Wigfield & Eccles, 2000), these results are important and suggest that, although mastery-based goal setting is a promising implementation strategy, both teacher and student attitudes toward software are influenced by multiple factors and relationships between implementation practices and outcomes are often complex (Bonner et al., 2020; Datnow, 2020; Imants & Van der Wal, 2020). Indeed, conversations with teachers that informed the development of the survey used in the current study clearly indicated that there is no "one-size-fits-all" model for effective implementation of math personalized learning software (Altermatt et al., 2022). Instead, teachers noted that effective implementation will require that educators can draw upon the personal and instructional strengths and that they have the flexibility, time, and resources to learn about and experiment with new, evidence-based instructional approaches (Altermatt et al., 2022) including approaches that are aligned with broader efforts to create personalized, competency-based learning environments (Brodersen et al., 2017).

Finally, while, in the current study, mastery-based goal setting was associated with positive outcomes, it is important to note that we focused on mastery-based goal setting for math learning software use in K-12 classrooms and on achievement-related attitudes. Given evidence that achievement goal structures and their impact vary by both academic level and subject area (Wolters et al., 2010), it will be important for future research to examine the impact of mastery-based goal setting in other contexts (e.g. for a range of digital learning platforms used in language arts classrooms or in post-secondary classrooms) and on other outcomes (e.g. student achievement). It is also important to keep in mind that mastery-based goals can take on various forms, some of which are more beneficial than others. Decades of research on Self-Determination Theory (Ryan & Deci, 2000) suggests that setting mastery-based goals for software use may lead to *poorer* (not better) outcomes when teachers communicate—intentionally or not—that students have little personal choice in how they use personalized learning software or that personalized learning software has little relevance to regular classroom instruction or the development of strong academic skills. Mastery-based goal setting is also likely to lead to poorer outcomes when it is accompanied by rewards, threats, or surveillance that students perceive as controlling (Benita et al., 2014). Future work will be important to examine how teachers communicate mastery-based goals for learning software use to their students and to empirically test these hypotheses.

Notes

1. Participation in the study was voluntary at the LEA and individual level. The survey link was available for LEA personnel and parents or guardians to review.
2. The Utah Education Policy Center (UEPC) has a data sharing agreement with the Utah State Board of Education for use of education data for evaluation and research purposes. The UEPC adheres to terms of the agreement, including terms of use, confidentiality and non-disclosure, data security, monitoring, and applicable laws. The UEPC also complies with University of Utah Institutional Review Board policies for educational research and evaluation.
3. For teachers who taught at more than one school in 2022-2023, school-level values were averaged across schools. Values were based on 2021-2022 data as 2022-2023 data were not yet available at the time that survey data and demographic data were joined.

Acknowledgments

The authors thank partners at the Utah STEM Action Center—Clarence Ames and Tami Goetz—and the Utah State Board of Education (USBE)—Jennifer Throndsen, Nathan Auck, Aaron Brough, Kristin Campbell, Katy Challis, Trish French, Lindsey Henderson, and Wynn Shooter—for engaging in conversations regarding the design and execution of the study (i.e. reviewing surveys, distribution protocols, and preliminary reports). Both the STEM Action Center and the USBE provide leadership for and commitment to serving administrators, teachers, and students through K-12 Math initiatives, including by providing math learning software licenses. The UEPC has served as the external evaluator for the STEM Action Centers K-12 Math Personalized Learning Software Grant program since 2016. The authors are grateful for the support of administrators from school districts and charter schools for facilitating the participation of teachers and students in research and evaluation efforts and for the time spent by teachers and students in completing surveys. Finally, the authors thank Julianne Zemaitis for reviewing survey drafts, Matt Doane for facilitating survey administration, Bill Altermatt for wrangling demographic data, and Marieke Timmer for supporting analysis and reporting.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributors

Ellen Altermatt, PhD, conducts basic and applied research focused on improving academic outcomes for students in preK-12, higher education, and out-of-school time settings. Areas of interest include STEM education, technology-enabled learning, high-dosage tutoring, and peer influences on achievement outcomes.

Andrea K. Rorrer, PhD, conducts research and evaluation on leadership, organizational, and policy change at the school, district, and state-level (state education agency and state legislature), particularly those changes aimed at increasing equity in student access and outcomes.

References

Altermatt, E. R., Rorrer, A. K., & Moore, B. (2022). *Exploring best practices in math personalized learning software use among educators identified as positive outliers*. Utah Education Policy Center. https://www.uepc.utah.edu/wp-content/uploads/sites/103/2022/11/Best-Practices-FINAL-REPORT-with-new-cover.pdf

Altermatt, E. R., Rorrer, A. K., Altermatt, T. W., Doane, M., & Timmer, M. (2022). *Blended learning research brief no. 2. Associations between student attitudes toward math and math personalized learning software use*. Utah Education Policy Center. https://www.uepc.utah.edu/wp-content/uploads/sites/103/2023/09/Associations-Between-Student-Attitudes-Toward-Math-and-Math-Software.pdf

Altermatt, E. R., Timmer, M., Doane, M., Altermatt, T. W., & Rorrer, A. K. (2023). *Best practices for creating strong blended learning environments for mathematics in Utah: Teacher and student survey results*. Utah Education Policy Center. https://www.uepc.utah.edu/our-work/best-practices-for-creating-strong-blendedlearning-environments-for-mathematics-in-utah-report-on-teacher-and-student-surveyresults/

Ames, C., & Archer, J. (1988). Achievement goals in the classroom: Students' learning strategies and motivation processes. *Journal of Educational Psychology*, *80*(3), 260–267. https://doi.org/10.1037/0022-0663.80.3.260

An, X., Schonberg, C., & Bashkov, B. M. (2022). *IXL implementation fidelity and usage recommendations*. IXL. https://www.ixl.com/materials/us/research/IXL_Implementation_Fidelity_and_Usage_Recommendations.pdf

Baker, R. (2016). Using learning analytics in personalized learning. In M. Murphy, S. Redding, & J. Twyman (Eds.), *Handbook on personalized learning for states, districts, and schools* (pp. 165–174). Temple University, Center on Innovations in Learning.

Bardach, L., Oczlon, S., Pietschnig, J., & Lüftenegger, M. (2020). Has achievement goal theory been right? A meta-analysis of the relation between goal structures and personal achievement goals. *Journal of Educational Psychology*, *112*(6), 1197–1220. https://doi.org/10.1037/edu0000419

Benita, M., Roth, G., & Deci, E. L. (2014). When are mastery goals more adaptive? It depends on experiences of autonomy support and autonomy. *Journal of Educational Psychology*, *106*(1), 258–267. https://doi.org/10.1037/a0034007

Bernacki, M. L., Greene, M. J., & Lobczowski, N. G. A. (2021). A systematic review of research on personalized learning: Personalized by whom, to what, how, and for what purpose(s)? *Educational Psychology Review*, *33*(4), 1675–1715. https://doi.org/10.1007/s10648-021-09615-8

Bonner, S. M., Diehl, K., & Trachtman, R. (2020). Teacher belief and agency development in bringing change to scale. *Journal of Educational Change*, *21*(2), 363–384. https://doi.org/10.1007/s10833-019-09360-4

Brizard, J.-C. (2023). *Breaking with the past: Embracing digital transformation in education*. Digital Promise. https://doi.org/10.51388/20.500.12265/176

Brodersen, R. M., Yanoski, D., Mason, K., Apthorp, H., Piscatelli, J. (2017). Overview of selected state policies and supports related to K–12 competency-based education *(REL 2017–249)*. U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance, Regional Educational Laboratory Central. https://files.eric.ed.gov/fulltext/ED572994.pdf

Callaghan, M. N., Long, J., van Es, E. V., Reich, S. M., & Rutherford, T. (2018). How teachers integrate a math computer game: Professional development use, teaching practices, and student achievement. *Journal of Computer Assisted Learning*, *34*(1), 10–19. https://doi.org/10.1111/jcal.12209

Campuzano, L., Dynarski, M., Agodini, R., Rall, K. (2009). *Effectiveness of reading and mathematics software products: Findings from two student cohorts (NCEE 2009-4041)*. U.S. Department of Education, Institute of Education Sciences. https://files.eric.ed.gov/fulltext/ED496015.pdf

Cheung, A. C. K., & Slavin, R. E. (2013). The effectiveness of educational technology applications for enhancing mathematics achievement in K-12 classrooms: A meta-analysis. *Educational Research Review*, *9*, 88–113. https://doi.org/10.1016/j.edurev.2013.01.001

Datnow, A. (2020). The role of teachers in educational reform: A 20-year perspective. *Journal of Educational Change*, *21*(3), 431–441. https://doi.org/10.1007/s10833-020-09372-5

Desimone, L. M., Porter, A. C., Garet, M. S., Yoon, K. S., & Birman, B. F. (2002). Effects of professional development on teachers' instruction: Results of a three-year longitudinal study. *Educational Evaluation and Policy Analysis*, *24*(2), 81–112. https://doi.org/10.3102/01623737024002081

Diseth, A., & Kobbeltvedt, T. (2010). A mediation analysis of achievement motives, goals, learning strategies, and academic achievement. *The British Journal of Educational Psychology*, *80*(Pt 4), 671–687. https://doi.org/10.1348/000709910X492432

Elliot, A. J., Murayama, K., & Pekrun, R. (2011). A 3×2 achievement goal model. *Journal of Educational Psychology*, *103*(3), 632–648. https://doi.org/10.1037/a0023952

Fahle, E. M., Kane, T. J., Patterson, T., Reardon, S. F., Staiger, D. O., Stuart, E. A. (2023). *School district and community factors associated with learning loss during the COVID-19 pandemic*. Center for Education Policy Research. https://cepr.harvard.edu/sites/hwpi.harvard.edu/files/cepr/files/explaining_covid_losses_5.23.pdf

Gallup. (2017). Education technology use in schools: Student and educator perspectives. NewSchools Venture Fund. https://www.newschools.org/wp-content/uploads/2019/09/Gallup-Ed-Tech-Use-in-Schools-2.pdf

Hillmayr, D., Ziernwald, L., Reinhold, F., Hofer, S. I., & Reiss, K. M. (2020). The potential of digital tools to enhance mathematics and science learning in secondary schools: A context-specific meta-analysis. *Computers & Education*, *153*, 103897. https://doi.org/10.1016/j.compedu.2020.103897

Huang, C. (2011). Achievement goals and achievement emotions: A meta-analysis. *Educational Psychology Review*, *23*(3), 359–388. https://doi.org/10.1007/s10648-011-9155-x

Huang, C. (2016). Achievement goals and self-efficacy: A meta-analysis. *Educational Research Review*, *19*, 119–137. https://doi.org/10.1016/j.edurev.2016.07.002

Huebner, T. A., Burstein, R. (2023). *Strategies for encouraging effective technology-enabled instructional practices in K–12 education: A thought piece drawing on research and practice*. WestEd. https://www.wested.org/resources/strategies-for-encouraging-effective-technology-enabled-instructional-practices-in-k-12-education-a-thought-piece-drawing-on-research-and-practice/

Imants, J., & Van der Wal, M. M. (2020). A model of teacher agency in professional development and school reform. *Journal of Curriculum Studies*, *52*(1), 1–14. https://doi.org/10.1080/00220272.2019.1604809

Johansen, M., Eliassen, S., & Jeno, L. M. (2023). The bright and dark side of autonomy: How autonomy support and thwarting relate to student motivation and academic functioning. *Frontiers in Education*, *8*, 1153647. https://doi.org/10.3389/feduc.2023.1153647

Kaplan, A., & Maehr, M. L. (1999). Achievement goals and student well-being. *Contemporary Educational Psychology*, *24*(4), 330–358. https://doi.org/10.1006/ceps.1999.0993

Kerssens, N., & van Dijck, J. (2022). Governed by edtech? Valuing pedagogical autonomy in a platform society. *Harvard Educational Review*, *92*(2), 284–303. https://doi.org/10.17763/1943-5045-92.2.284

King, R. B., & McInerney, D. M. (2014). The work avoidance goal construct: Examining its structure, antecedents, and consequences. *Contemporary Educational Psychology*, *39*(1), 42–58. https://doi.org/10.1016/j.cedpsych.2013.12.002

Kuhfeld, M., Soland, J., & Lewis, K. (2022). Test score patterns across three COVID-19-impacted school years. *Educational Researcher*, *51*(7), 500–506. https://doi.org/10.3102/0013189X221109178

Locke, E. A., & Latham, G. P. (2002). Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *The American Psychologist*, *57*(9), 705–717. https://doi.org/10.1037/0003-066X.57.9.705

Lüftenegger, M., Tran, U. S., Bardach, L., Schober, B., & Spiel, C. (2017). Measuring a mastery goal structure using the TARGET framework: Development and validation of a classroom Goal Structure Questionnaire. *Zeitschrift Für Psychologie*, *225*(1), 64–75. https://doi.org/10.1027/2151-2604/a000277

Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. *Journal of Educational Psychology*, *106*(4), 901–918. https://doi.org/10.1037/a0037123

Macnamara, B. N., & Burgoyne, A. P. (2022). Do growth mindset interventions impact students' academic achievement? A systematic review and meta-analysis with recommendations for best practices. *Psychological Bulletin*, *149*(3-4), 133–173. https://doi.org/10.1037/bul0000352

Martin, A. J., & Elliot, A. J. (2016). The role of personal best (PB) goal setting in students' academic achievement gains. *Learning and Individual Differences*, *45*, 222–227. https://doi.org/10.1016/j.lindif.2015.12.014

McCombs, B. L., & Miller, L. (2007). *Learner-centered classroom practices and assessments: Maximizing student motivation, learning, and achievement*. Corwin Press.

Midgley, C., & Urdan, T. (2001). Academic self-handicapping and achievement goals: A further examination. *Contemporary Educational Psychology*, *26*(1), 61–75. https://doi.org/10.1006/ceps.2000.1041

National Science Board, National Science Foundation. (2021). *Elementary and secondary STEM education: Science and engineering indicators 2022. NSB-2021-1*. https://ncses.nsf.gov/pubs/nsb20211/

Nolan, A., & Molla, T. (2017). Teacher confidence and professional capital. *Teaching and Teacher Education*, *62*, 10–18. https://doi.org/10.1016/j.tate.2016.11.004

OECD. (2022). Mathematics performance (PISA) (indicator). OECD Library. https://doi.org/10.1787/04711c74-en

Pane, J. F., Steiner, E. D., Baird, M. D., Hamilton, L. S. (2015). Continued progress: Promising evidence on personalized learning. RAND Corporation. https://www.rand.org/pubs/research_reports/RR1365.html

Pane, J. F., Steiner, E. D., Baird, M. D., Hamilton, L. S., Pane, J. D. (2017). Informing progress: Insights on personalized learning implementation and effects. RAND Corporation. https://www.rand.org/pubs/research_reports/RR2042.html

Pape, B., Vander Ark, T. (2021). Making learning personal for all: Policies and practices that meet learners where they are. Digital Promise Global. https://files.eric.ed.gov/fulltext/ED614345.pdf

Patrick, H., & Kaplan, A. (2022). Promoting students' growth motivation: Mastery-structured classrooms. In K.-A. Allen, M. J. Furlong, D. Vella-Brodrick, & S. M. Suldo (Eds.), *Handbook of positive psychology in schools: Supporting process and practice* (3rd ed., pp. 295–308). Routledge. https://doi.org/10.4324/9781003013778-23

Patrick, H., Kaplan, A., & Ryan, A. M. (2011). Positive classroom motivational environments: Convergence between mastery goal structure and classroom social climate. *Journal of Educational Psychology*, *103*(2), 367–382. https://doi.org/10.1037/a0023311

Patrick, H., Turner, J. C., Meyer, D. K., & Midgley, C. (2003). How teachers establish psychological environments during the first days of school: Associations with avoidance in mathematics. *Teachers College Record: The Voice of Scholarship in Education*, *105*(8), 1521–1558. https://doi.org/10.1111/1467-9620.00299

Rammstedt, B., Grüning, D. J., & Lechner, C. M. (2024). Measuring growth mindset: Validation of a three-item and a single-item scale in adolescents and adults. *European Journal of Psychological Assessment*, *40*(1), 84–95. https://doi.org/10.1027/1015-5759/a000735

Reber, R., Canning, E. A., & Harackiewicz, J. M. (2018). Personalized education to increase interest. *Current Directions in Psychological Science*, *27*(6), 449–454. https://doi.org/10.1177/0963721418793140

Retelsdorf, J., & Günther, C. (2011). Achievement goals for teaching and teachers' reference norms: Relations with instructional practices. *Teaching and Teacher Education*, *27*(7), 1111–1119. https://doi.org/10.1016/j.tate.2011.05.007

Ritzhaupt, A. D., Cheng, L., Luo, W., & Hohlfeld, T. N. (2020). The digital divide in formal educational settings: The past, present, and future relevance. In M. J. Bishop, E. Boling, J. Elen, & V. Svihla (Eds.), *Handbook of research in educational communications and technology: Learning design* (pp. 483–504). Springer International Publishing. https://doi.org/10.1007/978-3-030-36119-8_23

Rutherford, T., Liu, A. S., Lam, A. S., & Schenke, K. (2020). Impact on mathematics self-beliefs from a mastery-based mathematics software. *Journal of Research on Technology in Education*, *52*(1), 79–94. https://doi.org/10.1080/15391523.2019.1689210

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *The American Psychologist*, *55*(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

Schoenherr, J. (2024). Personalizing real-world problems: Posing own problems increases self-efficacy expectations, intrinsic value, attainment value, and utility value. *The British Journal of Educational Psychology*, *94*(2), 407–424. https://doi.org/10.1111/bjep.12653

Shabrina, P., Akintunde, R. O., Maniktala, M., Barnes, T., Lynch, C., & Rutherford, T. (2020). Peeking through the classroom window: A detailed data-driven analysis on the usage of a curriculum integrated math game in authentic classrooms [Proceedings]. Tenth International Conference on Learning Analytics & Knowledge. Frankfurt, Germany. https://doi.org/10.1145/3375462.3375525

Shim, S. S., Cho, Y., & Cassady, J. (2013). Goal structures: The role of teachers' achievement goals and theories of intelligence. *The Journal of Experimental Education*, *81*(1), 84–104. https://doi.org/10.1080/00220973.2011.635168

Tipton, E., Bryan, C., Murray, J., McDaniel, M., Schneider, B., & Yeager, D. S. (2023). Why meta-analyses of growth mindset and other interventions should follow best practices for examining heterogeneity: Commentary on Macnamara and Burgoyne (2023) and Burnette et al. (2023). *Psychological Bulletin*, *149*(3–4), 229–241. https://doi.org/10.1037/bul0000384

Tschannen-Moran, M., & Barr, M. (2004). Fostering student learning: The relationship of collective teacher efficacy and student achievement. *Leadership and Policy in Schools*, *3*(3), 189–209. https://doi.org/10.1080/15700760490503706

U.S. Department of Education. (2017). *Reimaging the role technology in education. 2017 National Education Technology Plan update*. https://tech.ed.gov/files/2017/01/NETP17.pdf

Valadez, J. R., & Durán, R. P. (2007). Redefining the digital divide: Beyond access to computers and the Internet. *The High School Journal*, *90*(3), 31–44. http://www.jstor.org/stable/40364198 https://doi.org/10.1353/hsj.2007.0013

Vu, T. V., Scharmer, A. L., van Triest, E., van Atteveldt, N., & Meeter, M. (2024). The reciprocity between various motivation constructs and academic achievement: A systematic review and multilevel meta-analysis of longitudinal studies. *Educational Psychology*, *44*(2), 136–170. https://doi.org/10.1080/01443410.2024.2307960

Wang, H., Hall, N. C., Goetz, T., & Frenzel, A. C. (2017). Teachers' goal orientations: Effects on classroom goal structures and emotions. *The British Journal of Educational Psychology*, *87*(1), 90–107. https://doi.org/10.1111/bjep.12137

Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology*, *25*(1), 68–81. https://doi.org/10.1006/ceps.1999.1015

Wolters, C. A. (2004). Advancing achievement goal theory: Using goal structures and goal orientations to predict students' motivation, cognition, and achievement. *Journal of Educational Psychology*, *96*(2), 236–250. https://doi.org/10.1037/0022-0663.96.2.236

Wolters, C. A., & Daugherty, S. G. (2007). Goal structures and teachers' sense of efficacy: Their relation and association to teaching experience and academic level. *Journal of Educational Psychology*, *99*(1), 181–193. https://doi.org/10.1037/0022-0663.99.1.181

Wolters, C. A., Fan, W., & Daugherty, S. (2010). Teacher-reported goal structures: Assessing factor structure and invariance. *The Journal of Experimental Education*, *79*(1), 1–29. https://doi.org/10.1080/00220970903292934

Zheng, L., Long, M., Zhong, L., & Gyasi, J. F. (2022). The effectiveness of technology-facilitated personalized learning on learning achievements and learning perceptions: A meta-analysis. *Education and Information Technologies*, *27*(8), 11807–11830. https://doi.org/10.1007/s10639-022-11092-7