RESEARCH REPORT

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The Impact of IXL on Students' Math Self-Efficacy

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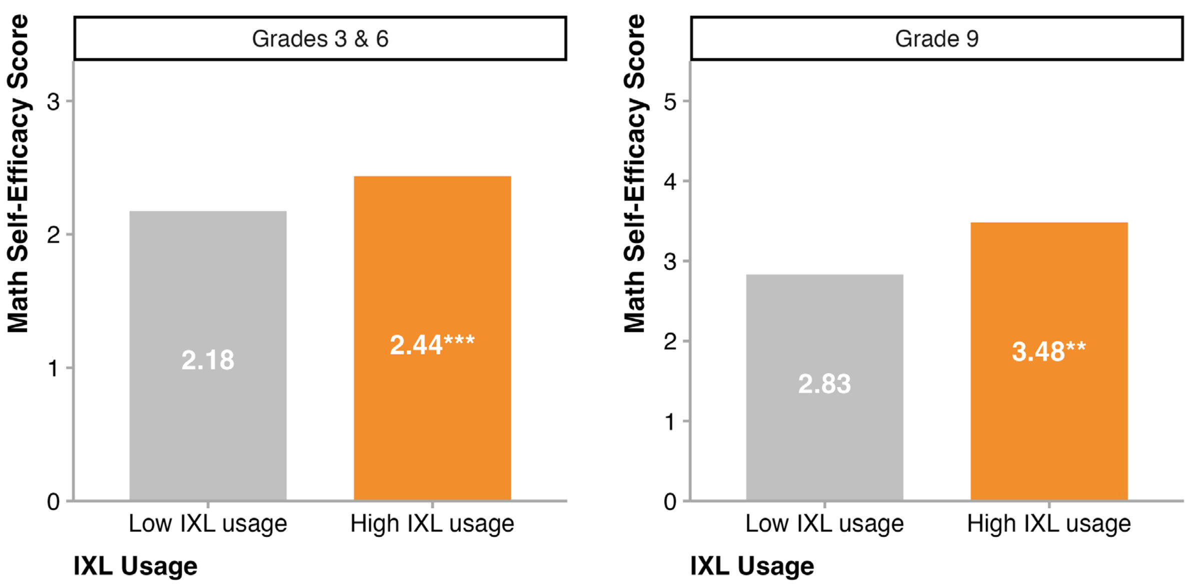
Executive Summary

IXL is an end-to-end teaching and learning solution that engages learners in Pre-K through 12th grade with a comprehensive curriculum and personalized recommendations for meeting learning goals. Previous research has shown that IXL can have a significant positive impact on students' academic performance (Copeland et al., 2023; also see https://www.ixl.com/research).

While a number of studies have investigated the positive impacts of IXL on students' academic achievement across various subjects and grade levels, IXL's potential role in enhancing students' interest, confidence, and belief in their ability to succeed academically had not yet been studied empirically. Therefore, this study aimed to examine the impact of IXL on students' math self-efficacy using data from 3rd, 6th, and 9th grade students in one Ontario district school board[1]. Students' self-efficacy in math was assessed through self-reported questions on the Ontario Education Quality and Accountability Office (EQAO) Assessment of Mathematics. Using a structural equation model, we found that:

- **IXL helps improve students' math self-efficacy, in addition to its positive effects on math achievement.** Students with higher IXL Math usage exhibited substantially higher levels of self-efficacy (i.e., interest and confidence) in math compared to their peers with lower IXL Math usage[2], after accounting for students' baseline math achievement (pretest), IXL's impact on math achievement at posttest, and demographics[3].



[1] *This is equivalent to a school district in the U.S.*

[2] *In all figures, ** indicates statistical significance at p < .01, and *** indicates p < .001.*

[3] *See the full structural equation modeling results in the main report below.*

The Impact of IXL on Students' Math Self-Efficacy

Background

IXL is an end-to-end teaching and learning solution that engages learners in Pre-K through 12th grade with a comprehensive curriculum and personalized recommendations for meeting learning goals. It covers five main subject areas: mathematics, English language arts (ELA), science, social studies, and Spanish. As of this writing, IXL is used by 15 million students and by over 1 million educators worldwide. IXL is deeply rooted in learning sciences research (see Bashkov et al., 2021) and engages each student in a personalized learning experience tailored to their working level. As a result, students work through problems that are neither too easy nor too difficult, promoting optimal learning and growth.

Numerous studies have examined and demonstrated IXL's positive effects on students' academic achievement (Copeland et al., 2023; also see https://www.ixl.com/research); however, no prior research has studied IXL's impact on students' self-efficacy (i.e., one's perception of one's ability to succeed academically). Given its highly adaptive engine and design features grounded in learning sciences research (see Bashkov et al., 2021), there is reason to believe that IXL's benefits may span beyond academic achievement as measured by standardized tests. According to Bandura's social cognitive theory (Bandura, 2001), there is a reciprocal relationship between academic achievement and self-efficacy. Prior research has shown that the success students experience with high academic performance enhances their perceptions of their capacity to meet future performance expectations (e.g., Hwang et al., 2016). Conversely, academic self-efficacy influences students' effort, perseverance, and the activities in which they choose to engage (e.g., Honicke, & Broadbent, 2016). In other words, levels of achievement and self-efficacy go hand-in-hand (Bandura et al., 1996). Thus, it stands to reason that if IXL boosts academic achievement, it should also boost self-efficacy.

In addition to the theoretical background on a potential relationship between IXL usage and self-efficacy, there is some limited empirical evidence supporting this idea as well. One study that examined the impact of perseverance during IXL practice found that persisting through temporary setbacks to reach proficiency in IXL skills led to significantly larger academic gains than "breezing" through skills (i.e., making fewer mistakes), controlling for baseline performance (see Schonberg, 2023). Another study (An et al., 2022) found that 90% of the surveyed teachers reported that their students were motivated to use IXL Math. However, neither of these studies examined students' self-reported levels of academic motivation or self-efficacy and its relation to IXL usage. Importantly, investigating IXL's influence on self-efficacy will provide a more comprehensive understanding of IXL's overall impact on students' learning outcomes beyond performance on standardized tests.

RESEARCH QUESTION

The present study aims to expand on the research of IXL's impact on student learning by examining its effects on math self-efficacy. Previous studies have found that academic self-efficacy and academic achievement are closely intertwined (e.g., Talsma et. al., 2018), yet self-efficacy remains malleable and subject to change through targeted interventions (e.g., Schunk, & Ertmer, 2000). Using a structural equation model with data from students in 3rd, 6th, and 9th grade in an Ontario district school board, we examined the relationships among students' IXL usage, academic achievement, and math self-efficacy as measured by the Ontario Education Quality and Accountability Office (EQAO) Assessment of Mathematics. The main research question was:

- What is the impact of IXL on students' math self-efficacy? In other words, to what degree does IXL Math usage predict students' math self-efficacy, beyond IXL's effects on math achievement?

Study Design and Methodology

DATA SOURCES

IXL Usage Data

We obtained IXL usage data from IXL's database. When students use IXL, they answer questions organized within "skills," which are specific topic areas within a subject. The study used the average weekly number of questions answered as the primary IXL usage metric.

IXL Diagnostic Data

IXL Real-Time Diagnostic data were also obtained from IXL's database. When a student completes a sufficient number of questions in a subject (math or ELA) in IXL's Diagnostic, they receive a pinpointed score that indicates their overall grade-level proficiency in that subject. For example, a score of 600 indicates that the student is ready to begin learning 6th-grade material, whereas a score of 650 indicates that the student has acquired about 50% of 6th-grade material. Students' IXL Diagnostic scores in math from the beginning of the 2022-23 academic year were used as measures of baseline performance (i.e., pretest) in the analysis. For 9th graders who took their math course in the spring, we used midyear diagnostic scores to account for baseline math proficiency.

Academic Assessment Data

The participating district school board provided student-level Spring 2023 assessment performance data. The EQAO Assessment of Mathematics is administered to students in 3rd grade (Primary Division) and 6th grade (Junior Division) as an end-of-year assessment. Students in 9th grade complete the EQAO Grade 9 Assessment of Mathematics at the end of the semester in which they take the Ontario Grade 9 mathematics course (MTH1W). EQAO Assessment of Mathematics performance levels range from 0-4, with levels 3 and 4 indicating that a student has met the provincial standard for mathematics achievement. For more information about the EQAO assessments, see the EQAO assessments homepage. We used students' EQAO Mathematics performance levels as the posttest variable in the model.

Self-Efficacy Data

The EQAO Assessment of Mathematics includes several self-reported items related to self-efficacy. There are four items measuring math interest (e.g., "I enjoy solving math problems.") and four items measuring math confidence (e.g., "I can answer difficult math questions."). Students respond to these items using a Likert-type scale indicating the extent to which they agree with each item (see Appendix A for the full list of items). Students in 3rd and 6th grade respond on a scale of 1-3, and students in 9th grade use a scale of 1-5. In order to combine self-efficacy data across grades, we standardized the raw scores across grade levels prior to analysis.

Demographic Data

The district school board also provided student-level demographic information data, including whether the student belonged to an Indigenous group (i.e., First Nations, Métis, Inuit, or FNMI), English Language Learner status (ELL; i.e., did not learn English as a first language at home), disability status (i.e., enrollment in special education programs), and gender. These demographic variables were dummy coded and included in the model.

PARTICIPANTS

We included data from students with any amount of IXL usage in the 2022-23 school year as well as non-missing pretest and posttest data. The sample size for students in 3rd and 6th grade was 397, and the sample size for 9th graders was 105. The total sample of 502 students included 53.2% boys, 8.2% ELLs, and 27.7% students receiving special education services. In addition, 18.3% of the sample identified as FNMI. Descriptive statistics of students' IXL usage are reported in Table 1, and descriptive statistics of students' pretest and posttest performance are presented in Table B (Appendix B).

Table 1. **Students' IXL Usage During the Study Period**

Weekly IXL usage	Grades 3 and 6 (*n* = 397)				Grade 9 (*n* = 105)			
	M	*SD*	Min	Max	*M*	*SD*	Min	Max
Questions answered	43.07	30.93	0.00	177.78	45.23	35.42	0.00	200.75
Skills proficient	1.07	0.91	0.00	5.95	1.15	1.28	0.00	9.94
Time spent (in minutes)	14.79	8.94	0.00	56.14	26.25	19.58	0.00	97.91

ANALYSIS

We used structural equation modeling (SEM) to specify and test the fit of a theoretical model aligned with our main research question. Our hypothesized model included a measurement component and a structural model (see Figure 1).

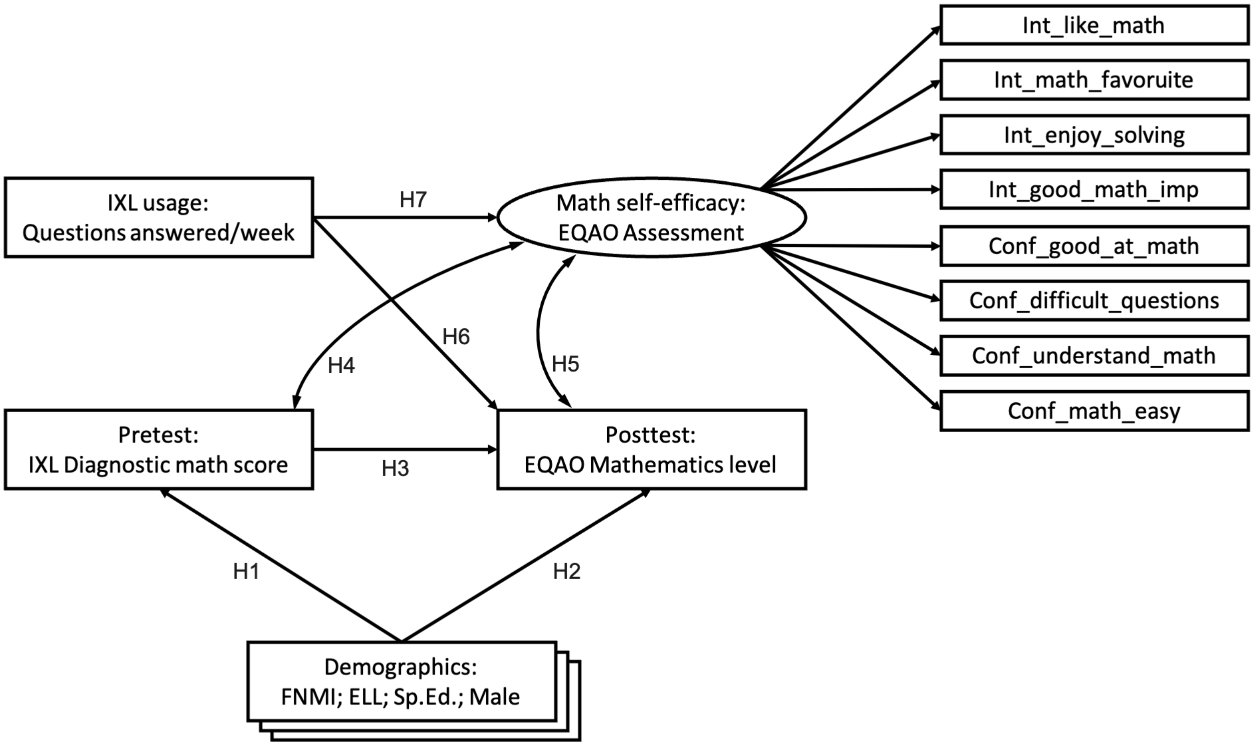


Figure 1. Representation of the SEM[3]

Measurement Model

We ran a series of analyses to examine the construct validity of the EQAO measures of math self-efficacy prior to specifying the full model along with IXL, math performance, and demographic variables shown in Figure 1. Exploratory factor analysis suggested a one-factor model, which explained 51% of the variance in item responses with $\chi^2 = 202.3$ ($df = 20$, $p < .001$). However, based on the wording of the items, it is possible that a two-factor model may fit the data better, with math "interest" and "confidence" items modeled as related but distinct dimensions. A two-factor confirmatory factor analysis indicated that the latent correlation between "interest" and "confidence" was 0.81. Taking these results together, we opted to model "math self-efficacy" as one latent variable with eight observed indicators as the measurement model. The variance of the latent "math self-efficacy" factor was fixed to 1, while the factor pattern coefficients to all eight items were freely estimated.

[3] *The predictive paths of demographic variables are combined in this representation for simplicity.*

Structural Model

There were five key variables in the structural model: IXL usage, math self-efficacy, math achievement at pretest, math achievement at posttest, and demographics (including Indigenous status, ELL status, disability status, and gender). Based on previous studies and the literature, we estimated the following hypothesized paths (labeled in Figure 2): **H1 & H2:** Demographic background is often related to students' math achievement; **H3:** Students' math scores earlier in the school year can predict their scores later in the school year; **H4 & H5:** There is a reciprocal relationship between math achievement and math self-efficacy; **H6:** IXL Math has a positive effect on students' math achievement; and **H7 (key research question):** IXL Math has a positive effect on students' math self-efficacy.

We used the *lavaan* R package (Rosseel, 2012) to estimate model parameters with full information maximum likelihood estimation, which accommodated variables with missing values (about 2% of the data). Several prevailing indices were used to evaluate absolute model fit, including the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). CFI values greater than or equal to .95, and RMSEA and SRMR values less than or equal to .08, were considered indicative of satisfactory model-data fit (Hu & Bentler, 1999).

Following What Works Clearinghouse (2022) guidelines, each effect is accompanied by a test of statistical significance using a probability (p) value and a measure of effect size. The p-value is the probability of observing the current or more extreme data, assuming the effect is zero (Cohen, 1994). The smaller the p-value, the less likely it is that the result occurred at random, with p-values less than .05 considered statistically significant. We used the standardized path coefficients to measure effect size. For broad-scope educational assessments, moderate effect sizes range from about .05 – .20, and effect sizes of about .20 or higher are considered large (Kraft, 2020; Lipsey et al., 2012).

Results

Given good model fit ($\chi^2 = 268.4$ [$df = 74$; $p < .001$], CFI = .980, RMSEA = .060, SRMR = .064) and high reliability (McDonald's omega = .94; Cronbach's alpha = .89), we were able to interpret all hypothesized causal and correlational relationships, including the path testing our main research question about the effect of IXL on math self-efficacy. Full results are presented in Table C (Appendix C).

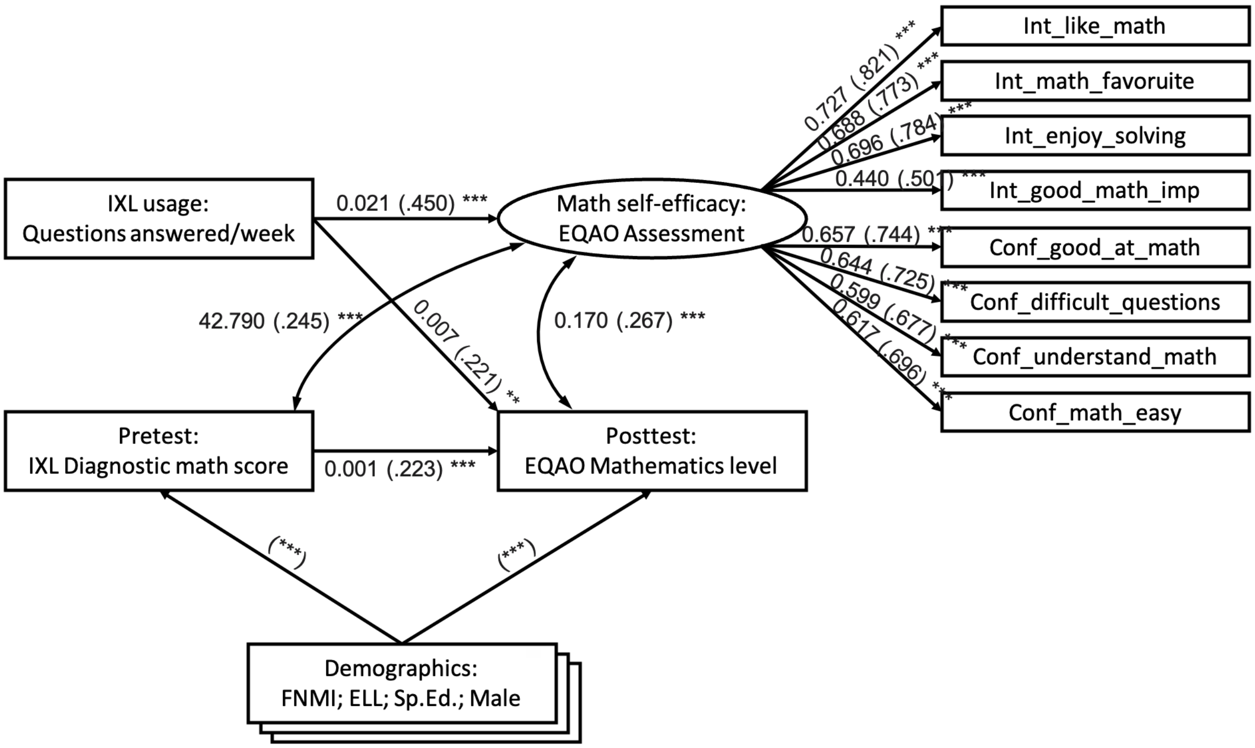


Figure 2. Representation of the SEM. Standardized path coefficients appear in parentheses.

The results of this model support our hypotheses (see Figure 2). Aligned with Bandura's social cognitive theory (Bandura, 2001), we found medium to large positive correlations between math self-efficacy and math achievement (*p*s < .001). Consistent with previous studies, we also found that IXL Math positively affected students' math achievement (*p* < .01) with a medium effect size. With respect to our key research question, we found that IXL Math usage enhanced students' math self-efficacy (*p* < .001) with a large effect size, controlling for prior math achievement and demographics. Specifically, the more students used IXL Math during the school year, the higher their self-reported math interest and confidence at posttest.

Discussion and Recommendations

In this study, we explored the impact of IXL Math on students' math self-efficacy and achievement using data from students in an Ontario district school board. Employing a structural equation model, our analysis revealed that IXL Math not only boosted students' math achievement, but it also positively impacted their self-efficacy in math. This study adds to the body of work on the efficacy of IXL and provides a more comprehensive understanding of the impact of IXL on students' learning experiences. It demonstrates that beyond test scores, IXL has a substantial positive impact on students' academic interest and confidence, thereby enhancing the overall quality of their educational journey.

Importantly, this is the first empirical study of IXL's impact on math self-efficacy, controlling for prior math achievement, IXL's overall impact on math achievement, and demographics. Prior research indicates that teachers report their students are motivated to learn math with IXL (An et al., 2022) and that students report an increase in enjoyment and confidence in learning math (IXL Learning, n.d.). However, the present study tested the direct link between IXL usage levels and students' math self-efficacy at posttest. By accounting for baseline math achievement, which is known to impact students' math self-efficacy (e.g., Hwang et al., 2016), and controlling for IXL's impact on math achievement at posttest, our study provides evidence that IXL has a unique and sizable positive impact on students' self-efficacy, beyond achievement. Therefore, educators who wish to spark students' interest in math—and boost their confidence that they *can* learn and be good at math—should consider implementing IXL in their classrooms to give their students a chance to regain agency in their math learning.

With the present study uncovering additional ways in which IXL can improve students' learning experiences, educators can make better decisions about how to effectively integrate IXL into their classrooms and help students succeed. Beyond IXL's positive effect on achievement, this research reveals that IXL can have a direct impact on students' perceptions of their ability to do well in math. This finding is key because this belief is the cornerstone of Dweck's (2006) growth mindset theory and a pillar in Eccles' expectancy-value theory (Eccles, 1987; Wigfield & Eccles, 2000). In the former, IXL promotes a growth mindset by boosting self-efficacy. In other words, once students realize and internalize that their ability to learn math is not fixed or predetermined, they are free to take agency over their math learning journey and grow. In the latter, IXL drives student motivation by increasing students' confidence and expectancy to do well. Both of these theories and our findings speak to the profound benefits for students that IXL can unlock.

With IXL's personalized and highly adaptive approach to learning and a powerful algorithm that is forgiving of mistakes (see Bashkov et al., 2021), IXL can have truly transformative effects on students, classrooms, and schools. IXL puts students in the driver's seat of their own learning by creating a positive and supportive learning environment, where students feel comfortable exploring and making mistakes. By boosting their interest and confidence, IXL equips students with higher motivation to persist through temporary setbacks, which has been linked to achieving significantly greater learning gains (Schonberg, 2023). In summary, coupled with prior research, this study provides essential information for educators looking to motivate their students and boost students' math learning beyond improving test scores. Our findings show that regardless of a student's starting point or background, IXL substantially boosts their self-efficacy and propels them to even greater success.

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Appendix A: EQAO Items Measuring Math Interest and Math Confidence

Question Prompt
"Please tell us how you feel about math. Do you agree with each of the following?"

Self-Reported Items
(Abbreviations shown in the SEM model are in parentheses.)

4 Items for Math Interest

a. I like math.	(Int_like_math)
b. Math is one of my favourite subjects.	(Int_math_favoruite)
c. I enjoy solving math problems.	(Int_enjoy_solving)
d. Being good at math is important to me.	(Int_good_math_imp)

4 Items for Math Confidence

a. I am good at math.	(Conf_good_at_math)
b. I can answer difficult math questions.	(Conf_difficult_questions)
c. I understand most of the math I am taught.	(Conf_understand_math)
d. Math is an easy subject.	(Conf_math_easy)

Likert Scales

For Grade 3 and 6:

1 No, I do not agree
2 I am not sure
3 Yes, I agree

For Grade 9:

1 Strongly disagree
2 Somewhat disagree
3 Neither agree nor disagree
4 Somewhat agree
5 Strongly agree

Appendix B: Pretest and Posttest Performance Descriptives

Table B. **Means (Standard Deviations) of Students' Math Pretest and Posttest Performance**

Grade	IXL Real-Time Diagnostic math score (Pretest)	EQAO Assessment of Mathematics level (Posttest)
3	213.75 (81.84)	2.27 (0.81)
6	393.33 (121.17)	2.10 (0.74)
9	587.33 (156.85)	2.17 (0.67)

Appendix C: SEM Results

Table C. **Summary of Full SEM Results**

	Estimate	*SE*	Std. Est.	*z*	*p*
Measurement Model					
Math self-efficacy =~					
Int_like_math	0.73	0.03	0.82	23.22	<.001
Int_math_favoruite	0.69	0.03	0.77	23.72	<.001
Int_enjoy_solving	0.70	0.03	0.78	24.67	<.001
Int_good_math_imp	0.44	0.04	0.50	10.56	<.001
Conf_good_at_math	0.66	0.04	0.74	18.64	<.001
Conf_difficult_questions	0.64	0.03	0.73	20.65	<.001
Conf_understand_math	0.60	0.04	0.68	14.85	<.001
Conf_math_easy	0.62	0.03	0.70	20.26	<.001
Structural Model					
Math self-efficacy ~					
IXL usage	0.02	0.00	0.45	5.66	<.001
Posttest: EQAO ~					
IXL usage	0.01	0.00	0.22	3.15	.002
Pretest: IXL's Diagnostic	0.00	0.00	0.22	5.70	<.001
FNMI	-0.21	0.08	-0.11	-2.79	.005
ELL	0.01	0.11	0.00	0.07	.948
Special education	-0.50	0.08	-0.30	-6.33	<.001
Male	0.05	0.07	0.03	0.68	.494
Pretest: IXL's Diagnostic ~					
FNMI	-68.38	20.38	-0.14	-3.36	.001
ELL	5.84	30.51	0.01	0.19	.848
Special education	-94.55	17.88	-0.23	-5.29	<.001
Male	37.56	15.91	0.10	2.36	.018
Math self-efficacy ~~					
Posttest: EQAO	0.17	0.03	0.27	4.95	<.001
Pretest: IXL's Diagnostic	42.79	9.23	0.25	4.58	<.001