Title

Prior technology exposure, keyboard/mouse activity, and writing achievement: Analysis of the 2011 National Assessment of Educational Progress writing assessment

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Prior technology exposure, keyboard/mouse activity, and writing achievement: An Analysis of the 2011 National Assessment of Educational Progress writing assessment

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Education

by

Tamara P. Tate

Dissertation Committee:
Professor Mark Warschauer, Chair
Professor Carol Booth Olson
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2018

DEDICATION

To Bill, Will, and Christopher, you inspire me daily.

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ACKNOWLEDGMENTS

Thank you to my advisor, Mark Warschauer, who took a chance on an unconventional PhD student and continues to provide me with support, opportunities, and friendship. I love to come to work every day.

I would also like to thank my committee members, who not only served on my committee but reviewed and provided thought-provoking comments on each of my milestones (Carol Booth Olson), coauthored the article from study 3 (Young-Suk Grace Kim), and co-advised me on my GSR adventure with middle school students and co-wrote so many grant applications over the summers (Penelope Collins). You are amazing people and scholars.

Finally, thanks to my friends in our little corner of the Education building and the Digital Learning Lab. You are doing cutting edge work to improve learning for all students and my work is better because of your support.

I also thank Elsevier for permission to include Chapter One of my dissertation, which was originally published in Computers & Education. This work has been supported by funding from the Spencer Foundation, Grant 201500153. This work is based on the 2011 National Assessment of Educational Progress in Writing Restricted-Use Data, available from the National Center for Education Statistics (NCES Pub. No. 2014476).
https://nces.ed.gov/nationsreportcard/researchcenter/datatools.aspx

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PUBLICATIONS

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Tate, T., Warschauer, M., & Abedi, J. (2016). Data on NAEP 2011 Writing Assessment Prior Computer Use, *Data in Brief,* doi:10.1016/j.dib.2016.07.002

Book Chapters

Tate, T., & Warschauer, M. (2018). Digital divides and social inclusion. In K. Mills, A. Stornaiuolo, A. Smith, & J. Pandya (Eds.), *Handbook of Writing, Literacies, and Education in Digital Cultures* (pp. 63-75): Routlege.

Tate, T., & Warschauer, M. (2017). One-to-one device initiatives. In K. Peppler (Ed.), *The SAGE Encyclopedia of Out-of-School Learning* (p. xx-xx). Thousand Oaks, CA: Sage. http://dx.doi.org/10.4135/9781483385198

Tate, T., & Warschauer, M. (2017). Computer Access in the Home. In K. Peppler (Ed.), *The SAGE Encyclopedia of Out-of-School Learning* (pp. 120-121). Thousand Oaks, CA: Sage.

Tate, T.,& Warschauer, M. (2017). The digital divide in language and literacy education. In S. May (Ed.), *Encyclopedia of Language and Education,* Vol. 9, Language, Education and Technology, S. Thorne (Ed.) doi:10.1007/978-3-319-02328-1_5-1

Zinger, D., **Tate, T.,** Warschauer, M., (2017). Learning and teaching with digital media: Technological pedagogy and classroom practice. In J. Clandinin, & J. Husu (Eds.) *The SAGE Handbook of Research on Teacher Education.* (pp. 577-593) London, UK: SAGE

Other Publications

Warschauer, M., Collins, P., Farkas, G., **Tate, T**., Krishnan, J., Yau, J., Xu, Y., & Prado, Y. (Nov. 29, 2017). Report to Garden Grove Unified School District on US Department of Education Award R305A150429, Project 84.305A Digital Scaffolding for English Language Arts.

Warschauer, M. & **Tate, T**. (2015). Going one-to-one, 2.0. *Educational Leadership*, 72 (8), 60-65.

Warschauer, M., **Tate, T**., Niiya, M., Yim, S., & Park, Y. (2014). Supporting digital literacy in educational contexts: Emerging pedagogies and technologies. Report to the International Baccalaureate Program.

Manuscripts under Review

Tate, T., & Warschauer, M. What's in a Keystroke? Analysis of the 2011 NAEP Computer-Based 8th Grade Writing Assessment.

Tate, T., & Warschauer, M. What's so special about digital writing? A look at the research in U.S. K-12 education.

Tate, T., Warschauer, M., & Kim, Y.-S. G. Learning to Compose Digitally: The Effect of Prior Computer Use and Keyboard Activity on NAEP Writing.

Manuscripts in Preparation

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SELECTED CONFERENCE PRESENTATIONS

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From Keystrokes to Achievement Scores: The Effects of Prior Computer Use on Computer-based Writing, Poster, Text and Data Mining for Interactive Online Learning, May 8, 2015, University of California, Irvine

From Keystrokes to Achievement Scores: The Effects of Prior Computer Use on Computer-based Writing, Graduate Student Roundtable, American Educational Research Association, April 2015, Chicago, IL.

Krishnan, J, Tate, T, Yau, Joanna, Xu, Ying, Prado, Y. Digital scaffolding for English language arts. Poster presented at: Institute of English Sciences Annual Principal Investigators' Meeting; 2018 Jan 9-10; Washington, DC.

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TEACHING EXPERIENCE

Guest Lecture, Winter 2018, Education 50, Issues in K-12 Education, Brandy Jenner. Lecture on exceptional learners.

Guest Lecture, Fall 2017, Education 212, Literacy and Technology, Mark Warschauer. Panel on data mining in educational research.

Guest Lecture, Winter 2017, Education 30, 21st Century Literacies, Mark Warschauer. Lecture on Digital Media for Personalized Literacy Learning

Teaching Assistant, Spring 2014

Education 30, 21st Century Literacies, Viet Vu. Lead 2 discussion sections of approximately 40 students each. Prepared quizzes, graded quizzes, projects, midterms, and finals. Lectured to entire class of approximately 160 students on assessment.

Teaching Assistant, Winter 2014

Education 50, Issues in K-12 Education, Viet Vu. Duties included monitoring Facebook groups, guiding discussion groups in class discussions, preparing quizzes, and grading of papers, midterms, and finals for class of undergraduates. Lectured on history of education from 1965 to present.

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Education 125, Children in Schools and Cinema, Susan Guilfoyle. Duties included grading weekly film reflections and final film analysis paper for class of 70 undergraduates.

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PROFESSIONAL DEVELOPMENT

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The Stanford Education Data Archive: Using Big Data to Study Academic Performance, AERA 2017, Sean F. Reardon, Stanford University

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Santa Ana Unified School District Advanced Learning Academy Charter School Board member, 2015-2018

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University of California, Irvine, School of Education ADSE Cohort Representative, 2017-18

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University of California, Irvine, School of Education ADSE Professional Development Chair, 2015-16

Information doctoral and undergraduate student mentoring

Pioneer Middle School, School Site Council 2015-2016

Peters Canyon Elementary School, PTO President 2011-2013, School Site Council

Managed $140,000 annual budget; lead board of volunteers; communicated with administration, teachers, staff, and parents; implemented technology plan; developed Parent Teacher Resource Center; created Sensory Lab with grant funding.

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Research Methods: Ordinary Least Squares & Logistic Regression (including fixed effects, clustered errors), Analysis of Variance, Structural Equation Modeling (including advanced longitudinal methods), Multilevel Modeling, Factor Analysis, Cluster Analysis

Statistical Software: Stata, R, Mplus

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CapFin Partners, LLC, 2010-2013

Managing Director of boutique financial services firm engaged in providing equity capital, investment management, and advisory services. Asset acquisitions included shopping centers, chocolate manufacturer, and finance company.

Morrison & Foerster, LLP, 1990-2007

Partner in top tier international firm in the corporate finance group, with emphasis on securities offerings, mergers and acquisitions, and corporate counseling. Represented companies in a variety of industries, including biotechnology, consumer goods and services, financial services, gaming, healthcare, and high technology. Counseled both public and private companies on corporate finance, securities, and business restructuring and regulatory compliance issues. Advised companies and their Boards of Directors on disclosure and compliance issues and corporate governance matters. Prepared disclosure documents and agreements. Counseled companies on technology licensing and intellectual property issues. Technology committee; recruiting; interactive forms project; numerous profession development and client trainings; assistant managing partner for Orange County office.

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REFERENCES

Available on request

ABSTRACT OF THE DISSERTATION

Prior technology exposure, keyboard/mouse activity, and writing achievement:
The 2011 National Assessment of Educational Progress writing assessment

By

Tamara P. Tate

Doctor of Philosophy in Education

University of California, Irvine, 2018

Professor Mark Warschauer, Chair

Given the importance of digital writing in the workforce and in academia (DeVoss, Eidman-Aardahl, & Hicks, 2010), students need to be able to communicate in the normative modality (Bazerman, 2012; Leu et al., 2014). It is critical to expand our understanding about technology exposure and keyboard activity and their relations to writing skills. This 3-part dissertation brings together my work analyzing the first national digital writing assessment, the 2011 National Assessment of Educational Progress (NAEP). Using data from over 24,100 eighth grade students, I analyzed the teacher and student reports of prior technology use of various types, specific keyboard and mouse activity during the writing assessment, and the paths through which these factors may relate to writing achievement on the test.

Study one looked primarily at the relationship between teacher and student reports of prior technology use and student writing achievement. We showed that use of technology for school-related purposes predicted increased writing achievement. We also found that use of technology for personal purposes, writing emails, blogging, etc., did not predict improved (or reduced)

writing achievement. Study two looked at the relationship between the actual keyboard and mouse activity of students during the assessment and their writing achievement. Not only were we able to show that students who write more (both words and keystrokes) predicted higher achievement outcomes, but for the first time we were able to gather descriptive information about how often students use editing tools (hardly at all) and begin to use datamining techniques like cluster analysis to look at whether students exhibited different patterns of keystroke and editing feature usage and how these patterns related to both writing achievement and prior use. In study three, we put the information from the prior studies together and modeled the relationship among all three of our variables of interest: prior technology exposure, keyboard and mouse activity during the assessment, and writing achievement scores. We found evidence that not only did prior technology exposure have the expected impact on students' keyboarding activity during the writing assessment, but that it had an independent effect on writing achievement over and above the transcription-level keyboarding effect.

CHAPTER 1

Introduction

This 3-part dissertation brings together my work analyzing the first national digital writing assessment, the 2011 National Assessment of Educational Progress (NAEP). Using data from over 24,100 eighth grade students, I have analyzed the teacher and student reports of prior technology use of various types, specific keyboard and mouse activity during the writing assessment, and the paths through which these factors may relate to writing achievement on the test. Although descriptive relationships about these data have been published (National Center for Education Statistics [NCES], 2012), the paths of relations among prior technology exposure, keyboard activity during the assessment, and writing achievement have not been investigated. By understanding the model of how prior technology exposure, keyboard activity during assessment, and writing achievement relate, we can generate insight and strategies for teaching diverse students to write better with digital media.

Writing

Writing is a crucial component of college and career readiness (Graham & Perin, 2007; Applebee, 2011; Graham, 2012; Leu, Forzani, Rhoads, Maykel, Kennedy, & Timbrell, 2014) and is central to academic language development, critical thinking, and development of reasoning in diverse content areas (Intersegmental Committee of the Academic Senates of the California Community Colleges, the California State University, and the University of California, 2002). It is also an essential, threshold skill for employment and promotion (The National Commission on Writing in America's Schools and Colleges, 2003, 2004). The challenge of improving students' writing to meet college and career demands stems from the fact that writing is a complex cognitive process, drawing on neurological, motor, cognitive, language, and visual processes.

Developmentally, writing proceeds from the emergent ability to denote symbols with a crayon or pencil to the sophisticated ability to compose clear and compelling descriptions, narratives, or arguments. Most U.S. middle school students are not proficient at writing: Only 27% of all 8th grade students, 11% of Black students, and 14% of Hispanic students score at or above proficient levels and, even more troubling, 1 in 5 secondary students score in the below basic range (National Center for Education Statistics, 2012).

Digital Writing

Today, nearly all serious writing in vocational, professional, and academic domains is done via digital media (DeVoss, Eidman-Ardahl, & Hicks, 2010), and computers are becoming the main vehicle for K-12 student writing from approximately upper elementary grades on (Graham et al., 2016). Digital writing includes features that are simply not possible when writing by hand, such as the ability to copy, move, and paste chunks of text, thus making it a distinct, albeit closely related, process. Students thus need to be prepared for evolving digital literacy practices, including, for example, simultaneous collaborative writing by multiple authors on a single text (Graham et al., 2016; Graham et al., 2012; Warschauer, Zheng, Niiya, Cotton, & Farkas, 2014). In many instances, however, students receive inadequate explicit instruction in writing on computers (Applebee & Langer, 2011). Digital technologies present specific cognitive challenges and opportunities (Bazerman, 2012; Leu et al., 2014) that students must be able to negotiate, including the ability to embed mechanical supports such as spell check into the writing environment and the ability to cleanly cut and paste text from one paragraph to another. Students need to learn both how to use technology to enhance their own writing processes in ways that are effective for them and how to reflect upon their practices to ensure that the modality chosen for each stage of writing is used in ways that help, not hinder, the generation of quality writing (Van Ittersum, 2011).

Theoretical Background

These studies are situated in cognitive and sociocultural theories of writing. As for the cognitive models, the process models are particularly relevant to the present study (e.g., Flower & Hayes, 1981; see Kim & Schatschneider, 2017 for component-based models). According to Flower and Hayes (1981), writing is composed of planning, translating, and reviewing and revising. During the planning phase, writers form an internal representation of the knowledge that will be used in writing, by using sub-processes like generating and organizing ideas. During the translation phase, writers generate written text, which involves syntactic and lexical skills as well as motor skills and working memory. Finally, during the reviewing and revising phase, writers improve existing text. The Flower and Hayes model was developed to describe the writing of proficient, skilled adults. In later research with beginning and developing writers, Berninger et al. (1996) argued that (a) text generation (which itself has the components for producing words, sentences, and paragraphs) is distinguished from idea generation, and (b) that planning is of two types: advanced planning prior to any translation and in-process planning of the next thing to write. They noted further that neurodevelopmental skills (such as orthographic coding) place constraints on writing development to varying degrees throughout the lifespan (Berninger et a.l, 1996). Skill development influences transcription, higher level linguistic and cognitive skills such as planning, translation of ideas into appropriate structures, and revision (Berninger & Swanson, 1994; Kim, 2015; Kim & Schatschneider, 2017).

Composition is a recursive process (McCutchen, 1996; Berninger et al., 1996): writers cycle through the planning, translating, and reviewing multiple times, and these stages all interact with one another throughout the composing process (Flower & Hayes, 1981). These processes are especially difficult to disentangle in *digital* writing, where writers can move fluidly around a text to generate initial text, then jump to a prior section to refine meaning as needed, then jump back to text generation without leaving a trail of crossed out text or arrows on the draft.

The challenge of successful writing is further complicated because writing is greatly influenced by the tools that enable it and the media that encapsulate it (see Bolter, 1991). Scholars ascribing to sociocultural theory focus on the social environment, or context, and its effects on learning (Wertsch, 1998). Literacy is seen as multiply situated, mediated sociocultural practices, and as motivated and socially organized activity (Deane, Sabatini, & Fowles, 2012; Prior, 2006; Scribner & Cole, 1981). The writing process is shaped by the author's tools (Wertsch, 1991) and like all tools digital tools have specific affordances. These affordances encompass the perceived and actual properties of the tool, primarily those fundamental properties that determine just how the tool could possibly be used (McGrenere & Ho, 2000). In the digital writing environment, we see affordances such as synchronous collaboration, the ability to "publish" readable texts, and embedded supports changing students' writing processes. We also find that communities of practice using digital devices tend to write more during the school year (Warshauer, 2011).

The studies in this dissertation also fill a gap in the literature, which has tended to focus on early writing development in the primary grades or the proficient writing of adult writers, with sparse data on students in adolescence (see discussion in Graham & Hebert, 2010; Carnegie, 2010). For example, in a recent meta-analysis on the component skills of writing, only 2 of the 43 studies cited were conducted among students in grades 7-12 (Kent & Wanzek, 2016). There is a critical need for more research on adolescent writing, particularly given great demands for developing analytic and argumentative writings skills across the curriculum in secondary schools (National Center for Education Research, 2017).

2011 NAEP Writing Assessment

Data Source. This research analyzed the data from over 24,600 eighth grade students. NAEP assessments are widely regarded as high quality, with strong construct and measurement validity (see, e.g., Wenglinsky, 2005). The weighted national school participation rates for the assessment were 97 percent (100 percent for public schools; National Center for Education Statistics (NCES), 2012). To the extent certain subgroups fell below 70 percent, NCES conducted an analysis of potential bias. Compared with the distribution of all eligible students, the distribution of the weighted sample did not differ with respect to any of the variables utilized in this analysis (Rogers, Stoeckel, & Sikali, 2013). This analysis utilized the restricted data set, which includes scaled and raw scores, detailed survey data, and individual keystroke data. As suggested by NCES, the following were treated as missing: multiple responses, responses not reached or administered, omitted responses, non-ratable responses, illegible responses, and off task responses.

Sampling. NAEP sampling techniques strive to create a representative nationwide sample of students in grades 4, 8, and 12. Participants are selected using a stratified cluster sampling, where the population is divided into different strata, or geographic areas of interest, from which the schools were selected (Beaton, et. al, 2011). In order to approximate the population, sample weights are used to correct for oversampling of certain low incidence populations and adjust the overall results by the actual population proportion (Johnson, 1992). These weights allow for valid inferences to be made about the population (Beaton, et. al, 2011).

While traditional analysis procedures assume that observed data from different individuals are independent of each other and randomly distributed, NAEP results may be stratified and clustered (Johnson, 1992; Zwick, 1987). Through clustering, weighting, and marginal estimation procedures, NAEP allows for population and group estimates (Beaton & Zwick, 1992). Ignoring these effects leads to biased estimates of variance and generally to underestimating the biases (Johnson, 1992). In addition, the deeply stratified cluster samples influence the likelihood ratio and inflate the differences in the chi-squares, and the design effect for item *p* values is estimated to be roughly 2 (an estimate of percent of examinees with a given response pattern should be equivalent in precision to a simple random sample approximately half as large; Haertel, 1984). Where the analysis looked at the individual booklet-level responses, weighting was not applied (Allen & Donoghue, 1996). Where I looked at aggregated values of individual, unscaled scores, I used jackknife weights for the analysis.

Population. I focus on eighth grade students, as prior research suggests that the middle school years are critical for the development of academic writing (De La Paz & Graham, 2002; Zheng & Warschauer, 2015). Indeed, some refer to an eighth-grade literacy cliff (e.g., Zheng & Warschauer, 2015). In addition, the NAEP data for eighth grade, unlike twelfth, has a teacher survey reporting on technology exposure allowing for potential correlation between student-reported use and teacher-reported use.

Assessment. NAEP assessments are known for their robust construct validity (see, e.g., Applebee, 2007; Wenglinsky, 2005). Over the course of 18 months, more than 500 individuals developed a framework for the NAEP writing test (NAGB, 2010). These individuals included leading educators and experts in the field of assessment (Applebee, 2007). The NAEP writing framework was designed to reflect the way students write today, using word processing software and commonly available tools (NAGB, 2010). As a result, the assessment allowed students to use common word-processing tools:

- editing (cut, copy, paste, delete, backspace);
- formatting (indenting, underlining, highlighting, bolding, and italicizing);
- spelling check, grammar check, thesaurus, and dictionary; and
- viewing and reviewing during the assessment (NAGB, 2010).

In addition, the assessment included student and teacher surveys that gathered information about students' and teachers' prior use of computers and other areas of interest to researchers.

The students were given two different writing tasks and had 30 minutes to complete each task. There were a total of 22 writing prompts in three areas: (a) to persuade, (b) to explain, and (c) to convey experience, either real or imagined. Responses were scored by three trained evaluators on a 6-point scale—effective skill, adequate skill, developing skill, marginal skill, and little or no skill—across three areas of writing: (a) development of ideas, (b) organization of ideas, and (c) language facility and conventions (NCES, 2012; NAGB, 2010). NAEP evaluators used holistic scoring rubrics to evaluate the response as a whole, rather than assessing independent parts of the response (NAGB, 2010). NAEP ensures scorers' reliability through back reading where scoring supervisors selectively review at least five percent of each scorer's work, periodic calibration of multiple scorers, and an inter-rater reliability statistics check of 25 percent of the responses (NCES, 2009).

The presentation of the items was alternated so that the same item appeared first in some booklets and second in others. This balancing of order of presentation is important, because NAEP has found that assessments with open-ended responses show decreased scores in the later items (Johnson, 1992). However, because of this balanced incomplete block (BIB) spiraling method of sampling, NAEP data is complex to model (Beaton & Zwick, 1992). BIB spiraling presents each item to a large number of participants and pairs items to allow correlations between the items (Beaton, et. al, 2011; Johnson, 1992). BIB spiraling is used to allow broad coverage of the item pool, yet not impose excessive test taking upon individual students (Beaton, et. al, 2011; Applebee, 2007). This design has two major limitations. Each student only receives a fraction of the test, which weakens any ability to determine individual achievement in any of the subject areas (and increases measurement error). Second, the scores from each block may not be highly comparable (Beaton, et. al, 2011; Applebee, 2007).

Variables. Initial variable selection included: (a) reported prior technology exposure; (b) achievement scores on the writing assessment, either scaled or mean scores; and (c) group variables for gender, ethnicity/race, eligibility for free/reduced lunch, highest level of parental education, English-learner status, and disability status.

NAEP uses Item Response Theory (IRT) scaling to allow for estimates of item characteristics and difficulties, as well as multiple imputation to estimate student achievement values in terms of plausible values (Beaton, et. al, 2011; Zwick, 1987). However, the NAEP Primer cautions that researchers interested in interaction effects should not work with plausible values, but should perform their own marginal estimation (Beaton, et. al, 2011). Thus, some of my analyses looked at both the mean of all the individual raters' scores for a particular student's response and scaled scores at the booklet level and as an aggregated group, but I did not use plausible values since I was interested in the possible interactions between prior use and our demographic variables and, in the case of the keystroke analyses, wanted to stay at the individual response level.

The scaled booklet-level scores (-2.18 to 3.04) were used as the achievement variable or dependent variable for the initial analyses in Study 1. This allowed us to get a sense of student performance normed (using IRT) across the various booklets and allowed analysis of a larger number of cases for low incidence demographics. The main purpose of NAEP's IRT analyses is to provide a common scale on which to compare achievement across groups (Messick et al., 1983). Researchers can then compare performance across groups, if the subgroups are of sufficient size (Messick et al., 1983).

Additional analysis of student scores was done with the mean of the unscaled scores (interval scale, 1-6) sorting the students and analyzing them by booklet. However, the booklet grouping reduces the number of students in the smaller incidence groups, such as students with disabilities.

The scaled writing achievement score had a mean of -0.04 and a standard deviation of 0.96. The raw scores had a mean of 2.64 and a standard deviation of 0.98 (see Table 1, Tate, Warschauer, & Abedi, 2016, for additional descriptive statistics on the scaled and mean score variables). Both outcome variables were quite close to a standard curve, with a slight skew (particularly for the mean scores) to the right.

The NAEP data includes survey information from teachers and students with respect to two primary background variables, technology exposure (especially with respect to writing with computers) and types and amount of writing practice. This research focused on the first background variable, amount of prior technology exposure, using the responses to questions related to prior use and access to create a latent construct (Haertel, 1984).

Variables relating to prior technology exposure and access included student-reported measures of how often: (a) the Internet is used to get information, (b) a computer is used for a first draft, (c) a computer is used to make changes in writing, (d) a computer is used to complete writing, (e) a computer is used to write school assignments, (f) a computer is used to write not for school, (g) a computer is used for emails, and (h) a computer is used to write on the Internet. Similar teacher-reported measures of students' classroom use of computers for writing, teacher use of technology in the classroom, and teacher professional development relating to technology use were used. I also considered the effect of having a computer at home, but over 90 percent of the students reported having a computer at home so the variable was of little predictive value. The prior use variables were all standardized for the analyses.

I looked at differences in various demographic groups: (a) gender, (b) national school lunch eligibility and parental education (as proxies to indicate socioeconomic status), (c) English language learner status (prior, current, or not applicable), (d) students with individualized education plans (IEPs) or 504 plans under the American with Disabilities Act, and (e) race/ethnicity. Dichotomous variables were created for these groups. I considered both parental high school completion and parental college completion as potential control variables. Ultimately, I used the parent college completion variable; literature suggests that first generation college students have unique challenges and that as such it is a useful designation for understanding certain aspects of socioeconomic status (see, e.g., Bowen, Kurzweil, & Tobin, 2005; Saenz, Hurtado, Barrera, Wolf, & Yeung, 2007; Sirin, 2005; Pascarella & Terenzini, 1991; Jackman & Jackman, 1983; Snibbe & Markus, 2005). In addition, the high school completion variable had less predictive strength, because only 9 percent of the students had parents who did not complete high school, whereas 44 percent had parents who did not complete college.

The Studies

Study 1. Tate, T. P., Warschauer, M., & Abedi, J. (2016). The effects of prior technology exposure on computer-based writing: The 2011 NAEP writing assessment. *Computers & Education, 101*, 115-131.

This secondary data analysis looks at the relationship between prior use of computers for writing and achievement on the 2011 NAEP computer-based writing assessment. It is published in *Computers & Education*. Our research questions and findings were as follows:

1. Does the prior use of computers positively affect students' results on a computer-based assessment? We found that certain types of prior use did predict higher writing achievement on the computer-based NAEP assessment.

    a. Does it matter whether the prior computer use is school-related or personal? We found that only school-related use was predictive of increased performance.

    b. Are reports of school-related use by students or teachers more predictive of improved writing achievement? Student-reported use was more predictive.

    c. Does a teacher's use of technology for writing instruction predict students' improved writing achievement? Teachers' reported technology use was not predictive of improved writing achievement.

    d. Does technology-related professional development for the teacher predict students' improved writing achievement? Technology-related professional development did not predict improved student writing achievement.

2. Does the effect of prior use of computers on writing achievement vary by demographic group? The results suggest a slightly positive increase in the benefit of prior use for students with a parent who graduated college and a slightly reduced benefit for students

who were eligible for free/reduced lunch, currently designated as English learners, or have a disability.

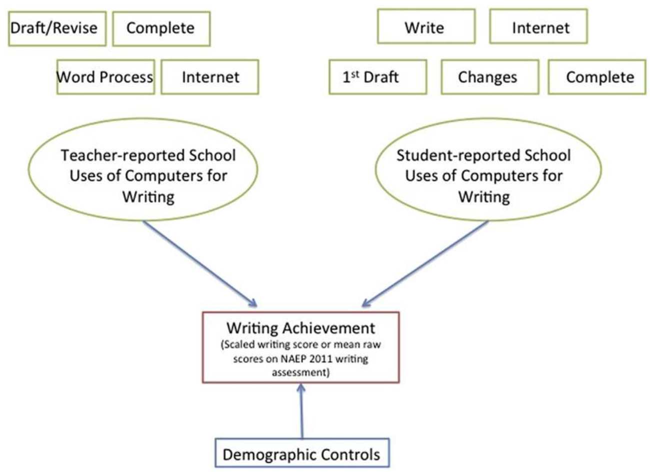

Figure 1. Model of latent prior use variables. Student and teacher-reported amount of prior use was used to create the latent variables. The relationship between the latent variables and writing achievement was determined.

Study 2. Tate, T. P., & Warschauer, M. (under review). Keypresses and mouse Clicks: Analysis of the first national computer-based writing assessment.

This analysis of the NAEP data looks closer at the keyboard and mouse activity of students as they write their texts during the assessment and how it might predict students' writing achievement scores, focusing on two research questions:

1. What is the effect of keyboard and mouse activity during the assessment, looking at word count, keypresses, and individual keyboard and mouse functions, on writing scores?
2. Are there discrete patterns of keyboard and mouse activity during the assessment? If so, how do they relate to positive or negative writing achievement?

For each of these questions, we also examine heterogeneous effects across demographic groups.

We find that, as expected, word count is highly predictive of writing achievement; but we also found that over and above word count, the number of keypresses also predicted writing achievement. These benefits were not uniform across the population however. Additional keypresses were especially beneficial for females and students with a parent who graduated college, but less beneficial for students who were English learners or had a disability. We provide descriptive details on use of specific keyboard and mouse functions, noting little if any use of controversial tools such as speech-to-text and spellcheck. Finally, we identify five patterns of keyboard and mouse activity through our cluster analysis: Productive Activity, High Delete, Typing Only, High Indent, and Unproductive Activity. We discuss the demographics and prior technology exposure of these clusters.

Study 3. Tate, T.P., Warschauer, M., & Kim, Y.-S. G. (under review). Learning to compose digitally: The effect of prior technology exposure and keyboard/mouse activity on NAEP writing.

Having found that both prior technology exposure for school writing and the keyboard and mouse activity during the writing assessment predicted writing achievement on the 2011 NAEP writing assessment, our final analysis revolves around the relationship of these two predictors and writing achievement. Given prior research related to transcription, we hypothesized that increased familiarity with keyboarding and using computer functions like cut and paste gained from prior technology exposure would reduce the cognitive demands of transcription and lead to increased keyboard and mouse activity. Thus, much of the relationship between prior technology exposure and improved writing could be mediated by keyboard and mouse activity during the assessment. However, prior technology exposure might still have a direct relationship with improved writing, if other benefits are gained from prior exposure that would not be reflected in keyboard and mouse activity, such as increased writing practice leading to improved writing fluency. Although less likely, we also considered it possible that prior technology exposure and keyboard and mouse activity might interact and amplify their direct individual impacts on writing, for example making the keyboard or mouse activity more productive, effective, or efficient.

The third study thus examined the impact of (a) prior technology exposure and (b) keyboard and mouse activity during an assessment as direct effects as well as potential mediators and moderators on the 2011 NAEP writing test. Prior technology exposure was operationalized as prior access to and use of computers for academic writing as reported by students; keyboard and mouse activity during the assessment included a suite of variables (e.g., keypresses, cut, and spellcheck) related to the actual behaviors of students when transcribing their texts digitally. Although descriptive relationships about these data have been published (NCES, 2012), the paths of relations among prior technology exposure, keyboard and mouse activity during the assessment, and writing achievement have not been investigated. By understanding the model of how prior technology exposure, keyboard and mouse activity during the assessment, and writing achievement relate, we can generate insight and strategies for teaching diverse students to write better with digital media.

Based on our earlier findings of effects of both prior technology exposure and keyboard and mouse activity during the assessment on writing achievement, the study sought to extend those findings and describe the relationship among them through the following research questions:

1. Does prior technology exposure have a direct relation to writing achievement or is the relation mediated by keyboard and mouse activity during the assessment?

2. Is there an interaction between the effect of prior technology exposure and keyboard and mouse activity on writing achievement?
3. Do the relationships among prior technology exposure, keyboard and mouse activity, and writing achievement vary for different groups of students?

Our analysis found a direct relation of prior technology exposure to writing achievement and an additional relation mediated by certain types of keyboard and mouse activity during the assessment. Solely with respect to keypresses, we also found an interaction with prior technology exposure when predicting writing achievement. With respect to group differences, all students benefited from prior technology exposure, but the benefit was reduced for students from low SES backgrounds, ELL students, and those with a disability.

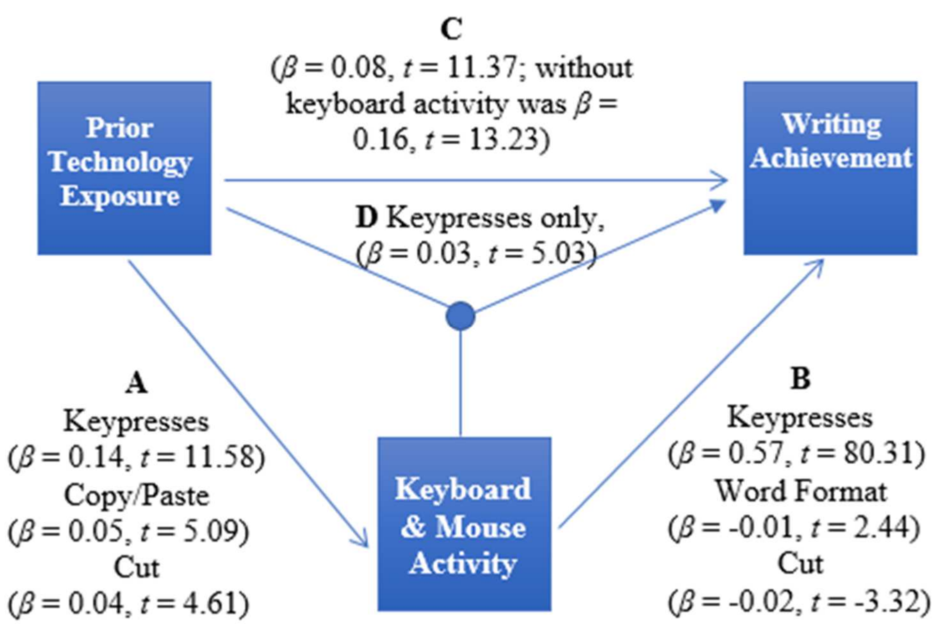

Figure 2. Final partial mediation and moderation model. Some keyboard and mouse activity during the test is impacted by prior technology exposure (Path A), this same keyboard and mouse activity predicts writing achievement (Path B), and prior technology exposure has an independent direct effect on writing achievement (Path C). The effect of prior technology exposure and keypresses (but not on other keyboard activity; Path D) on writing achievement is moderated.

Structure of the Dissertation

Each study within this dissertation will be laid out as a separate manuscript in turn. The three studies have study-specific literature reviews, research questions, methods, discussions, and conclusions. I will end the dissertation by discussing the overarching conclusion that summarizes and includes the significance of the three studies and implications for future research.

REFERENCES

Allen, N.L., & Donoghue, J.R. (1996). Applying the Mantel-Haenzel Procedure to complex samples of items. *Journal of Educational Measurement, 33*(2), 231-251.

Applebee, A.N. (2007). Issues in large-scale writing assessment perspectives from the National Assessment of Educational Progress. *Journal of Writing Assessment, 3*(2), 81-98. Retrieved from http://www.journalofwriting assessment.org/archives/3-2.2pdf.

Applebee, A.N. (2011). Issues in Large-Scale Writing Assessment. *Journal of Writing Assessment, 3*(2), 81-98.

Applebee, A.N., & Langer, J.A. (2009). What is happening in the teaching of writing? *English Journal, 98(*5), 18-28.

Bazerman, C. (2012). Writing, cognition and affect from the perspectives of sociocultural and historical studies of writing. *Past, present and future contributions of cognitive writing research to cognitive psychology*, 89-104.

Beaton, A., Rogers, A., Gonzalez, E., Hanly, M., Kolstad, A., Rust, K., Sikali, E., Stokes, L., & Jia, Y. (2011). *The NAEP Primer.* Washington, DC: National Center for Educational Statistics.

Beaton, A. E., & Zwick, R. (1992). Overview of the National Assessment of Educational Progress. *Journal of Educational and Behavioral Statistics, 17*(2), 95-109.

Berninger, V. W., & Swanson, H. L. (1994). Modifying Hayes and Flower's model of skilled writing to explain beginning and developing writing. *Children's writing: toward a process theory of the development of skilled writing* (Vol. 2, pp. 57-81). Greenwich, CT: JAI Press Inc.

Berninger, V. W., Whitaker, D., Feng, Y., Swanson, H. L., & Abbott, R. D. (1996). Assessment of planning, translating, and revising in junior high writers. *Journal of School Psychology, 34*(1), 23-52.

Bowen W.G., Kurzweil, M.A., Tobin, E.M. (2005). *Equity and excellence in American higher education*. Charlottesville, VA: University of Virginia Press.

De La Paz, S., & Graham, S. (2002). Explicitly teaching strategies, skills, and knowledge: Writing instruction in middle school classrooms. *Journal of Educational Psychology, 94*(4), 687-698.

Deane, P., Sabatini, J., & Fowles, M. (2012). Rethinking K-12 writing assessment to support best instructional practices. *International Advances in Writing Research: Cultures, Places, Measures*, 83-101.

DeVoss, D. N., Eidman-Aadahl, E., & Hicks, T. (2010). *Because digital writing matters: Improving student writing in online and multimedia environments*. John Wiley & Sons.

Flower, L., & Hayes, J. R. (1981). A cognitive process theory of writing. *College Composition and Communication*, *32*(4), 365-387.

Graham, S. (2012). Introduction to special issue on writing assessment and instruction. *Exceptionality, 20*, 197-198.

Graham, S., Bruch, J., Fitzgerald, J., Friedrich, L., Furgeson, J., Greene, K., Kim, J., Lyskawa, J., Olson, C.B., & Smither Wulsin, C. (2016). *Teaching secondary students to write effectively* (NCEE 2017-4002). Washington, DC: National Center for Education Evaluation and Regional Assistance (NCEE), Institute of Education Sciences, U.S. Department of Education. Retrieved from the NCEE website: http://whatworks.ed.gov.

Graham, S., & Hebert, M. (2010). *Writing to read: Evidence for how writing can improve reading: A report from Carnegie Corporation of New York*. Carnegie Corporation of New York.

Graham, S., & Perin, D. (2007). A meta-analysis of writing instruction for adolescent students. *Journal of Educational Psychology, 99*(3), 445-476.

Haertel, E. (1984). An application of latent class models to assessment data. *Applied Psychological Measurement, 8*(3), 333-346.

Intersegmental Committee of the Academic Senates (ICAS) of the California Community Colleges, the California State University, and the University of California (2002). *Academic literacy: A statement of competencies expected of students entering California public colleges and universities.*

Jackman M.R. & Jackman, R.W. (1983). *Class awareness in the United States*. Berkeley, CA: University of California Press.

Johnson, E. G. (1992). The design of the National Assessment of Educational Progress. *Journal of Educational Measurement, 29*(2), 95-110.

Kent, S. C., & Wanzek, J. (2016). The relationship between component skills and writing quality and production across developmental levels: A meta-analysis of the last 25 years. *Review of Educational Research, 86*(2), 570-601. doi:10.3102/0034654315619491

Kim, Y-S. (2015). Multicomponent view of vocabulary acquisition: An investigation with primary grade children. *Journal of Experimental Child Psychology, 162*, 120-133.

Kim, Y. S. G., & Schatschneider, C. (2017). Expanding the developmental models of writing: A direct and indirect effects model of developmental writing (DIEW). Journal of educational psychology, 109(1), 35.

Leu, D., Forzani, E., Rhoads, C., Maykel, C., Kennedy, C. & Timbrell, N. (2015). The new literacies of online research and comprehension: Rethinking the reading achievement gap. *Reading Research Quarterly 50*(1), 37-59.

McCutchen, D. (1996). A capacity theory of writing: Working memory in composition. *Educational Psychology Review, 8,* 299–325.

McGrenere, J., & Ho, W. (2000). *Affordances: Clarifying and evolving a concept*. Paper presented at the Proceedings of Graphics Interface 2000, Montreal.

Messick, S., Beaton, A., & Lord, F. (1983). *National Assessment of Educational Progress Reconsidered: A New Design for a New Era*. Princeton, NJ: Educational Testing Service.

National Assessment Governing Board (NAGB) (2010). *Writing Framework for the 2011 National Assessment of Educational Progress*. Washington, D.C.: U.S. Department of Education.

National Center for Education Research and National Center for Special Education Research (2017). *Future directions for writing research at the secondary level*. Technical Working Group Meeting Summary Report. Washington, DC: Institute of Education Sciences, U.S. Department of Education. https://ies.ed.gov/ncer/whatsnew/techworkinggroup/pdf/WritingTWG.pdf

National Center for Education Statistics (NCES, 2009). *The Nation's Report Card: An Overview of Procedures for the NAEP Assessment.* Washington, D.C.: Institute of Education Sciences, U.S. Department of Education.

National Center for Education Statistics (2012). *The Nation's Report Card: Writing 2011*. Washington, D.C.: Institute of Education Sciences, U.S. Department of Education.

The National Commission on Writing for America's in America's Schools and Colleges (2003). *The Neglected "R": The Need for a Writing Revolution*. College Entrance Examination Board. http://www.collegeboard.com/prod_downloads/writingcom/neglectedr.pdf

The National Commission on Writing for America's Families, Schools, and Colleges (2004). *Writing: A Ticket to* Work. College Entrance Examination Board. Retrieved from: http://www.collegeboard.com/prod_downloads/writingcom/writing-ticket-to-work.pdfx

Pascarella E.T., & Terenzini, P.T. (1991). *How college affects students: Findings and insights from twenty years of research*. San Francisco, CA: Jossey-Bass.

Prior, P. (2006). A sociocultural theory of writing. Handbook of writing research, 54-66.

Rogers, A., Stoeckel, J., & Sikali, E. (2013). *National Assessment of Educational Progress (NAEP) 2011 Writing Assessment Restricted-Use Data Files Data Companion.* Washington, D.C.: National Center for Education Statistics.

Saenz, V.B,, Hurtado S., Barrera, D., Wolf, D., & Yeung, F. (2007*). First in my family: A profile of first-generation college students at four-year institutions since 1971*. Los Angeles, CA: Higher Education Research Institute.

Scribner, S., & Cole, M. (1981). *The psychology of literacy* (Vol. 198, No. 1). Cambridge, MA: Harvard University Press.

Sirin, S.R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research*, *75*, 417–453.

Snibbe, A.C., & Markus, H.R. (2005). You can't always get what you want: Educational attainment, agency, and choice*. Journal of Personality and Social Psychology, 88*,703–720.

Tate, T. P., & Warschauer, M. (under review). What's in a keystroke? Analysis of the 2011 NAEP computer-based 8th grade writing assessment. *Technology, Knowledge, & Learning.*

Tate, T. P., Warschauer, M., & Abedi, J. (2016). The effects of prior computer use on computer-based writing: The 2011 NAEP writing assessment. *Computers & Education, 101*, 115-131.

Tate, T.P., Warschauer, M., & Kim, Y.-S. G. (under review). Learning to compose digitally: The effect of prior computer use and keyboard activity on NAEP. *Scientific Studies of Reading.*

Van Ittersum, D. (2011). Augmenting Literacy: The Role of Expertise in Digital Writing. *Composition Studies, 39*(2), 61-77.

Warschauer, M. (2011). *Learning in the cloud: How (and why) to transform schools with digital media.* NY: Teachers College Press.

Warschauer, M., Zheng, B., Niiya, M., Cotten, S., & Farkas, G. (2014). Balancing the one-to-one equation: Equity and access in three laptop programs. *Equity & Excellence in Education*, 47(1), 46-62.

Wenglinsky, H. (2005). *Using technology wisely: The keys to success in schools*. NY: Teachers College Press.

Wertsch, J. V. (1991). *Voices of the mind: A sociocultural approach to mediated action*. Cambridge, MA: Harvard University Press.

Wertsch, J. V. (1998). Mind as action. Oxford, UK: Oxford University Press.

Zheng, B., & Warschauer, M. (2015). Participation, interaction, and academic achievement in an online discussion environment. *Computers & Education, 84*, 78-89.

Zwick, R. (1987). Assessing the dimensionality of NAEP reading data. *Journal of Educational Measurement, 24*(4), 293-308.

CHAPTER 2

Study 1. Tate, T. P., Warschauer, M., & Abedi, J. (2016). The effects of prior computer use on computer-based writing: The 2011 NAEP writing assessment. *Computers & Education, 101*, 115-131.

1. Introduction

Writing is a complex and highly challenging activity (Deane, 2011). It is not only a problem-solving process, but also a constructive process of transforming, formulating, and constituting new knowledge (Bazerman, 2011). Most learners struggle with the prerequisite coordination of multiple processes and linguistic conventions (DeBono, Hosseini, Cairo, Ghelani, Tannock, & Toplak, 2012; De La Paz & Graham, 2002; Deane, et al., 2008). For decades, the National Assessment of Educational Progress (NAEP) has tested U.S. students in a number of disciplines, including writing. NAEP has shown that the majority of students are not even minimally proficient writers, let alone skillful ones, with only 27 percent of all students, 11 percent of Black students, and 14 percent of Hispanic students at or above proficient levels (NCES, 2012). Similarly, the College Board (2015) has announced that the SAT writing results continue to decline at a rate nearly twice as large as the declines in math and reading over the same period. In addition, despite its importance and complexity, writing receives less instructional attention than subjects like reading and math, particularly in the elementary and middle school grades (Berninger, 2015; Lyon & Weiser, 2013; Warschauer, 2011; Graham & Perin, 2007). Nonetheless, writing is connected to all content areas and the deficiencies in students' writing proficiency are hindering their development of academic English (Zheng & Warschauer, 2015) and subsequent college and career readiness (Graham & Perin, 2007).

Our society calls for vastly complex and ever-changing genres and text modalities to be learned. Children should be prepared for these evolving practices; in fact the Institute for Education Sciences (IES) Practice Guide recommends that students be taught to use the writing process for a variety of purposes and become fluent in multiple modalities of transcription including word processing (Graham, et al., 2012). In particular, today's students need to successfully negotiate computer-based writing in order to have equal access to college and career options (cf., Applebee, 2007; Graham, 2012). High-stakes assessments are migrating to computer-based formats (e.g., Smarter Balanced and PARCC assessments of Common Core State Standards), and gateway tests for higher education are increasingly computer-based. In order for students to emerge from K-12 education "college and career ready"—the goal under the current Common Core State Standards—they need to be able to write using computers. Teaching students current forms of literacy, such as computer-based writing, are important to prepare them to participate fully in the community (Langer, 1991 Deane, 2011). In many instances, however, students receive inadequate explicit instruction in writing on computers (Berninger, Nagy, Tanimoto, Thompson, & Abbott, 2015).

These new technologies present new cognitive challenges and opportunities (Brazerman, 2011; Leu, et al. 2014) that students and teachers will need to address. We know that the writing process is shaped by the author's tools (see discussion in Wertsch, 1991). Each development in technology affects the writing process itself. For example, current research finds that students write more and write better on computers (see discussion in Morphy & Graham, 2012; Collins, Hwang, Zheng, & Warschauer, 2014; Graham & Perin, 2007; Sandene, et al., 2005; Russell & Haney, 1997; Russell & Plati, 2002; Applebee, 2011; Applebee & Langer, 2009). This leads us to query how the introduction of a powerful tool such as a computer may transform the writing process and how that transformation may be shaped by prior experiences in individual students' lives.

In order to test the computer-based writing skills of our youth, computer-based writing assessments provide the closest measure (NAGB, 2010). However, most studies of computer writing by and computer assessment of K-12 students have used fairly small samples (see discussion in Horkay, 2006; Bangert-Drowns, 1993). This secondary data analysis looks at the relationship between prior use of computers for writing and achievement on the 2011 NAEP computer-based writing assessment. Our research questions were as follows:

1. Does the prior use of computers positively affect students' results on a computer-based assessment?
    a. Does it matter whether the prior computer use is school-related or personal?
    b. Are reports of school-related use by students or teachers more predictive of improved writing achievement?
    c. Does a teacher's use of technology for writing instruction predict students' improved writing achievement?
    d. Does technology-related professional development for the teacher predict students' improved writing achievement?
2. Does the effect of prior use of computers on writing achievement vary by demographic group?

By understanding the model of how prior use of computers and writing achievement on a computer-based writing assessment relate, we hope to inform both assessment and instructional efforts to teach all students how to write effectively on computers.

2. Conceptual Framework

Our work is based on a broad notion of the role of tools, which encompass the mental, linguistic, and physical devices used to enhance writers' performance (Englert, Mariage, & Dunsmore, 2006). We believe that writing is culturally situated and mediated by these tools (Deane, Odendahl, Quinlan, Fowles, Welsh, & Bivens-Tatum, 2008; Wertsch, 1998). New technologies allow us to produce, transmit, store, and process written texts (Bazerman, 2011). Each development in technology affects the writing process itself (cf., Berninger & Winn, 2006). For example, some tools may constrain idea generation and elaboration (Berninger & Winn, 2006). Success with composing on these new devices depends upon a willingness and ability to change modes, adapt prior strategies (Cochran-Smith, 1991), and navigate the specific tool affordances that both promote and inhibit good writing. These concerns led us to our research questions, a desire to understand whether (and for who) the prior use of computers (the tool) improves students' writing in a computer-based writing assessment.

We expected that practice using a specific tool would affect the writing process with that same tool. We thought that it was possible for computer use beyond writing for school, such as e-mailing, could provide a comfort level and familiarity with the mode of digital writing that would impact the writing process in an assessment setting. Thus, we initially looked at a wide range of variables related to digital technology use.

Our variable selection was also impacted by our belief that literacy is culturally situated. Because of this, cognitive apprenticeships are important in the acquisition of writing skills. Cognitive apprenticeships teach novices the practices of the community, including the acquisition of the discourse, tools and actions (Englert & Mariage, 2013). Teachers can make these practices of the writing process visible (Englert & Mariage, 2013; Bazerman, 2012); and effective teachers model and describe the knowledge they have about writing (Vygotsky, 1981; Englert, Mariage, & Dunsmore, 2006). These teachers provide support as novices acquire the discourses, strategies, tools, and actions needed. For this reason, one group of the survey questions examined for our prior use latent variable related to the use of technology by teachers when teaching writing (Bate, 2010). We also included teacher professional development in technology as a potential component of relevant prior computer use, hypothesizing that increased professional development could lead to increased or improved modeling and direct teaching of the use of technology for writing.

The comprehensive data available from the NAEP 2011 assessment and current statistical methods allow us to look closely at students' computer-based writing. Insights for teaching diverse students to be better writers on computers may arise from better understanding the model of how prior computer use and computer-based writing achievement relate. We are also mindful of a prior study done in preparation for NAEP's implementation of computer-based assessments. In the earlier work researchers compared scores for paper and computer versions of the 2002 NAEP writing assessment and found no significant population-level differences (Horkay, Bennett, Allen, Kaplan, & Yan, 2006; Sandene, et al., 2005). A repeated-measures analysis of variance failed to detect a significant effect for delivery mode on achievement score (Sandene, et al., 2005), even when controlling for gender, race/ethnicity, parents' education level, eligibility for free/reduced-price school lunch, and school type. Analysis of essay length showed no measurable differences on the number of words written on paper or on computer (Sandene, et al., 2005). Sandene, et al. (2005) found no equity-related differences between pencil and paper assessments and computer-based assessment at a population (versus individual) level, except with respect to urban students who performed 15 percent higher on paper and pencil tests. There was a small but significant gender effect on writing length but not on scores, with males writing approximately two percent fewer words on paper than on computer for the second task, and two percent more females responding to the second question on paper (Sandene, et al., 2005).

Although the 2002 study showed no significant mean score differences between those taking the computer tests and those taking the tests with pencil and paper at a population level, it indicated that computer familiarity did significantly predict performance at an *individual student level* (Horkay et al., 2006). Using students' self-reported computer experience to create a composite score to measure familiarity, Sandene, et al. (2005) found no significant effect for prior use of computers on achievement scores, but there was an effect for keyboarding skills. Sample size limitations prevented further analysis of these differences, except for gender, which was inconclusive.

Our study explores the issue of computer familiarity in further depth and at scale across a nationwide sample nearly a decade later. With the growing prevalence of computer-based writing and writing assessment, concerns about the impact on students without regular access to digital technology abound. There are widely differing degrees of school and home computer access and use; research shows that social factors can be even more important than technical factors in shaping productive use of technology (Warschauer, 2011). Further, demographic impacts may exacerbate differences among students' computer skills in ways that need to be understood and, perhaps, addressed. Large-scale assessments like NAEP are useful for exploring these types of achievement gaps and differences among groups (Schneider, et al., 2007).

3. Methods

3.1. Data Source

This research analyzed the data from over 24,600 eighth grade students. NAEP assessments are widely regarded as high quality, with strong construct and measurement validity (see, e.g., Wenglinsky, 2005). The weighted national school participation rates for the assessment were 97 percent (100 percent for public schools; National Center for Education Statistics (NCES), 2012). To the extent certain subgroups fell below 70 percent, NCES conducted an analysis of potential bias. Compared with the distribution of all eligible students, the distribution of the weighted sample did not differ with respect to any of the variables utilized in this analysis (Rogers, Stoeckel, & Sikali, 2013). This analysis utilized the restricted data set, which includes scaled and raw scores, detailed survey data, and individual keystroke data. As suggested by NCES, the following were treated as missing: multiple responses, responses not reached or administered, omitted responses, non-ratable responses, illegible responses, and off task responses.

3.1.1. Sampling. NAEP sampling techniques strive to create a representative nationwide sample of students in grades 4, 8, and 12. Participants are selected using a stratified cluster sampling, where the population is divided into different strata, or geographic areas of interest, from which the schools were selected (Beaton, et. al, 2011). In order to approximate the population, sample weights are used to correct for oversampling of certain low incidence populations and adjust the overall results by the actual population proportion (Johnson, 1992). These weights allow for valid inferences to be made about the population (Beaton, et. al, 2011).

While traditional analysis procedures assume that observed data from different individuals are independent of each other and randomly distributed, NAEP results may be stratified and clustered (Johnson, 1992; Zwick, 1987). Through clustering, weighting, and marginal estimation procedures, NAEP allows for population and group estimates (Beaton &

Zwick, 1992). Ignoring these effects leads to biased estimates of variance and generally to underestimating the biases (Johnson, 1992). In addition, the deeply stratified cluster samples influence the likelihood ratio and inflate the differences in the chi-squares, and the design effect for item *p* values is estimated to be roughly 2 (an estimate of percent of examinees with a given response pattern should be equivalent in precision to a simple random sample approximately half as large; Haertel, 1984). Where our current analysis looked at the individual booklet-level responses, weighting was not applied (Allen & Donoghue, 1996). Where we looked at aggregated values of individual, unscaled scores, we used jackknife weights for the analysis.

3.1.2. Population. We focus on eighth grade students, as prior research suggests that the middle school years are critical for the development of academic writing (De La Paz & Graham, 2002; Zheng & Warschauer, 2015). Indeed, some refer to an eighth-grade literacy cliff (e.g., Zheng & Warschauer, 2015). In addition, the NAEP data for eighth grade, unlike twelfth, has a teacher survey reporting on computer use allowing for potential correlation between student-reported use and teacher-reported use.

3.1.3. Assessment. NAEP assessments are known for their robust construct validity (see, e.g., Applebee, 2007; Wenglinsky, 2005). Over the course of 18 months, more than 500 individuals developed a framework for the NAEP writing test (NAGB, 2010). These individuals included leading educators and experts in the field of assessment (Applebee, 2007). The NAEP writing framework was designed to reflect the way students write today, using word processing software and commonly available tools (NAGB, 2010). As a result, the assessment allowed students to use common word-processing tools:

- editing (cut, copy, paste, delete, backspace);
- formatting (indenting, underlining, highlighting, bolding, and italicizing);

- spelling check, grammar check, thesaurus, and dictionary; and
- viewing and reviewing during the assessment (NAGB, 2010).

In addition, the assessment included student and teacher surveys that gathered information about students' and teachers' prior use of computers.

The students were given two different writing tasks and had 30 minutes to complete each task. There were a total of 22 writing prompts in three areas: (a) to persuade, (b) to explain, and (c) to convey experience, either real or imagined. Responses were scored by three trained evaluators on a 6-point scale—effective skill, adequate skill, developing skill, marginal skill, and little or no skill—across three areas of writing: (a) development of ideas, (b) organization of ideas, and (c) language facility and conventions (NCES, 2012; NAGB, 2010). NAEP evaluators used holistic scoring rubrics to evaluate the response as a whole, rather than assessing independent parts of the response (NAGB, 2010). NAEP ensures scorers' reliability through back reading where scoring supervisors selectively review at least five percent of each scorer's work, periodic calibration of multiple scorers, and an inter-rater reliability statistics check of 25 percent of the responses (NCES, 2009).

The presentation of the items was alternated so that the same item appeared first in some booklets and second in others. This balancing of order of presentation is important, because NAEP has found that assessments with open-ended responses show decreased scores in the later items (Johnson, 1992). However, because of this balanced incomplete block (BIB) spiraling method of sampling, NAEP data is complex to model (Beaton & Zwick, 1992). BIB spiraling presents each item to a large number of participants and pairs items to allow correlations between the items (Beaton, et. al, 2011; Johnson, 1992). BIB spiraling is used to allow broad coverage of the item pool, yet not impose excessive test taking upon individual students (Beaton, et. al, 2011; Applebee, 2007). This design has two major limitations. Each student only receives a fraction of the test, which weakens any ability to determine individual achievement in any of the subject areas (and increases measurement error). Second, the scores from each block may not be highly comparable (Beaton, et. al, 2011; Applebee, 2007).

3.2. Variables

Initial variable selection included: (a) reported prior computer use; (b) achievement scores on the writing assessment, either scaled or mean scores; and (c) group variables for gender, ethnicity/race, eligibility for free/reduced lunch, highest level of parental education, English-learner status, and disability status.

3.2.1. Achievement Measure.

NAEP uses Item Response Theory (IRT) scaling to allow for estimates of item characteristics and difficulties, as well as multiple imputation to estimate student achievement values in terms of plausible values (Beaton, et. al, 2011; Zwick, 1987). However, the NAEP Primer cautions that researchers interested in interaction effects should not work with plausible values, but should perform their own marginal estimation (Beaton, et. al, 2011). Thus, this analysis looked at both the mean of all the individual raters' scores for a particular student's response and scaled scores at the booklet level and as an aggregated group, but did not use plausible values since we were interested in the possible interactions between prior use and our demographic variables.

The scaled booklet-level scores (-2.18 to 3.04) were used as the achievement variable or dependent variable for the initial analyses. This allowed us to get a sense of student performance normed (using IRT) across the various booklets and allowed analysis of a larger numbers of cases for low incidence demographics. The main purpose of NAEP's IRT analyses is to provide a common scale on which to compare achievement across groups (Messick et al., 1983). Researchers can then compare performance across groups, if the subgroups are of sufficient size (Messick et al., 1983).

Additional analysis of student scores was done with the mean of the unscaled scores (interval scale, 1-6) sorting the students and analyzing them by booklet. However, the booklet grouping reduces the number of students in the smaller incidence groups, such as students with disabilities. The final analysis used the mean score for each individual participant and considered aggregate effects.

The scaled writing achievement score had a mean of -0.04 and a standard deviation of 0.96. The raw scores had a mean of 2.64 and a standard deviation of 0.98 (see Table 1, Tate, Warschauer, & Abedi, in press, for additional descriptive statistics on the scaled and mean score variables). Both outcome variables were quite close to a standard curve, with a slight skew (particularly for the mean scores) to the right. Thus, our use of linear regression is supported by these descriptive statistics.

3.2.2. Prior Computer Use and Access. The NAEP data includes survey information from teachers and students with respect to two primary background variables, computer use (especially with respect to writing with computers) and types and amount of writing practice. This research focused on the first background variable, amount of prior computer use, using the responses to questions related to prior use and access to create a latent construct (Haertel, 1984).

Variables relating to prior computer use and access included student-reported measures of how often: (a) the Internet is used to get information, (b) a computer is used for a first draft, (c) a computer is used to make changes in writing, (d) a computer is used to complete writing, (e) a computer is used to write school assignments, (f) a computer is used to write not for school, (g) a computer is used for emails, and (h) a computer is used to write on the Internet. Similar teacher-reported measures of students' classroom use of computers for writing, teacher use of technology in the classroom, and teacher professional development relating to technology use were used. We also considered the effect of having a computer at home, but over 90 percent of the students reported having a computer at home so the variable was of little predictive value. The prior use variables were all standardized for the analyses.

3.2.3. Group variables. We looked at differences in various demographic groups: (a) gender, (b) national school lunch eligibility and parental education (as proxies to indicate socioeconomic status), (c) English language learner status (prior, current, or not applicable), (d) students with individualized education plans (IEPs) or 504 plans under the American with Disabilities Act, and (e) race/ethnicity. Dichotomous variables were created for these groups. We considered both parental high school completion and parental college completion as potential control variables. Ultimately, we used the parent college completion variable; literature suggests that first generation college students have unique challenges and that as such it is a useful designation for understanding certain aspects of socioeconomic status (see, e.g., Bowen, Kurzweil, & Tobin, 2005; Saenz, Hurtado, Barrera, Wolf, & Yeung, 2007; Sirin, 2005; Pascarella & Terenzini, 1991; Jackman & Jackman, 1983; Snibbe & Markus, 2005). In addition, the high school completion variable had less predictive strength, because only 9 percent of the students had parents who did not complete high school, whereas 44 percent had parents who did not complete college.

3.2.4. Variables Used in Quasi-Longitudinal Analysis

The 2007 assessment used in our quasi-longitudinal analysis had several differences from the 2011 assessment beyond the mode switch from paper to computer in 2011. The changes include somewhat different frameworks, with slightly adjusted emphases on genres, a decision in 2011 to include a specifically designated audience for the writing task, and different questions on the student survey. Although we note these differences, we believe that a comparison of the 2007 and 2011 assessments for the purpose of determining the impact of prior computer use on writing achievement in different modes is illustrative and consistent with our analysis of the 2011 results. The scaled student scores (scaled -2.18 to 3.04; mean -0.04; sd 0.96 in 2011; scaled -2.30 to 3.10; mean -0.04; sd 0.96 in 2007) were used as the initial achievement variable in the analyses.

Our analysis of the 2011 assessment suggested that student reports of computer usage were more predictive of writing achievement than teacher reports of classroom computer usage. In addition, it suggested that school-based use, rather than recreational use, of computers was more associated with achievement levels on the assessment. Therefore, we chose as our independent variable from the 2011 survey "how often do you use a computer to write school assignments" and from the 2007 survey, "write paper for school - use computer from beginning." We refer to these measures as "prior use."

The 2007 survey scale was 1 (never), 2 (sometimes), and 3 (almost always); the 2011 scale was 1 (never or hardly ever), 2 (once/twice a month), 3 (once or twice a week), and 4 (every day or almost). We considered 1 on both scales to be the same, determined that once or twice a week was close to "sometimes" and coded both 2, and combined the 3 and 4 values into a single 3 value, so that weekly and daily use were both coded the same as "always or almost always." We checked our calculations by combining the 2 and 3 values instead, and found the same trends and levels of significance, with generally decreased coefficients on the prior use variable. Nonetheless, we believe that "weekly" and "daily" are closer to "almost always" than "monthly" and "weekly" are to "sometimes" and have presented our results in a consistent manner.

3.3. Analytic Methods

We used Stata Version 14.0 SE statistical software to analyze the results of the 2011 NAEP writing assessment.

3.3.1. Structural Equation Modeling

The analysis included structural equation modeling (SEM) of the data using both the IRT scaled scores ("scaled scores") and the mean of the individual scores by trained reviewers on each essay ("mean scores") at an aggregate (all essays, regardless of different writing tasks) and booklet-level analysis (isolating each writing) to check for robustness and comparability. Analysis separating the criterion instrument into booklets addresses the BIB spiraling in NAEP instruments (Welch, Anderson, & Harris, 1982; Haertel, 1984). Thus, in order to observe individual-level correlations, this study looked at each booklet individually, then cross-validated the results among booklets (see Allen & Donoghue, 1996). All booklets are considered parallel in BIB sampling, so the expectation was that the booklet-level results would not be statistically different from aggregate results, and the missing data can be regarded as random (Zwick, 1987).

The use of SEM allowed us to model the potential causal relationships between prior computer use and achievement scores (cf., Schreiber, et. al, 2006). SEM allows simultaneous estimation of the full model parameters and offers flexibility in modeling reciprocal relationships and creating latent variables, greatly enhancing the ability to analyze the NAEP data (Messick, Beaton, & Lord, 1983; Abedi, 2002).

The NAEP assessment surveys students and teachers about a number of items including the amount of time they spend on certain types of computer-based writing and related tasks. Based on our theoretical belief that the tools used in writing affect the writing process and that teachers modeling of writing with technology could be an important factor, we chose a total of 28 survey questions related to prior technology use and access by both students and teachers, for our initial analysis. These questions included: (a) student reports of frequency of computer-based writing for school purposes, (b) student reports of frequency of computer-based writing for outside of school uses, (c) teacher reports of school-related computer-based writing, (d) teacher reports of the use of technology for writing instruction, and (e) teacher reports of professional development related to technology and instruction. We sorted the 28 variables into 5 latent variables reflecting these categories. We correlated teacher and student reports of school use of computers for writing, because both teachers and students should both be reporting at least a portion of the same school writing assignments using computers. We also correlated teacher instruction with digital devices and teacher professional development related to digital technology, because teachers with more professional development in the use of technology should be more comfortable and therefore inclined to use devices in instruction. Next, we controlled for student gender, ethnicity, ELL status, disability, free and reduced lunch status, and whether or not a parent graduated college. Estimations were done using maximum likelihood with missing variables.

Our initial SEM contained a number of variables with factor loadings below 0.40 or that were statistically insignificant. Based on the direct effects and factor loadings found in our SEM results, we created a more parsimonious model. We removed any questions from the latent variable that was not significant. Our final model retained both teacher and student-reported use of computers for school-related writing (see Figure 1). Finally, jackknife weighting was used (sampling units, PSUID; Strata, REPGRP1; Sample weight, ORIGWT; Student Replicate Weights, SRWT01-62).

Our booklet level analysis used Stata's "if" function to generate direct effects for each latent variable on the mean individual writing scores for each of the 22 writing tasks. The same controls as in the aggregate analysis were used.

3.3.2. Regression

As a robustness check, we also used ordinary least squares (OLS) regression to look at the relationship between reported prior computer use and achievement scores. We tested the following model: *Writing Achievement* = B_0 + B_1*(teacher-reported prior use)* + B_2*(student-reported prior use)* + B_3*(female)* + B_4 *(Black)* + B_5 *(Hispanic)* + B_6 *(Asian)* + B_7 *(other)* + B_8 *(free/reduced lunch)* + B_9 *(college graduate parent)* + B_{10} *(former ELL)* + B_{11} *(current ELL)* + B_{12} *(student with disability)* +B_{13} *(teacher-reported prior use)(female)* + B_{14} *(teacher-reported prior use) (Black)* + B_{15} *(teacher-reported prior use) (Hispanic)* + B_{16} *(teacher-reported prior use) (Asian)* + B_{17} *(teacher-reported prior use) (other)* + B_{18} *(teacher-reported prior use) (free/reduced lunch)* + B_{19} *(teacher-reported prior use) (college graduate parent)* + B_{20} *(teacher-reported prior use) (former ELL)* + B_{21} *(teacher-reported prior use) (current ELL)* + B_{22} *(teacher-reported prior use) (student with disability)*+ B_{23} *(student-reported prior use)(female)* + B_{24} *(student-reported prior use)(Black)* + B_{25} *(student-reported prior use)(Hispanic)* + B_{26} *(student-reported prior use)(Asian)* + B_{27} *(student-reported prior use)(other)* + B_{28} *(student-reported prior use)(free/reduced lunch)* + B_{29} *(student-reported prior use)(college graduate parent)* + B_{30} *(student-reported prior use)(former ELL)* + B_{31} *(student-reported prior use)(current ELL)* + B_{32} *(student-reported prior use)(student with disability)*+ *e*. We used the standardized coefficients from the final SEM to create the weighted teacher-reported and student-reported prior use variables (Table 1). Regressions were done using each of the scaled writing score and the mean writing score to operationalize writing achievement. Linear regression was appropriate for our data, which showed little skewness or kurtosis.

3.3.3. Factor Analysis

As a second robustness check, we used factor analysis to confirm our latent variable construction. Stata's principal factor analysis attempts to identify a small number of latent variables or dimensions that explain the shared variance of a set of measures (Acock, 2012). We used the Kaiser criterion (Kaiser, 1960), initially retaining factors with eigenvalues greater than 1 as our lower bound, but also considering whether that bound was appropriate for our data by looking at scree plots for large drops in values (Preacher & MacCallum, 2003). If an item has a loading of over 0.40 on a factor, it may be considered a good indicator of that factor (Acock, 2012), although there is debate on exact levels (see, e.g., Preacher & MacCallum, 2003). Finally, we considered rotations to see if they would improve our analysis, particularly an oblique rotation, which allowed for correlations between the latent variables as seen in our SEM (Preacher & MacCallum, 2003).

3.3.4. Quasi-longitudinal Analysis

Finally, we used OLS regression to assess the relationship between achievement scores and prior computer use for an earlier paper-based NAEP assessment in 2007. If prior computer use is, in fact, important for computer-based writing in a unique way, we would not expect to see the same correlation of writing achievement and prior computer use on paper and pen based assessments. As discussed under "Variables," above, there are differences worth noting between the assessments in 2007 and 2011 beyond the fact that 2007 and earlier were paper-based.

4. Results

Our first research questions was, “Does the prior use of computers positively affect students’ results on a computer-based assessment?” Writing achievement was measured by the score received by the individual for holistic writing quality (either the scaled score or the mean of the ratings). Prior use was measured by our latent variables based on responses to teacher and student surveys about technology use for school-related writing. By looking at both teacher and student reports, we examined sub-question “a” regarding the predictive value of each. Our initial analyses also included personal uses of computers for writing in order to look at sub-question “b” regarding the impact of both types of use. Finally, our initial analyses included reports by teachers about their use of technology during writing instruction (sub-question “c”) and prior relevant professional development in order to assess the effect of those factors on subsequent writing achievement (sub-question “d”).

Group effects and interactions were included through the use of individual dummy variables (e.g., female, Asian) for each demographic group, which acted as controls with the prior use variables. We also looked for potential interactions between prior use and our control variables, which allowed us to address our second research question regarding heterogeneous effects.

4.1. Structural Equation Modeling

We found that student-reported not for school writing, teacher professional development, and teacher instruction using technology were not statistically significant in our SEM of the scaled scores (see Figure 1 and Table 2, Tate, Warschauer, & Abedi, 2016). Both student-reported and teacher-reported use of computers for school-related writing were significant. Our more parsimonious final model is shown in Figure 1.

We found that the final latent prior use variables had a direct positive effect of 0.03 ($p < 0.001$) on the mean achievement score for teacher-reported and 0.10 ($p < 0.001$) for student-reported prior use (see Figure 2, Tate, Warschauer, & Abedi, 2016, for the Stata SEM results and Table 3 for the correlation matrix of scaled score, mean score, prior use components, and demographic controls). Goodness of fit statistics included an RMSEA of 0.04 and a CFI of 0.96, which indicate acceptable model fit and an improvement over the initial model (see discussion in Schreiber, et al., 2006). We found that these latent prior use variables had a direct positive effect on the scaled achievement score of 0.07 ($p < 0.001$) for teacher-reported and 0.09 ($p < 0.001$) for student-reported prior use. Goodness of fit statistics were similar, with an RMSEA of 0.04 and a CFI of 0.95.

Using jackknife weighting, the coefficients for the mean score teacher-reported latent variable was 0.03 ($p < 0.05$) and student-reported school writing was 0.11 ($p < 0.001$) for a total of 0.14. The coefficients for the scaled score analysis were 0.07 ($p < 0.001$) for teacher-reported writing and 0.09 ($p < 0.001$) for student-reported writing, for a total of 0.16. See Table 2 for these results.

Using the latent variables of teacher and student-reported use of computers for writing for school and the dependent variable of mean individual scores, we ran a pooled booklet analysis on each of the 22 writing tasks controlling for demographics (without jackknife weighting). There was significant variability across the writing tasks, with the direct effect of teacher-reported school writing ranging from 0.05 ($p < 0.05$) to 0.10 ($p < 0.001$) and student-reported school writing ranging from 0.07 ($p < 0.01$) to 0.15 ($p < 0.001$). Please refer to Table 3 for full task-level results. Our SEM results show modest variation between analyses done at the booklet level and aggregated findings, with 17 out of 22 of the teacher-reported effect sizes and 15 out of 22 of the student-reported effect sizes of the booklet analyses falling within the confidence intervals of the aggregated findings (0.01 to 0.04 and 0.09 to 0.12, respectively).

4.2. OLS Regression

Our regression analysis, with controls and interactions, using scaled and mean writing scores, also found positive effect sizes for student-reported prior use: 0.07 ($p < 0.001$) for the scaled achievement variable and 0.08 ($p < 0.001$) for the mean achievement scores. Teacher-reported writing effects were not statistically significant once controls were added into the regressions. These numbers are somewhat lower than those found in the SEM analysis, which would be expected. SEM allows stronger predictive power because measurement error is assumed to be a random error. This results in estimates of the path coefficients that are usually larger than if we had assumed no error in predictors, as with traditional regression models (Acock, 2013). Booklet-level results show an effect of student-reported writing ranging from 0.05 ($p < 0.05$) to 0.20 ($p < 0.01$) and similar interaction figures as the aggregated data, discussed below (see Table 4, Tate, Warschauer, & Abedi, 2016). Table 4 sets out the results of the aggregate regression analysis, which is consistent with our finding of a small positive relationship between prior student-reported use of computers for school writing and achievement on the 2011 NAEP writing assessment.

The only statistically significant interactions noted were slight, with teacher-reported use and parent's college education showing 0.02 ($p < 0.01$) effect on the scaled variable and 0.03 ($p < 0.01$) effect on the mean variable; student-reported prior use and free/reduced lunch status having -0.03 ($p < 0.001$) effect on both variables, student-reported prior use and current ELL status having mixed results depending on the achievement variables; and student-reported use and students with disabilities showing -0.04 ($p < 0.001$) effect on the scaled variable and -0.03

($p < 0.01$) effect on the mean variable. Thus, the slightly positive benefits of prior computer use may be somewhat amplified if the student's parents have gone to college, and slightly reduced for students who are eligible for free/reduced lunch, currently designated ELLs, or are students with a disability. These interactions are small and not consistent across all of the achievement measures, thus warranting further research.

4.3. Factor Analysis

We conducted a factor analysis to confirm that our latent variables were properly constructed using the complete group of 28 teacher and student survey questions. Principal factor analysis (unrotated) revealed that four factors had eigenvalues over 1 (Kaiser, 1960), and a significant decrease in eigenvalues for the subsequent factors (a drop from 1.51 to 0.67, suggesting a reasonable break point, see Preacher & MacCallum, 2003; see Tables 5 and 6, Tate, Warschauer, & Abedi, 2016). The underlying questions tended to relate to four topics: teacher-reported classroom use of computers for writing tasks ("Class Use," Factor 1, with eigenvalue of 3.93); student reported use of school-related computer-based writing ("Student Use," Factor 2, with eigenvalue of 3.15); teacher professional development in technology and instruction ("Teacher Development," Factor 3, with eigenvalue of 2.21) and teacher use of technology for writing instruction ("Teacher Use, " Factor 4, with eigenvalue of 1.501).

Checking the rotated model (oblique), we found similar eigenvalues, ranging from 3.17 to 1.55 for the first 10 factors (see Table 5 for the details of the oblique rotation eigenvalues and factor loadings). Factor loadings were sizable for the student-reported school writing questions (loadings of 0.70 to 0.85 for Factor 1), teacher-reported student use (0.60 to 0.79 for Factor 2), and student-reported home use (0.62 to 0.69 for Factor 3). Thus, the rotated factor analysis supported our three constructs: (a) student-reported school use of computers, (b) student-reported home use of computers, and (c) teacher-reported student use of computers. While teacher development was also supported as a construct in the unrotated analysis, it was not in the rotated analysis.

4.4. Quasi-Longitudinal Check

As a final check of our theory that computer-based writing benefits from practice writing *on computers* in a manner different from writing *on paper*, we used OLS regression to examine the relationship between prior computer use and achievement in a prior (paper-based) NAEP writing assessment.

The correlation between prior use and writing scores in 2007 is very small, 0.07, compared with the 2011 results that show a correlation of 0.19. Correlations between prior use and the other variables in both years are quite small, generally in the range of 0.01 to 0.08, with the higher correlations negative and relating to socioeconomic indicators in most cases (with the exception of similar correlations in this higher end of this negative range for current English language learners. Please refer to Table 6 for the correlation results.

By creating dichotomous variables for each level of prior use, we were able to test if the mean achievement was significantly different across each level of prior use. T-tests showed that in 2007 the difference in the means for students across these levels of prior use were statistically significant, but small in magnitude. The mean for students “never or hardly ever” using the computer for writing was -0.08, “sometimes” was -0.08, and “almost always” was 0.12. On the other hand, in 2011 students who never used the computer for school writing had a mean of -0.48, or 0.52 below students who sometimes or always used computers ($p < 0.001$). Thus, prior use of computers is associated with over one-half of a standard deviation increase in the computer-based writing scores of 2011. One sample t-tests confirm that the different means at each level in 2007 and 2011 are statistically significant. The prior use of computers has a small association with writing achievement in 2007, and in fact at low levels is showing a slightly negative relationship with scores. This is consistent with prior research suggesting that occasional use of computers, as compared to regular use, can be distracting for students, especially when preparing for paper-based testing (see discussion in Warschauer, 2006).

Regressions

We also ran an OLS regression of prior use on the scaled writing score, controlling for demographic measures. Table 7 shows the regression of scaled writing scores for the 2011 and 2007 assessments on the single variable relating to prior use. In 2011, each additional level of prior use (e.g., never to sometimes) was associated with a 0.17 standard deviation increase in the scaled writing score with all controls included. In 2007, an additional level of prior use is only associated with a 0.04 standard deviation increase. Although these numbers are all statistically significant, the 2007 results show that prior computer use had little practical effect on writing achievement scores in this assessment. The increase in scaled score in 2011 is four times that of 2007. The difference between the two effect sizes further confirms that prior use had a much larger effect on writing scores in 2011 when the assessment was computer based than it did in 2007 when the assessment was given on paper.

5. Discussion and conclusions

5.1. Prior Use

Students' use of computers for school-related writing increased writing achievement on the NAEP computer-based writing assessment. Use of computers for other purposes, such as writing emails or writing blogs on the Internet, had no significant impact on achievement. Personal and home use of computers for unrelated matters did not increase writing achievement as measured by the NAEP assessment; whether or not the teacher used computers to model computer-based writing had only minimal effect on writing achievement as measured by the NAEP assessment. The benefit of prior computer use is slightly decreased for students who receive free/reduced price lunch or who have a disability. Other interactions were not consistent across the scaled and mean writing achievement variables and warrant further investigation.

Thus, as commonsense as it sounds, if schools want to increase the ability of students to write on computers, they need to provide more opportunities for the students to write for school on computers. Practice matters. Students will become more proficient at writing skills across modalities to use in their future college and career settings, allowing them to more fully participate in the community at large

5.2. Implications

The affordances of computers as writing tools and the amount that these affordances lead to both improved quality and increased quantity of writing has been highly variable in research to date (Zheng, Warschauer, Lin, & Chang, 2016; Graham & Perin, 2007; Applebee, 2011; Applebee & Langer, 2011; Collins, Hwang, Zheng, & Warschauer, 2014; Morphy & Graham, 2012; Schwartz & Bridwell, 1984; Russell & Haney, 1997; Russell & Plati, 2002, Goldberg, Russell, & Cook, 2003; Bangert-Drowns, 1993; Cochran-Smith, 1991). Computer-based writing is often implemented in schools with contextual changes that support improved writing more generally—both on and off computers. For example, the affordances of digital tools encourage increased collaboration, authentic writing audiences, meaningful tasks, mentoring, and motivation (Warschauer, 2011).

The fact that school-related digital writing had a greater impact on the students' achievement on the NAEP assessment than did personal, casual computer use is consistent with the large research base showing the need for technology to be implemented in instructionally sound ways (see discussion in Warschauer, 2011). Simply putting digital tools in students' hands will not improve their learning (OECD, 2015). Rather, the tools must be integrated in a way that supports and extends the curriculum in meaningful ways (Tate & Warschauer, in press; Warschauer, 2011).

Our analyses confirm the preliminary findings of a recent working paper commissioned by NCES of three NAEP digitally based assessments in math (2011), writing (2011), and technology and engineering literacy (2013); eighth graders' self-reported familiarity with and prior use of digital technology positively impacted their scores on the assessments (Zhang, et al., 2016). Their factor analysis of the student surveys revealed two distinct types of prior computer use, use for school-related writing and use for more general writing (e.g., emails, personal writing; Zhang, et al., 2016). Regressed on students' writing achievement (using plausible values, rather than scaled or mean scores), the researchers found that both types of activities led to positive increases in writing scores, but that school-related computer writing was much more predictive of higher writing scores, controlling for gender, ethnicity, free/reduced lunch status, and urbanicity (but not controlling for parent education, ELL, or special education status; Zhang, et al., 2016).

Given the prevalence of computer-based writing in the world beyond the school gates, we believe that school writing should at least in part consist of digital writing. Schools are situated to provide the necessary access, instruction, and support to enable students to become proficient writers on computers. Because disparities in access to technology and the Internet remain significant (Darling-Hammond, Zielezinski, & Goldman, 2014), both at home and at school, improving school use of computers for writing can help reduce the digital divide. We note, however, that certain sub-groups of students show reduced improvement from the prior use of computers. These differences are worth additional research to ensure that efforts to improve students' digital writing do not increase the divide.

Despite the lack of statistical findings with respect to teacher's use of technology to provide writing instruction, teachers should still be encouraged to incorporate technology into their lessons. Tools that make writing visible, by the teacher, the student, and peers, still provide useful instruction. They are also increasingly the way writing is done in professional and academic settings, with collaboration becoming increasingly important. Similarly, teachers' need for quality professional development in integrating technology into quality curriculum remains despite the lack of a direct statistically significant effect in our analysis.

Two areas need further investigation: (a) what are the reasons for the differences in results depending on the use of scaled or mean writing scores and (b) what are the reasons for the variability in our booklet compared to aggregated analyses. Our analysis found a larger booklet-to-aggregate results variation than found in the Horkay et al. (2006) analysis, which warrants further analysis. We suspect that there may be a link to the writing genre involved in the task or the order of presentation of the task (first versus second question answered), though preliminary results are not clear.

Finally, we think that it would be helpful to look at more specifics of how prior use is improving writing achievement, both quantitatively and qualitatively. The NAEP assessment collected keystroke data, which may further illuminate how and for whom prior use impacts achievement (e.g., do students with more prior use tend to delete more). We expect to find patterns of both productive and unproductive keystrokes. In addition, case studies observing adolescents actually in the process of writing on computers should give us a better understanding of the writing process and how it progresses and, perhaps, changes as students become more proficient writing on computers. Computers will have both positive and negative affordances for writing, and different students will navigate those affordances differently.

5.3. Limitations

5.3.1. NAEP Assessment. The nature of our writing achievement variable, based on the NAEP assessment, is inherently limited. The NAEP assessment measures only two 30-minute writing sessions. The time limit means that the writing samples are rough drafts and not polished final versions. By design, the NAEP assessment is not reflective of students' abilities to edit and refine their work. The time limit advantages students who are used to writing for similar lengths of time. The time limit may disadvantage students with language production disabilities or English-language learners who could use additional time, but additional time could frustrate other students and create fatigue (see Applebee, 2007). In addition, the functionality of the NAEP interface used in the 2011 test could be improved, as seen during the usability studies conducted in 2012 with fourth grade students (NCES, 2014). As these functionality improvements are made in future years, we might find that the interface is simpler and easier to use for students with less prior exposure to computers, which could in turn reduce the correlation of prior use with writing achievement.

5.3.2. Variables. This analysis is limited to modeling the effect of student-reported prior computer use on writing achievement. Future analyses will also consider use of the computer during the assessment itself and the relationship between use during the assessment and achievement, as well as the interaction between prior computer use and use of the computer during testing on achievement. Simple reported frequency of use does not speak to the quality of instruction in computer-based writing, nor is student-reported frequency as accurate as real-time measures of computer use might be. Finally, we note that our research intentionally does not address total prior time spent writing or quality of writing instruction received, which we expect would be more directly related to writing achievement than computer usage information.

In conclusion, systematic analysis of the 2011 NAEP writing test scores demonstrates that frequency of prior computer-based writing in school is moderately correlated with computer-based writing achievement. This adds weight to the argument that increased integration of technology in K-12 education is required if we are to prepare students fairly for a future of computer-based writing.

References

Abedi, J. (2002). A latent-variable modeling approach to assessing reliability and validity of a creativity instrument. *Creativity Research Journal, 14*(2), 267-276.

Allen, N.L., & Donoghue, J.R. (1996). Applying the Mantel-Haenzel Procedure to complex samples of items. *Journal of Educational Measurement, 33*(2), 231-251.

Applebee, A.N. (2007). Issues in large-scale writing assessment perspectives from the National Assessment of Educational Progress. *Journal of Writing Assessment, 3*(2), 81-98. Retrieved from http://www.journalofwriting assessment.org/archives/3-2.2pdf.

Applebee, A.N., & Langer, J.A. (2009). What is happening in the teaching of writing? *English Journal, 98(*5), 18-28.

Applebee, A. N., & Langer, J. A. (2011). A snapshot of writing instruction in middle schools and high schools. *The English Journal, 100*(6), 14-27.

Asher-Shapiro, A. (2013). Innovation Report. *University Business, 16*(11).

Bangert-Drowns, R. (1993). The word-processor as an instructional tool: A meta-analysis of word processing in writing instruction. *Review of Educational Research, 63(*1), 69-93.

Bazerman, C. (2011). Standpoints: The disciplined interdisciplinarity of writing studies. *Research in the Teaching of English,* 46(1), 8-21.

Beaton, A., Rogers, A., Gonzalez, E., Hanly, M., Kolstad, A., Rust, K., Sikali, E., Stokes, L., & Jia, Y. (2011). *The NAEP Primer.* Washington, DC: National Center for Educational Statistics.

Beaton, A. E., & Zwick, R. (1992). Overview of the National Assessment of Educational Progress. *Journal of Educational and Behavioral Statistics, 17*(2), 95-109.

Berninger, V. W., & Winn, W. D. (2006). Implications of advancements in brain research and technology for writing development, writing instruction, and educational evolution. In C. A. MacArthur, S. Graham, & J. Fitzgerald (Eds.), *Handbook of Writing Research*. NY: Guilford Press.

Bowen W.G., Kurzweil, M.A., Tobin, E.M. (2005). *Equity and excellence in American higher education*. Charlottesville, VA: University of Virginia Press.

College Board (2015). *SAT College-Bound Seniors Total Group Profile Report*. Retrieved from https://securemedia.collegeboard.org/digitalServices/pdf/sat/total-group-2015.pdf September 6, 2015.

Collins, P., Hwang, J. K., Zheng, B., & Warschauer, M. (2014). Writing with laptops: A Quasi-Experimental Study. *Writing & Pedagogy, 5*(2), 203–230.

Cochran-Smith, M. (1991). Word processing and writing in elementary classrooms: A critical review of related literature. *Review of Educational Research, 61*(1), 107-155.

Culp, K. M., Honey, M., & Mandinach, E. (2005). A retrospective on twenty years of education technology policy. *Journal of Educational Computing Research, 32*(3), 279-307.

De La Paz, S., & Graham, S. (2002). Explicitly teaching strategies, skills, and knowledge: Writing instruction in middle school classrooms. *Journal of Educational Psychology, 94*(4), 687-698.

DeBono, T. Husseini, A., Cairo, C., Ghelani, K., Tannoch, R., & Toplak, M.E. (2012). Written expression performance in adolescents with attention-deficit/hyperactivity disorder (ADHD). *Reading & Writing, 25*, 1403-1426.

Deane, P., Odendahl, N., Quinlan, T., Fowles, M., Welsh, C., & Bivens-Tatum, J. (2008). Cognitive models of writing: Writing proficiency as a complex integrated skill. Princeton, NJ: Educational Testing Service.

Duran, R. P. (2000). *Implications of Electronic Technology for the NAEP Assessment.* American Institutes for Research. Retrieved from http://www.air.org/sites/default/files/downloads/report/Duran_technology12_4_0.pdf

Englert, C.S., Mariage, T.V., & Dunsmore, K. (2006). Tenets of sociocultural theory in writing instruction research, in C.A. MacArthur, S. Graham, & J. Fitzgereald (Eds.), *Handbook of Writing Research* (pp. 208-221). NY: Guilford.

Goldberg, A., Russell, M., & Cook, A. (2003). The effect of computers on student writing: A meta-analysis of studies from 1992-2002. *The Journal of Technology, Learning, and Assessment, 2*(1).

Graham, S., & Perin, D. (2007). A meta-analysis of writing instruction for adolescent students. *Journal of Educational Psychology, 99*(3), 445-476.

Haertel, E. (1984). An application of latent class models to assessment data. *Applied Psychological Measurement, 8*(3), 333-346.

Horkay, N., Bennett, R. E., Allen, N., Kaplan, B., & Yan, F. (2006). Does it matter if I take my writing test on computer? An empirical study of mode effects in NAEP. *Journal of Technology, Learning, and Assessment, 5*(2).

Jackman M.R. & Jackman, R.W. (1983). *Class awareness in the United States*. Berkeley, CA: University of California Press.

Johnson, E. G. (1992). The design of the National Assessment of Educational Progress. *Journal of Educational Measurement, 29*(2), 95-110.

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement, 20*, 141-151.

Langer, J. A. (1991). Literacy and schooling: A sociocognitive perspective. *Literacy for a diverse society: Perspectives, practices, and policies*, 9-27.

Lyon, G.R., & Weiser, B. (2013). The state of the science in learning disabilities: Research impact on the field from 2001 to 2011. In H.L. Swanson, K.R. Harris, & S. Graham (Eds.), *Handbook of Learning Disabilities (2nd ed.,* pp. 118-151). NY: Guilford.

Messick, S., Beaton, A., & Lord, F. (1983). *National Assessment of Educational Progress Reconsidered: A New Design for a New Era*. Princeton, NJ: Educational Testing Service.

Morphy, P., & Graham, S. (2012). Word processing programs and weaker writers/readers: A meta-analysis of research findings. *Read Write, 25*, 641-678.

National Assessment Governing Board (NAGB) (2010). *Writing Framework for the 2011 National Assessment of Educational Progress*. Washington, D.C.: U.S. Department of Education.

National Center for Education Statistics (NCES, 2009). *The Nation's Report Card: An Overview of Procedures for the NAEP Assessment.* Washington, D.C.: Institute of Education Sciences, U.S. Department of Education.

National Center for Education Statistics (2012). *The Nation's Report Card: Writing 2011*. Washington, D.C.: Institute of Education Sciences, U.S. Department of Education.

National Center for Education Statistics (2014a). *Lessons Learned from the 2012 Grade 4 Writing Computer-based Assessment Study*. Washington, D.C.: Institute of Education Sciences, U.S. Department of Education. Retrieved from http://nces.ed.gov/nationsreportcard/writing/lessons/default.aspx.

National Center for Education Statistics (2014b). *NAEP 2012 Pilot Writing Computer-Based Assessment Study--Grade 4: Technical Memorandum*. Washington, D.C.: Institute of Education Sciences, U.S. Department of Education.

National Research Council (Pellegrino, J. and Hilton, M., Eds.) (2012). *Education for Life and Work in the 21st Century.* Committee on Defining Deeper Learning and 21st Century Skills, Center for Education, Division of Behavioral and Social Sciences and Education, National Research Council. Washington D.C.: The National Academies Press.

Nystrand, M. Green, S. & Wiemelt, J. (1993). Where did composition studies come from? An intellectual history. *Written Communication, 10*(3)*,* 267-333.

Organisation for Economic Co-operation and Development (OECD) (2015). *Students, Computers and Learning: Making the Connection*. Retrieved from http://dx.doi.org/10.1787/9789264239555-en

Pascarella E.T., & Terenzini, P.T. (1991). *How college affects students: Findings and insights from twenty years of research*. San Francisco, CA: Jossey-Bass.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (Vol. 1): Sage.

Resnick, L. B. (2010). Nested learning systems for the thinking curriculum. *Educational Researcher, 39*(3), 183-197.

Rogers, A., Stoeckel, J., & Sikali, E. (2013). *National Assessment of Educational Progress (NAEP) 2011 Writing Assessment Restricted-Use Data Files Data Companion.* Washington, D.C.: National Center for Education Statistics.

Russell, M., & Haney, W. (1997). Testing writing on computers: An experiment comparing student performance on tests conducted via computer and via paper-and-pencil. *Education Policy Analysis Archives, 5*(3), 1-18.

Russell, M. & Plati, T. (2002). Does it matter with what I write? Comparing performance on paper, computer and portable writing devices. *Current Issues in Education, 5*.

Saenz, V.B,, Hurtado S., Barrera, D., Wolf, D., & Yeung, F. (2007*). First in my family: A profile of first-generation college students at four-year institutions since 1971*. Los Angeles, CA: Higher Education Research Institute.

Sandene, B., Horkay, N., Bennett, R.E., Allen N., Braswell, J., Kaplan, B., & Oranje, A. (2005). *Online Assessment in Mathematics and Writing: Reports from the NAEP Technology-Based Assessment Project*. Washington, DC: National Center for Education Statistics.

Schneider, B., Carnoy, M. Kilpatrick, J., Schmidt, W.H., & Shavelson, R.J. (2007). *Estimating Causal Effects Using Experimental and Observational Designs* (report from the Governing Board of the American Educational Research Association Grants Program). Washington, DC: American Educational Research Association.

Schreiber, J., Nora, A., Stage, F., Barlow, E., & King, J. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of Education Research, 99*(6), 323-338.

Schwartz, H. J., & Bridwell, L. S. (1984). A selected bibliography on computers in composition. *College Composition and Communication, 35*(1), 71-77.

Sirin, S.R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research*, *75*, 417–453.

Snibbe, A.C., & Markus, H.R. (2005). You can't always get what you want: Educational attainment, agency, and choice. *Journal of Personality and Social Psychology, 88*,703–720.

Sperling, M., & Freedman, S.W. (2001). Research on writing. In V. Richardson (Ed.), *Handbook of Research on Teaching*, 4th edition. Washington, DC: American Educational Research Association.

Sweller, J., van Merrienboer, J., & Paas, F. (1998). Cognitive architecture & instructional design. *Educational Psychology Review, 10:*3, 251-296.

Tate, T., & Warschauer, M. (under review). What's so special about digital writing? A look at the research in U.S. K-12 education,

Tate, T., Warschauer, M., & Abedi, J. (2016). Data on NAEP 2011 Writing Assessment Prior Computer Use, *Data in Brief,* doi:10.1016/j.dib.2016.07.002

Vygotsky, L. S. (1962). *Thought and language*. Cambridge, MA: MIT Press.

Vygotsky, L. S. (1981). The genesis of higher mental functions. In J. V. Wertsch (Ed.), *The Concept of Activity in Soviet Psychology* (pp. 144-188). Armonk, NY: M.E. Sharpe.

Warschauer, M. (2006). *Laptops and literacy: Learning in the wireless classroom*. NY: Teachers College Press.

Warschauer, M. (2011). *Learning in the cloud: How (and why) to transform schools with digital media.* NY: Teachers College Press.

Welch, W. W., Anderson, R. E., & Harris, L. J. (1982). The effects of schooling on mathematics achievement. *American Educational Research Journal, 19*(1), 145-153.

Wenglinsky, H. (2005). *Using technology wisely: The keys to success in schools*. NY: Teachers College Press.

Wertsch, J. V. (1991). *Voices of the mind: A sociocultural approach to mediated action*. Cambridge, MA: Harvard University Press.

Wertsch, J. V. (1998). *Mind as Action*. Oxford: Oxford University Press.

Zheng, B., & Warschauer, M. (2015). Participation, interaction, and academic achievement in an online discussion environment. *Computers & Education, 84*, 78-89.

Zhang, T., Xie, Q., Park, B. J., Kim, J., Yee, Broer, M., & Bohrnstedt, G. (2016). *Computer familiarity and its relationship to performance in three NAEP digital-based assessments*. Retrieved from Washington, DC.

Zheng, B. B., Warschauer, M., Lin, C.-H., & Chang, C. (2016). Learning in one-to-one laptop environments: A meta-analysis and research synthesis. *Review of Educational Research, XX*(X), 1-33. doi:10.3102/0034654316628645

Zwick, R. (1987). Assessing the dimensionality of NAEP reading data. *Journal of Educational Measurement, 24*(4), 293-308.

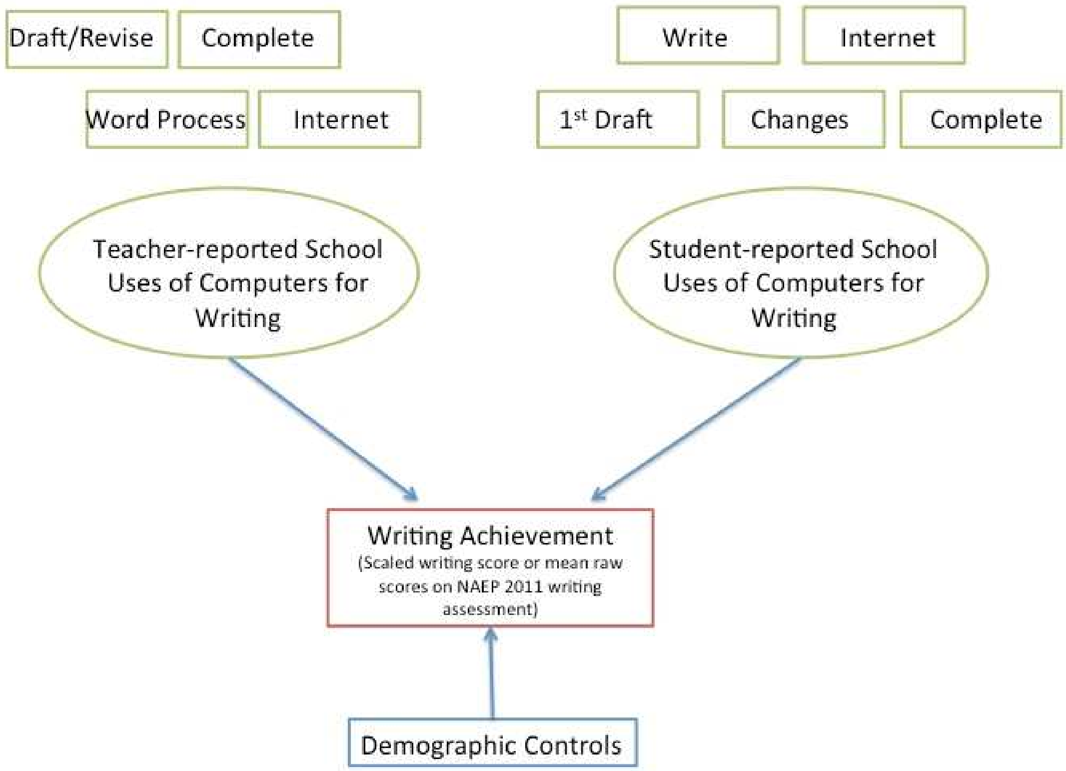

Figure 1.
Parsimonious final structural equation model showing direct effects of latent variables on writing achievement

Table 1.
Standardized coefficients and z scores for latent variables in final structural equation model, using scaled and mean writing dependent variables, with controls and jackknife weighting

Observed variable	Latent construct	Scaled β	Mean β
Draft/revise	Teacher-reported	0.79 (0.02) z 39.51	0.79 (0.03) z 30.09
Complete	Teacher-reported	0.85 (0.01) z 61.89	0.85 (0.02) z 44.76
Word processing	Teacher-reported	0.78 (.02) z 45.92	0.78 (0.02) z 36.66
Use Internet	Teacher-reported	0.63 (.03) z 21.63	0.63 (0.04) z 17.74
Use Internet	Student-reported	0.73 (.01) z 71.15	0.73 (0.01) z 70.18
First draft	Student-reported	0.74 (.01) z 59.89	0.74 (0.01) z 60.747
Make changes	Student-reported	0.85 (.01) z 155.97	0.85 (0.01) z 158.64
Complete	Student-reported	0.79 (.01) z 130.35	0.79 (0.01) z 128.34
Write for school	Student-reported	0.59 (.02) z 37.11	0.59 (0.02) z 37.22

Note: Standard errors in parentheses.

Table 2.
Final structural equation model factor loadings, using jackknife weighting

Mean Score Analysis						
Latent Variable	Coefficient	Standard Error	z	P>|z|	95% Confidence Interval	
Student-reported school writing	0.11	0.01	7.72	0.00	0.08	0.14
Teacher-reported writing	0.03	0.01	2.41	0.02	0.01	0.05
Aggregate	0.14	0.03				

Scaled Score Analysis						
Latent Variable	Coefficient	Standard Error	z	P>|z|	95% Confidence Interval	
Student-reported school writing	0.09	0.02	5.01	0.00	0.06	0.13
Teacher-reported writing	0.07	0.01	5.09	0.00	0.04	0.09
Aggregate	0.16	0.03				

Table 3.
SEM results, writing tasks (1-22) with individual mean scores as dependent variable, controls and no weighting

Writing Task	Sample Size	Teacher-Reported Effect	Student-Reported Effect	RMSEA	CFI
1	2220	0.02 (0.02)	0.14 (0.02)***	0.04	0.95
2	2270	0.00 (0.00)	0.07 (0.02)**	NA	NA
3	2210	0.02 (0.04)	0.09 (0.03)**	0.04	0.96
4	2260	0.03 (0.02)	0.10 (0.02)***	0.04	0.96
5	2230	0.02 (0.02)	0.15 (0.02)***	0.04	0.96
6	2260	0.06 (0.02)**	0.08 (0.02)***	0.04	0.95
7	2250	0.04 (0.02)	0.03 (0.02)	0.04	0.96
8	2230	0.03 (0.02)	0.02 (0.02)	0.04	0.96
9	2250	0.10 (0.02)***	0.08 (0.02) **	0.04	0.96
10	2230	0.00 (0.00)	0.10 (0.02)***	NA	NA
11	2200	0.05 (0.02)*	0.13 (0.02)***	0.04	0.95
12	2240	0.06 (0.02)**	0.08 (0.02)***	0.04	0.96
13	2210	0.00 (0.00)	0.23 (0.02)***	NA	NA
14	2250	0.05 (0.02)*	0.11 (0.02)***	0.04	0.96
15	2230	0.04 (0.02)	0.07 (0.02)**	0.04	0.95
16	2270	0.03 (0.02)	0.17 (0.02)***	0.04	0.96
17	2240	0.06 (0.02)**	0.10 (0.02)***	0.04	0.96
18	2230	0.02 (0.02)	0.11 (0.02)***	0.04	0.96
19	2220	0.05 (0.02)*	0.11 (0.02)***	0.04	0.95
20	2260	0.03 (0.02)	0.09 (0.02)***	0.04	0.95
21	2220	0.05 (0.02)	0.02 (0.02)	0.04	0.96
22	2260	.000 (.000)	.206 (.023)***	NA	NA

Note: Sample sizes rounded to the nearest 10. Standard errors in parentheses. $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 4.
Aggregate regression analysis, with controls and interactions, using scaled and mean writing scores

	Scaled	Mean
Teacher-reported writing	0.01	0.01
	(0.01)	(0.01)
Student-reported writing	0.07***	0.08***
	(0.01)	(0.01)
Female	0.41***	0.45***
	(0.01)	(0.02)
Black	-0.42***	-0.46***
	(0.02)	(0.03)
Hispanic	-0.15***	-0.15***
	(0.02)	(0.03)
Asian	0.11***	0.16***
	(0.03)	(0.05)
Other	-0.10	-0.12
	(0.09)	(0.16)
Free/reduced lunch	-0.30***	-0.33***
	(0.01)	(0.02)
Parent college graduate	0.18***	0.18***
	(0.01)	(0.02)
Former ELL	-0.09*	-0.12*
	(0.03)	(0.06)
Current ELL	-0.72***	-0.57***
	(0.03)	(0.05)
Student w disability	-0.76***	-0.74***
	(0.02)	(0.04)
Teacher/female	0.00	-0.01
	(0.00)	(0.01)
Teacher/Black	0.00	-0.01
	(0.01)	(0.01)
Teacher/Asian	0.01	0.03
	(0.01)	(0.02)
Teacher/Hispanic	0.01	-0.01
	(0.01)	(0.01)
Teacher/free lunch	0.01*	0.01
	(0.01)	(0.01)
Teacher/parent college	0.02**	0.03**
	(0.01)	(0.01)
Teacher/current ELL	0.00	-0.01
	(0.01)	(0.02)

Teacher/former ELL	0.00	0.00
	(0.01)	(0.02)
Teacher/student w disability	-0.01	0.00
	(0.01)	(0.01)
Student/ female	-0.01	0.00
	(0.00)	(0.01)
Student/Black	-0.02**	0.00
	(0.01)	(0.01)
Student/Asian	0.01	-0.01
	(0.01)	(0.02)
Student/Hispanic	-0.01	-0.01
	(0.01)	(0.01)
Student/free lunch	-0.03***	-0.03***
	(0.01)	(0.01)
Student/parent college	0.01*	-0.01
	(0.00)	(0.01)
Student/current ELL	-0.04***	0.08***
	(0.01)	(0.02)
Student/former ELL	0.01	0.00
	(0.01)	(0.02)
Student/student w disability	-0.04***	-0.03**
	(0.01)	(0.01)
Constant	0.04**	2.69***
	(0.01)	(0.02)
N	18,340	18,330
R-sq	0.33	0.15

Note: N rounded to the nearest 10. Standard errors in parentheses. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table 5.
Eigenvalues and factor loadings for principal factor analysis (rotated, oblique) of computer use in the NAEP teacher and student surveys

Factor	Variance	Proportion
Factor 1	3.17	0.03
Factor 2	2.81	0.27
Factor 3	2.35	0.23
Factor 4	2.26	0.22
Factor 5	2.14	0.20
Factor 6	2.00	0.19
Factor 7	1.97	0.19
Factor 8	1.67	0.16
Factor 9	1.45	0.14
Factor 10	1.15	0.11

Note. Rotated factors are correlated. Method: principal factors. Rotation: Oblique Oblimin (Kaiser on). Observations: 22,150. Retained factors = 10. Number of parameters: 235. LR test: independent vs. saturated: chi2(378) = 2.0e+05 Prob>chi2 = 0.0000

Rotated factor loadings (pattern matrix) and unique variances

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Factor 10	Uniqueness
Student, School, Internet	**0.70**	-0.01	0.05	0.00	0.01	-0.02	0.02	-0.04	0.03	0.00	0.47
Student, School 1st Draft	**0.71**	-0.03	0.04	-0.01	-0.01	-0.02	0.02	0.01	0.05	-0.03	0.46
Student, School, Changes	**0.85**	-0.01	-0.05	0.00	0.01	0.01	-0.01	0.01	-0.02	0.01	0.33
Student, School, Complete	**0.78**	0.05	-0.04	-0.01	-0.01	0.01	-0.02	0.02	-0.05	0.02	0.40
Student, School, Write	0.36	0.05	0.39	-0.02	-0.01	0.01	-0.01	0.02	0.04	-0.03	0.55
Student, Not School, Write	0.01	-0.02	**0.62**	0.00	-0.01	-0.00	0.01	-0.02	0.03	-0.00	0.60
Student, Not School, Email	-0.02	0.00	**0.69**	0.01	-0.01	-0.00	-0.00	0.02	-0.01	0.00	0.54
Student, Not School, Internet	-0.01	0.00	**0.63**	0.00	0.02	0.01	-0.01	-0.01	-0.03	0.01	0.62
Teacher Instruction, Desktop	0.00	0.12	-0.00	0.05	0.39	0.00	0.01	0.02	-0.01	0.03	0.77
Teacher Instruction, Laptop	0.01	0.02	0.01	0.32	-0.10	0.09	-0.10	0.20	0.19	0.12	0.71
Teacher Instruction, Tablet	-0.00	-0.04	0.01	0.15	0.109	0.00	0.04	0.07	0.00	0.36	0.77
Teacher Instruction, Projector	-0.00	0.02	0.00	**0.69**	0.06	-0.04	0.03	-0.01	-0.01	-0.02	0.47
Teacher Instruction, CD/DVD	0.01	0.00	-0.02	0.24	0.32	0.15	-0.08	0.05	0.17	0.05	0.60
Teacher Instruction, Digital Device	0.03	-0.02	-0.02	0.09	0.20	0.03	-0.00	0.09	0.15	0.30	0.64
Teacher Instruction, TV	-0.01	-0.02	0.00	-0.06	0.26	0.01	0.05	0.12	0.18	0.30	0.63
Teacher Instruction, Digital Content	-0.02	0.02	0.02	0.28	0.25	-0.05	0.05	0.10	0.22	0.02	0.56
Teacher Instruction, Computer Available	0.00	0.11	0.00	-0.02	0.020	-0.01	0.04	0.31	0.01	-0.01	0.87
Teacher Instruction, Internet Available	-0.01	0.09	0.01	-0.11	-0.05	0.01	-0.02	-0.10	0.07	0.23	0.89
Teacher, Students Draft/Revise on	0.02	**0.74**	-0.01	-0.00	0.02	0.01	0.02	0.13	-0.03	-0.02	0.36

Computer											
Teacher, Students Complete Writing on Computer	0.02	**0.79**	-0.01	0.03	0.02	0.02	-0.03	0.05	-0.07	0.01	0.33
Teacher, Students use Word Processing	0.00	**0.78**	-0.00	0.05	-0.02	0.02	-0.02	0.00	-0.03	-0.00	0.39
Teacher, Students use Internet for Writing	0.00	**0.60**	0.00	0.03	0.07	-0.03	0.05	-0.03	0.14	0.02	0.55
Teacher, Use Computer for Instruction	-0.02	0.12	0.01	0.65	0.07	-0.06	0.04	-0.01	0.01	-0.01	0.48
Professional Development, Basic Computer	-0.02	0.00	0.01	-0.07	0.04	0.69	0.01	-0.01	0.01	-0.00	0.51
Professional Development, Software	0.01	-0.01	-0.01	0.03	-0.04	0.40	0.36	0.01	0.00	-0.01	0.51
Professional Development, Internet	0.01	0.01	0.00	0.02	-0.02	0.68	0.06	-0.01	-0.02	-0.02	0.49
Professional Development, Other Technology	0.00	0.01	0.00	0.02	0.00	0.04	**0.68**	-0.00	0.01	0.01	0.51
Professional Dev., Integrating Technology	0.01	-0.01	-0.00	-0.01	-0.02	0.04	**0.69**	0.03	-0.00	0.02	0.48

Factor rotation matrix

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Factor 10
Factor 1	0.56	0.71	0.39	0.53	0.57	0.16	0.19	0.58	0.46	0.34
Factor 2	0.77	-0.21	0.67	-0.42	-0.44	-0.14	-0.13	-0.30	-0.30	-0.30
Factor 3	0.02	-0.17	0.05	-0.15	-0.07	0.90	0.88	-0.03	-0.04	0.01
Factor 4	0.00	-0.63	0.30	0.51	0.33	-0.05	-0.05	0.10	0.35	0.18
Factor 5	-0.01	-0.01	0.01	-0.18	0.29	-0.34	0.33	-0.01	-0.11	0.12
Factor 6	-0.29	0.13	0.54	-0.17	-0.09	0.05	-0.07	-0.10	0.14	0.21
Factor 7	0.07	-0.02	-0.12	-0.42	0.09	0.16	-0.24	-0.17	0.52	0.73
Factor 8	0.01	0.05	-0.01	0.12	-0.27	-0.03	0.04	-0.47	0.05	0.34
Factor 9	0.00	-0.02	0.01	0.03	0.10	0.02	-0.02	0.12	-0.52	0.19
Factor 10	-0.00	-0.03	-0.01	0.01	-0.43	-0.04	0.03	0.55	0.13	0.14

Correlation matrix of the oblimin(0) rotated common factors

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Factor 10
Factor 1	1.00									
Factor 2	0.19	1.00								
Factor 3	0.57	0.01	1.00							
Factor 4	-0.01	0.16	0.03	1.00						
Factor 5	0.01	0.29	-0.03	0.56	1.00					
Factor 6	0.00	0.03	0.00	-0.03	0.02	1.00				
Factor 7	0.02	0.04	0.01	0.06	0.14	0.69	1.00			
Factor 8	0.11	0.37	0.02	0.53	0.39	0.07	0.15	1.00		
Factor 9	0.03	0.19	0.09	0.33	0.39	0.17	-0.08	0.27	1.00	
Factor 10	-0.05	0.21	0.01	0.09	0.34	0.17	-0.04	0.09	0.64	1.00

Table 6.
Correlation of scaled writing score, frequency of computer use for writing (single question variable), and demographic variables, 2011

	Scaled Score	Prior Use	Female	Hispanic	Black	Asian	Free/Red Lunch	Parent HS Grad	ELL Current	ELL Former	Student w Disab
Scaled Score	1.00										
Prior Use	0.19* (0.00)	1.00									
Female	0.24* (0.00)	0.07* (0.00)	1.00								
Hispanic	-0.16* (0.00)	-0.07* (0.00)	0.00 (0.66)	1.00							
Black	-0.20* (0.00)	0.01 (0.18)	0.00 (0.61)	-0.27* (0.00)	1.00						
Asian	0.08* (0.00)	0.07 (0.00)	0.00 (0.68)	-0.13* (0.00)	-0.11* (0.00)	1.00					
Free/Red Lunch	-0.34* (0.00)	-0.11* (0.00)	0.01 (0.29)	0.28* (0.00)	0.25* (0.00)	-0.05* (0.00)	1.00				
Parent HS Grad	0.14* (0.00)	0.09* (0.00)	-0.05* (0.00)	-0.28* (0.00)	0.06* (0.00)	0.03* (0.00)	-0.25* (0.00)	1.00			
ELL Current	-0.23* (0.00)	-0.04* (0.00)	-0.02* (0.00)	0.26* (0.00)	-0.07* (0.00)	0.07* (0.00)	0.17* (0.00)	-0.17* (0.00)	1.00		
ELL Former	-0.05* (0.00)	-0.01 (0.13)	0.00 (1.00)	0.27* (0.00)	-.008* (0.00)	0.04* (0.00)	0.13* (0.00)	-0.12* (0.00)	-0.05* (0.00)	1.00	
Student w Disab	-0.28* (0.00)	-0.04* (0.00)	-0.08* (0.00)	-0.01 (0.51)	0.03* (0.00)	-0.05* (0.00)	0.07* (0.00)	-0.02* (0.00)	0.03* (0.00)	-0.01 (0.23)	1.00

Note. Standard errors in parentheses. *$p < 0.05$, ** $p < 0.01$, *** $p < 0.005$

Correlation of scaled writing score, frequency of computer use for writing (single question variable), and demographic variables, 2007

	Scaled Score	Prior Use	Female	Hispanic	Black	Asian	Free/R Lunch	Parent HS Gr	ELL Current	ELL Former	Student w Disab
Scaled	1.00										
Score											
Prior	0.07*	1.00									
Use	(0.00)										
Female	0.25*	0.02*	1.00								
	(0.00)	(0.00)									
Hispanic	-0.13*	-0.05*	0.02*	1.00							
	(0.00)	(0.00)	(0.00)								
Black	-0.16*	-0.03*	0.012*	-0.18	1.00						
	(0.00)	(0.00)	(0.00)	(0.00)							
Asian	0.05*	0.03*	-0.01*	-0.08*	-0.10*	1.00					
	(0.00)	(.000)	(0.04)	(0.00)	(0.00)						
Free/Red	-0.27*	-0.09*	0.02*	0.25*	0.28*	-0.02*	1.00				
Lunch	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					
Parent	0.13*	0.07*	-0.04*	-0.27*	0.03*	0.02*	-0.23*	1.00			
HS Grad	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
ELL	-0.23*	-0.04*	-0.02*	0.26*	-0.07*	0.07*	0.17*	-0.17*	1.00		
Current	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)			
ELL	-0.02*	-.001*	0.01*	0.20*	-0.04*	0.05*	0.08*	-0.10*	-0.02*	1.00	
Former	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
Student	-0.21*	-0.01*	-0.09*	-0.01	0.03*	-0.03*	0.08*	-0.03*	0.02*	-0.02	1.00
w Disab	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Table 7.

Regression of scaled writing scores, frequency of computer use for writing (single question variable), demographic variables, 2011

	Scaled Writing Score					(Parent College)		
Prior Use	0.28***	0.25***	0.23***	0.19***	0.18***	0.16***	0.18***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female		0.43***	0.44***	0.45***	0.45***	0.41***	0.44***	0.41***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Black			-0.64***	-0.42***	-0.44***	-0.45***	-0.44***	-0.45***
			(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Hispanic			-0.53***	-0.32***	-0.26***	-0.17***	-0.17***	-0.19***
			(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Asian			0.06*	0.10***	0.12***	0.13***	0.20***	0.15***
			(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Other			omitted	omitted	omitted	omitted	omitted	omitted
Free/Red Lunch				-0.47***	-0.43***	-0.32***	-0.40***	-0.37***
				(0.03)	(0.01)	(.01)	(0.01)	(0.01)
Parent HS Grad					0.20***		0.15***	0.14***
					(0.02)		(0.02)	(0.02)
Parent College Grad						0.20***		
						(.01)		
Former ELL						-0.10**	-0.09**	-0.10*
						(0.03)	(0.03)	(0.03)
Current ELL						-0.71***	-0.73***	-0.70***
						(0.3)	(0.03)	(0.03)
Student w						-0.75***		-0.75***

Disability								
						(0.02)		(0.02)
Constant	-0.66***	-0.82***	-0.52***	-0.32***	-0.48***	-0.30***	-0.42***	-0.32***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)
N	23850	23850	23220	21950	19760	19760	19760	19760
R-sq	0.04	0.09	0.19	0.23	0.23	0.31	0.25	0.30

Note. *N* rounded to the nearest 10. Standard errors in parentheses. $*p < 0.05$, $**p < 0.01$, $***p < 0.005$

Regression of scaled writing scores, frequency of computer use for writing (single question variable), demographic variables, 2007

	Scaled Writing Score					(Parent College)		
Prior Use	0.10***	0.09***	0.07***	0.05***	0.04***	0.03***	0.04***	0.04***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female		0.48***	0.49***	0.49***	0.49***	0.45***	0.49***	0.45***
		(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Black			-0.49***	-0.31***	-0.33***	-0.33***	-0.33***	-0.34***
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Hispanic			-0.49***	-0.30***	-0.24***	-0.17***	-0.15***	-0.17***
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Asian			0.01	0.07***	0.09***	0.10***	0.14***	0.11***
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Other			-0.50***	-0.33***	-0.33***	-0.26***	-0.29***	-0.28***
			(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Free/Red Lunch				-0.40***	-0.36***	-0.27***	-0.35***	-0.31***
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Parent HS Grad					0.27***		0.24***	0.22***
					(0.01)		(0.01)	(0.01)
Parent College						0.21***		
						(0.01)		

Former ELL						-0.05*	0.01	-0.03
						(0.02)	(0.02)	(0.02)
Current ELL						-0.55***	-0.55***	-0.53***
						(0.01)	(0.01)	(0.01)
Student w Disability						-0.75***		-0.76***
						(0.01)		(0.01)
Constant	-0.22***	-0.45***	-0.24***	-0.10***	-0.31***	-0.10***	-0.29***	-0.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	138020	138020	136630	132010	117210		117200	117200
R-sq	0.01	0.07	0.13	0.16	0.16		0.17	0.23

Note. *N* rounded to the nearest 10. Standard errors in parentheses. $*p < 0.05$, $**p < 0.01$, $***p < 0.005$

Tate, T., Warschauer, M., & Abedi, J. (2016). Data on NAEP 2011 Writing Assessment Prior Computer Use, *Data in Brief,* doi:10.1016/j.dib.2016.07.002

Data article

Title: ***Data on NAEP 2011 Writing Assessment Prior Computer Use***

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Abstract

This data article contains information based on the 2011 National Assessment of Educational Progress in Writing Restricted-Use Data, available from the National Center for Education Statistics (NCES Pub. No. 2014476). https://nces.ed.gov/nationsreportcard/researchcenter/datatools.aspx The data include the statistical relationships between survey reports of teachers and students regarding prior use of computers and other technology and writing achievement levels on the 2011 computer-based NAEP writing assessment. This data article accompanies [1].

Specifications Table

Subject area	*Education*
More specific subject area	*Writing*
Type of data	*Tables, Figures*
How data was acquired	*NCES restricted database*
Data format	*Analyzed*
Experimental factors	*Prior access to and use of technology based on survey question responses*
Experimental features	*Jackknife weighting*
Data source location	*USA*
Data accessibility	Data is within this article and available from the National Center for Education Statistics (NCES Pub. No. 2014476). https://nces.ed.gov/nationsreportcard/researchcenter/datatools.aspx

Value of the data

- **Details of the relationship between 28 survey questions relating to teacher and student use of technology and the 2011 NAEP writing assessment illustrate the outcomes associated with various uses of and access to technology to guide future instruction and investments in resources.**
- **Models the impact of prior technology use on writing achievement to indicate the positive association between academic use of technology for writing, but not personal or ancillary uses and access.**

- **Multiple methods used to analyze data to ensure robust understanding of the relationships between access to and use of technology and its potential impact on writing achievement.**

Data

The data in this article models the relationship between students' reported prior use of and access to computers and their achievement on the first national computer-based writing assessment in the United States, the 2011 National Assessment of Educational Progress (NAEP) assessment. The data models the relationship of survey responses from students and teachers regarding their access to and use of technology for personal and academic uses and students' scores on 2 timed writing tasks.

Experimental Design, Materials and Methods

Details of the Survey and Assessment

The assessment was comprised of a total of 22 writing prompts in three areas, to persuade, to explain, and to convey experience, either real or imagined. Responses were scored by three trained evaluators on a 6-point scale, representing effective skill, adequate skill, developing skill, marginal skill, and little or no skill across three areas of writing--development of ideas, organization of ideas, and language facility and conventions [2, 3]. NAEP evaluators used holistic scoring rubrics to evaluate the response as a whole, rather than assessing independent parts of the response [3]. The scaled booklet-level scores (-2.18 to 3.04) were used as the achievement variable or independent variable for the initial analyses. Additional analysis of student scores was done with the mean of the unscaled scores (interval scale, 1-6) sorting the students and analyzing them by booklet. Variables relating to prior computer use and access included separate student and teacher reported measures of how often (a) the Internet is used to get information, (b) a computer is used for a first draft, (c) a computer is used to make changes in writing, (d) a computer is used to complete writing, (e) a computer is used to write school assignments, (f) a computer is used to write not for school, (g) a computer is used for emails, and (h) a computer is used to write on the Internet. Additionally, self-report measures of teacher use of technology in the classroom were available, providing insight into the degree to which classroom interventions might offset lack of use at home, and teacher professional development relating to technology use. Various demographic groups are included in the data though dichotomous controls for gender, national school lunch eligibility and parental education (as proxies to indicate socioeconomic status), English language learner status (prior, current, or not applicable), students with individualized education plans (IEPs) or 504 plans under the American with Disabilities Act, and race/ethnicity.

Structural Equation Modeling

The analysis included structural equation modeling (SEM) of the data using both the IRT scaled scores ("scaled scores") and the mean of the individual scores by trained reviewers on each essay ("mean scores") at an aggregate (all essays, regardless of different writing tasks) and booklet-level analysis (isolating each writing) to check for robustness and comparability.

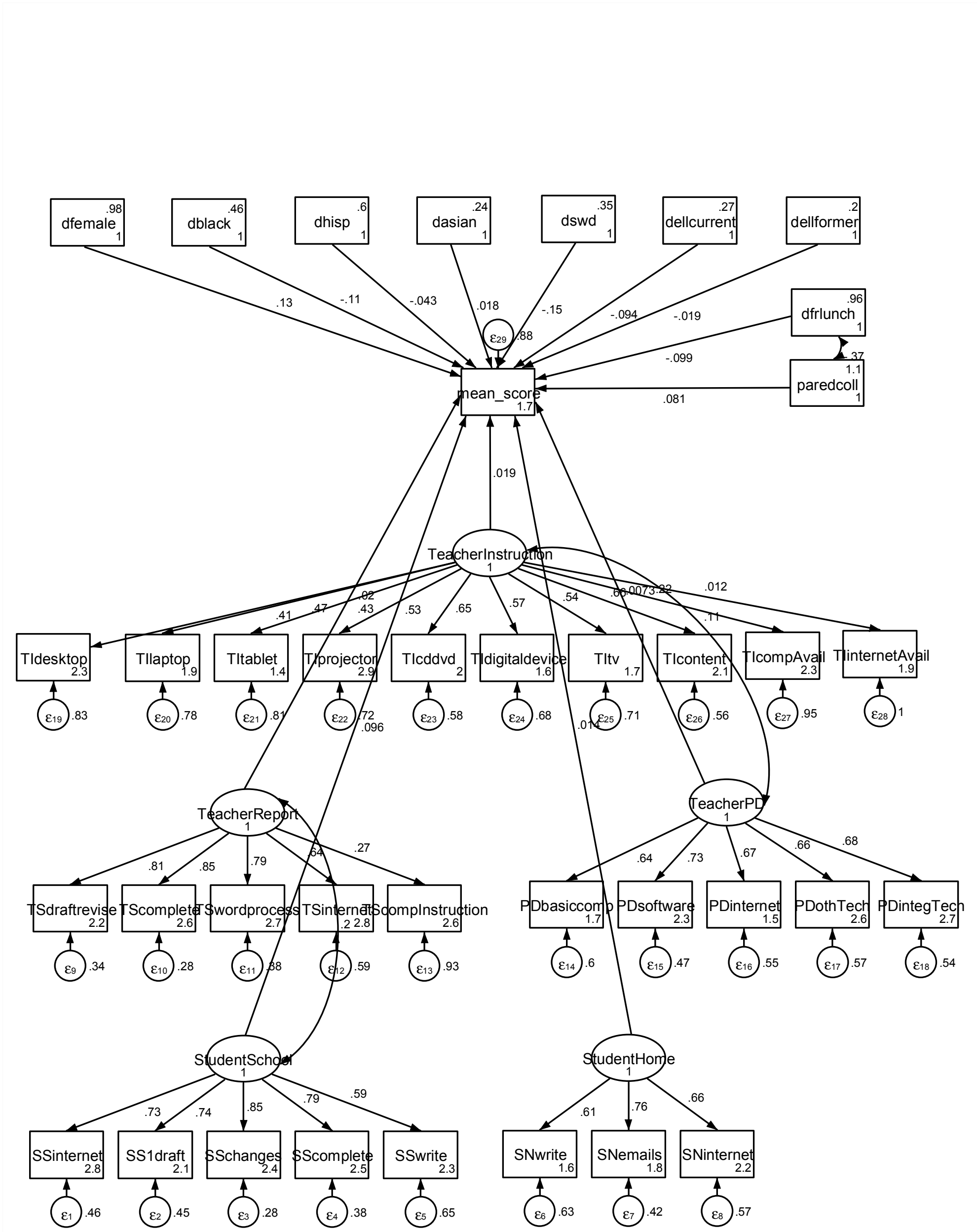

Figure 1.
Initial structural equation model showing direct effects of latent variables, with controls, using mean writing score, standardized

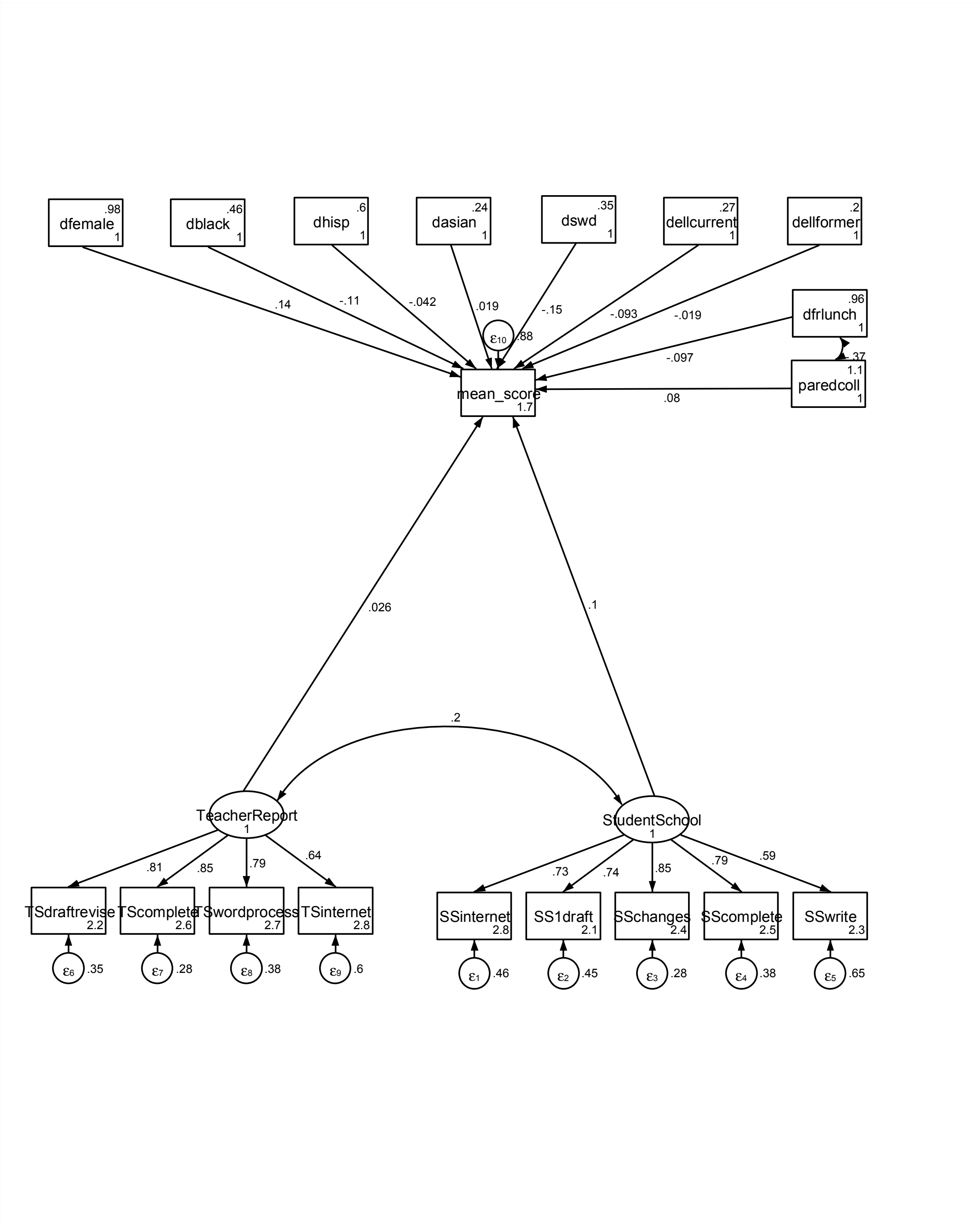

Figure 2.

Parsimonious final structural equation model showing direct effects of latent variables on mean writing score, standardized, with controls and no jackknife weighting

Table 1.
Quartile and other descriptive detail for scaled and mean writing scores outcome variables

Percentile	Scaled Score	Mean Score
1%	-1.96	1.00
5%	-1.69	1.00
10%	-1.32	1.50
25%	-0.79	2.00
50%	-0.03	2.50
75%	0.61	3.33
90%	1.17	4.00
95%	1.54	4.50
99%	2.29	5.00
Mean	-0.04	2.64
Standard Deviation	0.96	0.98
Variance	0.92	0.96
Skewness	0.14	0.35
Kurtosis	2.66	2.65

Table 2.
Initial structural equation model loadings. Final loadings can be found in [1]

Mean Score Analysis						
Latent Variable	Coefficient	Standard Error	z	P>|z|	95% Confidence	Interval
Student-reported school writing	0.10	0.01	12.78	0.000	0.08	0.11
Student-reported not for school writing	0.01	0.01	2.13	0.033	0.00	0.03
Teacher-reported writing	0.02	0.01	2.76	0.006	0.01	0.03
Teacher instruction	0.02	0.01	2.50	0.013	0.00	0.03
Student-reported and teacher-reported writing (cov)	0.20	0.01	26.61	0.000	0.19	0.21
Teacher PD and teacher instruction (cov)	0.11	0.01	13.35	0.000	0.10	0.13

Note. Teacher professional development latent variable was not statistically significant. RMSEA 0.05 and CFI 0.81

Scaled Score Analysis						
Latent Variable	Coefficient	Standard Error	z	P>|z|	95% Confidence	Interval
Student-reported school writing	0.09	0.01	14.63	0.000	0.08	0.01
Teacher-reported writing	0.07	0.01	11.02	0.000	0.06	0.09
Student-reported and teacher-reported writing (cov)	0.20	0.01	26.64	0.000	0.19	0.21
Teacher PD and teacher instruction (cov)	0.11	0.01	13.35	0.000	0.10	0.13

Note. Student not for school writing, teacher professional development, and teacher instruction latent variables were not statistically significant.

Table 3.
Correlation matrix of scaled score, mean score, prior use components, and demographic controls in final SEM regression

	Scaled Score	Mean Score	Teacher Draft	Teacher Complete	Teacher Word Process	Teacher Internet	Student Internet	Student 1st Draft	Student Changes	Student Complete	Student Write	Female	White
Scaled Score	1.00												
Mean Score	0.64	1.00											
Teacher Draft	0.15	0.09	1.00										
Teacher Complete	0.16	0.10	0.70	1.00									
Teacher Word Process	0.13	0.09	0.62	0.67	1.00								
Teacher Internet	0.07	0.04	0.51	0.51	0.52	1.00							
Student Internet	0.23	0.15	0.11	0.12	0.10	0.10	1.00						
Student 1st Draft	0.10	0.09	0.12	0.10	0.09	0.08	0.49	1.00					
Student Changes	0.22	0.17	0.15	0.16	0.13	0.09	0.55	0.57	1.00				
Student Complete	0.26	0.19	0.19	0.20	0.16	0.11	0.51	0.49	0.64	1.00			
Student Write	0.11	0.07	0.13	0.13	0.12	0.08	0.37	0.38	0.39	0.38	1.00		
Female	0.25	0.17	-0.00	-0.00	0.00	-0.00	0.08	0.01	0.08	0.05	0.06	1.00	
White	0.26	0.17	0.09	0.12	0.11	0.04	0.07	0.05	0.11	0.14	-0.01	-0.01	1.00
Black	-0.20	-0.14	-0.06	-0.08	-0.06	-0.01	-0.00	-0.01	-0.04	-0.07	0.03	0.01	-0.49
Hispanic	-0.16	-0.10	-0.08	-0.10	-0.08	-0.04	-0.11	-0.07	-0.12	-0.13	-0.05	0.00	-0.59
Asian	0.09	0.06	0.05	0.05	0.02	0.01	0.06	0.05	0.06	0.05	0.06	0.00	-0.24
Other	-0.01	-0.00	0.01	0.01	0.00	0.00	-0.00	-0.00	-0.01	-0.00	0.01	-0.01	-0.06
Free/Red Lunch	-0.34	-0.23	-0.16	-0.18	-0.16	-0.07	-0.12	-0.10	-0.18	-0.20	-0.07	0.01	-0.41

Student Disability	-0.28	-0.18	-0.02	-0.02	-0.01	-0.02	-0.10	-0.01	-0.05	-0.06	0.01	-0.08	0.00
Current ELL	-0.22	-0.14	-0.06	-0.05	-0.07	-0.03	-0.09	-0.02	-0.07	-0.09	0.00	-0.02	-0.20
Former ELL	-0.05	-0.04	-0.03	-0.04	-0.03	-0.03	-0.03	-0.02	-0.04	-0.06	-0.01	0.00	-0.19
Parent College	0.24	0.16	0.12	0.12	0.09	0.05	0.15	0.12	0.18	0.19	0.12	-0.04	0.21

	Black	Hispanic	Asian	Other	Free/Red Lunch	Student Disabil	Current ELL	Former ELL	Parent College
Black	1.00								
Hispanic	-0.27	1.00							
Asian	-0.11	-0.13	1.00						
Other	-0.03	-0.03	-0.01	1.00					
Free/Red Lunch	0.25	0.27	-0.05	0.01	1.00				
Student Disability	0.02	-0.00	-0.05	-0.00	0.07	1.00			
Current ELL	-0.06	0.26	0.06	0.02	0.17	0.03	1.00		
Former ELL	-0.08	0.27	0.04	-0.01	0.13	-0.01	-0.04	1.00	
Parent College	-0.03	-0.26	0.08	-0.01	-0.36	-0.05	-0.11	-0.09	1.00

Regression

As a robustness check, we also used ordinary least squares (OLS) regression to look at the relationship between reported prior computer use and achievement scores. The regression analysis of the aggregated data can be found in [1]. Following is the analysis of responses by task (the 22 separate writing tasks in the assessment).

Table 4.
Regression analysis, by writing task, with controls and interactions, using mean writing scores.

	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6	Task 7	Task 8	Task 9	Task 10
Teacher-reported writing	0.01	-0.03	-0.05	-0.03	0.02	0.00	0.00	0.02	0.08**	-0.03
	(0.03)	(0.06)	(0.06)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.06)
Student-reported writing	0.14***	0.14*	0.12*	0.09***	0.11***	0.12***	0.05*	0.03	0.00	0.20**
	(0.03)	(0.06)	(0.05)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.06)
Female	0.48***	0.72***	0.36***	0.38***	0.43***	0.48***	0.46***	0.41***	0.36***	0.39**
	(0.06)	(0.12)	(0.10)	(0.05)	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	(0.12)
Black	-0.46***	-0.50**	-0.35*	-0.47***	-0.41***	-0.56***	-0.45***	-0.47***	-0.37***	-0.30
	(0.08)	(0.17)	(0.16)	(0.07)	(0.08)	(0.07)	(0.06)	(0.08)	(0.07)	(0.18)
Hispanic	-0.15	0.03	-0.24	-0.13	-0.16*	-0.31***	-0.15*	-0.18*	-0.06	-0.17
	(0.08)	(0.17)	(0.15)	(0.07)	(0.08)	(0.07)	(0.06)	(0.07)	(0.07)	(0.18)
Asian	0.06	0.16	0.43	0.07	0.50***	0.11	0.13	0.26*	0.42***	0.40
	(0.14)	(0.32)	(0.23)	(0.12)	(0.14)	(0.12)	(0.11)	(0.13)	(0.12)	(0.30)
Other	-0.10	-0.48	-0.83	0.14	-0.30	-0.20	0.23	-0.51	-0.35	-0.81
	(0.47)	(1.42)	(0.88)	(0.33)	(0.51)	(0.35)	(0.31)	(0.44)	(0.74)	(1.25)
Free/Red	-0.28***	-0.32*	-0.22	-0.40***	-0.34***	-0.32***	-0.35***	-0.23***	-0.37***	-0.16
Lunch	(0.07)	(0.14)	(0.13)	(0.06)	(0.07)	(0.05)	(0.05)	(0.06)	(0.06)	(0.15)
Parent	0.13*	0.16	0.17	0.21***	0.10	0.22***	0.21***	0.24***	0.18**	0.18
College	(0.06)	(0.13)	(0.12)	(0.06)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.14)
Former ELL	0.01	-0.22	-0.22	0.14	-0.21	-0.19	0.01	-0.04	-0.12	-0.28
	(0.21)	(0.40)	(0.29)	(0.16)	(0.16)	(0.13)	(0.12)	(0.15)	(0.15)	(0.41)
Current ELL	-0.67***	0.14	-0.56*	-0.67***	-0.22	-0.66***	-0.80***	-0.76***	-0.86***	-0.83*
	(0.16)	(0.32)	(0.26)	(0.13)	(0.14)	(0.12)	(0.11)	(0.15)	(0.13)	(0.33)
Student w/	-0.77***	-0.83***	-0.27	-0.93***	-0.95***	-0.94***	-0.84***	-0.76***	-0.61***	0.00
Disability	(0.11)	(0.23)	(0.18)	(0.09)	(0.10)	(0.08)	(0.08)	(0.10)	(0.09)	(0.23)
Teacher/	0.01	-0.07	0.01	0.02	-0.02	-0.01	0.02	-0.01	-0.04	0.00

Female	(0.02)	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)
Teacher/	-0.01	-0.02	-0.08	0.01	0.02	0.00	-0.02	-0.01	-0.04	-0.08
Black	(0.03)	(0.06)	(0.06)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.06)
Teacher/	0.00	-0.02	0.12	0.02	0.09	0.01	0.00	0.06	0.03	0.03
Asian	(0.05)	(0.13)	(0.11)	(0.06)	(0.05)	(0.04)	(0.06)	(0.05)	(0.05)	(0.11)
Teacher/	-0.02	-0.14*	0.04	0.03	0.03	0.01	0.01	-0.05	-0.06	-0.11
Hispanic	(0.03)	(0.07)	(0.07)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.07)
Teacher/	0.00	0.06	0.03	0.03	-0.01	0.00	0.04	0.04	-0.02	-0.03
Free/Red	(0.03)	(0.05)	(0.05)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)
Teacher/ Pt	0.01	0.11*	0.12**	0.01	0.01	0.03	0.00	0.00	-0.01	0.12*
College	(0.03)	(0.05)	(0.05)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.05)
Teacher/	-0.02	0.14	0.15	-0.02	-0.18**	0.01	0.00	-0.05	-0.01	0.43***
C ELL	(0.05)	(0.12)	(0.11)	(0.05)	(0.06)	(0.04)	(0.04)	(0.06)	(0.05)	(0.13)
Teacher/ For	-0.01	0.10	-0.03	-0.24***	-0.02	0.05	-0.02	0.01	0.05	0.18
ELL	(0.09)	(0.17)	(0.11)	(0.06)	(0.05)	(0.06)	(0.04)	(0.04)	(0.05)	(0.16)
Teacher/ St w	-0.04	0.11	-0.19*	0.03	0.05	0.07*	-0.03	0.05	0.07	-0.24*
Dis	(0.04)	(0.08)	(0.08)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.10)
Student/	-0.01	0.02	-0.03	-0.01	0.00	-0.04*	0.00	0.01	0.01	-0.15**
Female	(0.02)	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)
Student/	-0.02	-0.01	0.24***	0.04	-0.08**	-0.02	0.01	0.00	-0.02	0.30***
Black	(0.03)	(0.07)	(0.06)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.07)
Student/	-0.04	-0.04	-0.03	0.01	-0.08	-0.03	0.06	0.01	-0.08	-0.09
Asian	(0.06)	(0.15)	(0.10)	(0.05)	(0.06)	(0.04)	(0.05)	(0.06)	(0.05)	(0.13)
Student/	-0.03	-0.09	-0.05	0.02	-0.02	-0.01	0.04	0.01	0.02	-0.12
Hispanic	(0.03)	(0.07)	(0.06)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.07)
Student/	-0.08**	-0.08	0.02	-0.08***	-0.01	-0.04*	-0.05*	0.01	0.01	-0.05
Free/Red	(0.03)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.06)

Student/ Pt College	-0.04	-0.09	-0.14**	0.01	-0.05*	-0.03	0.02	0.05*	0.06**	-0.12*
	(0.03)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)
Student/ C ELL	0.03	0.38***	-0.13	-0.05	0.34***	-0.03	-0.08*	0.04	-0.02	-0.29**
	(0.06)	(0.09)	(0.10)	(0.05)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)	(0.11)
Student/ For ELL	0.16	0.20	-0.04	-0.08	-0.01	-0.02	-0.08	-0.06	0.00	-0.01
	(0.08)	(0.15)	(0.11)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.14)
Student/ St w Dis	-0.03	-0.19*	0.25***	-0.03	-0.12***	-0.08**	-0.04	-0.09*	-0.08**	0.48***
	(0.03)	(0.07)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.08)
Constant	2.59***	2.62***	2.77***	2.84***	2.77***	2.76***	2.69***	2.54***	2.60***	2.68***
	(0.07)	(0.15)	(0.13)	(0.06)	(0.07)	(0.05)	(0.05)	(0.07)	(0.06)	(0.15)
N	1680	1700	1660	1660	1690	1660	1670	1670	1710	1660
R-sq	0.21	0.07	0.10	0.25	0.28	0.32	0.32	0.21	0.24	0.10

	Task 11	Task 12	Task 13	Task 14	Task 15	Task 16	Task 17	Task 18	Task 19	Task 20	Task 21	Task 22
Teacher-reported writing	0.00	0.00	0.01	0.01	0.03	0.02	0.08**	-0.03	0.02	0.00	-0.01	0.02
	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Student-reported writing	0.12***	0.07**	0.12**	0.10***	0.04	0.08**	-0.02	0.10***	0.08*	0.09**	0.08**	0.07***
	(0.02)	(0.02)	(0.04)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Female	0.46***	0.39***	0.55***	0.44***	0.47***	0.44***	0.40***	0.34***	0.45***	0.48***	0.45***	0.47***
	(0.04)	(0.04)	(0.07)	(0.04)	(0.09)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.04)
Black	-0.48***	-0.44***	-0.51***	-0.49***	-0.44***	-0.51***	-0.44***	-0.50***	-0.51***	-0.51***	-0.47***	-0.39***
	(0.06)	(0.06)	(0.11)	(0.06)	(0.13)	(0.08)	(0.07)	(0.08)	(0.09)	(0.09)	(0.08)	(0.06)
Hispanic	-0.24***	-0.17**	-0.14	-0.27***	-0.08	-0.16*	-0.17*	-0.19*	-0.06	-0.08	-0.15	-0.18**
	(0.06)	(0.06)	(0.11)	(0.06)	(0.12)	(0.08)	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.06)
Asian	-0.02	0.19	-0.06	0.17	0.10	0.16	0.11	0.06	0.14	0.30*	-0.01	-0.04
	(0.10)	(0.10)	(0.18)	(0.11)	(0.23)	(0.13)	(0.12)	(0.15)	(0.15)	(0.14)	(0.14)	(0.10)
Other	0.04	-0.35	0.07	-0.01	-0.40	-0.11	-0.05	0.04	0.17	-0.44	0.20	0.64

	(0.27)	(0.38)	(0.45)	(0.43)	(0.89)	(0.45)	(0.44)	(0.39)	(0.52)	(0.36)	(0.36)	(0.60)
Free/Red	-0.35***	-0.33***	-0.31***	-0.26***	-0.27*	-0.36***	-0.42***	-0.32***	-0.50***	-0.32***	-0.25***	-0.33***
Lunch	(0.05)	(0.05)	(0.09)	(0.05)	(0.11)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.05)
Parent	0.15**	0.19***	0.09	0.24***	0.15	0.19**	0.14*	0.16**	0.17**	0.30***	0.14*	0.17***
College	(0.05)	(0.05)	(0.08)	(0.05)	(0.10)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.05)
Former ELL	-0.23	0.01	-0.20	0.02	-0.18	-0.21	0.03	0.05	-0.30	-0.19	-0.22	-0.01
	(0.12)	(0.11)	(0.24)	(0.11)	(0.28)	(0.17)	(0.14)	(0.16)	(0.15)	(0.17)	(0.16)	(0.12)
Current ELL	-0.90***	-0.70***	-0.90***	-0.64***	0.37	-0.42**	-0.85***	-0.83***	-0.97***	-0.57**	-0.88***	-0.86***
	(0.12)	(0.11)	(0.22)	(0.11)	(0.22)	(0.14)	(0.12)	(0.16)	(0.14)	(0.19)	(0.15)	(0.11)
Student w/	-0.80***	-0.90***	-0.48***	-0.87***	-1.04***	-0.90***	-0.76***	-0.78***	-0.91***	-0.60***	-0.49***	-0.81***
Disability	(0.07)	(0.07)	(0.14)	(0.07)	(0.16)	(0.10)	(0.09)	(0.10)	(0.09)	(0.11)	(0.10)	(0.07)
Teacher/	-0.03	0.02	0.03	-0.03	-0.05	-0.03	-0.03	0.03	-0.04	0.01	0.01	-0.01
Female	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Teacher/	-0.01	0.02	0.01	0.00	-0.01	0.02	-0.04	0.03	0.02	-0.01	-0.04	-0.01
Black	(0.02)	(0.02)	(0.04)	(0.02)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Teacher/	0.03	0.03	0.04	0.04	0.05	0.14**	-0.02	0.05	-0.05	0.01	0.01	0.01
Asian	(0.04)	(0.05)	(0.08)	(0.04)	(0.07)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)	(0.05)
Teacher/	0.01	0.02	-0.01	0.02	-0.07	0.02	0.00	0.03	0.00	-0.02	0.00	-0.02
Hispanic	(0.02)	(0.02)	(0.04)	(0.02)	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
Teacher/	0.05**	-0.03	-0.02	0.00	0.03	-0.02	-0.06*	0.03	0.04	-0.01	0.06*	-0.01
Free/Red	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Teacher/	0.03	0.03	0.02	0.03	0.04	0.00	-0.02	0.02	0.03	0.02	0.03	0.03
Pt College	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)
Teacher/	0.02	-0.01	-0.04	0.01	0.00	-0.16**	-0.06	-0.07	0.00	-0.01	0.02	-0.06
C ELL	(0.04)	(0.04)	(0.08)	(0.04)	(0.08)	(0.05)	(0.04)	(0.06)	(0.06)	(0.07)	(0.06)	(0.04)
Teacher/	-0.05	-0.04	0.10	0.03	-0.01	0.00	-0.01	-0.06	-0.04	0.00	-0.04	0.05
For ELL	(0.04)	(0.04)	(0.11)	(0.05)	(0.11)	(0.07)	(0.04)	(0.05)	(0.06)	(0.08)	(0.06)	(0.06)
Teacher/	-0.02	0.03	0.04	0.01	-0.04	0.05	0.06*	0.03	-0.04	0.08	-0.03	-0.01

St w Dis	(0.03)	(0.03)	(0.05)	(0.02)	(0.06)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)
Student/	-0.01	-0.01	0.01	0.00	0.08*	0.04	0.01	-0.03	0.00	-0.03	0.01	0.01
Female	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Student/	-0.05*	-0.02	-0.04	-0.01	-0.03	-0.06*	-0.02	0.00	-0.04	0.00	-0.01	-0.01
Black	(0.02)	(0.02)	(0.04)	(0.02)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)
Student/	-0.05	0.04	0.06	-0.04	-0.06	-0.08	0.03	0.07	0.00	0.00	0.07	0.05
Asian	(0.04)	(0.04)	(0.08)	(0.04)	(0.11)	(0.06)	(0.05)	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)
Student/	-0.03	-0.03	-0.02	-0.01	0.05	-0.02	0.04	0.01	-0.06	-0.01	0.01	0.03
Hispanic	(0.02)	(0.02)	(0.05)	(0.02)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Student/	-0.07***	0.01	-0.04	-0.07***	0.01	-0.04	0.04	-0.05*	-0.03	0.00	-0.05*	-0.05**
Free/Red	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
Student/ Pt	0.01	0.01	-0.06	-0.02	-0.03	-0.01	0.09***	0.02	0.05	0.00	-0.01	-0.01
College	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)
Student/	-0.09*	-0.01	-0.08	0.00	0.34***	0.38***	-0.09*	-0.06	0.01	0.05	-0.05	-0.10**
C ELL	(0.04)	(0.04)	(0.07)	(0.04)	(0.07)	(0.04)	(0.04)	(0.06)	(0.05)	(0.07)	(0.05)	(0.04)
Student/	0.08	0.03	-0.07	0.03	-0.10	0.06	-0.02	-0.04	0.05	-0.04	0.02	-0.06
For ELL	(0.05)	(0.05)	(0.09)	(0.05)	(0.10)	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)	(0.05)
Student/	0.00	-0.08**	-0.14**	-0.02	-0.07	-0.09*	-0.12***	-0.07*	-0.04	-0.09	-0.07*	-0.04
St w Dis	(0.03)	(0.02)	(0.05)	(0.02)	(0.05)	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)	(0.03)	(0.02)
Constant	2.73***	2.72***	2.77***	2.57***	2.61***	2.69***	2.68***	2.72***	2.78***	2.71***	2.68***	2.60***
	(0.05)	(0.05)	(0.09)	(0.05)	(0.11)	(0.07)	(0.06)	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)
N	1660	1620	1630	1690	1670	1640	1640	1640	1650	1680	1690	1700
R-sq	0.37	0.34	0.13	0.34	0.12	0.30	0.27	0.21	0.29	0.20	0.18	0.32

Note: *N* rounded to the nearest 10. Standard errors in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Factor Analysis

We next used factor analysis to check our latent variable construction. Stata's principal factor analysis was used for our confirmatory analysis to check the latent variables we had used in our SEM model. Following are the results from our unrotated factor analysis. The results of the rotated factor analysis can be found in [1].

Table 5.
Eigenvalues for principal factor analysis (unrotated) of computer use in the NAEP teacher and student surveys.

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	**3.93**	**0.78**	**0.38**	**0.38**
Factor 2	**3.15**	**0.94**	**0.30**	**0.68**
Factor 3	**2.21**	**0.70**	**0.21**	**0.89**
Factor 4	**1.51**	**0.84**	**0.14**	**1.03**
Factor 5	0.67	0.08	0.06	1.10
Factor 6	0.59	0.34	0.06	1.16
Factor 7	0.25	0.14	0.02	1.18
Factor 8	0.11	0.02	0.01	1.19
Factor 9	0.08	0.05	0.01	1.20
Factor 10	0.03	0.03	0.00	1.20
Factor 11	-0.00	0.01	-0.00	1.20
Factor 12	-0.02	0.03	-0.00	1.20
Factor 13	-0.04	0.01	-0.00	1.19
Factor 14	-0.05	0.02	-0.00	1.19
Factor 15	-0.07	0.00	-0.01	1.18
Factor 16	-0.07	0.01	-0.01	1.18
Factor 17	-0.08	0.03	-0.01	1.17
Factor 18	-0.11	0.01	-0.01	1.16
Factor 19	-0.12	0.01	-0.01	1.15
Factor 20	-0.14	0.01	-0.01	1.14
Factor 21	-0.14	0.01	-0.01	1.12
Factor 22	-0.15	0.00	-0.01	1.11
Factor 23	-0.15	0.02	-0.01	1.09
Factor 24	-0.17	0.01	-0.02	1.08
Factor 25	-0.18	0.01	-0.02	1.06
Factor 26	-0.19	0.02	-0.02	1.04
Factor 27	-0.21	0.00	-0.02	1.02
Factor 28	-0.21	.	0.02	1.00

Note: LR test: independent vs. saturated: chi2 (378) = 2.0e+05 Prob > chi2 = 0.0000
Factor analysis/correlation; Number of observations = 22,150; Method: principal factors
Retained factors =10 Rotation: (unrotated) Number of parameters = 235

Table 6.

Factor loadings (pattern matrix) and unique variances for 28 student and teacher survey questions relating to writing with computers.

Variable	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Factor 10	Uniqueness
Student-reported School-related use											
Internet	**0.40**	**0.57**	0.02	0.03	-0.17	0.065	0.01	-0.02	0.03	-0.02	0.47
1st draft	**0.40**	**0.58**	0.02	0.04	-0.19	0.05	0.00	0.01	-0.00	-0.03	0.46
Changes	**0.45**	**0.62**	0.02	-0.01	-0.28	0.06	-0.01	-0.00	0.00	0.2	0.33
Complete	**0.44**	**0.58**	0.01	-0.05	-0.24	0.06	-0.01	0.00	0.00	0.03	0.40
Write	0.39	**0.53**	0.02	0.08	0.11	-0.02	-0.01	0.01	-0.02	-0.02	0.54
Home use											
Write	0.23	**0.42**	0.04	0.21	0.34	-0.06	0.01	-0.01	0.00	-0.01	0.60
Emails	0.26	**0.44**	0.03	0.20	0.38	-0.10	0.01	0.01	-0.01	0.01	0.54
Internet	0.24	**0.41**	0.03	0.19	0.34	-0.08	0.01	-0.02	-0.00	0.02	0.62
Teacher-reported Instructional uses											
Desktop	0.35	-0.23	-0.05	0.08	-0.03	0.03	0.11	-0.16	-0.09	0.05	0.77
Laptop	0.36	-0.22	-0.07	0.22	-0.01	0.03	-0.15	0.18	0.02	-0.03	0.71
Tablet	0.28	-0.23	0.02	0.21	0.03	0.19	0.06	0.04	0.08	0.09	0.77
Projector	**0.40**	-0.31	-0.12	0.36	-0.13	-0.31	-0.08	-0.02	0.07	0.03	0.47
Cd/dvd	**0.43**	-0.34	-0.01	0.29	-0.04	0.09	-0.04	-0.09	-0.06	-0.03	0.60
Digital device	0.38	-0.28	-0.01	0.23	0.02	0.27	0.05	0.02	0.02	0.01	0.64
TV	0.37	-0.28	0.03	0.20	0.06	0.32	0.11	0.02	-0.02	-0.00	0.63
Content	**0.47**	-0.33	-0.07	0.30	-0.03	-0.01	0.03	-0.01	-0.06	-0.07	0.56

Comp available	0.26	-0.11	-0.01	-0.05	-0.02	-0.06	0.02	0.16	-0.15	0.03	0.86
Internet	0.02	-0.02	-0.00	-0.08	0.11	0.27	0.01	0.00	0.13	-0.01	0.89
Student use											
Draft/revise	**0.61**	-0.18	-0.11	**-0.46**	0.06	-0.07	0.00	0.04	-0.04	0.01	0.36
Complete	**0.60**	-0.17	-0.15	**-0.50**	0.08	-0.05	-0.01	-0.01	0.01	0.03	0.33
Word process	**0.56**	-0.17	-0.13	**-0.49**	0.09	-0.05	-0.03	-0.02	0.04	0.00	0.39
Internet	**0.56**	-0.21	-0.10	-0.30	0.09	0.06	0.02	-0.04	0.04	-0.08	0.55
Computer instruct	**0.46**	-0.33	-0.14	0.28	-0.09	-0.28	-0.07	-0.03	0.07	0.01	0.48
Professional Dev											
Basic comp	0.09	-0.09	**0.63**	-0.05	0.05	0.14	-0.21	-0.05	-0.03	0.01	0.51
Software	0.12	-0.09	**0.68**	-0.03	-0.02	-0.05	-0.03	0.02	0.01	-0.00	0.51
Internet	0.11	-0.08	**0.66**	-0.05	0.02	0.06	-0.22	-0.03	-0.01	0.02	0.49
Other tech	0.16	-0.11	**0.62**	-0.02	-0.04	-0.15	0.21	0.02	0.03	-0.02	0.51
Integr tech	0.14	-0.09	**0.65**	-0.03	-0.04	-0.15	0.21	0.04	0.02	-0.01	0.48

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References

[1] Tate, T., Warschauer, M., & Abedi, J. (2016). The Effects of Prior Computer Use on Computer-Based Writing: The 2011 NAEP Writing Assessment, *Computers & Education 101*, 115-131.

[2] National Center for Education Statistics (NCES, 2012). *The Nation's Report Card: Writing 2011*. Washington, D.C.: Institute of Education Sciences, U.S. Department of Education.

[3] National Assessment Governing Board (NAGB, 2010). *Writing Framework for the 2011 National Assessment of Educational Progress*. Washington, D.C.: U.S. Department of Education.

CHAPTER 3

Study 2. Tate, T., & Warschauer, M. Keypresses and mouse clicks: Analysis of the first national computer-based writing assessment.

Abstract

The quality of students' writing skills continues to concern educators. Because writing is essential to success in both college and career, poor writing can have lifelong consequences. Writing is now primarily done digitally, but students receive limited explicit instruction in digital writing. This lack of instruction means that students fail to take advantage of the affordances of digital tools. The writing process is shaped by the tools used, which makes digital writing, to an extent, different from writing with pen and paper. To better understand students' digital writing skills, we take advantage of the information provided by computer-based assessments—keyboard and mouse activity data. We examine the relationship between students' use of the keyboard and mouse during the assessment and students' writing achievement. Our data comes from the first national computer-based writing assessment in the United States, the 2011 National Assessment of Educational Progress (NAEP) assessment. Using data from over 24,100 eighth-grade students, we found that the number of keypresses had a distinct and direct effect on writing achievement scores, controlling for word count. We also identified several different patterns of keyboard and mouse activity on the computer-based NAEP assessment.

Improving student writing skills is an essential task for educators because writing is connected to all academic content areas. Deficiencies in students' writing proficiency are hindering their development of academic English (Zheng & Warschauer, 2015) and subsequent college and career readiness (Graham & Perin, 2007). Secondary school is a critical time to reach students during their mandatory education and ensure that they are equipped with the necessary writing skills to be successful in both college and career. At this developmental stage, students have learned the foundations of oral language, but still need to work on developing the additional structures to accomplish writing across genres as learners engage with increasingly abstract concepts (Bazerman, et al., 2018; Schleppegrell & Christie, 2018). Students have already mastered many of the basic foundational skills such as spelling, punctuation/capitalization, and sentence construction, and they now must progress to refine their thinking skills and develop specialized knowledge across genres (Bazerman, et al., 2018; Schleppegrell & Christie, 2018). The movement to secondary school is the point at which many students begin to fall behind as disciplines become more segregated and specialized, and numerous discourse styles must be negotiated by the students (Schleppegrell & Christie, 2018)

The ability of educators to improve students' writing skills is complicated in this population by the fact that students in middle school are at a heightened risk for declines in both student achievement and motivation (Eccles & Midgley, 1990; Wang & Pomerantz, 2009; Wigfield & Eccles, 2000), at the same time that the requirements for writing proficiency increase dramatically. The challenges faced by struggling adolescent writers are likely exacerbated by the language demands of secondary school; the adoption of the Common Core State Standards (CCSS) places greater emphasis on higher order literacy skills and asks students to demonstrate "increasing sophistication in all aspects of language use, from vocabulary and syntax to the development and organization of ideas" (CCSSI, 2017, p. 56). This includes a greater emphasis on more complex language and text structures (Porter, McMaken, Hwang, & Yang, 2011) and the increasing text complexity trajectory across grades (Fang, Schleppegrell, & Cox, 2006; Williamson, Fitzgerald, & Stenner, 2013). Nonetheless, even in English Language Arts classes students do very little writing (Murphy & Smith, 2018), with the typical student expected to produce approximately 1.6 pages a week (Applebee & Langer, 2011). Even less extended writing is done in other areas of the curriculum (Wilcox & Jeffery, 2014). In addition, not all kinds of writing are the same, and students must learn to navigate multiple academic writing genres, writing for various purposes and audience, and writing in multiple modalities (Graham, 2018; *cf*., Leu, D. J., Kiili, C., & Forzani, E., 2016). Now that writing is a predominant form of labor (Bazerman, et al., 2018) and most serious writing after high school is done digitally, students' writing skills need to include digital writing competency (DeVoss, Eidman-Ardahl, & Hicks, 2010).

Student (and teacher) familiarity with, and acceptance of, digital writing varies widely (Graham, 2018). In many instances students receive inadequate explicit instruction in writing on computers (Applebee & Langer, 2011). The quality of technology use is also inconsistent, for example 76% of secondary school English teachers reported that students typically used word processing for final versions, while only 42% reported using the computer for first drafts and 49% for editing and revising (Applebee & Langer, 2011, noting that even these estimates appeared to be overstated compared to observational data). A 2013 survey of Advanced Placement and National Writing Project teachers showed that even for this sophisticated group of teachers only 47% of English language arts teachers have had their students ever edit or revise their work using a collaborative web-based tools such as GoogleDocs and teachers noted that students bring widely varying technology skills into the classroom (Purcell, Buchanan, & Friedrich, 2013). Digital writing opportunities are stratified by socioeconomic status: More than half of the teachers of upper income students (56%), compared to 37% of teachers of the lowest income students reported that students used tablet computers as part of the learning process in any manner (primarily for research purposes, not writing), and only 54% of these teachers said all or almost all of their students have sufficient access to digital tools while in school (Purcell, Heaps, Buchanan, & Friedrich, 2013). Home resources to complete digital writing assignments remain problematic as well (KewalRamani, et al., 2018), with teachers needing to consider access and alternatives.

Believing that important digital writing skills are best measured through computer-based assessments that reflect the way people write today (NAGB, 2010), the National Assessment of Educational Progress instituted the first nationwide computer-based writing assessment in 2011. The digital nature of the assessment creates an opportunity to analyze student writing in ways not previously explored at scale. We examined eighth grade students' keyboard and mouse activity during the assessment, focusing on word count (a traditional metric in writing research, see Morphy & Graham, 2012); the number of total keypresses (a metric available in this new, digital modality, see Almond, et al., 2012); and the frequency of specific physical events—the pressing of a keyboard function (delete, backspace) and or the clicking of a mouse to access digital affordances via icon or dropdown menu (cut, italics, etc.). We look at the relationship between these measures and writing achievement. In addition, we use datamining techniques to explore whether there are discrete patterns of keyboard and mouse activity during the assessment and how the patterns relate to writing achievement. For each of these questions, we also examine heterogeneous effects across demographic groups.

The cognitive processes behind writing have been a fundamental part of research on writing since the 1970's (Nystrand, Green, & Wiemelt, 1993; Sperling & Freedman, 2001). In particular, Flower and Hayes (1981) delineated a model of writing that includes planning *(*rarely done by elementary or secondary students; McCutchen, 1995; DeLaPaz & Graham, 2002), translating plans into written text/text generation, which includes syntactic and lexical skills as well as motor skills and working memory, and reviewing and revising to improve existing text. Composing is a recursive process (McCutchen, 1996; Deane et al., 2008): writers cycle through the planning, translating, and reviewing multiple times, and these stages all interact with one another throughout the process (Flower & Hayes, 1981). Graham notes that "[w]riting is challenging because it is a very complex skill involving the execution and coordination of attention; motor, visual, and executive functioning; memory; and language skills" (2018, p. 286)

Not only is writing difficult, but differences in modality matter and the process of writing is shaped in part by the available tools (Wertsch, 1991; Graham, 2018; Bazerman, et al., 2018). For example, students write more and write better on computers than by hand (see discussion in Graham & Perin, 2007; Sandene, et al., 2005; Russell & Haney, 1997; Russell & Plati, 2002; Applebee, 2007).

Transcription is particularly tool-specific and varies widely ((Almond, Deane, Quinlan, Wagner, & Sydorenko, 2012; MacArthur, 2009; see Horkay et al., 2006). Depending on the capabilities and processes of the individual student, the benefits and burdens of different tools may differ. The resource-intensive processing required for transcription can affect storage capacity and some information is lost from working memory as students transcribe their sentences (McCutchen, 1996; Graham, 2018). When a writer masters the tool, such as keyboarding, the automaticity gained means transcription extracts less cognitive load, freeing up resources for ideation, reviewing, and improving writing (Graham, 2018).

Digital text production has several benefits, including the speed of text production compared to handwritten text. Word processing also promotes the creation of neat, legible, printed work (MacArthur, 1999). Our own observations of student writers suggest that digital devices may allow for less fatigue than handwriting for some students, may allow for easier movement of passages and editing, and may allow students to put down their thoughts quickly before their ephemeral ideas are lost in transcription (Warschauer, 2006; cf., MacArthur, 1999). Despite concerns over the ability of younger students to manipulate keyboards, no serious difficulties in doing so have been reported even in an early review of the research by Cochran-Smith (1991). The lack of keyboarding difficulty was recently confirmed in the fourth grade NAEP pilot study (White, Kim, Chen, & Liu, 2015): Students reported only minor keyboarding difficulties and were unintimidated by keyboards.

Where digital devices are new and students are not yet familiar with them, students may regress in revision skills as they deal with learning the new physical processes of keyboarding and word processing (Greenleaf, 1994). In addition, some researchers have raised concerns about the negative affordances of digital technology for revision, particularly with respect to detecting errors and developing spelling and vocabulary skills (Goldfine, 2001). Spelling and grammar correction tools trigger educator concerns that students will no longer actively engage in the process of these corrections and will not internalize the skills needed to do them on their own, but such concerns have not been tested by researchers. Overall, using word processing has been found to increase both the quality of writing and the number of revisions made by writers from middle school to adulthood (Daiute, 1986; Cochran-Smith, 1991).

Modality also shapes the research of writing: For decades, research on handwritten writing generally required laborious transcription prior to analysis, thus limiting the number of participants in any given study. Digital writing opens up the availability of automated analytic tools that capture information in a nonintrusive way (Almond, et al., 2012). For example, where traditional studies might look at the number of words in a text since word count has been found to be predictive of writing quality (Morphy & Graham, 2012; Crossley, Weston, McLain, Sullivan, &

McNamara, 2011; McNamara, et al., 2013), digital writing can access the number of keypresses used to create the text (Almond, et al., 2012). As Almond, et al. note, this data "could potentially reveal information about the student's writing process that is not readily apparent in the final essay" (Almond, et al., 2012, p. 2). Digital writing also allows us to consider the frequency of specific physical acts—the pressing of specific keys or the click of a mouse—to access functions while writing. Fine-grained analyses of K-12 digital writing have been limited to date, though promising research on the understanding of pauses and near and far edits (whether the writer is editing immediately preceding or following text—near--or going to passages several paragraphs distant from the point of last input--far) as evidence of the revision process, and automated linguistic and syntactic measures of writing, are ongoing (Almond, et al., 2012; Deane, 2011).

With a general sociocultural perspective that human activity is mediated by available tools (Vygotsky, 1981; Wertsch, 1991) and the more specific prior research on digital writing in mind, our analysis looks at the relationship between frequency and patterns of keyboard and mouse activity and writing achievement. We examine (1) the relationship between writing achievement and (a) word count and (b) keypresses, and (2) the patterns of keyboard and mouse activity.

1. Method

1.1. Data Source

NAEP assessments are known for their robust construct validity (see, e.g., Applebee, 2007; Wenglinsky, 2005), and the NAEP writing test is based on a framework developed by leading educators and experts in the field of assessment over 18 months, with participation by over 500 individuals (Applebee, 2007; NAGB, 2010). The NAEP writing framework was designed to reflect the way students write today, using word-processing software and commonly available tools (NAGB, 2010; see also Way, Davis, & Strain-Seymour, 2008). As a result, the assessment allowed students to use common functions for editing (e.g., cut, copy, paste); formatting (e.g., indenting, bold); spelling, grammar, and reference (e.g., spell check, thesaurus, dictionary); and viewing and reviewing during the assessment (NAGB, 2010).

NAEP assessments maintain strong measurement validity as well (see, e.g., Wenglinsky, 2005; Mo & Troia, 2017). The weighted national school participation rates for the NAEP 2011 writing assessment were 97% (100% for public schools; NCES, 2012). To the extent certain subgroups fell below 70%, NCES conducted an analysis of potential bias. Compared with the distribution of all eligible students, the distribution of the weighted sample did not differ with respect to any of the variables utilized in this analysis (Rogers, Stoeckel, & Sikali, 2013). This analysis utilizes the restricted data set for this assessment, which includes scaled and raw scores, detailed survey data, and individual keyboard and mouse activity data. As suggested by NCES, multiple responses, responses not reached or administered, omitted responses, non-ratable responses, illegible responses, and off task responses were each treated as missing.

While traditional analysis procedures assume that observed data from different individuals are independent of each other and randomly distributed, NAEP results are stratified and clustered (Johnson, 1992; Zwick, 1987). Through clustering, weighting, and marginal estimation procedures, NAEP allows for population and group estimates (Beaton & Zwick, 1992). Ignoring these effects leads to biased estimates of variance and generally to underestimating the biases (Johnson, 1992). In addition, the deeply stratified cluster samples influence the likelihood ratio and inflate the differences in the chi-squares, and the design effect for item *p* values is estimated to be roughly 2 (an estimate of percent of examinees with a given response pattern should be equivalent in precision to a simple random sample approximately half as large; Haertel, 1984). Where our current analysis is exploratory, as in the clustering, weighting was not applied (Allen & Donoghue, 1996). Where indicated, we used a replication method (jackknife weighting) to estimate the variance of statistics derived from the full sample. The method involves repeatedly selecting portions of the sample and calculating the desired statistic, using the variability among the calculated replicate estimates to obtain the variance of the full sample (NCES, *n.d.*).

1.2. Population

This research analyzed the data from over 24,100 eighth-grade students. We focus on eighth-grade students, as prior research suggests that the middle school years are critical for the development of academic writing (De La Paz & Graham, 2002; Zheng & Warschauer, 2015). The eighth-grade sample also served as the basis of our earlier analyses of prior technology exposure and its effect on writing achievement (Tate, Warschauer, & Abedi, 2016).

1.3. Variables

Using the prior research on digital writing discussed above to guide our selection, we chose a total of 16 variables for our initial analysis. These variables ranged from word count (Crossley, Weston, McLain, Sullivan, & McNamara, 2011; McNamara, et al., 2013) to frequency counts of specific keyboard and mouse activity. Keyboard functions included keypresses, delete, and backspace. Sidebar icons required mouse clicks to activate the highlight or text-to-speech function. Drop down menus and/or icons were available to access cut, copy, past, indent, outdent, underline, bold, italicize, spellcheck, grammar check, and thesaurus functions. For example, the “cut” variable reflects the frequency of a student clicking the mouse on the icon with the scissors or clicking on “cut” from the drop down menu on the tool bar. The teacher-reported and student-reported prior technology exposure variables were created using the weighting found in our prior work (Tate, Warschauer, & Abedi, 2016). Our achievement measure was the NAEP scaled writing score. The scaled writing achievement score had a mean of -0.04 and a standard deviation of 0.96. Scaled scores were quite close to a standard curve, with a slight skew to the right.[1] Thus, our use of linear regression is supported by these descriptive statistics.

We looked at differences in various demographic groups, including gender, national school lunch eligibility and parental education (as proxies to indicate socioeconomic status), English language learner status (prior, current, or not applicable), students with individualized education plans (IEPs) or 504 plans under the American with Disabilities Act, and race/ethnicity.

1.4. Analytic Methods

We used Stata Version 14.0 SE statistical software to analyze the results of the 2011 NAEP writing assessment.

1.4.1. Effect of keyboard and mouse activity on writing achievement: Regression. We used ordinary least squares (OLS) regression to look at the relationship between keyboard and mouse activity during the assessment and achievement scores. We began by looking at the relationship of writing achievement, controls, and word count, then looked at keypresses, and then finally considered specific keyboard and mouse functions. Jackknife weighting was used (sampling units, PSUID; Strata, REPGRP1; Sample weight, ORIGWT; Student Replicate Weights, SRWT01-62; see Beaton et al., 2011).

[1] We note that NAEP reports plausible values to improve the ability to draw inferences about a population's true proficiency level (Rogers, Stoeckel, & Sikali, 2013). Our analysis is not intended to be representative of the population's proficiency level, but instead to understand the relationship of this micro-level keyboard and mouse activity on an individual, human-scored writing test. We acknowledge that the writing tasks were varied across the sample.

The false discovery rate (FDR) procedure (Benjamini & Hochberg, 1995) was used to control the certainty level of our analyses. Unlike the other multiple comparison procedures (e.g., the Bonferroni procedure) that control the familywise error rate (i.e., the probability of making even one false rejection in the set of comparisons), the FDR procedure controls the expected proportion of falsely rejected hypotheses. Furthermore,
familywise procedures are considered conservative for large families of comparisons (Williams, Jones, & Tukey, 1999). Therefore, the FDR procedure is more suitable for multiple comparisons in NAEP than other procedures (Allen, Donoghue, & Schoeps, 2001).

1.4.2. Patterns of writing on computers: Cluster analysis. We applied k-means cluster analysis to understand patterns in students' keyboard and mouse activity during the assessment. We compared the factor cluster models for clusters ranging in size from 3-11 and looked at the profiles for each of these models (Bergman, Magnusson, & El-Khouri, 2002; Vargha, Torma, & Bergman, 2015). The k-means technique improves a cluster solution by relocating cases after an initial classification and moves cases from one cluster to another if this leads to a reduction in the total error sum of squares (ESS) of the cluster solution. We performed a reliability check of 5 independent repetitions. We ran descriptive statistics on the variables in each of these clusters to examine the achievement levels and demographics of the students in each cluster. For robustness, we performed some additional analyses using both Stata and RopStat (Vargha, Torma, & Bergman, 2015) on a random sample of our data, including a hierarchical cluster analysis (Bergman, Magnusson, & El-Khouri, 2002; Vargha, Torma, & Bergman, 2015) using average squared Euclidean distance and Wards method, with clusters ranging in size from 1-20. Figure 1 shows the ESS Plus and EESS% of cluster solutions ranging from 2 clusters to 20 clusters (the horizontal). Graphing the solutions allows us to look for large changes in the reduction of distances between cases in the various cluster models. While no particular number is indicative of the appropriate number of clusters, large changes in the distances between cases suggests a reasonable break point in the data, which is then considered in light of theory for the relevant explanatory power of the solution.

2. Results

2.1. Effect of keyboard and mouse activity on writing achievement.

2.1.1. Descriptive statistics and correlations. Descriptive data of keyboard and mouse activity (Table 1) showed that functions other than backspace were not used at all by a large population of students. Most students did not use the digital platform's features—speech-to-text, thesaurus, spellcheck—or even cut and paste. Only 5 percent of students used the spellcheck 4 or more times and thesaurus 2 or more times. Further research is needed to understand whether the lack of usage is due to students' lack of digital or keyboarding sophistication or the nature of the assessment (a 30-minute quick write with little time for revision).

We also considered the amount of keyboard and mouse activity by writing achievement level to see if there were patterns depending on the writing skill of the student (Table 2). We found that while number of keypresses and the use of the backspace key rose along with writing achievement, the story was less clear with respect to other digital functions (Figure 2). Our cluster analysis provides some information about use patterns and demographics of students who did use these features more extensively.

Looking at correlations among our variables (Table 3), as we would expect from prior research we found that the scaled writing score was highly correlated with average word count (0.77), as was the number of keypresses (0.71), both of which were highly correlated themselves

(0.87). Certain of the keyboard and mouse activity functions were also highly correlated, e.g., copy and paste; bold, italic, and underline.

2.1.2. Regression. Four regression models were used to analyze the relationships between students' keyboard and mouse activity during the assessment and their scaled writing score (Table 4). Model 1 looked at the relationship of writing achievement to average word count and keypresses. Model 2 added the demographic controls to this analysis. Model 3 added an interaction between word count and keypresses, because words require keypresses to instantiate them, and then Model 4 added in interactions with the control variables as well. All models were done using jackknife weighting. Once the controls were added, the models had an R^2 of 0.67 (Model 2) and 0.68 (Models 3 and 4).

In Model 4, average word count and keypresses accounted for 0.59 and 0.31 of a standard deviation of writing achievement (both significant at $p < 0.001$). While the strong role that word count plays in writing scores was consistent with prior research, the fact that additional keypresses continued to play a sizeable role in writing achievement after controlling for word count was new information gleaned from the data. Demographic controls showed expected increases for females (0.10), and for students with at least one parent with a college education (0.11); and showed decreases for Black students (-0.15), Hispanic students (-0.07), free/reduced lunch eligible students (-0.18), former ELL students (-0.06), current ELL students (-0.47), and students with disabilities (-0.41; all significant at $p < 0.001$).

Significant interactions with *keypresses* were found for the following categories of students: female (0.04, $p < 0.05$), current ELL (-0.11, $p < 0.05$), and students with disability (-0.05, $p < 0.05$). Thus, while more typing predicted higher writing achievement scores for females and higher SES students, students with significant language barriers found more typing to be counterproductive. Interactions with average *word count* were only significant free/reduced lunch eligible students (-0.05, $p < 0.05$).

Looking at mean keyboard and mouse activity during the assessment by percentiles of writing scores, we found some additional interesting relationships (Table 2). As expected, higher performing writers show an increased number of keypresses than lower performing students; they even showed more use of backspace, which presumably reduces word count (which is itself highly predictive of achievement score) to some extent. The keyboard/mouse-level data from the NAEP assessment suggests that the backspace function may play a role in higher quality writing. The use of the backspace key for these high-performing writers may indicate that they had time to make some revisions to the text or had the cognitive bandwidth to monitor their writing as they went along and correct or change it. Higher scoring writers showed slightly less use of spell check, highlight, copy, and bold than the lower scoring writers. The use of the thesaurus and italics increased slightly for better writers, indicating potentially helpful strategies or simply cognitive bandwidth to use these tools. The patterns for text-to-speech usage are more complex, with use decreasing as writers improve, but we found a particularly sharp drop off occurring between the 75th and 90th percentiles of performance. Indent usage also had an odd pattern, with a slight increase, then decrease as writers' skill increases. These results suggest that linear regression may not illustrate the full story of what goes on when different types of students use these digital writing functions. Our cluster analysis explores the varying usage patterns for these functions and their relationship to writing achievement. The use of cut, paste, underscore, outdent, and delete is fairly low and stable across writing skill at this grade level and for this task. In general, we found that, for writers performing below the 50th percentile, there was little variability in the keyboard and mouse activity. Only at the higher levels of performance were meaningful differences in usage seen.

2.2. Patterns of writing on computers: Cluster analysis.

The interactions found in our regression analysis suggested that several different writing patterns existed, with different kinds of writers benefiting from different keyboard and mouse usage during the assessment. In order to more clearly understand these patterns, we conducted a cluster analysis. Clusters of varying sizes were considered to determine which were consistent with prior research and offered useful explanations for student writing patterns. We chose to focus on the 5-variable cluster (Figure 3 and Table 5) for reasons explained below.

Not surprisingly, the five clusters of keyboard and mouse activity were differentially associated with writing proficiency. Two of the patterns we saw were particularly effective (or used by effective writers)—the Productive Activity and the High Delete use. The Productive Activity group (7%) consisted of students with higher scores for most of the variables, particularly keypresses, and a correspondingly high scaled writing score (0.33) and prior technology exposure (0.31). Demographically, this group had a particularly high concentration of female students and somewhat higher socioeconomic status than average. These students may have been comfortable with the computer interface and able to benefit from the affordances of the mode. Alternatively, they may be more fluent writers who were able to access sufficient cognitive bandwidth to utilize some of the platform's digital affordances.

A similar-sized group of students (8%) used the delete function 2.96 standard deviations above the average ("High Delete"). The High Delete group also had higher than average keypresses (though much lower than the Productive Activity group) and higher than average use of backspace, thesaurus, and text-to-speech, but lower use of most of the other functions. This group had the highest socioeconomic status of all the clusters, with significantly lower numbers of students qualified for free/reduced lunch and higher numbers of students with parents who graduated college. Their unusual use of the delete key may represent the highest level of familiarity with keyboarding and writing on computers, which is consistent with their report of high prior technology exposure (0.49). Different from the backspace key, the delete key on these devices was a separate function above the backspace key (see Figure 4 to see the digital user interface and keyboard) and its use may be indicative of a higher level of editing, although without access to the written texts this is simply a hypothesis. The mean scaled writing score for this group was 0.17.

Two clusters were associated with typical writing proficiency. A large proportion of students (67%) fell in what we called the “Typing Only” group. These students showed roughly average use of backspace and number of keypresses, with low use of the other functions. Their scaled scores and demographics reflected the averages, with a mean scaled writing score of -0.19 and a slightly lower prior technology exposure of -0.17. Another group of average performers were the “High Indent” users. This small group of students (8%) used the indent and outdent features 1.75 and 1.5 standard deviations, respectively, above average. Otherwise, these students were only slightly different than those Typing Only group, using the other keyboard and mouse functions a bit more and having roughly the same demographics. High Indent users had an average writing score of -0.16 and low prior technology exposure of -0.33.

The least effective writing was seen in the final group (“Unproductive Activity,” 10%), which had a lower than average number of keypresses and lower use of backspace, but quite higher than average use of the other keyboard and mouse functions. These students had an average scaled score of -0.73 and lower prior technology exposure (-0.50). One hypothesis is that these students may have been distracted by the new computer interface and additional digital functions available while writing. On the other hand, they may simply be less fluent or less productive writers in general, who then resorted to experimenting with the other digital functions to keep up the appearance of productivity or to make their written text more attractive. They may also have had less background knowledge with respect to the prompt. Finally, they may have simply reached the limit of their cognitive resources and moved from text production to formatting.

Our choice of the five cluster model was initially based on the explanatory value provided by this model over lesser numbers of clusters and the reduction in useful information provided by models with additional clusters. We decided that the High Delete and High Indent groups provided interesting characteristics that were left out of the 3-variable cluster (Typing Only, Unproductive Activity, and Productive Activity groups). The 7-cluster model provided less useful additional information, suggesting that the High Indent use comes in three types that varied by total number of keypresses and backspace use. As noted by the ovals in Figure 1, significant reductions in distance between cases occur at the 3 and 7 cluster solutions which provided additional, quantitative evidence that we were looking at the relevant range of clusters.

3. Discussion

Our research question examined the effect of eighth grade students' keyboard and mouse activity during the NAEP writing assessment on writing achievement scores, focusing on:

1. The relationship between keyboard and mouse activity during the assessment and NAEP writing achievement, including
    i. The relationship between word count and NAEP writing achievement.
    ii. The relationship between the number of keypresses and NAEP writing

achievement.

2. Patterns of keyboard and mouse activity during the assessment.

3.1. The relationship between keyboard and mouse activity during the assessment and writing scores.

As expected based on prior research (Morphy & Graham, 2012), the most significant predictor of high writing scores was the number of words written. The more students were able to write during the 30-minute assessment, the higher their achievement score was. While prior data generally was restricted to word, the NAEP data also contains the number of keypresses performed by the student writers, which allowed us to parse out any differential effects. We found that over and above the effect of additional words, increased keypresses also predicted higher writing scores. This suggests that keypresses do not simply represent additional words. Additional keypresses might suggest the use of longer, more sophisticated words or that a student is editing his or her work through the use of backspace keys or changes to the written text. Without the actual text to analyze, we can only hypothesize the meaning of the keypresses and suggest that further work be done to understand this phenomena. The value of additional words and keypresses was not the same for every student, however. For example, more *keypresses* were especially valuable for females and students with college-educated parents and less productive for students who were English learners or in special education.

Finally, the data showed that middle school students do not use many of the affordances of digital tools when writing a 30-minute assessment. Perhaps in a longer duration, process writing context we would have seen more exploration and use of the keyboard and mouse functions beyond backspace. In addition, the assessment was given in 2011, when very few middle schools had significant penetration of digital devices. If students had computers, they generally used them in a computer lab and were unlikely to prepare initial drafts on digital devices. Students in 2017 have more frequent one-device per student access in English Language Arts classes, although access is far from uniform and students still have very little practice composing digitally. Nonetheless, we would expect to see that in future years as the students' digital exposure evolves, their use of digital tools will evolve as well.

3.2. Patterns of keyboard and mouse activity.

This analysis allowed us to see that even eighth-grade students have distinct patterns of writing on a timed digital writing assessment, some of which appeared to be more correlated with good writing than others. These patterns may have resulted from their writing fluency level, with more skilled writers accessing more digital functions and more average students exhibiting the Typing Only mode. We also saw that students with more prior technology exposure tended to be in the Productive Activity or High Delete groups and wrote successfully. Students without as much practice with digital tools should be discouraged from Unproductive Activity and focus on simply getting words down, but may be exhibiting high use of the digital functions simply because they have reached the end of their writing resources. Signs of Unproductive Activity could serve as a signal to teachers that students are having production issues or require additional support or background knowledge to successfully navigate the writing prompt. We also see that the somewhat controversial functions, spellcheck and thesaurus, were not widely used by students and were even less used by English learners than native speakers. They were instead disproportionately used by students with college-educated parents.

3.3. Limitations

As noted in our earlier work (Tate, Warschauer, & Abedi, 2016), the nature of the NAEP assessment inherently limits the usefulness of this data for our understanding of the writing process. The assessment is a 30-minute on demand writing task in an artificial setting with no clear relevance to the student's school work. By design, the assessment does not capture the recursive process of writing over time. In addition, the assessment only captures two writing samples on a single day (see Chen, Niemi, Wang, Wang, & Mirocha, 2007, finding that 3-5 writing tasks are required for a reliable judgment of writing ability; *cf.* Kim, Schatschneider, Wanzek, Gatlin, & Al Otaiba, 2017). In addition, as noted by Olinghouse, Santangelo, and Wilson (2012), only limited information about students' writing abilities across a range of skills can be generated from a single occasion, single (or in this case 2 writing texts) genre, holistically-scored writing assessment. In addition, the functionality of the NAEP interface used in the 2011 test could be improved, as seen during the usability studies conducted in 2012 (NCES, 2014a, 2014b) that led to simplified instructions and the addition of more icons on the toolbar, enlargement of text and icons, and rollover labels on the icons to increase the accessibility of the word processing tools. As these functionality improvements are made in future years, we might find that the interface is simpler and easier to use for students with less prior exposure to computers, which could, in turn, reduce the correlation of prior technology exposure with writing achievement. Finally, because of the NAEP sampling design and booklet sampling, these results may not be representative at a population level.

4. Conclusion

Ultimately, this article describes the digital writing done by eighth grade students on the NAEP assessment at the small grain of keyboard and mouse activity. This unprecedented access to a national digital writing sample begins to illuminate how the digital footprints students leave behind may eventually help us to better understand their writing process, in turn informing future research and, eventually, writing instruction. The data shows that students who write more and those who show higher levels of keypresses on the assessment receive higher scores. We also find that, at least through eighth-grade, few students utilize the varied affordances of digital writing tools during a 30-minute, on-demand writing task. Finally, we illustrate through the use of cluster analysis that adolescents' writing practices are not a singular construct. Rather there are at least 5 types of writers who share similar writing practices, with these practices associated to higher and lesser degrees with effective writing: *Productive Activity, High Delete, Typing Only, High Indent, and Unproductive Activity.* The practices are more (*Productive Activity* and *High Delete*) or less (*Unproductive Activity*) effective at supporting high quality writing.

To better understand these patterns further, access to the texts as written, analysis of longer, untimed process writing, and qualitative observations of students' writing in classrooms would allow researchers to see if the patterns outlined in the cluster analysis are evident in practice, across different contexts, and with particular types of students. We could then build into middle school writing curriculum specific, targeted efforts to teach the most effective patterns to the appropriate students and enhance their ability to communicate through computer-based writing. We could also build automated scaffolding into our digital devices that alerts the student and teacher when the student falls into less successful patterns.

References

Acock, A. C. (2012). *A gentle introduction to Stata* (5^{th} Edition). College Station, TX: Stata press.

Allen, N. L., & Donoghue, J. R. (1996). Applying the Mantel-Haenszel Procedure to Complex Samples of Items. *Journal of Educational Measurement*, *33*(2), 231-251.

Allen, N.L., Donoghue, J.R., & Schoeps, T.L. (2001). *The NAEP 1998 Technical Report*. NCES 2001-509. Washington, DC: National Center for Education Statistics.

Applebee, A.N. (2007). Issues in large-scale writing assessment perspectives from the National Assessment of Educational Progress. *Journal of Writing Assessment, 3*(2), 81-98. Retrieved from http://www.journalofwriting assessment.org/archives/3-2.2pdf.

Applebee, A.N., & Langer, J.A. (2011). A snapshot of writing instruction in middle schools and high schools. *English Journal 100*(6), 14-27.

Bazerman, C., Applebee, A., Berninger, V., Brandt, D., Graham, S., Jeffery, J., Matsuda, P., Murphy, S., Rowe, D., Schleppegrell, M., & Wilcox, C. (Eds.), *The lifespan development of writing*. Urbana, IL: National Council of English.

Beaton, A., Rogers, A., Gonzalez, E., Hanly, M., Kolstad, A., Rust, K., Sikali, E., Stokes, L., & Jia, Y. (2011). *The NAEP Primer.* Washington, DC: National Center for Educational Statistics.

Beaton, A. E., & Zwick, R. (1992). Chapter 1: Overview of the National Assessment of Educational Progress. *Journal of Educational Statistics*, *17*(2), 95-109.

Bergman, L. R., & Magnusson, D. (1991). Stability and change patterns in extrinsic adjustment problems. In D. Magnusson, L.R. Bergman, G. Rudinger, B. Torestad (Eds.), *Problems and methods in longitudinal research: Stability and change* (pp. 323-346). New York, NY: Cambridge University Press.

Bergman, L. R., Magnusson, D., & El-Khouri, B. M. (2002). *Studying individual development in an interindividual context. A Person-oriented approach.* Mahwah. New Jersey, London: Lawrence-Erlbaum Associates.

Chen, E., Niemi, D., Wang, J., Wang, H., & Mirocha, J. (2007). Examining the generalizability of direct writing assessment tasks. CSE technical report 718. Los Angeles, CA: National Center for Research on Evaluation, Standards, and Student Testing (CRESST).

Cochran-Smith, M. (1991). Word processing and writing in elementary classrooms: A critical review of related literature. *Review of Educational Research, 61*(1), 107-155.

Collier, R. M. (1983). The word processor and revision strategies. *College Composition and Communication*, *34*(2), 149-155.

Common Core State Standards Initiative ("CCSSI," 2017). Language Progressive Skills. Retrieved June 07, 2017, from http://www.corestandards.org/ELA-Literacy/L/language-progressive-skills/

Crossley, S. A., Weston, J., McLain Sullivan, S. T., & McNamara, D. S. (2011). The development of writing proficiency as a function of grade level: A linguistic analysis. *Written Communication, 28* (3), 282-311.

Daiute, C. (1986). Physical and cognitive factors in revising: Insights from studies with computers. *Research in the Teaching of English*, *20*(2), 141-159.

De La Paz, S., & Graham, S. (2002). Explicitly teaching strategies, skills, and knowledge: Writing instruction in middle school classrooms. *Journal of Educational Psychology*, *94*(4), 687.

DeVoss, D.N., Eidman-Aadahl, E., & Hicks, T. (2010). *Because digital writing matters: Improving student writing in online and multimedia environments*. John Wiley & Sons.

Deane, P. (2011). Writing assessment and cognition. *ETS Research Report Series*, 1, i-60.

Deane, P., Odendahl, N., Quinlan, T., Fowles, M., Welsh, C., & Bivens-Tatum, J. (2008). *Cognitive models of writing: Writing proficiency as a complex integrated skill.* Princeton, NJ: Educational Testing Service.

Eccles, J., Midgley, C. (1990). Changes in academic motivation and self-perception during early adolescence. In R. Montemayor (Ed.), *Early adolescence as a time of transition*, (pp. 1-29). Beverly Hills, CA: Sage Publishing

Fang, Z., Schleppegrell, M. J., & Cox, B. E. (2006). Understanding the language demands of schooling: Nouns in academic registers. *Journal of Literacy Research*, *38*(3), 247-273.

Flower, L., & Hayes, J. R. (1981). A cognitive process theory of writing. *College Composition and Communication*, *32*(4), 365-387.

Flower, L., & Hayes, J. R. (1980). The cognition of discovery: Defining a rhetorical problem. *College Composition and Communication*, *31*(1), 21-32.

Goldfine, R. (2001). Making word processing more effective in the composition classroom. *Teaching English in the Two-Year College, 28*(3), 307-315.

Graham, S. (2018). A writer(s) within community model of writing. In C. Bazerman, A. Applebee, V. Berninger, D. Brandt, S. Graham, J. Jeffery, P. Matsuda, S. Murphy, D. Rowe, M. Schleppegrell, & K. Wilcox (Eds.), *The lifespan development of writing* (pp. 271-325). Urbana, IL: National Council of English.

Graham, S., & Perin, D. (2007). A meta-analysis of writing instruction for adolescent students. *Journal of Educational Psychology, 99*(3), 445-476.

Greenleaf, C. (1994). Technological indeterminacy: The role of classroom writing practices and pedagogy in shaping student use of the computer. *Written Communication, 11*(1), 85-130.

Horkay, N., Bennett, R. E., Allen, N., Kaplan, B., & Yan, F. (2006). Does it matter if I take my writing test on computer? An empirical study of mode effects in NAEP. *Journal of Technology, Learning, and Assessment, 5*(2).

Johnson, E. G. (1992). The design of the National Assessment of Educational Progress. *Journal of Educational Measurement, 29*(2), 95-110.

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement, 20*, 141-151.

KewalRamani, A., Zhang, J., Wang, X., Rathbun, A., Corcoran, L., Diliberti, M., and Zhang, J. (2018). *Student Access to Digital Learning Resources Outside of the Classroom* (NCES 2017-098). U.S. Department of Education. Washington, DC: National Center for Education Statistics. Retrieved April 6, 2018 from https://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2017098.

Kim, Y. S. G., Schatschneider, C., Wanzek, J., Gatlin, B., & Al Otaiba, S. (2017). Writing evaluation: rater and task effects on the reliability of writing scores for children in Grades 3 and 4. *Reading and Writing*, *30*(6), 1287-1310.

Leu, D. J., Kiili, C., & Forzani, E. (2016). Individual differences in the new literacies of online research and comprehension. In P. Afflerbach (Ed*.), Handbook of Individual Differences in Reading: Reader, Text, and Context* (pp. 259-272). New York: Routledge.

Macarthur, C. A. (1999). Overcoming barriers to writing: Computer support for basic writing skills. *Reading & Writing Quarterly*, *15*(2), 169-192.

MacArthur, C. A. (1988). The impact of computers on the writing process. *Exceptional Children*, *54*(6), 536-542.

MacArthur, C. A. (2006). The effects of new technologies on writing and writing processes. In C. MacArthur, S. Graham & J. Fitzgerald (Eds.), *Handbook of writing research* (pp. 248-262). New York: Guilford Press.

McCutchen, D. (1995). Cognitive processes in children's writing: Developmental and individual differences. *Issues in Education: Contributions from Educational Psychology*, *1*(1), 123-160.

McCutchen, D. (1996). A capacity theory of writing: Working memory in composition. *Educational Psychology Review*, *8*(3), 299-325.

McNamara, D. S., Crossley, S. A., & Roscoe, R. (2013). Natural Language Processing in an Intelligent Writing Strategy Tutoring System. Behavior Research Methods, 45 (2), 499-515.

Mo, Y., & Troia, G. (2017). Similarities and differences in constructs represented by U.S. States' middle school writing tests and the 2007 National Assessment of Educational Progress writing assessment. *Assessing Writing, 33* (July 2017), 48-67. doi:10.1016/j.asw.2017.06.001

Morphy, P., & Graham, S. (2012). Word processing programs and weaker writers/readers: A meta-analysis of research findings. *Reading and Writing*, *25*(3), 641-678.

Murphy, S. & Smith, M.A. (2018). "The faraway stick cannot kill the nearby snake." In C. Bazerman, A. Applebee, V. Berninger, D. Brandt, S. Graham, J. Jeffery, P. Matsuda, S. Murphy, D. Rowe, M. Schleppegrell, & K. Wilcox, (Eds.), *The lifespan development of writing* (pp. 210-243). Urbana, IL: National Council of English.

National Assessment Governing Board (NAGB; 2010). *Writing Framework for the 2011 National Assessment of Educational Progress*. Washington, D.C.: U.S. Department of Education.

National Center for Education Statistics (NCES, *n.d.*). *NAEP Technical Documentation: Calculation and Use of Replicate Weights*. Washington, D.C.: Institute of Education Sciences, U.S. Department of Education. Retrieved April 19, 2018 from https://nces.ed.gov/nationsreportcard/tdw/weighting/2000_2001/2000state_repweights.aspx

National Center for Education Statistics (NCES; 2012). *The Nation's Report Card: Writing 2011*. Washington, D.C.: Institute of Education Sciences, U.S. Department of Education.

National Center for Education Statistics (NCES, 2014a), Lessons Learned from the 2012 Grade 4 Writing Computer-based Assessment Study. Washington, DC: Institute of Education Sciences, U.S. Department of Education. Retrieved from: http://nces.ed.gov/nationsreportcard/writing/lessons/default.aspx

National Center for Education Statistics (NCES, 2014b), NAEP 2012 Pilot Writing Computer-Based Assessment Study--Grade 4: Technical Memorandum, Washington, DC: Institute of Education Sciences, U.S. Department of Education.

Nystrand, M., Greene, S., & Wiemelt, J. (1993). Where did composition studies come from? An intellectual history. *Written Communication*, *10*(3), 267-333.

Olinghouse, N., Santangelo, T., & Wilson, J. (2012). Examining the validity of single-occasion, single-genre, holistically scored writing assessments. In E. V. Steendam, M. Tillema, G. Rijlaarsdam, & H. V. D. Bergh (Eds.), Measuring writing: recent insights into theory, methodology and practices (pp. 55-82). New York: Guilford.

Owston, R. D., Murphy, S., & Wideman, H. H. (1992). The effects of word processing on students' writing quality and revision strategies. *Research in the Teaching of English*, *26*(3), 249-276.

Porter, A., McMaken, J., Hwang, J., & Yang, R. (2011). Common core standards: The new US intended curriculum. *Educational Researcher*, *40*(3), 103-116.

Purcell, K., Buchanan, J., & Friedrich, L. (2013). *The Impact of Digital Tools on Student Writing and How Writing is Taught in Schools.* Washington, DC: Pew Research Center's Interent & American Life Project. http://pewinternet.org/Reports/2013/Teachers-technology-and-writing

Purcell, K., Heaps, A., Buchanan, J., & Friedrich, L. (2013). *How Teachers are Using Technology at Home and in their Classrooms.* Washington, DC: Pew Research Center's Interent & American Life Project. http://pewinternet.org/Reports/2013/Teachers-and-technology

Preacher, K. J., & MacCallum, R. C. (2003). Repairing Tom Swift's electric factor analysis machine. *Understanding Statistics: Statistical Issues in Psychology, Education, and the Social Sciences*, *2*(1), 13-43.

Rogers, A., Stoeckel, J., & Sikali, E. (2013). *National Assessment of Educational Progress (NAEP) 2011 Writing Assessment Restricted-Use Data Files Data Companion.* Washington, DC: National Center for Education Statistics.

Russell, M., & Haney, W. (1997). Testing writing on computers. *Education Policy Analysis Archives*, *5*(3), 1-20.

Russell, M., & Plati, T. (2002). Does it matter with what I write? Comparing performance on paper, computer and portable writing devices. *Current Issues in Education*, *5*(4), 1-15.

Sandene, B., Horkay, N., Bennett, R. E., Allen, N., Braswell, J., Kaplan, B., & Oranje, A. (2005). *Online Assessment in Mathematics and Writing: Reports from the NAEP Technology-Based Assessment Project, Research and Development Series*. NCES 2005-457. Washington, DC: Institute of Education Sciences, U.S. Department of Education.

Schleppegrell, M., & Christie, F. (2018). Linguistic features of writing development: A functional perspective. In C. Bazerman, A. Applebee, V. Berninger, D. Brandt, S. Graham, J. Jeffery, P. Matsuda, S. Murphy, D. Rowe, M. Schleppegrell, & K. Wilcox, (Eds.), *The lifespan development of writing* (pp. 111-150). Urbana, IL: National Council of English.

Sperling, M., & Freedman, S. W. (2001). Research on writing. In V. Richardson (Ed.), *Handbook of research on teaching*, 4th edition (pp. 370-389). Washington, D.C.: American Educational Research Association.

Tate, T.P., Warschauer, M., & Abedi, J. (2016). The effects of prior computer use on computer-based writing: The 2011 NAEP Writing Assessment, *Computers & Education, 101,* 115-131. doi: 10.1016/j.compedu.2016.06.001

Vargha, A., Torma, B., & Bergman, L.R. (2015), ROPstat: A general statistical package useful for conducting person-oriented analyses. *Journal for Person-Oriented Research,* 1(1-2). 87-98. doi: 10.17505/jpor.2015.09

Vygotsky, L. S. (1981). The genesis of higher mental functions. In J. V. Wertsch (Ed.), *The Concept of Activity in Soviet Psychology* (pp. 144-188). Armonk, NY: M.E. Sharpe.

Wang, Q., & Pomerantz, E. M. (2009). The motivational landscape of early adolescence in the United States and China: A longitudinal investigation. *Child Development*, *80*(4), 1272-1287.

Warschauer, M. (2006). *Laptops and literacy: Learning in the wireless classroom.* New York: Teachers College Press.

Way, W. D., Davis, L. L., & Strain-Seymour, E. (2008). The validity case for assessing direct writing by computer. *A Pearson Assessments & Information White Paper*.

Wenglinsky, H. (2005). *Using technology wisely: The keys to success in schools*. NY: Teachers College Press.

Wertsch, J. V. (1991). *Voices of the mind: A sociocultural approach to mediated action*. Cambridge, MA: Harvard University Press.

White, S., Kim, Y. Y., Chen, J., & Liu, F. (2015). *Performance of fourth-grade students in the 2012 NAEP computer-based writing pilot assessment: Scores, text length, and use of editing tools,* NCES 2015-119. Washington, DC: Institute of Education Sciences, US Department of Education.

Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology*, *25*(1), 68-81.

Wilcox, Kristen Campbell and Jeffery, Jill V. (2014). Adolescents' Writing in the Content Areas: National Study Results. *Educational Theory and Practice Faculty Scholarship. 17*. http://scholarsarchive.library.albany.edu/etap_fac_scholar/17

Williamson, G. L., Fitzgerald, J., & Stenner, A. J. (2013). The Common Core State Standards' quantitative text complexity trajectory: Figuring out how much complexity is enough. *Educational Researcher*, *42*(2), 59-69.

Withey, M. M. (1983). The computer and writing. *The English Journal*, *72*(7), 24-31.

Zwick, R. (1987). Assessing the dimensionality of NAEP reading data. *Journal of Educational Measurement*, *24*(4), 293-308.

Table 1.

Keyboard and mouse activity during the assessment broken into percentiles of use. Note the large number of "0" or no use and "1" for used once.

	1%	5%	25%	50%	75%	95%	99%
Keypresses	0-1000	0-1000	1001-2000	2001-3000	2001-3000	4001+	4001+
Spellcheck	0	0	0	1	3	4+	4+
Thesaurus	0	0	0	0	1	2+	2+
Text 2 Speech	0	0	0	1	2	2	2
Highlight	0	0	0	0	1-6	7+	7+
Backspace	1-100	1-100	101-200	201-300	301-400	401-500	401-500
Cut	0	0	0	0	0	1	2+
Paste	0	0	0	0	0	1	2+
Copy	0	0	0	0	0	1	2+
Bold	0	0	0	0	1	3+	3+
Italic	0	0	0	0	1	3+	3+
Underscore	0	0	0	0	1	3+	3+
Indent	0	0	0	0	1	4	5
Outdent	0	0	0	0	1	3	5
Delete	0	0	0	0	0	1+	1+

Table 2.

Mean keyboard and mouse activity during the assessment by percentiles of scaled writing scores.

	-1.955	-1.692	-1.323	-0.787	-0.027	0.607	1.170	1.550	2.289
Writing Score	1%ile	5%ile	10%ile	25%ile	50%ile	75%ile	90%ile	95%ile	99%ile
Keypresses	2.74	2.79	2.85	3.01	3.30	3.66	4.06	4.24	4.42
Spellcheck	2.48	2.47	2.46	2.41	2.35	2.26	2.16	2.16	1.96
Thesaurus	1.41	1.42	1.42	1.44	1.49	1.56	1.63	1.66	1.77
Text 2 Speech	2.51	2.49	2.47	2.40	2.29	2.17	1.10	1.91	1.88
Highlight	1.53	1.53	1.52	1.51	1.48	1.46	1.42	1.40	1.48
Backspace	4.07	4.11	4.15	4.27	4.46	4.61	4.79	4.84	4.94
Cut	1.15	1.14	1.14	1.14	1.14	1.14	1.15	1.15	1.14
Paste	1.24	1.23	1.23	1.23	1.24	1.24	1.25	1.25	1.25
Copy	1.20	1.20	1.20	1.20	1.19	1.19	1.18	1.19	1.19
Bold	1.66	1.66	1.65	1.16	1.59	1.54	1.50	1.47	1.40
Italic	1.56	1.56	1.56	1.54	1.56	1.60	1.69	1.75	1.98
Underscore	1.44	1.44	1.44	1.44	1.43	1.42	1.44	1.44	1.31
Indent	1.78	1.81	1.81	1.81	1.80	1.76	1.71	1.64	1.60
Outdent	1.59	1.60	1.60	1.60	1.58	1.54	1.49	1.45	1.44

Delete	1.10	1.11	1.11	1.12	1.13	1.15	1.16	1.17	1.16

Note. Keypress 1 = 0-1000 keypresses, 5 = 4001 or more keypresses; Backspace 1 = 0, 2 = 1-100, etc. 6= 401-500 times; delete 1= 0 times, 2 = 1 time or more; Cut, copy, paste, thesaurus 1 = 0 times, 3 = 2 times or more; Bold, italic, underscore 1=0 times, 4 = 3 times or more; Spellcheck, text-to-speech 1 = 0, 5 = 4 or more; Indent, outdent 1 = 0 times, 6 = 5 times; and Highlight 1 = 0, 2 = 1-6 times, 3 = 7 times or more.

Table 3.

Correlation of variables.

	Scaled Writing	Word Count	Key-presses	Cut	Copy	Paste	Bold	Italic	Under-line	Indent
Scaled Writing	1.00									
Word Count	0.77	1.00								
Keypresses	0.71	0.87	1.00							
Cut	-0.04	-0.06	-0.02	1.00						
Copy	-0.04	-0.06	-0.03	0.26	1.00					
Paste	-0.01	-0.04	-0.01	0.43	0.71	1.00				
Bold	-0.07	-0.07	-0.05	0.12	0.12	0.12	1.00			
Italic	0.01	-0.02	0.00	0.12	0.12	0.11	0.52	1.00		
Underline	-0.00	-0.03	-0.01	0.12	0.12	0.12	0.48	0.44	1.00	
Indent	0.02	-0.02	-0.01	0.08	0.08	0.08	0.18	0.14	0.16	1.00
Outdent	0.02	-0.02	-0.01	0.07	0.07	0.06	0.15	0.13	0.14	0.82
Spellcheck	-0.09	-0.05	-0.05	0.01	0.04	0.04	0.07	0.07	0.05	0.08
Thesaurus	0.14	0.04	0.08	0.08	0.09	0.11	0.08	0.11	0.10	0.11
Highlight	-0.10	-0.12	-0.10	0.11	0.10	0.10	0.21	0.17	0.17	0.11
Text to Speech	-0.20	-0.22	-0.20	0.10	0.10	0.10	0.19	0.14	0.14	0.09
Backspace	0.36	0.41	0.61	0.01	0.03	0.03	-0.01	0.02	0.01	0.01
Delete	0.10	0.08	0.09	0.05	0.04	0.07	0.02	0.03	0.03	0.03

	Outdent	Spell-check	Thesaurus	High-light	Text to Speech	Back-space	Delete
Outdent	1.00						
Spellcheck	0.07	1.00					
Thesaurus	0.11	0.07	1.00				
Highlight	0.11	0.06	0.14	1.00			
Text to Speech	0.09	0.07	0.10	0.46	1.00		
Backspace	0.01	-0.02	0.08	0.07	-0.13	1.00	
Delete	0.03	-0.03	0.08	0.04	0.03	0.08	1.00

Table 4.

Regression table: Total words and keypresses. Model 1 includes only average word count and keypresses, Model 2 adds controls, Model 3 adds an interaction between word count and keypresses, and Model 4 adds all interactions. All models use jackknife weighting. The outcome variable is the scaled writing score.

	Model 1	Model 2	Model 3	Model 4
	Scaled Writing	Scaled Writing	Scaled Writing	Scaled Writing
Word Count	0.58***	0.52***	0.56***	0.59***
	(0.01)	(0.01)	(0.01)	(0.02)
Keypresses	0.19***	0.14***	0.29***	0.31***
	(0.01)	(0.01)	(0.01)	(0.02)
Female		0.11***	0.11***	0.10***
		(0.01)	(0.01)	(0.01)
Black		-0.16***	-0.16***	-0.15***
		(0.01)	(0.01)	(0.01)
Hispanic		-0.06***	-0.07***	-0.07***
		(0.01)	(0.01)	(0.01)
Asian		0.03	0.04	0.04
		(0.02)	(0.02)	(0.02)
Fr/Red Lunch		-0.18***	-0.19***	-0.18***
		(0.01)	(0.01)	(0.01)
Parent College		0.12***	0.12***	0.11***
		(0.01)	(0.01)	(0.01)
Former ELL		-0.08**	-0.07**	-0.07**
		(0.03)	(0.03)	(0.03)
Current ELL		-0.42***	-0.40***	-0.47***
		(0.02)	(0.02)	(0.02)
Stud w/Disability		-0.40***	-0.36***	-0.41***
		(0.02)	(0.02)	(0.03)
Keypress x			-0.00***	0.00***
Words			(0.00)	(0.00)
Keypress x				0.04*
Female				(0.02)
Keypress x				-0.03
Black				(0.02)
Keypress x				0.00
Hispanic				(0.03)
Keypress x				-0.02
Asian				(0.03)
Keypress x				-0.02
Fr/Red Lunch				(0.02)

Keypress x				0.03
Parent College				(0.02)
Keypress x				-0.02
Former ELL				(0.05)
Keypress x				-0.11*
Current ELL				(0.05)
Keypress x				-0.05*
Stud w/Disability				(0.03)
Words x				-0.03
Female				(0.02)
Words x				0.05
Black				(0.03)
Words x				0.00
Hispanic				(0.03)
Words x				0.04
Asian				(0.04)
Words x				-0.05*
Fr/Red Lunch				(0.02)
Words x				0.02
Parent College				(0.02)
Words x				0.02
Former ELL				(0.05)
Words x				-0.05
Current ELL				(0.05)
Words x				-0.05
Stud w/Disability				(0.04)
Constant	-0.04***	0.06***	0.11***	0.11***
	0.00	(0.01)	(0.01)	(0.01)
N	*24070*	*19950*	*19950*	*19950*
R-sq	0.62	0.67	0.68	0.68

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

Note: Keypress x Words is shown as 0 only due to rounding, actual values are -0.0005 and -0.00067.

Table 5. Cluster statistics. The table sets out the scaled writing score, keyboard and mouse activity, and demographic percentages for each of the 5 cluster groups.

	Effective Patterns		*Average Students*		*Negative Pattern*
	Sophisticated	Deleter	Indenter	Typing only	Unproductive activity
Scaled Writing Score	0.33	0.17	-0.16	-0.19	**-0.73**
Keypresses	**0.47**	0.01	-0.33	-0.28	**-0.90**
Cut	-0.05	-0.09	-0.12	**-0.18**	**0.05**
Copy	-0.03	-0.09	-0.10	**-0.19**	**0.09**
Paste	-0.03	-0.05	-0.10	**-0.20**	**0.09**
Bold	**0.81**	-0.15	0.02	**-0.38**	**0.98**
Italic	**0.76**	-0.12	-0.08	**-0.37**	**0.86**
Underscore	**0.64**	-0.13	-0.04	**-0.34**	**0.71**
Indent	0.05	-0.11	**1.75**	**-0.35**	0.12
Outdent	-0.09	-0.16	**1.50**	**-0.37**	-0.02
Spellcheck	0.04	**-0.16**	0.13	-0.10	0.23
Thesaurus	0.12	0.01	0.04	**-0.22**	-0.03
Highlight	0.05	-0.06	0.03	**-0.22**	**0.33**
Text-to-Speech	0.03	0.01	0.19	**-0.19**	**0.63**
Backspace	**0.85**	0.21	-0.07	-0.11	**-0.69**
Delete	-0.31	**2.96**	-0.24	**-0.34**	-0.23
Cluster Demographics					
Student-reported Prior Tech Use	0.31	0.49	-0.33	-0.17	-0.50
Female	0.64	0.44	0.44	0.45	0.33
Hispanic	0.24	0.19	0.30	0.28	0.28
Black	0.19	0.13	0.18	0.18	0.27
Asian	0.05	0.05	0.04	0.04	0.03
Free/red Lunch	0.47	0.33	0.52	0.52	0.63
Parent College	0.57	0.68	0.49	0.53	0.48
Current ELL	0.04	0.03	0.05	0.07	0.10
Former ELL	0.03	0.03	0.05	0.04	0.04
Student w/ Disability	0.05	0.08	0.08	0.12	0.14
Students in Cluster	*7%*	*8%*	*8%*	*67%*	*10%*

Note: Sample sizes rounded to the nearest 10. Green font indicates particularly high use/percentage of population; red is particularly low use/percentage of population.

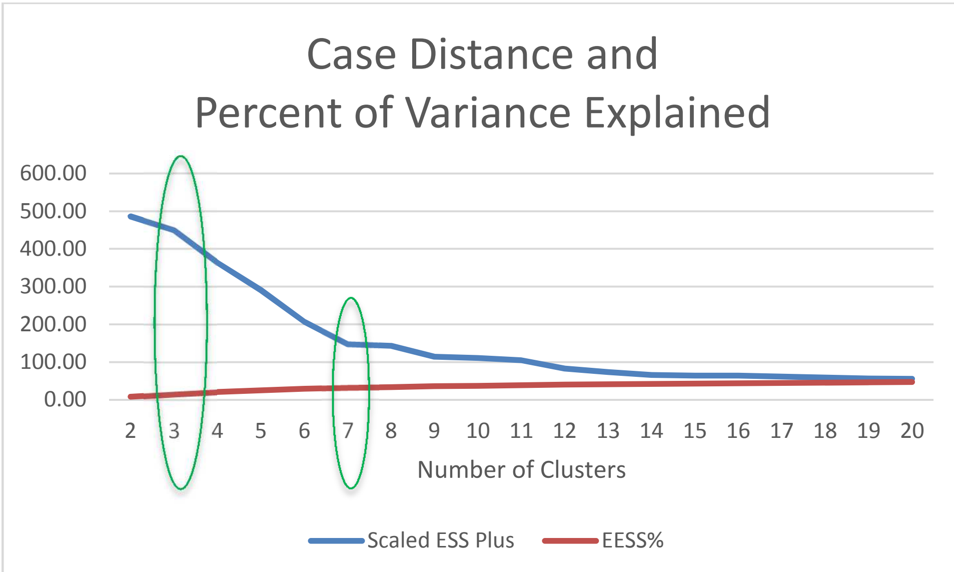


Figure 1

Graph showing the reduction in distances between cases in the various cluster models for 2-20 cluster solutions. EES Plus has been re-scaled (multiplied by .25) for presentation purposes. Large changes are seen at 3 and 7 cluster solutions, so these were the focus of our consideration.

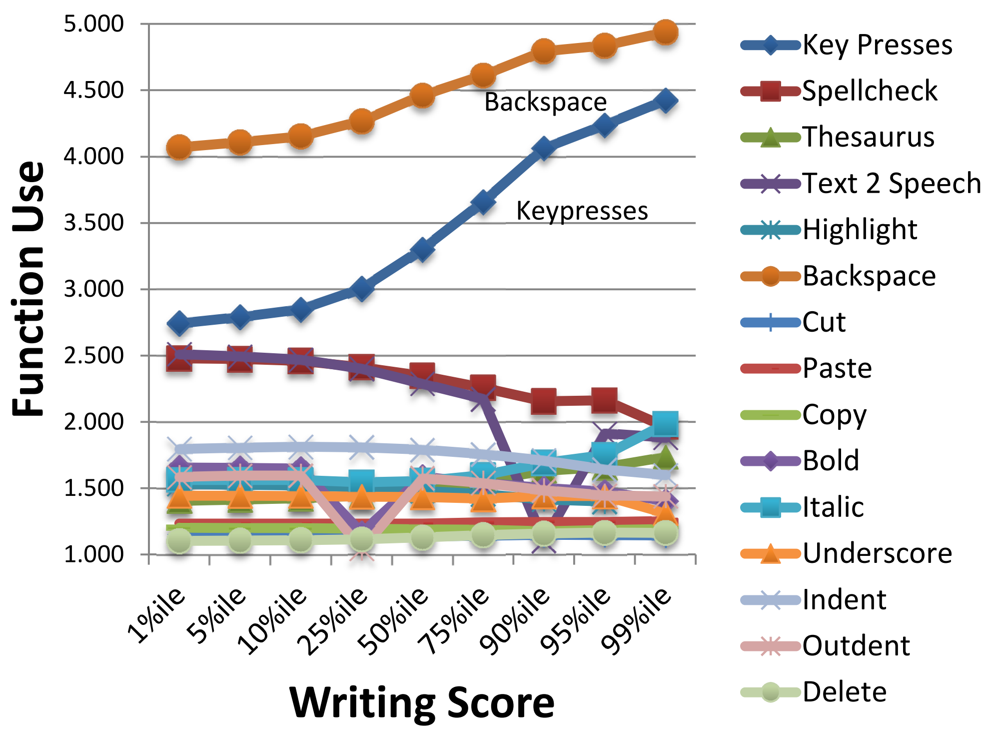


Figure 2.

Mean keyboard and mouse activity by writing achievement level. Mean use of each function (y axis) by percentile of writing achievement (x axis). Keypress 1 = 0-1000 keypresses, 5 = 4001 or more keypresses; Backspace 1 = 0, 2 = 1-100, etc. 6= 401-500 times; delete 1= 0 times, 2 = 1 time or more; Cut, copy, paste, thesaurus 1 = 0 times, 3 = 2 times or more; Bold, italic, underscore 1=0 times, 4 = 3 times or more; Spellcheck, text-to-speech 1 = 0, 5 = 4 or more; Indent, outdent 1 = 0 times, 6 = 5 times; and Highlight 1 = 0, 2 = 1-6 times, 3 = 7 times or more.

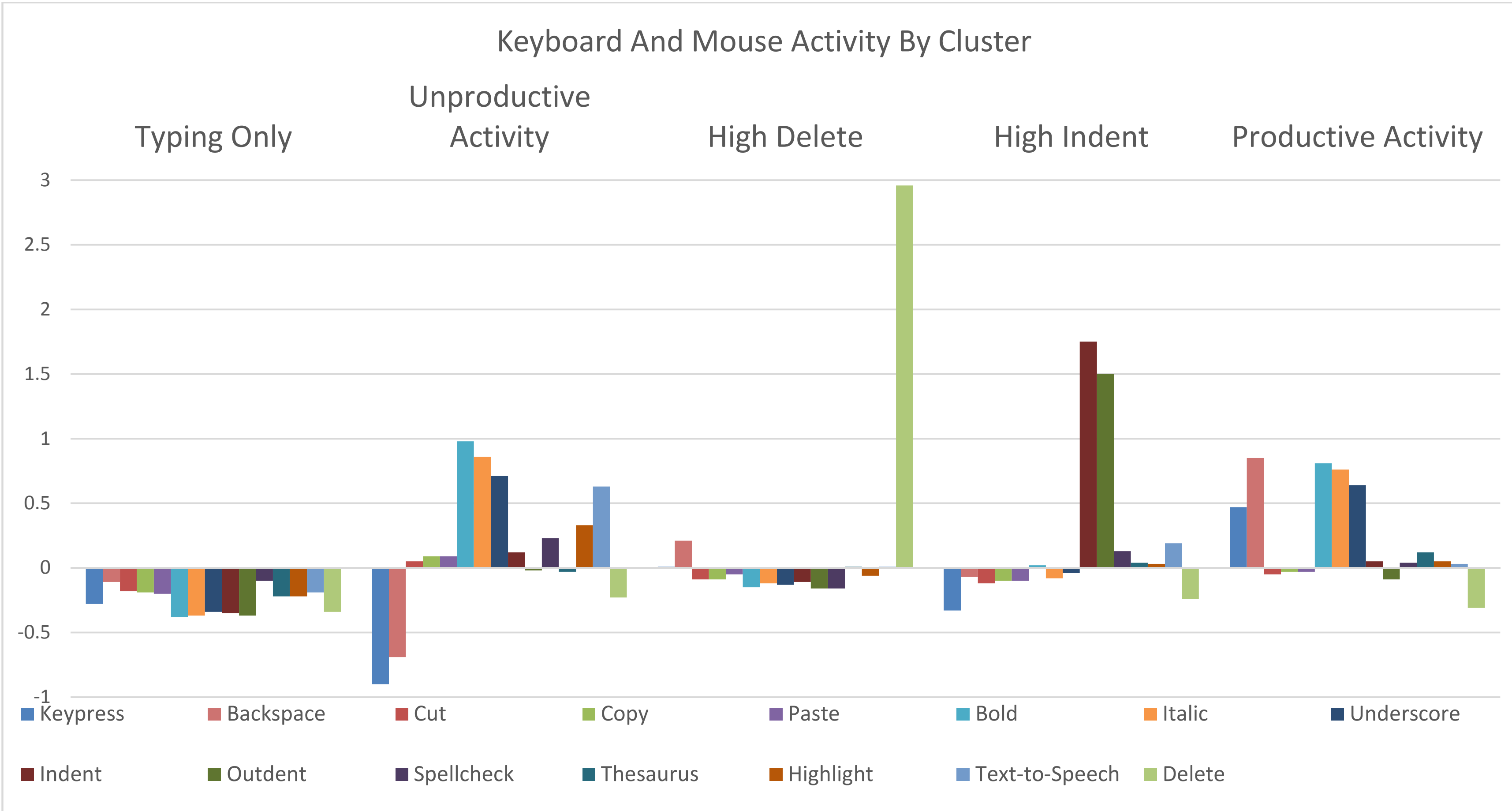
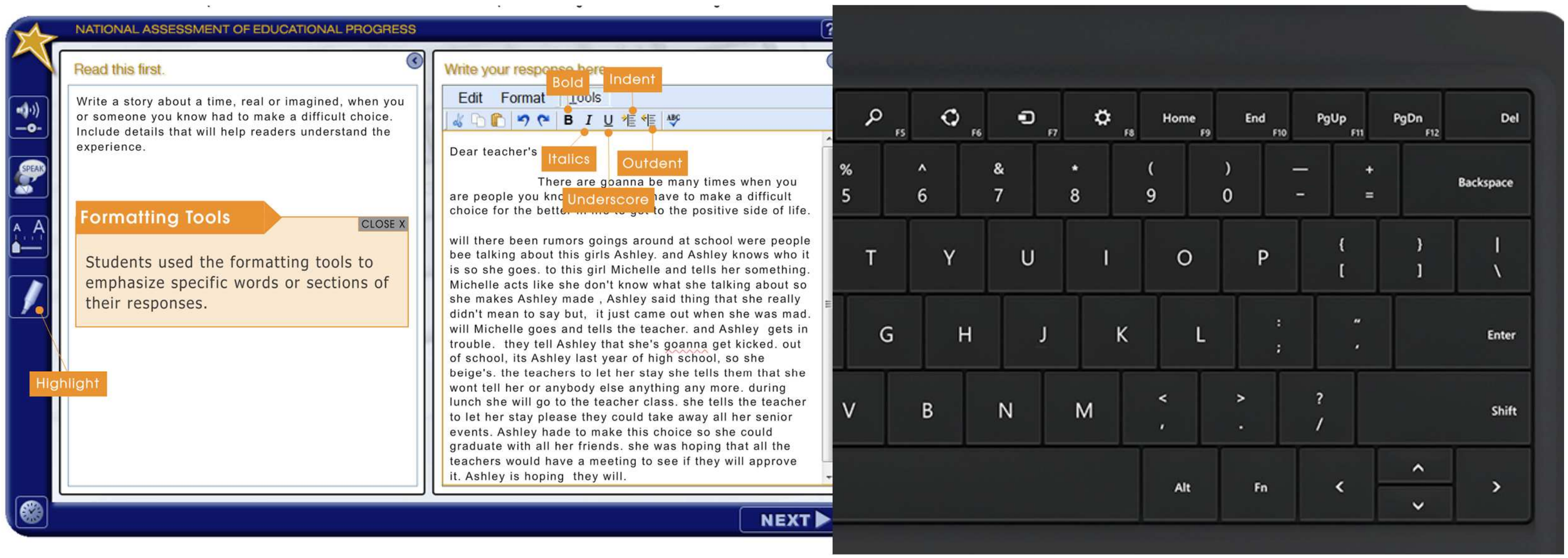


Figure 3.

Chart showing the keyboard and mouse activity (standardized) by students (y axis).



https://www.nationsreportcard.gov/writing_2011/writing_tools.aspx

Figure 4.

NAEP 2011 Writing Assessment user interface and keyboard.

CHAPTER 4

Study 3. Tate, T., Warschauer, M., and Kim, Y.-S.G.

Learning to Compose Digitally: The Effect of Prior Technology Exposure and Keyboard/Mouse Activity on NAEP Writing.

Writing is a crucial component of college and career readiness (Applebee, 2011; Graham, 2012; Graham & Perin, 2007; Leu et al., 2015) and is central to academic achievement, critical thinking, and development of reasoning in diverse content areas (Intersegmental Committee of the Academic Senates of the California Community Colleges, the California State University, and the University of California, 2002). It is also an essential, threshold skill for employment and promotion (The National Commission on Writing in America's Schools and Colleges, 2003, 2004). Despite the well-recognized importance of writing, most U.S. middle school students are not proficient at writing. Only 27% of all 8th grade students, 11% of Black students, and 14% of Hispanic students score at or above proficient levels and, even more troubling, 1 in 5 secondary students scores in the below basic range (National Center for Education Statistics, 2012). The challenge of developing students' writing skills stems from the fact that writing is a complex cognitive process, drawing on neurological, motor, cognitive, language, and visual processes (e.g., Abbott & Berninger, 1993; Kim et al., 2015; Kim & Schatschneider, 2017; Berninger & Swanson, 1994; Coker, 2006; McCutchen, 1996). Unfortunately, "Despite this reality, little research has been conducted on writing, especially writing in secondary schools" (Institute of Education Sciences, 2017, p. 34).

Today, nearly all serious writing in vocational, professional, and academic domains is done via digital media (DeVoss, Eidman-Aardahl, & Hicks, 2010), and computers are becoming the main vehicle for K-12 student writing from approximately upper elementary grades on (Graham et al., 2016). Although writing, either via handwriting and digital writing, involves similar processes and draws on similar component skills, digital writing includes features that are simply not possible when writing by hand, such as the ability to copy, move, and paste chunks of text, thus making it a distinct, albeit closely related, process. Students thus need to be prepared for evolving digital literacy practices, including, for example, simultaneous collaborative writing by multiple authors on a single text (Yim, Warschauer, Zheng, & Lawrence, 2014; Graham et al., 2012, 2016). In many instances, however, students receive inadequate explicit instruction in writing on computers (Applebee & Langer, 2011). Digital technologies present specific cognitive challenges and opportunities (Bazerman, 2012; Leu et al., 2014) that students must be able to negotiate, including the ability to embed mechanical supports such as spell check into the writing environment and the ability to cleanly cut and paste text from one paragraph to another. Students need to learn both how to use technology to enhance their own writing processes in ways that are effective for them and how to reflect upon their practices to ensure that the modality chosen for each stage of writing is used in ways that help, not hinder, the production of quality writing (Van Ittersum, 2011).

This study is situated in cognitive and sociocultural theories of writing. With respect to the cognitive models, the process models are particularly relevant to the present study (e.g., Flower & Hayes, 1981; see Kim & Schatschneider, 2017; Berninger & Winn, 2006 for component-based models). According to Flower and Hayes (1981), writing is composed of planning, translating, and reviewing and revising. During the planning phase, writers form an internal representation of the knowledge that will be used in writing, by using sub-processes like generating and organizing the ideas. During the translation phase, writers generate written text, which involves syntactic and lexical skills as well as motor skills and working memory. Finally, during the reviewing and revising phase, writers improve existing text. The Flower and Hayes model was developed to describe the writing of proficient, skilled adults. In later research with beginning and developing writers, Berninger, Whitaker, Feng, Swanson, and Abbott (1996) argued that (a) text generation (which itself has the components for producing words, sentences, and paragraphs) is distinguished from idea generation, and (b) planning is of two types, advanced planning prior to any translation and in-process planning of the next thing to write. They noted further that neurodevelopmental skills (such as orthographic coding) places constraints on fluent writing to varying degrees throughout the development of writing proficiency, presumably through their influence on transcription, as are higher level linguistic and cognitive skills such as planning, translating ideas into appropriate structures, and revising (Kim et al., 2011, 2014, 2015; Kim & Schatschneider, 2017; Berninger & Swanson, 1994; Coker, 2006).

The challenge of successful writing is further complicated because writing is greatly influenced by the tools that enable it and the media that encapsulate it (see Bolter, 1991; Wertsch, 1991). Scholars ascribing to sociocultural theory focus on the social environment, or context, and its effects on learning (Wertsch, 1998). Literacy is seen as multiply situated, mediated sociocultural practices, as motivated and socially organized activity (Deane, Sabatini, & Fowles, 2012; Prior, 2006; Scribner & Cole, 1981). The author's tools, in particular, have specific affordances. These affordances encompass the perceived and actual properties of the tool, primarily those fundamental properties that determine just how the tool could possibly be used (McGrenere & Ho, 2000). In the digital writing environment, we see affordances such as synchronous collaboration, the ability to "publish" readable texts, and embedded supports changing students' writing processes. Studies have also found that students participating in communities of practice using digital devices tend to write more during the school year (Warschauer, 2011).

In our recent study (Tate, Warschauer, & Abedi, 2016), we investigated the relationship between various kinds of exposure to digital technology and writing achievement on a computer-based assessment using the 2011 NAEP writing data. We used the responses from questionnaires administered along with the writing assessment to evaluate the relationship between reported technology exposure and writing achievement. We found that reported prior technology exposure for school-related writing had a direct effect of 0.14-0.16 standard deviation on writing achievement scores on the computer-based assessment. Casual, personal use of computers did not predict increased writing achievement, however. Our subsequent study (Tate & Warschauer, under review) looked at keyboard and mouse activity to examine the relationship between students' activity during the assessment and their writing achievement. We found that the number of keypresses had a distinct and direct effect on writing achievement scores over and above the word count for each essay. We also identified several different patterns of keyboard and mouse activity, some of which correlated with higher or lower achievement scores and higher or lower levels of prior technology exposure for school writing.

Although informative, these previous studies did not investigate the relationship among students' prior technology exposure, keyboard and mouse activity during writing, and writing achievement, the goal of the present study. Specifically, in this study we investigated (a) whether keyboard and mouse activity would at least partially mediate the relation of prior technology exposure to writing achievement; (b) whether the relation of keyboard and mouse activity to writing varies as a function of prior technology exposure; and (c) whether the relations of prior technology exposure and keyboard and mouse activity to writing varies for different groups of students (e.g., English learners and those with a learning disability). We hypothesized that prior technology exposure would lead to increased keyboard and mouse activity as measured by word count, keystrokes, and use of digital affordances like cut and paste. Since keyboard and mouse activity is related to writing (Tate & Warschauer, under review) we hypothesized that keyboard and mouse activity would, at least in part, mediate the relationship between prior technology exposure and improved writing. However, prior technology exposure might still have a direct relationship with writing achievement if prior technology exposure does not solely improve the mechanical transcription aspects of writing, but instead also improves other writing processes, such as idea generation or revision, motivation, or changes in the learning context. These additional benefits could be reflected in a direct effect of prior technology exposure on writing after accounting for keyboard and mouse activity. Furthermore, we considered the possibility that prior technology exposure and keyboard and mouse activity might interact and amplify their impact on writing, for example making the keyboard activity more productive, effective, or efficient.

The literature suggests that the hypothesized impact of prior technology exposure for school writing could come about in various ways (Warschauer, 2006; Bangert-Drowns, 1993). For example, students may be less reluctant to put preliminary thoughts down if editing digital texts is known to be easier in the computer environment than hand correcting. Conversely, students' perception of typed text as more polished and final might lead to less revision or increased concern about generating the precise language desired before committing it to transcription. Even more simply, students in environments with one-to-one digital devices (one device per student) tend to quantitatively write more during the year and so have more practice writing generally than students without such access (Yim, Warschauer, Zheng, & Lawrence, 2014). They also tend to collaborate more, which may provide modeling and apprenticeship opportunities (Yim, Warschauer, Zheng, & Lawrence, 2014). Finally, the research suggests that students with access to computers may exhibit improved motivation and self-efficacy related to writing (Morphy & Graham, 2012).

Prior technology exposure was operationalized as prior access to and use of computers for academic writing; keyboard and mouse activity during the assessment includes a suite of variables (e.g., key presses, cut, and spellcheck) related to the actual behaviors of students when transcribing their texts digitally. Although descriptive relationships about these data have been reported (National Center for Educational Statistics [NCES], 2012), the paths of relations among prior technology exposure, keyboard activity, and writing achievement have not been investigated. The findings will generate insight about the nature of these relations and provide preliminary ideas about further research and instructional opportunities to support instruction on writing with digital media.

Furthermore, we examined whether the relations vary as a function of various background factors such as students' socioeconomic, English learner, and disability status. Literature, and indeed the NAEP results themselves, show us significant disparities in writing achievement among these groups, with students not eligible for free/reduced lunch scoring on average higher (a 161 mean scaled score on the writing assessment) than those who were eligible (134) and with students whose parents did not finish high school (133) scoring on average lower than children of high school graduates (138) and college graduates (160; NCES, 2012). Similarly, students identified as having a disability (113) scored below their non-disabled peers (154), as did English learners (108) compared to non-English learners (152; NCES, 2012) on the 2011 writing assessment. We were interested in understanding whether the impact of prior technology exposure and keyboard and mouse activity on writing would be different for these groups. Understanding group differences of this type allows educators to provide more directed instruction to struggling students.

This study also fills a gap in the literature by investigating writing skills for students in adolescence, as previous studies tended to focus on either early writing development in the primary grades or the proficient writing of adult writers (see discussion in Graham & Hebert, 2010; Carnegie, 2010). For example, in a recent meta-analysis on the component skills of writing, only 2 of the included 43 studies were conducted among students in grades 7-12 (Kent & Wanzek, 2016). There is a critical need for more research on adolescent writing, particularly given great demands for developing analytic and argumentative writings skills across the curriculum in secondary schools (National Center for Education Research, 2017). We focused on eighth-grade students, as prior research suggests that the middle school years are critical for the development of academic writing (Zheng et al., 2015; De La Paz & Graham, 2002).

We sought to investigate the relationship among prior technology exposure, keyboard and mouse activity during the test, and eighth-grade students' writing achievement on the 2011 NAEP assessment through the following specific research questions:

1. Does prior technology exposure have a direct relation to writing achievement or is the relation mediated by keyboard and mouse activity during the assessment?
2. Is there an interaction between the effect of prior technology exposure and keyboard and mouse activity on writing achievement?
3. Do the relationships among prior technology exposure, keyboard and mouse activity, and writing achievement vary for different groups of students?

Method

Sample

This research analyzed the data from over 24,100 eighth-grade students from the restricted public use NAEP data set available from NCES. These data include raw and scaled writing scores, detailed survey data, and individual keystroke data. Because the dataset is prepared with the intent of making them available for public use, they are not individually identifiable and do not involve human subjects requiring Institutional Review Board approval.

NAEP sampling techniques strive to create a representative nationwide sample of students, but the results may be stratified and clustered (Johnson, 1992; Zwick, 1987). The weighted national school participation rates for the assessment were 97% overall, and 100% for public schools (NCES, 2012). In order to approximate the population, sample weights are used to correct for the oversampling of certain low incidence populations and to adjust the overall results by the actual population proportion (Johnson, 1992). These weights allow for valid inferences to be made about the population (Beaton, et al., 2011). Jackknife weights were used for the analysis. To the extent certain subgroups fell below 70%, NCES conducted an analysis of potential bias. Compared with the distribution of all eligible students, the distribution of the weighted sample did not differ with respect to any of the variables utilized in this analysis (Rogers, Stoeckel, & Sikali, 2013). As suggested by NCES, multiple responses, responses not reached or administered, omitted responses, non-ratable responses, illegible responses, and off task responses were each treated as missing.

Measures

Writing. The NAEP framework is based on research-based constructs of quality writing developed by leading educators and experts in the field of assessment over 18 months (Applebee, 2011), with participation by over 500 individuals, according to the National Assessment Governing Board (2010). The assessment was designed to reflect the way students write today, using word processing software and commonly available tools (National Assessment Governing Board, 2010).

Students were given two different writing tasks and had 30 minutes to complete each writing task. The prompts were in three genres: to persuade, explain, and convey experience. Responses were scored by three trained evaluators on a scale representing effective skill, adequate skill, developing skill, marginal skill, and little or no skill across three areas of writing: development of ideas, organization of ideas, and language facility and conventions (National Assessment Governing Board, 2010; NCES, 2012). NAEP evaluators used holistic scoring rubrics to evaluate the response as a whole, rather than assessing independent parts of the response. NAEP ensures scorers' reliability through back reading (scoring supervisors selectively review at least 5% of each scorer's work), periodic calibration of multiple scorers, and an inter-rater reliability statistics check of 25% of the responses (NCES, 2009). NAEP uses Item Response Theory (IRT) scaling to allow for estimates of item characteristics and difficulties (Beaton et al., 2011; Zwick, 1987) among the 22 different prompts. The main purpose of NAEP's IRT analyses is to provide a common scale on which to compare achievement across groups (Messick, Beaton, & Lord 1983). The scaled writing scores were used as the achievement variable, the dependent variable for the analyses in this article. We note that NAEP reports plausible values to improve the ability to draw inferences about a population's true proficiency level (Rogers, Stoeckel, & Sikali, 2013). Our analysis is not intended to be representative of the population's proficiency level, but instead to understand the relationship of prior technology exposure and keystroke activity on a human-scored writing test. We acknowledge that students in the sample had 22 different writing prompts.

Prior technology exposure. NAEP assessments include student questionnaires that are designed to place the achievement results in context and collect information required by federal legislation (https://nces.ed.gov/nationsreportcard/bgquest.aspx). Students complete the questionnaires voluntarily and their responses are kept confidential; some of these prior questionnaires are publicly available (https://nces.ed.gov/nationsreportcard/bgquest2003archive.aspx). The 2011 writing assessment included student questions about technology use for school and home, such as "For school, how often do you use the Internet to get information?" and "How often do you use the computer to write emails?" In our prior work (Tate, Warschauer, & Abedi, 2016), we analyzed the responses to these questions and used confirmatory factor analysis to create a latent factor combining questions related to prior technology exposure for school purposes. The student-reported prior technology exposure variable in this study was created using the weighting found in our prior work (Tate, Warschauer, & Abedi, 2016). Our latent variable for prior technology exposure included the responses that we found to be significantly correlated with writing test score outcomes (Tate, Warschauer, & Abedi, 2016), including how often in the previous year (a) the Internet was used to get information (with a weight of 0.73), (b) a computer was used to write a first draft (weight = 0.74), (c) a computer was used to make changes in writing (weight = 0.85), (d) a computer was used to complete writing (weight = 0.79), and (e) a computer was used to write school assignments (weight = 0.59). Student responses ranged from 1 (never or hardly ever), 2 (sometimes), 3 (very often), to 4 (almost always or always) for all except the last variable regarding use of the computer to write school assignments, which ranged from 1 (never or hardly ever), 2 (once/twice a month), 3 (once/twice a week), to 4 (almost every day or every day).

Keyboard and mouse activity. The keyboard and mouse activity variables available in the NAEP data included the number of keypresses, as well as the number of times the student used cut, copy, paste, bold, italic, underscore, indent, outdent, spellcheck, thesaurus, highlight, text-to-speech, backspace, and delete for both writing prompts. These functions were accessed via mouse click on the icon or drop down menu item representing the function. Keypresses included the total number of times that students pressed any keys—whether typing the text of their response or using the backspace key to revise written text. The values for the other variables were the number of times these functions were used during students' writing. These variables were standardized for our analysis, because they were reported on several different scales. For example, keypresses were reported on a scale of 1 (for 0-1000 keypresses) to 5 (4001 or more keypresses), but paste was reported on a scale of 1 (no use of the function) to 3 (2 or more uses of the function). By standardizing the variables, variables were on the same scale (i.e., standard deviation units). In the analysis, we used both keypress and latent variables derived from factor analysis (see below). Although keypresses include some of the other activity variables accessed via the keyboard (e.g., backspace, but not the drop-down options), the variable was included in the regression models because it also captures the typing of the essay text itself.

Data Analytic Strategies

Data reduction. Given the large number of variables for keyboard activity and their highly-correlated nature, we employed principal factor analysis for data reduction, using Stata Version 14.0 SE statistical software (Stata's "factor" command; *note:* this is not principal component analysis, but a true factor analysis). We retained factors with Eigenvalues greater than 1 as our lower bound (Kaiser, 1960), but also checked scree plots for large drops in values (Costello & Ottsborne, 2006; Preacher & MacCallum, 2003). We retained items with a loading of over 0.4 (Acock, 2012; but see Preacher & MacCallum, 2003). We finally considered an oblique rotation which allowed for correlations between the latent variables (Preacher & MacCallum, 2003). As we did previously with the prior technology exposure latent variable, we created our latent keyboard and mouse variables through weighting based on the factor analysis results.

Relations among prior technology exposure, keyboard and mouse activity, and writing achievement. We used ordinary least square regression to look at the relationship between reported prior technology exposure, keyboard and mouse activity during the assessment, and achievement scores. Stata's survey estimation command (svy) was used to work with this data and perform jackknife weighting (sampling units, PSUID; Strata, REPGRP1; Sample weight, ORIGWT; Student Replicate Weights, SRWT01-62). Linear regression was appropriate for our data, which showed little skewness or kurtosis. As a robustness check, we ran a fixed effects model (xtreg, fe vce [jackknife]), using the school identification numbers (SCHID), to reduce omitted variable bias and a structural equation model (svyset PSUID [pweight=ORIGWT], strata[REPGRP], jkrweight [the 62 SWRTs], vce[jackknife]).

Our analysis looked at possible moderating and mediating relations. A mediating variable accounts for the relation between the predictor and the criterion and changes the relationship between the original variables (see Little, 2013). To be a mediator, the *ab* term must be significant, that is the (a) Variations in levels of the independent variable (prior technology exposure) account for variations in the presumed mediator (keyboard activity during the assessment shown by Path A, Figure 1); and (b) variations in the mediator (keyboard activity during the assessment) significantly account for variations in the dependent variable (writing achievement; Path B; Little, 2013). Some statisticians also require that when (a) and (b) are controlled, a previously significant relation (Path C) between the independent (prior technology exposure) and dependent variable (writing achievement) is no longer significant, or at least is significantly decreased (Baron & Kenny, 1986). Older methods (e.g., Baron & Kenny, 1986), assume that the *ab* product is normally distributed, but Little (2013) notes that the product of two parameters is not normally distributed and either the Monte Carlo or bootstrap estimation approach should be used to test the statistical significance of the mediation. For our analysis, the bootstrap approach was used to generate standard errors and *t* values.

Moderators amplify or reduce the strength of an effect by one variable on another (see Little, 2013). To examine moderation, we tested the differential effect of the independent variable (prior technology exposure) on the dependent variable (writing achievement) as a function of the potential moderator (various types of keyboard activity). Moderator effects are indicated by the significant effects of prior use x keyboard activity when the main effects of prior use and keyboard activity are controlled (Baron & Kenny, 1986; Little, 2013).

When examining the relation of prior technology exposure to keyboard and mouse activity (Path A), six models were fitted, one for each of the six keyboard activity outcomes (e.g., in/outdent, word format; see Results for details about data reduction to six keyboard and mouse activity variables). For the relation of keyboard and mouse activity to writing (Path B), again six regression models were examined, with each regression including a different keyboard activity variable as an independent variable. For the relation of prior technology exposure to writing (Path C) and the interaction between prior technology exposure and keyboard and mouse activity, three regression models were examined: Model 1 regresses writing achievement on prior technology exposure, Model 2 adds keyboard and mouse activity independent variables, and Model 3 adds interaction terms between prior technology exposure and keyboard and mouse activity variables. To increase precision in the estimated relations, we controlled for student gender, ethnicity, free/reduced lunch status, whether a parent graduated college, ELL status (both current and former), and disability status as dichotomous variables in all the models. An additional model (Path D) included statistical interactions between prior technology exposure, keyboard and mouse activity, and demographics (i.e., free/reduced lunch status, parent's college degree, ELL status, and disability status).

Results

Descriptive Statistics and Bivariate Correlations

Descriptive statistics are displayed in Table 1. Keypresses were moderately skewed and exhibited minimal kurtosis; most other keyboard and mouse activity variables were strongly skewed and exhibited greater kurtosis. Prior technology exposure, which had a mean of 0, standard deviation of 2.98, variance of 8.85, skewness of 1.65, and kurtosis of 11.42, was made up of student responses about the frequency with which they used the Internet for school (M = 2.93), used the computer to write a first draft (M = 2.44), used the computer to make changes in writing (M = 2.79), used the computer to complete their draft (M = 2.97), and used the computer to write school assignments (M = 2.46). The scaled writing achievement score had a mean of -0.04 and a standard deviation of 0.96.

Correlations between variables are presented in Table 2. Writing score was strongly and positively correlated with keypresses (r = .71, p < .05). Note that although word count is known to be predictive of writing achievement (see, e.g., Graham, Kiuhara, Harris, & Fishman, 2017), keypresses and word count were highly positively correlated with each other ($r = .87, p < .05$) so only the keypress variable was included in subsequent regressions due to multicollinearity. Keypresses is more analogous and closer to the remaining keyboard activity variables than word count. Word count is an additional step beyond simply input and looks at lexical sense, so word count is more like sentence and paragraph counts, for example, not "cut." We wanted to keep our variables of interest at close to the same level of abstraction. Prior technology exposure was correlated with the scaled writing score ($r = .20, p < .05$) and with keypresses ($r = .16, p < .05$). Certain functions were also correlated, for example, copy and cut ($r = .26, p < .05$), cut and paste ($r = .42, p < .05$), and copy and paste ($r = .71, p < .05$).

Data Reduction for Keyboard and Mouse Activity Variables

Principal factor analysis indicated two or three factors among the keyboard and mouse activity variables. The first two factors had Eigenvalues of 2.26 and 1.29, the third factor had an Eigenvalue of 0.98, and the fourth factor had an Eigenvalue of 0.52. Factor 1 included bold, italic, and underscore; factor 2 included copy, paste, indent, and outdent. These groupings did not appear to match our understanding of keyboarding and drafting practices in any meaningful way. In order to better fit our data, we then used an *oblimin* oblique rotation to allow for the known correlations between the variables. This analysis showed a significant decline of Eigenvalues after four factors (Eigenvalues of 1.67, 1.67, 1.54, 1.53, 0.96, 0.92, and 0.28, respectively), with satisfactory loadings for the four factors (see Table 3). The variables included in the identified factors were (1) indent and outdent; (2) bold, italic, and underscore; (3) copy and paste, and (4) cut. Using the factor loadings, we created four keyboard and mouse activity variables (in/outdent, word format, copy/paste, and cut) for use in our subsequent regressions along with the variable for total keypresses.

The Relations Among Prior Technology Exposure, Keyboard and Mouse Activity, and Writing Achievement

First, in order to examine the relation between prior technology exposure and keyboard and mouse activity (Path A in Figure 1), we regressed each of the keyboard and mouse activity variables on prior technology exposure, controlling for demographics (see Table 4). Prior technology exposure predicted the following keyboard and mouse activity variables: keypresses ($\beta = 0.14$, $t = 11.58$), copy/paste ($\beta = 0.05$, $t = 5.09$), and cut ($\beta = 0.04$, $t = 4.61$). Prior technology exposure did not statistically significantly predict the use of in/outdent or word formatting. Next, for the relation of keyboard and mouse activity to writing achievement (Path B in Figure 1), we regressed the scaled writing score on keyboard and mouse activity variables, controlling for demographics (see Table 5). As shown in Model 6, keypresses ($\beta = 0.57$, $t = 80.31$), word format ($\beta = -0.01$, $t = -2.44$), and cut ($\beta = -0.02$, $t = -3.32$) predicted the writing score. We also found that prior technology exposure was related to writing achievement ($\beta = 0.16$, $t = 13.23$), controlling for demographics but without accounting for keyboard and mouse activity (Path C in Figure 1; see Model 1, Table 6).

Mediation. We next regressed the writing score on prior technology exposure and each keyboard and mouse activity variable, controlling for demographics (see Model 2, Table 6). We found that the coefficient for prior technology exposure remained statistically significant, but was reduced by half ($\beta = 0.08$, $t = 11.37$) after accounting for keyboard and mouse activity. The direct effect of keypresses was particularly large ($\beta = 0.57$, $t = 78.36$) in comparison to the direct effects for word format ($\beta = -0.01$, $t = -2.43$) and cut ($\beta = -0.02$, $t = -3.67$). Only keypresses and cut were in both paths. Thus, we see evidence that a large portion of the impact of prior technology exposure on writing achievement is mediated by two keyboard and mouse activity variables, but primarily keypresses.

Moderation. Only one of the interactions of prior technology exposure and the keyboard and mouse activity variables was statistically significant, prior technology exposure x keypresses ($\beta = 0.03$, $t = 5.03$; see Model 3, Table 6), indicating moderation with respect to keypresses and no moderation with respect to the other keyboard and mouse activities (Path D in Figure 1).

Group differences. We found differences in the effect of keypresses on writing for different demographic groups (see Table 7), with decreased values for students qualifying for free/reduced lunch (approaching significant, $\beta = -0.02$, $t = -1.80$) and for current ELLs ($\beta = -0.10$, $t = -2.96$), but an increased value for students with a parent who graduated college (approaching significant, $\beta = 0.02$, $t = 1.90$). Furthermore, the relation of prior technology exposure on writing differed as a function of free/reduced lunch ($\beta = -0.03$, $t = -2.40$), current ELL status ($\beta = -0.05$, $t = -2.17$), disability status ($\beta = -0.05$, $t = -2.53$), and parent's college graduation (approaching significant, $\beta = 0.03$, $t = 1.95$). Thus, all students still benefited from prior technology exposure, but the benefit was reduced for students from low SES backgrounds, for ELL students, and for those with a disability.

The relationship between other keyboard and mouse activity variables and writing achievement did not generally differ by demographics, except that the slight negative impact of copy/paste became larger for students currently classified as ELL. We also found that the small positive impact of in/outdent on writing achievement became negative in the case of students with a parent who graduated college, while former ELL students received additional positive benefit, as did students with a disability. We found no statistically significant interactions for the word formatting or cut variables.

In summary, our analysis showed the following results: For the path from prior technology exposure to keyboard activity (Path A), prior technology exposure predicted some keyboard and mouse activity, including keypresses ($\beta = 0.14$, $t = 11.58$). Variations in some keyboard and mouse activity during the assessment predicted writing achievement (Path B), with the largest effect related to the number of keypresses ($\beta = 0.57$, $t = 80.31$). After accounting for keyboard and mouse activity, the effect size of prior technology exposure on writing achievement (Path C) was reduced from 0.16 to 0.08 ($\beta = 0.08$, $t = 11.37$). The product of Paths A and B (using keypresses as the independent keyboard activity variable for this illustration since it was primarily responsible) is 0.08. Finally, we found an interaction effect between keypresses and prior technology exposure ($\beta = 0.03$, $t = 5.03$). Thus, the data support a partial mediation and moderation model (with respect to keypresses only; Figure 1).

Discussion

The primary goal of this study was to investigate the relations among prior technology exposure, keyboard and mouse activity, and writing achievement using eighth grade NAEP writing data. In particular, we examined whether keyboard and mouse activity mediates the relation of prior technology exposure to writing achievement, and whether these results differ as a function of students' backgrounds. As noted above, almost all serious writing is now done on computers, both in the workforce and in academia (DeVoss, Eidman-Aardahl, & Hicks, 2010). If we want to prepare students for long-term success, they need to be able to communicate in the normative modality—computer-based writing (Bazerman, 2012; Leu et al., 2014). This shift to computer-based writing is migrating to our K-12 schools (Graham et al., 2016), with assessments increasingly being given on computers (e.g., NAEP assessments; see Carr, 2017). Therefore, it is critical to expand our understanding about technology exposure and keyboard and mouse activity while writing and their relations to writing skills.

Students with more prior technology exposure showed a small increase in their writing scores, even in a 30-minute quick writing situation. More importantly, our analysis showed that not only did prior technology exposure have the expected impact on students' keyboard and mouse activity during the writing assessment, but that it had an independent effect on writing achievement over and above the transcription-level keyboarding effect. Prior technology exposure had a direct effect on writing achievement (.08) as well as an indirect effect through the students' keyboard activity (e.g., keypresses, .08). These results suggest that prior technology exposure for academic purposes captures experiences important to writing beyond what is captured in the keyboard activity. Unfortunately, understanding the exact mechanism of this relation is beyond the scope of the present study, but there are several potential explanations. First, frequent use of computers for academic purposes may have provided students with more opportunities with writing, which, in turn, improved writing (Warschauer, 2006, 2011). This speculation is consistent with a previous study's findings of no real benefit from the use of a computer for writing transcription over pen and pencil writing at the letter, word, or 10-minute essay level (Berninger, Abbott, Augsburger, & Garcia, 2009). Thus, while teaching students to type is a useful practice, schools would not want to limit computer-related instruction simply to typing, but rather to composing, editing, collaborating, and writing on computers in a more comprehensive and authentic manner. Second, students may have simply been able to compose their drafts more fluently because the experience of writing on computers reduced the cognitive load of transcription and freed them to ideate more effectively. Finally, other possible mechanisms include increased writing motivation through additional opportunities for collaboration, authentic writing, and modeling. Digital tools may have more impact on key social contexts than on writing at an individual cognitive level (Bruce, Michaels, & Watson-Gegeo, 1985).

We also found a small positive interaction effect of prior technology exposure and keypresses on writing achievement. That is, the benefits of prior technology exposure and the value of students' additional keypresses on writing achievement were amplified when both were present. Interaction effects do not show us which variable influenced the other. Perhaps students with more prior technology exposure benefitted more from their keypresses--from better habits and strategies, increased fluency, reduced cognitive load, or simply fewer ineffective keyboarding habits like excessive use of underlining or indenting. It is also possible that students with more keypresses, more output, were able to show increased benefits from their prior technology exposure experience in their written texts. Once again, it is possible that the contextual changes supported by practice writing digitally in school helped these students become better writers through the modelling and scaffolding provided by collaborative and authentic writing activities. While we did not find any moderating effect related to any other keyboard activity, this might be due to the small number of times students actually used the digital functionality of the computer. Very few students made much use of even the most popular features (see Table 1), so the variation in the other variables was quite limited.

Implications, Limitations, and Future Directions

Students need access to digital technology, as well as instruction and support in using it, in order to increase their practice writing on digital devices. If students are not given these tools and are not provided with explicit instruction on using them skillfully, they will be at a disadvantage on future assessments and in college and career preparation. We also note that in our analysis, students of all demographic backgrounds benefitted from increased practice in computer-based writing for school. However, the benefits were somewhat reduced for more disadvantaged or at-risk students. Future studies are needed to investigate the cause of such reduced benefits.

This research suggests several research opportunities. For example, we can explore the use of keypress count to indicate revision activity. Perhaps a ratio of word count to keypresses will provide an automated signal of revision activity that can be used to alert students and teachers to the need for additional revision work, for example. In addition, we should explore patterns of digital writing activity to develop interventions and improve instruction for all students. Again, once we better understand which patterns of keyboard and mouse use are productive and for which types of students, small automated nudges could be imbedded as writing supports in digital environments. Ultimately, the studies suggest that we need to understand effective digital writing practices well enough to explicitly and transparently instruct students in the use of digital affordances and ensure that students are competent digital writers regardless of socioeconomic background.

Our analysis has several limitations, some of which are inherent in the NAEP writing assessment itself. The NAEP assessment measures only two 30-minute writing sessions with 22 different prompts. The time limit means that the writing samples are rough drafts and not polished final versions. By design, the NAEP assessment is not reflective of students' abilities to edit and refine their work, although some editing during initial draft is expected. The time limit advantages students who are used to writing for similar lengths of time. The time limit may disadvantage students with language production disabilities or English-language learners who could use additional time; however, additional time could also frustrate other students and create fatigue (Applebee, 2011). In addition, the functionality of the NAEP interface used in the 2011 test could be improved, as seen during the usability studies conducted in 2012 (NCES, 2014a, 2014b) that led to simplified instructions and the addition of more icons on the toolbar, enlargement of text and icons, and rollover labels on the icons to increase the accessibility of the word processing tools. As these functionality improvements are made in future years, we might find that the interface is simpler and easier to use for students with less prior exposure to computers, which could, in turn, reduce the correlation of prior technology exposure with writing achievement. This analysis is also limited to modeling the effect of prior technology exposure on writing achievement. Simple reported frequency of use is not likely to capture the quality of instruction in computer-based writing, nor is student-reported frequency as accurate as real-time measures of technology exposure. Additional research in these areas could further inform our understanding of how students write on computers and how to improve their writing with digital technology.

References

Applebee, A.N. (2011). Issues in Large-Scale Writing Assessment. *Journal of Writing Assessment, 3*(2), 81-98.

Applebee, A.N., & Langer, J.A. (2011). A snapshot of writing instruction in middle schools and high schools. *The English Journal, 100*(6), 14-27.

Bangert-Drowns, R. (1993). The word processor as an instructional tool: A meta-analysis of word processing in writing instruction. *Review of Educational Research, 63* (1), 69-93.

Baron, R. M. and Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, (51), 1173–1182.

Bazerman, C. (2012). Writing, cognition and affect from the perspectives of sociocultural and historical studies of writing. *Past, present and future contributions of cognitive writing research to cognitive psychology*, 89-104.

Beaton, A., Rogers, A., Gonzalez, E., Hanly, M., Kolstad, A., Rust, K., Sikali, E., Stokes, L., & Jia, Y. (2011). *The NAEP Primer.* Washington, DC: National Center for Educational Statistics.

Berninger, V. W., Abbott, R. D., Augsburger, A., & Garcia, N. (2009). Comparison of pen and keyboard transcription modes in children with and without learning disabilities. *Learning Disability Quarterly, 32*(3), 123-141.

Berninger, V. W., & Swanson, H. L. (1994). Modifying Hayes and Flower's model of skilled writing to explain beginning and developing writing. *Children's writing: toward a process theory of the development of skilled writing* (Vol. 2, pp. 57-81). Greenwich, CT: JAI Press Inc.

Berninger, V. W., Whitaker, D., Feng, Y., Swanson, H. L., & Abbott, R. D. (1996). Assessment of planning, translating, and revising in junior high writers. *Journal of School Psychology, 34*(1), 23-52.

Bolter, J.D. (1991). Writing space: The computer, hypertext, and the history of writing. Hillsdale, New Jersey: Lawrence Erlbaum.

Bruce, B., Michaels, S., & Watson-Gegeo, K. (1985). How computers can change the writing process. *Language Arts*, *62*(2), 143-149.

Carnegie Council on Advancing Adolescent Literacy (2010). *Time to Act: An Agenda for Advancing Adolescent Literacy for College and Career Success*. New York, NY: Carnegie Corporation of New York. Retrieved from: https://www.carnegie.org/media/filer_public/8c/8d/8c8dfd82-b5fc-4bb9-8bd1-bb262175eaf4/ccny_report_2010_tta_agenda.pdf

Carr, P. (Oct. 31, 2017). Statement on NAEP's Transition to Digitally Based Assessments. https://nces.ed.gov/nationsreportcard/dba/statement.aspx

Costello, Anna B. & Jason Osborne (2005). Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis. *Practical Assessment Research & Evaluation, 10*(7). Available online: http://pareonline.net/getvn.asp?v=10&n=7

Deane, P., Odendahl, N., Quinlan, T., Fowles, M., Welsh, C., & Bivens-Tatum, J. (2008). Cognitive models of writing: Writing proficiency as a complex integrated skill. ETS Research Report Series, 2008(2).

Deane, P., Sabatini, J., & Fowles, M. (2012). Rethinking K-12 writing assessment to support best instructional practices. *International Advances in Writing Research: Cultures, Places, Measures*, 83-101.

De La Paz, S. & Graham, S. (2002). Explicitly teaching strategies, skills & knowledge: Writing instruction in middle school classrooms. *Journal of Education Psychology 94*(4), 687.

DeVoss, D. N., Eidman-Aadahl, E., & Hicks, T. (2010). *Because digital writing matters: Improving student writing in online and multimedia environments*. John Wiley & Sons.

Flower, L., & Hayes, J. R. (1981). A cognitive process theory of writing. *College Composition and Communication*, *32*(4), 365-387.

Goldberg, A., Russell, M., & Cook, A. (2003). The effect of computers on student writing: A meta-analysis of studies from 1992 to 2002. *The Journal of Technology, Learning and Assessment*, *2*(1).

Graham, S. (2012). Introduction to special issue on writing assessment and instruction. *Exceptionality, 20*, 197-198.

Graham, S., Bruch, J., Fitzgerald, J., Friedrich, L., Furgeson, J., Greene, K., Kim, J., Lyskawa, J., Olson, C.B., & Smither Wulsin, C. (2016). *Teaching secondary students to write effectively* (NCEE 2017-4002). Washington, DC: National Center for Education Evaluation and Regional Assistance (NCEE), Institute of Education Sciences, U.S. Department of Education. Retrieved from the NCEE website: http://whatworks.ed.gov.

Graham, S., & Hebert, M. (2010). *Writing to read: Evidence for how writing can improve reading: A report from Carnegie Corporation of New York*. Carnegie Corporation of New York.

Graham, S., McKeown, D., Kiuhara, S., & Harris, K. R. (2012). A meta-analysis of writing instruction for students in the elementary grades. *Journal of Educational Psychology, 104*(4), 879.

Graham, S., & Perin, D. (2007). A meta-analysis of writing instruction for adolescent students. *Journal of Educational Psychology, 99*(3), 445-476.

Hawisher, G. E. (1986). Studies in word processing. *Computers and Composition, 4*, 6-31. doi:10.1016/S8755-4615(86)80003-2

Hayes, J. R. (2012). Modeling and Remodeling Writing. *Written Communication, 29*(3), 369-388. doi:10.1177/0741088312451260

Institute of Education Sciences (2017). *Request for Applications* (CFDA number 84.305C). Washington, DC: US Department of Education.

Intersegmental Committee of the Academic Senates (ICAS) of the California Community Colleges, the California State University, and the University of California (2002). *Academic literacy: A statement of competencies expected of students entering California public colleges and universities.*

Johnson, E. G. (1992). The design of the national assessment of educational progress. *Journal of Educational Measurement, 29*(2), 95-110.

Kent, S. C., & Wanzek, J. (2016). The relationship between component skills and writing quality and production across developmental levels: A meta-analysis of the last 25 years. *Review of Educational Research, 86*(2), 570-601. doi:10.3102/0034654315619491

Kim, Y. S., Al Otaiba, S., Folsom, J. S., Greulich, L., & Puranik, C. (2014). Evaluating the dimensionality of first-grade written composition. Journal of Speech, Language, and Hearing Research, 57(1), 199-211.

Kim, Y. S., Al Otaiba, S., Puranik, C., Folsom, J. S., Greulich, L., & Wagner, R. K. (2011). Componential skills of beginning writing: An exploratory study. *Learning and Individual Differences*, *21*(5), 517-525.

Kim, Y. S., Al Otaiba, S., Wanzek, J., & Gatlin, B. (2015). Toward an understanding of dimensions, predictors, and the gender gap in written composition. *Journal of Educational Psychology, 107*(1), 79.

Kim, Y. S. G., & Schatschneider, C. (2017). Expanding the developmental models of writing: A direct and indirect effects model of developmental writing (DIEW). *Journal of Educational Psychology*, *109*(1), 35.

Leu, D., Forzani, E., Rhoads, C., Maykel, C., Kennedy, C. & Timbrell, N. (2015). The new literacies of online research and comprehension: Rethinking the reading achievement gap. *Reading Research Quarterly 50*(1), 37-59.

Little, T. (2013). *Longitudinal structural equation modeling.* New York: Guilford.

McCutchen, D. (1996). A capacity theory of writing: Working memory in composition. *Educational Psychology Review, 8,* 299–325.

McGrenere, J., & Ho, W. (2000). *Affordances: Clarifying and evolving a concept*. Paper presented at the Proceedings of Graphics Interface 2000, Montreal.

Messick, S., Beaton, A., & Lord, F. (1983). National Assessment of Educational Progress Reconsidered: A New Design for a New Era.

Morphy, P., & Graham, S. (2012). Word processing programs and weaker writers/readers: A meta-analysis of research findings. *Reading and Writing, 25*(3), 641-678.

National Assessment Governing Board (NAGB) (2010). *Writing Framework for the 2011 National Assessment of Educational Progress*. Washington, D.C.: U.S. Department of Education.

National Center for Education Research and National Center for Special Education Research (2017). *Future directions for writing research at the secondary level*. Technical

Working Group Meeting Summary Report. Washington, DC: Institute of Education Sciences, U.S. Department of Education. https://ies.ed.gov/ncer/whatsnew/techworkinggroup/pdf/WritingTWG.pdf

National Center for Education Statistics (NCES, 2009). *The Nation's Report Card: An overview of procedures for the NAEP Assessment.* (NCES-2009-493) Washington, DC: Institute of Education Sciences, U.S. Department of Education.

National Center for Education Statistics (NCES, 2012). *The Nation's Report Card: Writing 2011*. (NCES 2012-4700) Institute of Education Sciences, Washington, DC: U.S. Department of Education. http://nces.ed.gov/nationsreportcard/pdf/main2011/2012470.pdf

National Center for Education Statistics (NCES, 2014a), *Lessons Learned from the 2012 Grade 4 Writing Computer-based Assessment Study*, Washington, DC: Institute of Education Sciences, U.S. Department of Education. Retrieved from: http://nces.ed.gov/nationsreportcard/writing/lessons/default.aspx

National Center for Education Statistics (NCES, 2014b), *NAEP 2012 Pilot Writing Computer-Based Assessment Study--Grade 4: Technical Memorandum,* Washington, DC: Institute of Education Sciences, U.S. Department of Education.

The National Commission on Writing for America's in America's Schools and Colleges (2003). *The Neglected "R": The Need for a Writing Revolution*. College Entrance Examination Board. http://www.collegeboard.com/prod_downloads/writingcom/neglectedr.pdf

The National Commission on Writing for America's Families, Schools, and Colleges (2004). *Writing: A Ticket to* Work. College Entrance Examination Board. Retrieved from: http://www.collegeboard.com/prod_downloads/writingcom/writing-ticket-to-work.pdf

Nystrand, M., Greene, S., & Wiemelt, J. (1993). Where did composition studies come from? An intellectual history. *Written Communication*, *10*(3), 267-333.

Peterson, S. S., & McClay, J. K. (2012). Assumptions and practices in using digital technologies to teach writing in middle-level classrooms across Canada. *Literacy*, *46*(3), 140-146.

Prior, P. (2006). A sociocultural theory of writing. Handbook of writing research, 54-66.

Purcell, K., Buchanan, J., & Friedrich, L. (2013). The impact of digital tools on student writing and how writing is taught in schools. *Washington, DC: Pew Research Center*.

Rogers, A., Stoeckel, J., & Sikali, E. (2013). *National Assessment of Educational Progress (NAEP) 2011 Writing Assessment Restricted-Use Data Files Data Companion.* Washington, D.C.: National Center for Education Statistics.

Scribner, S., & Cole, M. (1981). *The psychology of literacy* (Vol. 198, No. 1). Cambridge, MA: Harvard University Press.

Sperling, M., & Freedman, S. W. (2001). Research on writing. Handbook of research on teaching, 4, 370-389.

Tate, T., & Warschauer, M. What's in a Keystroke? Analysis of the 2011 NAEP Computer-Based 8th Grade Writing Assessment. *Technology, Knowledge, & Learning.*

Tate, T., Warschauer, M., & Abedi, J. (2016). The Effects of Prior Computer Use on Computer-Based Writing: The 2011 NAEP Writing Assessment, *Computers & Education, 101*, 115-131. doi:10.1016/j.compedu.2016.06.001

Van Ittersum, D. (2011). Augmenting Literacy: The Role of Expertise in Digital Writing. *Composition Studies, 39*(2), 61-77.

Warschauer, M. (2006). *Laptops and literacy: Learning in the wireless classroom*. NY: Teachers College Press.

Warschauer, M. (2011). *Learning in the cloud*. Teachers College Press.

Wertsch, J. V. (1991). *A sociocultural approach to socially shared cognition*. Oxford, UK: Oxford University Press.

Wertsch, J. V. (1998). *Mind as action*. Oxford, UK: Oxford University Press.

Yim, S., Warschauer, M., Zheng, B., & Lawrence, J. (2014). Cloud-Based Collaborative Writing and the Common Core Standards, *Journal of Adolescent & Adult Literacy 58*(3) 243-254.

Zheng, B**.,** Warschauer, M., Lin, C.-H., & Chang, C. (2016). Learning in one-to-one laptop environments: A meta-analysis and research synthesis. *Review of Educational Research, XX*(X), 1-33. doi:10.3102/0034654316628645

Zwick, R. (1987). Assessing the dimensionality of NAEP reading data. *Journal of Educational Measurement, 24*(4), 293-30.

Table 1

Descriptive Statistics

	Scale Approximation	Mean	Standard Deviation	Variance	Skewness	Kurtosis
Keyboard Activity Variables						
Keypresses	2000<K<3000	2.73	0.97	0.94	0.41	2.81
Cut	Almost never	1.15	0.40	0.16	2.78	10.36
Copy	Almost never	1.20	0.46	0.22	2.26	7.41
Paste	Almost never	1.24	0.51	0.26	2.07	6.46
Bold	Half used 1x	1.66	1.00	1.01	1.32	3.36
Italic	Half used 1x	1.56	0.96	0.92	1.57	4.13
Underscore	Half used 1x	1.44	0.86	0.73	1.91	5.53
Indent	¾ used 1x	1.79	1.23	1.52	1.71	5.28
Outdent	Half used 1x	1.58	1.04	1.09	2.18	7.71
Spellcheck	1-2 times	2.84	1.50	2.24	0.29	1.64
Thesaurus	Maybe 1x	1.40	0.69	0.47	1.41	3.55
Highlight	Maybe 1x	1.53	0.61	0.38	0.70	2.52
Text-to-Speech	1-2x	2.52	1.20	1.44	0.02	1.46
Backspace	201-300	4.06	1.18	1.40	0.08	2.12
Delete	Almost never	1.10	0.30	0.09	2.62	7.89
Student-Reported Frequency of Prior Technology exposure for Different School Purposes						
Use Internet to Get Information	Very often	2.93	1.04	1.07	1.00	7.24
Write a First Draft	Often	2.44	1.15	1.33	1.27	7.03
Make Changes in Writing	Very often	2.79	1.17	1.38	0.79	5.77
Complete Draft	Very often	2.97	1.20	1.44	0.51	5.08
Write School Assignments	Weekly	2.46	1.06	1.13	1.74	10.14
Scaled Writing Achievement						
WNORM11	N/A	-0.04	0.96	0.92	0.14	2.66

Note. Keyboard activity variables are raw scores with different scales. Keypresses: 1 = 0-1000; 2 = 1001-2000; 3 = 2001-3000; 4 = 3001-4000; 5 = 4001 or more; Cut, copy, paste, thesaurus, text-to-speech: 1 = never used, 2 = used once, 3 = used two or more times; Bold, italic, underscore: 1-4 = 0-3 uses; Indent, outdent: 1-7 = 0-6 or more uses; Spellcheck: 1-5 = 0-4 uses; Highlight: 1 = 0; 2 = 1-6; 3 = 7 or more uses; Backspace: 1 = 0; 2 = 1-100; 3 = 101-200; 4 = 201-300; 5 = 301-400; 6 = 401-500; 7 = 501 or more uses; Delete: 1 = 0; 2 = 1 or more uses. For prior technology exposure variables, *s*tudent responses ranged from 1 (never or hardly ever), 2 (sometimes), 3 (very often), to 4 (almost always or always) for all except the last variable regarding use of the computer to write school assignments, which ranged from 1 (never or hardly ever), 2 (once/twice a month), 3 (once/twice a week), to 4 (almost every day or every day).

Table 2

Correlation Matrix of Writing Score, Prior Technology Exposure, and Keyboard and Mouse Activity Variables

	Writing	Word Count	Keypresses	Prior Use	Cut	Copy	Paste	Bold	Italic	Underscore	Indent	Outdent	Spellcheck	Thesaurus	Highlight	Text-2-speech	Backspace
Writing	--																
Word Count	0.77*	--															
Keypresses	0.71*	0.87*	--														
Prior Use	0.20*	0.16*	0.16*	--													
Cut	-0.04*	-0.06	-0.02	0.04*	--												
Copy	-0.04*	-0.06*	-0.03*	0.04*	0.26*	--											
Paste	-0.01	-0.04*	-0.01	0.05*	0.42*	0.71*	--										
Bold	-0.07*	-0.07*	-0.05*	-0.02*	0.12*	0.12*	0.12*	--									
Italic	0.01	-0.02*	0.00	0.01	0.12*	0.12*	0.11*	0.52*	--								
Underscore	0.00	-0.03*	-0.01	0.01	0.11*	0.12*	0.12*	0.48*	0.44	--							
Indent	0.02*	-0.02*	-0.01	-0.01	0.08*	0.08*	0.08*	0.17*	0.14*	0.15*	--						
Outdent	0.02*	-0.02*	-0.01	0.00	0.07*	0.07*	0.06*	0.15*	0.13*	0.14*	0.82*	--					
Spellcheck	-0.10*	-0.07*	-0.07*	-0.04*	0.02*	0.06*	0.05*	0.11*	0.09*	0.08*	0.10*	0.09*	--				
Thesaurus	0.14*	0.04*	0.08*	0.08*	0.08*	0.09*	0.11*	0.08*	0.11*	0.10*	0.11*	0.11*	0.10*	--			
Highlight	-0.10*	-0.12*	-0.10*	0.03*	0.11*	0.10*	0.10*	0.21*	0.17*	0.17*	0.11*	0.11*	0.10*	0.14*	--		
Text-2-speech	-0.20*	-0.22*	-0.20*	-0.01	0.10*	0.10*	0.10*	0.19*	0.14*	0.14*	0.09*	0.09*	0.11*	0.10*	0.47*	--	
Backspace	0.36*	0.41*	0.61*	0.09*	0.01	0.03*	0.03*	-0.01	0.01*	0.01	0.01	0.01	-0.04*	0.08*	-0.07*	-0.12*	--
Delete	0.10*	0.08*	0.09*	0.07*	0.05*	0.04*	0.07*	0.02*	0.03*	0.03*	0.03*	0.03*	-0.02*	0.08*	0.04*	0.03*	0.08*

* $p < 0.05$.

Table 3

Results of Principal Factor Analysis with Rotation

Variable	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Uniqueness
Cut	0.00	0.02	0.04	**0.45**	-0.01	-0.02	-0.00	0.77
Copy	0.01	0.01	**0.79**	-0.05	0.01	0.02	0.00	0.42
Paste	-0.01	-0.02	**0.64**	0.21	0.00	-0.02	0.01	0.32
Bold	0.01	**0.69**	0.01	-0.01	-0.00	0.03	-0.03	0.52
Italic	-0.02	**0.66**	-0.01	0.01	0.01	-0.01	0.02	0.57
Underscore	0.01	**0.62**	0.00	0.01	-0.01	0.00	0.01	0.62
Indent	**0.86**	0.01	0.00	0.00	-0.00	-0.02	-0.01	0.26
Outdent	**0.87**	-0.01	-0.01	-0.01	-0.01	-0.00	0.01	0.26
Spellcheck	0.02	0.02	0.02	-0.01	0.23	0.03	-0.03	0.93
Thesaurus	0.02	0.01	-0.01	0.06	0.18	0.05	0.21	0.88
Highlight	0.01	0.07	0.02	0.01	0.07	0.52	0.06	0.65
Text-to-Speech	0.00	0.03	0.02	0.01	0.07	0.55	-0.00	0.65
Backspace	-0.00	0.02	0.02	-0.02	0.01	-0.16	0.25	0.91
Delete	0.01	0.00	0.01	0.02	-0.03	0.06	0.25	0.94

Table 4

Regression Models for the Relation Between Prior Technology Exposure and Keyboard and Mouse Activity (Path A)

	Model 1 In/Outdent	Model 2 Word Format	Model 3 Copy/Paste	Model 4 Cut	Model 5 Keypresses
Prior Technology Exposure	-0.01	0.01	0.05*	0.04*	0.14*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female	-0.01	0.02	0.03	-0.01	0.56*
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Black	0.08*	0.09*	0.10*	0.05*	-0.36*
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
Hispanic	0.06*	0.00	0.08*	0.04*	-0.08*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Asian	-0.04	-0.01	0.15*	0.12*	0.42*
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
Other	0.11	0.14	0.15	-0.13	0.01
	(0.07)	(0.11)	(0.10)	(0.08)	(0.12)
Free/Reduced Lunch	0.00	0.09*	0.03*	0.01	-0.21*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Parent College	-0.02	-0.01	0.04	0.01	0.14*
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
Former ELL	-0.01	-0.10*	0.02	-0.05	-0.03
	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)
Current ELL	-0.15*	-0.02	0.08	0.05	-0.35*
	(0.03)	(0.04)	(0.05)	(0.04)	(0.03)
Student w/ Disability	-0.15*	-0.05*	0.06	0.01	-0.54*
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)
Constant	0.01	-0.05*	-0.11*	-0.04*	-0.09*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
N	18460	19960	19960	19960	19960
R square	0.004	0.004	0.006	0.003	0.218

*$p < .05$

Note. Models show each keyboard activity variable regressed on student-reported prior use of computers for school writing. Standard errors are shown in parentheses. Sample sizes are rounded to the nearest 10. All independent variables are standardized except dichotomous dummies. Models use Stata's survey estimation command (svy) to allow for jackknife weighting.

Table 5

Regression Models for the Relation between Keyboard and Mouse Activity and Writing Achievement (Path B)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
In/Outdent	-0.01					0.01
	(0.01)					(0.01)
Word Format		-0.02*				-0.01*
		(0.01)				(0.00)
Copy/Paste			-0.01			0
			(0.01)			(0.00)
Cut				-0.02*		-0.02*
				(0.00)		(0.01)
Keypresses					0.56*	0.57*
					(0.01)	(0.01)
Female	0.45*	0.45*	0.45*	0.45*	0.12*	0.12*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Black	-0.44*	-0.43*	-0.43*	-0.43*	-0.23*	-0.23*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Hispanic	-0.15*	-0.15*	-0.15*	-0.15*	-0.10*	-0.10*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Asian	0.20*	0.20*	0.20*	0.20*	-0.06	-0.06*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Other	-0.15	-0.13	-0.14	-0.14	-0.15	-0.17
	(0.13)	(0.14)	(0.14)	(0.14)	(0.09)	(0.09)
Free/Reduced Lunch	-0.34*	-0.34*	-0.34*	-0.34*	-0.21*	-0.21*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Parent College	0.25*	0.24*	0.24*	0.24*	0.14*	0.14*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Former ELL	-0.12*	-0.11*	-0.11*	-0.11*	-0.09*	-0.10*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Current ELL	-0.74*	-0.73*	-0.72*	-0.72*	-0.52*	-0.53*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Student w/ Disability	-0.77*	-0.76*	-0.76*	-0.76*	-0.45*	-0.45*
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	0.04	0.03	0.03	0.03	0.09*	0.09*
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	18460	19950	19950	19950	19950	18460
R square	0.3	0.297	0.296	0.296	0.582	0.588

*$p < .05$

Note. Models show writing achievement regressed on keyboard activity variables both individually (Models 1-5) and aggregated (Model 6). Standard errors are shown in parentheses. Sample sizes are rounded to the nearest 10. All independent variables are standardized except dichotomous dummies. Models use Stata's survey estimation command (svy) to allow for jackknife weighting.

Table 6

Regression Models for the Relation between Prior Technology Exposure and Writing Achievement (Path C), Including Interactions Between Prior Technology Exposure and Keyboard and Mouse Activity (Path D)

	Model 1	Model 2	Model 3
Prior Technology Exposure	0.16*	0.08*	0.08*
	(0.01)	(0.01)	(0.01)
Female	0.42*	0.11*	0.11*
	(0.01)	(0.01)	(0.01)
Black	-0.43*	-0.24*	-0.23*
	(0.03)	(0.02)	(0.02)
Hispanic	-0.14*	-0.10*	-0.10*
	(0.02)	(0.01)	(0.01)
Asian	0.17*	-0.07*	-0.08*
	(0.04)	(0.03)	(0.03)
Other	-0.14	-0.17	-0.16
	(0.14)	(0.09)	(0.09)
Free/Reduced Lunch	-0.31*	-0.19*	-0.19*
	(0.02)	(0.01)	(0.01)
Parent College	0.20*	0.12*	0.12*
	(0.02)	(0.01)	(0.01)
Former ELL	-0.10*	-0.10*	-0.10*
	(0.04)	(0.03)	(0.03)
Current ELL	-0.71*	-0.52*	-0.52*
	(0.02)	(0.02)	(0.02)
Student w/ Disability	-0.75*	-0.45*	-0.45*
	(0.03)	(0.02)	(0.02)
In/Outdent		0.01	0.01
		(0.01)	(0.01)
Word Format		-0.01*	-0.01*
		(0.00)	(0.00)
Copy/Paste		-0.01	0.00
		(0.01)	(0.00)
Cut		-0.02*	-0.02*
		(0.01)	(0.01)
Keypresses		0.56*	0.55*
		(0.01)	(0.01)
Prior Technology Exposure x In/Outdent			0.00
			(0.01)

Prior Technology Exposure x Word Format			0.00
			(0.01)
Prior Technology Exposure x Copy/Paste			0.00
			(0.01)
Prior Technology Exposure x Cut			0.01
			(0.01)
Prior Technology Exposure x Keypresses			0.03*
			(0.01)
Constant	0.05*	0.10*	0.09*
	(0.03)	(0.02)	(0.02)
N	18460	18460	18460
R square	0.32	0.59	0.59

Note. Model 1 shows writing achievement regressed on prior technology exposure; Model 2 adds keyboard and mouse activity independent variables; Model 3 adds interactions between prior technology exposure and keyboard and mouse activity variables. Standard errors are shown in parentheses. Sample sizes are rounded to the nearest 10. All independent variables are standardized except dichotomous dummies. Models use Stata's survey estimation command (svy) to allow for jackknife weighting.

Table 7

Regression Model for the Relation Between Prior Technology Exposure and Writing Achievement, Including Interactions of Demographics With Keyboard and Mouse Activity and Prior Technology Exposure

	Writing Score	*t*
Prior Technology Exposure	.09 (.01)	6.20
Female	0.11 (0.01)	10.30
Black	-0.23 (0.02)	-13.90
Hispanic	-0.10 (0.01)	-7.33
Asian	-0.07 (0.03)	-2.22
Other	-0.16 (0.09)	1.87
Free/Reduced Lunch	-0.19 (0.01)	-14.68
Parent College	0.12 (0.01)	9.77
Former ELL	-0.10 (0.03)	-3.48
Current ELL	-0.57 (0.03)	-18.08
Student w/ Disability	-0.45 (0.03)	-16.64
In/Outdent	0.02 (0.01)	2.13
In/Outdent x Free/Reduced Lunch	-0.01 (0.01)	-0.74
In/Outdent x Parent College	-0.03 (0.01)	2.55
In/Outdent x Current ELL	0.02 (0.02)	0.84
In/Outdent x Former ELL	0.07 (0.03)	2.56
In/Outdent x Student w/ Disability	0.04 (0.01)	2.98
Word Format	-0.01 (0.01)	-1.36
Word Format x Free/Reduced Lunch	0 (0.01)	-0.35
Word Format x Parent College	0 (0.01)	0.39
Word Format x Current ELL	0.01 (0.02)	0.37
Word Format x Former ELL	-0.01 (0.02)	-0.27
Word Format x Student w/ Disability	0.01 (0.02)	0.37
Copy/Paste	-0.01 (0.01)	-0.60
Copy/Paste x Free/Reduced Lunch	0.01 (0.01)	0.75
Copy/Paste x Parent College	0.00 (0.01)	-0.15
Copy/Paste x Current ELL	-0.06 (0.03)	-2.28
Copy/Paste x Former ELL	-0.03 (0.03)	-1.02
Copy/Paste x Student w/ Disability	0.02 (0.02)	1.29
Cut	-0.02 (0.01)	-1.96
Cut x Free/Reduced Lunch	-0.01 (0.01)	-1.23
Cut x Parent College	0.01 (0.01)	1.33
Cut x Current ELL	-0.01 (0.02)	-0.55
Cut x Former ELL	0 (0.03)	0.04

Cut x Student w/ Disability	-0.02 (0.02)	-1.11
Keypresses	0.55 (0.01)	43.01
Keypresses x Free/Reduced Lunch	-0.02 (0.01)	-1.80
Keypresses x Parent College	0.02 (0.01)	1.90
Keypresses x Current ELL	-0.10 (0.04)	-2.96
Keypresses x Former ELL	0.01 (0.02)	0.38
Keypresses x Student w/ Disability	0.01 (0.02)	0.49
Prior Technology exposure x Free/Reduced Lunch	-0.03 (0.01)	-2.40
Prior Technology Exposure x Parent College	0.03 (0.01)	1.95
Prior Technology Exposure x Current ELL	-0.05 (0.02)	-2.17
Prior Technology Exposure x Former ELL	-0.02 (0.02)	-0.78
Prior Technology Exposure x Student w/ Disability	-0.05 (0.02)	-2.53
Constant	0.09 (0.02)	5.69
N	18460	
R square	0.60	

Note. Standard errors are shown in parentheses. Sample sizes are rounded to the nearest 10. All independent variables are standardized except dichotomous dummies. Models use Stata's survey estimation command (svy) to allow for jackknife weighting.

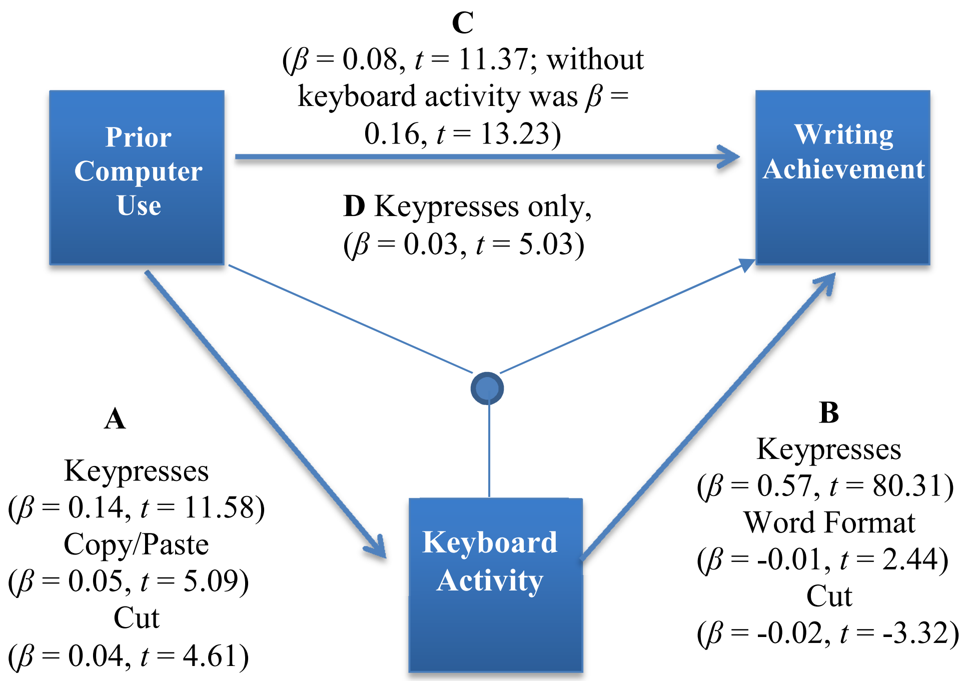


Figure 1. Final partial mediation and moderation model. Some keyboard and mouse activity during the test (keypresses, copy/paste, and cut, as shown above) is impacted by prior technology exposure (Path A). Some keyboard and mouse activity predicts writing achievement (Path B; keypresses, word format, and cut), and prior technology exposure has an independent direct effect on writing achievement (Path C). Only keypresses and cut are on both Path A and Path B. The effect of prior technology exposure and keypresses (but not other keyboard activity; Path D) on writing achievement is moderated.

CHAPTER 5

Discussion and Conclusion

The 2011 NAEP writing assessment provided our first national look at students' digital writing in a rigorous setting. We are able to triangulate our understanding of eighth graders' digital writing practice by looking at their writing achievement scores, their keyboarding and mouse activity while producing the assessment text, and their prior technology exposure as reported by both students and teachers. Each of the three studies took advantage of at least two of these types of data to examine middle school students' digital writing.

Summary of Findings

Study one looked primarily at the relationship between teacher and student reports of prior technology use and student writing achievement. We showed that use of technology for school-related purposes predicted increased writing achievement. Perhaps more surprising, however, we found that use of technology for personal purposes, writing emails, blogging, etc., did not predict improved (or reduced) writing achievement. The fact that school-related digital writing had a greater impact on the students' achievement on the NAEP assessment than did personal, casual technology exposure is consistent with the large research base showing the need for technology to be implemented in instructionally sound ways (see discussion in Warschauer, 2011). Simply putting digital tools in students' hands will not improve their learning (OECD, 2015). Rather, the tools must be integrated in a way that supports and extends the curriculum in meaningful ways (Warschauer, 2011). For those that argue students today are "digital natives" and will be able to compose digital texts with little explicit teaching, these results argue that specific skills are required for successful academic digital writing. Students need to learn how to navigate the digital space of their texts and use editing tools like cut and paste effectively to reorganize their initial drafts. The good news? For those concerned about a digital divide, differential levels of student home access to devices did not increase the difference in academic achievement. Our analysis was supported by the finding that prior technology exposure did not predict as large of an increase in writing achievement when the assessment was done on paper in the 2007 NAEP assessment.

We also found that students' reporting of their digital practices was more predictive than teacher reports of class use. There were some indications that the benefits of prior use might be amplified if the student's parents graduated college and slightly reduced for those who were eligible for free/reduced lunch, currently designated ELLs, or had a disability. These results were not consistent across our measures, but suggest that further group analyses would be appropriate to capture individual and group differences.

Other important findings include that teacher professional development and teacher instruction using technology were not significant predictors of improved writing achievement. Obviously I would not suggest that teacher development and instruction should be abandoned. I suggest instead that teacher professional development and instruction using technology needs to be done in more authentic, contextually-situated ways (see discussion in Zinger, Tate, & Warschauer, 2017). Teachers need to learn and practice using technology in support of specific curricular goals and types of content, rather than be subjected to generic instruction that has little relevance to how to actually use the technology to enhance instruction and pedagogy. Time for teacher collaboration to design and practice digital writing and instruction in context is important. Until these types of opportunities are more widely available, it is unlikely that reported development and instruction will show any predictive effect on student writing achievement.

Study two looked at the relationship between the actual keyboard and mouse activity by students during the assessment and their writing achievement. For the first time, researchers have the ability to consider the keystroke-level differences between students' texts in a national digital writing assessment. Not only were we able to show that students who write more (both words and keypresses) predicted higher achievement outcomes, but for the first time we were able to gather descriptive information about how often students use editing tools (hardly at all) and begin to use datamining techniques like cluster analysis to look at whether students exhibited different patterns of keyboard and mouse usage and how these patterns related to both writing achievement and prior technology exposure.

In 2011, eighth grade students rarely used tools like spellcheck or thesaurus, or even cut and paste, when writing for a 30 minute assessment. It is important to contextualize this finding. At this time, students were much less familiar with digital writing than they are today; today's students would be expected to be more familiar with the digital tool and use more of its affordances. Hopefully, we will be able to measure this the next time the NAEP writing assessment is given and the data is released. In addition, a 30-minute writing period leaves much less time for editing than a multi-day writing project might. Future studies situated in more process-based writing classes will be able to discern whether without the time constraint students would have used the editing affordances more.

The cluster analysis did show that students have different writing patterns. There were at least 5 types of writers who shared similar writing practices, with these practices associated to higher and lesser degrees with effective writing: *Typing Only, Unproductive Activity, High Delete, High Indent, and Productive Activity.* The practices are more (*Productive Activity*) or less (*Unproductive Activity*) effective at supporting high quality writing. Students with more experience with technology use were more likely to be Sophisticated Users and less likely to be Playing Around. Of course, this is only the beginning of looking at students' digital writing practices. Future work will require access to the texts as written, longer writing periods, and qualitative observations of students writing in classrooms.

In study three, we put the information from the prior studies together and modeled the relationship among all three of our variables of interest: prior technology exposure, keyboard and mouse activity during the assessment, and writing achievement scores. In order to reduce the number of keyboard and mouse activity variables, we used factor analysis and found four factors: (1) indent and outdent; (2) bold, italic, and underscore; (3) copy and paste, and (4) cut. Regressing these factors on prior technology exposure, we found that prior technology exposure predicted keypresses, copy/paste, and cut, but not indent and outdent or bold, italic, and underscore. So prior technology exposure only played a partial role in predicting students' writing practices during the assessment. Looking at the relationship between keyboard and mouse activity and writing achievement, we found that only keypresses and bold, italic, and underscore predicted writing achievement. The strength of prior technology exposure predicting writing achievement was reduced in half from $\beta = 0.16$, ($t = 13.23$) to $\beta = 0.08$ ($t = 11.37$) once keyboard and mouse activity was added to the model. We found evidence that a large portion of the impact of prior technology exposure on writing achievement is mediated primarily by keypresses. Keypresses was also the only moderating variable we found. The data supported a partial mediation and (with respect only to keypresses) moderation model.

Students with more prior technology exposure showed a small increase in their writing scores, even in a 30-minute quick writing situation. More importantly, our analysis showed that not only did prior technology exposure have the expected impact on students' keyboard and mouse activity during the writing assessment, but that it had an independent effect on writing achievement over and above the transcription-level keyboard and mouse activity effect. Prior technology exposure had a direct effect on writing achievement as well as an indirect effect through the students' keyboard and mouse activity. These results suggest that prior technology exposure for academic purposes captures experiences important to writing beyond what is captured in the keyboard and mouse activity, which would be expected since writing is influenced by the tools used (Bolter, 1991; Wertsch, 1991).

In addition to model-building, study three also examined group differences. We found differences in the effect of keypresses on writing for different demographic groups (see Table 7), with decreased values for students qualifying for free/reduced lunch (approaching significant, $\beta = -0.02$, $t = -1.80$) and for current ELLs ($\beta = -0.10$, $t = -2.96$), but an increased value for students with a parent who graduated college (approaching significant, $\beta = 0.02$, $t = 1.90$). The relationship between other keyboard and mouse activity variables and writing achievement did not generally differ by demographics, except that the slight negative impact of copy/paste became larger for students currently classified as ELL. We also found that the small positive impact of in/outdent on writing achievement became negative in the case of students with a parent who graduated college, while former ELL students received additional positive benefit, as did students with a disability. We found no statistically significant interactions for the word formatting or cut variables. We found that all students benefited from prior technology exposure, but the benefit was reduced for students from low SES backgrounds, for ELL students, and for students identified as disabled.

Implications

Given the importance of digital writing in the workforce and in academia (DeVoss, Eidman-Aardahl, & Hicks, 2010), students need to be able to communicate in the normative modality (Bazerman, 2012; Leu et al., 2014). It is critical to expand our understanding about prior technology exposure and keyboard and mouse activity and their relations to writing skills.

Given the prevalence of digital writing, writing in K-12 schools should at least in part consist of digital writing. Schools are situated to provide the necessary access, instruction, and support to enable students to become proficient writers on computers. Because disparities in access to technology and the Internet remain significant (Darling-Hammond, Zielezinski, & Goldman, 2014), both at home and at school, improving school use of computers for writing can help reduce the digital divide. If students are not given these tools and are not provided with explicit instruction on using them skillfully, they will be at a disadvantage on future assessments and in college and career preparation. We also note that in our analysis, students of all demographic backgrounds benefitted from increased practice in computer-based writing for school. However, the benefits were somewhat reduced for more disadvantaged or at-risk students. Future studies are needed to investigate the cause of such reduced benefits.

Despite the lack of statistical findings with respect to teacher's use of technology to provide writing instruction, teachers should still be encouraged to incorporate technology into their lessons. Tools that make writing visible, by the teacher, the student, and peers, still provide useful instruction. They are also increasingly the way writing is done in professional and academic settings, with collaboration becoming increasingly important. Similarly, teachers' need for quality professional development in integrating technology into quality curriculum remains despite the lack of a direct statistically significant effect in our analysis.

Limitations and Directions for Future Studies

These analyses have several limitations, some of which are inherent in the NAEP writing assessment itself. The NAEP assessment measures only two 30-minute writing sessions with 22 different prompts. The time limit means that the writing samples are rough drafts and not polished final versions. By design, the NAEP assessment is not reflective of students' abilities to edit and refine their work, although some editing during initial draft is expected. The time limit advantages students who are used to writing for similar lengths of time. The time limit may disadvantage students with language production disabilities or English-language learners who could use additional time; however, additional time could also frustrate other students and create fatigue (Applebee, 2011).

The NAEP assessment is also less authentic than classroom writing might be. Future studies of both longer, process writing practices, and classroom-based low stakes writing would provide additional depth to our understanding of how students write and what approaches lead to better writing quality in the end.

In addition, the functionality of the NAEP interface used in the 2011 test could be improved, as seen during the usability studies conducted in 2012 (NCES, 2014a, 2014b) that led to simplified instructions and the addition of more icons on the toolbar, enlargement of text and icons, and rollover labels on the icons to increase the accessibility of the word processing tools. As these functionality improvements are made in future years, we might find that the interface is simpler and easier to use for students with less prior exposure to computers, which could, in turn, reduce the correlation of prior technology exposure with writing achievement.

This analysis is also limited to modeling the effect of prior technology exposure on writing achievement. Simple reported frequency of use is not likely to capture the quality of instruction in computer-based writing, nor is student-reported frequency as accurate as real-time measures of technology exposure.

The NAEP data does not include the actual text produced by students for the assessment. Future studies would benefit from textual analysis and qualitative observations of student writing practices to better understand the reasons for some of the practices we saw and how they may impact writing quality. Interventions around quality writing instruction, and quality teacher development, are also clearly needed and areas of future study.

The field of adolescent digital writing research is fairly nascent, and the need for both depth and breadth in future studies is clear. Additional research in these areas could further inform our understanding of how students write on computers and how to improve their writing with digital technology. This understanding can then inform our instructional practices for diverse learners of all types.

Conclusion

Digital writing is increasing in importance and research is needed to help educators understand the differences (and similarities) with writing by hand. Research on adolescent writing is particularly sparse, yet we know adolescents need better education in writing effectively. Digital writing seems a natural fit to increase the authenticity and interest level for secondary school students as they practice and develop improved writing skills. Finally, one of the affordances for researchers of digital writing is the new types of information and data analyses we are able to do with the potentially vast amounts of data on student writing practices. Data mining techniques are available to illuminate the writing patterns and practices of diverse students, so we can better understand what leads to improved writing quality for all students. This look at the first national digital writing assessment lays the groundwork for future studies in improving the quality of prior digital writing practice and writing practices by adolescents by showing the clear and layered relationships between prior practice writing digitally for school, the actual process of writing, and ultimately, writing quality.

References

Applebee, A.N. (2011). Issues in Large-Scale Writing Assessment. *Journal of Writing Assessment, 3*(2), 81-98.

Bazerman, C. (2012). Writing, cognition and affect from the perspectives of sociocultural and historical studies of writing. *Past, present and future contributions of cognitive writing research to cognitive psychology*, 89-104.

Bolter, J.D. (1991). Writing space: The computer, hypertext, and the history of writing. Hillsdale, New Jersey: Lawrence Erlbaum.

Darling-Hammond, L., Zielezinski, M. B., & Goldman, S. (2014). Using technology to support at-risk students' learning. *Stanford Center for Opportunity Policy in Education. Online https://edpolicy. stanford. edu/publications/pubs/1241*.

De La Paz, S., & Graham, S. (2002). Explicitly teaching strategies, skills, and knowledge: Writing instruction in middle school classrooms. *Journal of Educational Psychology, 94*(4), 687-698.

DeVoss, D. N., Eidman-Aadahl, E., & Hicks, T. (2010). *Because digital writing matters: Improving student writing in online and multimedia environments*. John Wiley & Sons.

Leu, D., Forzani, E., Rhoads, C., Maykel, C., Kennedy, C. & Timbrell, N. (2015). The new literacies of online research and comprehension: Rethinking the reading achievement gap. *Reading Research Quarterly 50*(1), 37-59.

National Center for Education Statistics (2014a). *Lessons Learned from the 2012 Grade 4 Writing Computer-based Assessment Study*. Washington, D.C.: Institute of Education Sciences, U.S. Department of Education. Retrieved from http://nces.ed.gov/nationsreportcard/writing/lessons/default.aspx.

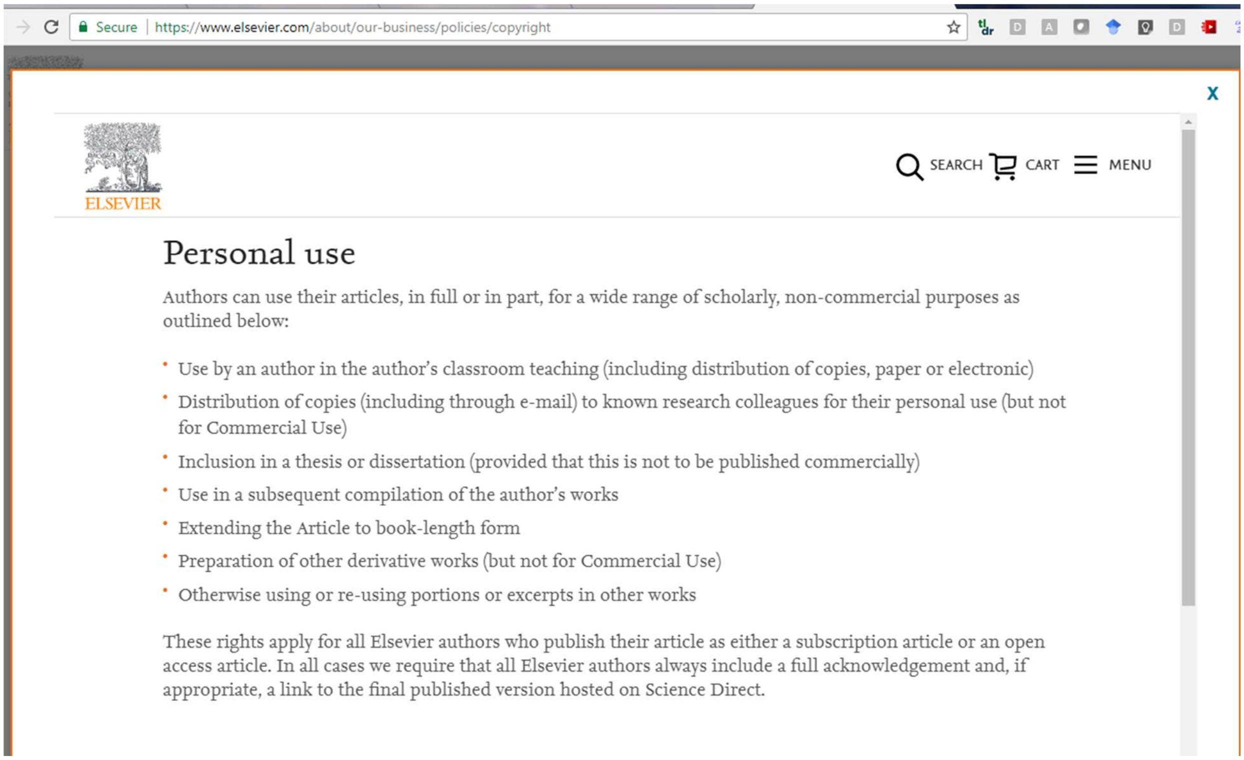
National Center for Education Statistics (2014b). *NAEP 2012 Pilot Writing Computer-Based Assessment Study--Grade 4: Technical Memorandum*. Washington, D.C.: Institute of Education Sciences, U.S. Department of Education.

Organisation for Economic Co-operation and Development (OECD) (2015). *Students, Computers and Learning: Making the Connection*. Retrieved from http://dx.doi.org/10.1787/9789264239555-en

Warschauer, M. (2011). *Learning in the cloud: How (and why) to transform schools with digital media.* NY: Teachers College Press.

Wertsch, J. V. (1991). *Voices of the mind: A sociocultural approach to mediated action*. Cambridge, MA: Harvard University Press.

Zinger, D., Tate, T**.,** Warschauer, M., (2017). Learning and teaching with digital media: Technological pedagogy and classroom practice. In J. Clandinin, & J. Husu (Eds.) *The SAGE Handbook of Research on Teacher Education.* (pp. 577-593) London, UK: SAGE



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