Will, Skill or Conscientiousness: What Predicts Teachers' ICT-Related Professional Development?

Abstract
This study protocol outlines a study to explore the predictive power of cognitive, motivational and personality traits for teachers' tendency of participation in as well as teachers' willingness for ICT-related PD. For the study we will use data of teachers from the project *tabletBW*. *TabletBW* is a school trial for learning with tablets in classrooms which is accompanied by longitudinal scientific research from 2018 to 2021. To test our hypotheses, we will conduct stepwise multivariate multiple regression models (SEM) including teachers' utility value of educational technology, teachers' technological ability as well as teachers' conscientiousness as main predictors for teachers' tendency of participation in as well as teachers' willingness for ICT-related PD.

Keywords: Utility Value, Technological Ability, Conscientiousness, Teachers' ICT-Related Professional Development

The structure of this study protocol is based on the template of van den Akker and colleagues (2019; https://osf.io/hvfmr).

Part 1: Study information

Q1: Provide the working title of your study.

A1: **Working Title:** Will, Skill or Conscientiousness: What Predicts Teachers ICT-Related Professional Development?

Q2: Name the authors of this preregistration.

A2:

Tim Fütterer https://orcid.org/0000-0001-5399-9557
Andreas Lachner https://orcid.org/0000-0001-5866-7164
Katharina Scheiter https://orcid.org/0000-0002-9397-7544
Ronny Scherer https://orcid.org/0000-0003-3630-0710
Kathleen Stürmer https://orcid.org/0000-0001-9916-0589

Q3: List each research question included in this study.

A3: The use of educational technology to create effective learning environments in classrooms seems extremely promising to support students learning (Ainley et al., 2008; Cheung & Slavin, 2013; Falloon, 2013; Haßler et al., 2016, p. 201; Hew & Brush, 2007; Ifenthaler & Schweinbenz, 2016; Jeno et al., 2019; OECD, 2015). And schools are increasingly being equipped with educational technology in particular with one-to-one devices like tablet computers (Banister, 2010; Falloon, 2013; Sung et al., 2016; Warschauer et al., 2014; Zhai et al., 2018). However, the scientific discussion more strongly shifts to the view that the quality of educational technology integration and not, for example, the quantity is important to promote successful learning processes (Backfisch et al., submitted; Fütterer et al., in preparation). To ensure that teachers integrate educational technology into the classroom in a high-quality manner, teachers must be well trained in necessary competences. Factors for educational technology integration in classrooms are 1) teachers' motivational traits (i.e., utility beliefs regarding educational technology, technology-related self-efficacy; see Backfisch, Lachner, Hische, et al., 2020; van Braak et al., 2004), and 2) teachers' professional knowledge related to technology (technological pedagogical knowledge, technological knowledge; Lachner et al., 2019; Mishra & Koehler, 2006). Teachers, who already finished teacher training, expand these competencies especially in professional development (PD). Information and communications technology (ICT)-related PD is regarded as a crucial prerequisite to acquire technological pedagogical knowledge and technological knowledge (see Gerard et al., 2011; C. Kim et al., 2013; Lawless & Pellegrino, 2007; Mishra & Koehler, 2006). However, it is still unknown which teachers actual participate in ICT-related PD. We assume that those variables related to the use of educational technology in the classroom (e.g., motivation, knowledge) are also suitable for predicting teachers' ICT-related PD behavior (e.g., tendency to participate in PD, willingness for PD). For example, if a teacher has negative attitudes towards educational technology, then this teacher will possibly show less ICT-related PD activities. Teachers might also more likely perceive the need for PD and are therefore more willing to attend ICT- related PD if teachers have already previous knowledge or are particularly advanced in this area (Tendency hypothesis; Richter et al., 2013). Besides motivational and cognitive factors, especially in systems in which PD must be chosen voluntarily by teachers, it can be assumed that conscientiousness could be important for predicting PD behavior. Conscientiousness describes, among other things, the tendency of people to follow norms and rules as well as to be highly responsible (L. E. Kim et al., 2019; Roberts et al., 2014). And from the literature on personality traits (Hogan & Holland, 2003; Jackson & Hill, 2019; Roberts et al., 2014; especially on teachers effectiveness: Kell, 2019; L. E. Kim et al., 2019; Klassen & Tze, 2014), we know that conscientiousness as a psychological construct predicts many important life outcomes, (e.g., occupational success, academic achievement). Therefore, teachers' conscientiousness might play an additional role for teachers' participation in PD programs. However, to date it is unclear how motivational and cognitive factors as well as personality traits interact in predicting teachers' PD behavior. Identifying which teachers take part in PD and which do not help to identify regulatory mechanisms to ensure, for example, that those teachers who indeed need PD (e.g., low knowledge) receive it. Our study addresses this issue. We are going to investigate which cognitive, motivational factors, but also individual personality traits, determine PD behavior.

For this reason, we are going to test external and internal boundary conditions for teachers' ICT-related PD activities by examining the following research questions:

What predicts the participation of teachers in professional development (PD) on educational technology best?

- RQ1.1: Does a reform initiative (introduction of tablets) predict teachers' perceived need of ICT-related PD?
  RQ1.2: Does a reform initiative (introduction of tablets) predict teachers' tendency to participate in ICT-related PD?
- RQ2.1: Does teachers' motivation predict teachers' perceived need of educational technology -related PD?
  RQ2.2: Does teachers' motivation predict teachers' tendency to participate in ICT-related PD?
- RQ3.1: Does teachers' professional knowledge have additional explanatory power for the variance of teachers' perceived need of ICT-related PD?
  RQ3.2: Does teachers' professional knowledge have additional explanatory power for the variance of teachers' tendency to participate in ICT-related PD?
- RQ4.1: Does teachers' conscientiousness have additional explanatory power for the variance of the teachers' perceived need of ICT-related PD?
  RQ4.2: Does teachers' conscientiousness have additional explanatory power for the variance of teachers' tendency to participate in ICT-related PD?

Q4: For each of the research questions listed in the previous section, provide one or more specific and testable hypotheses, and make it clear whether the hypotheses are directional (e.g., A > B) or non-directional (e.g., A ≠ B). If directional, state the direction.

A4: For all independent variables, arguments can be derived from theory and previous empirical evidence that the variables are predictive of perceived PD needs and actual PD activity. For example, it can be assumed that teachers are more likely to perceive the need for PD and are more likely to attend PD courses if they already have previous knowledge or are particularly good in this area (Tendency hypothesis; Richter et al., 2013). It can also be assumed that especially the generally committed teachers participate in PD (e.g., Fütterer et al., in prep.; Richter et al., 2011) or particularly teachers who are motivated to use educational technology in their lessons (e.g., Backfisch et al., in press). Currently there are no studies available which have looked at these variables together. However, we are more interested in the importance of each variable under control of the other variable. In particular, we are interested in whether teachers who need PD (low skill) actually perceive the need for PD and accordingly take more PD. Therefore, regarding the research questions, we posit the following hypotheses:

- H1.1 regarding RQ1.1: Reform initiatives (introduction of one-to-one tablet computers) are positive related with perceived need of educational technology-related PD.
  H1.2 regarding RQ1.2: Reform initiatives (introduction of one-to-one tablet computers) are not related with teachers' tendency to participate in ICT-related PD.
- H2.1 regarding RQ2.1: The higher teachers' motivation (A) the higher teachers' perceived need of educational technology-related PD (B).
  H2.2 regarding RQ2.2: The higher teachers' motivation (A) the higher teachers' tendency to participate in ICT-related PD (C).
- H3.1 regarding RQ3.1: The higher teachers' professional knowledge (D) the lower teachers' perceived need of educational technology-related PD (B).
  H3.2 regarding RQ3.2: The higher teachers' professional knowledge (D) the higher teachers' tendency to participate in ICT-related PD (C; Tendency hypothesis).
- H4.1 regarding RQ4.1: The higher teachers' conscientiousness (E) the higher teachers' perceived need of educational technology-related PD (B).
  H4.2 regarding RQ4.2: The higher teachers' conscientiousness (E) the higher teachers' tendency to participate in ICT-related PD (C).

Part 2: Data description

Q5: Name and briefly describe the dataset(s), and if applicable, the subset(s) of the data you plan to use.

A5: This study uses data of teachers from the project *tabletBW*. *TabletBW* is a school trial for learning with tablets in classrooms which is accompanied by longitudinal scientific research from 2018 to

2021. All Gymnasiums (highest track in the secondary school system in Germany) of the German federal state Baden-Wuerttemberg have been invited to participate in this project. 28 schools registered to participate in the school trial and from each school two classes participate per cohort (2 cohorts in total), starting with the seventh grade. From the pool of 28 registered schools, 14 schools were randomly assigned to a group of schools for which two classes (tablet classes) in grade seven received tablet computers for each student (one-to-one). The other 14 schools were randomly assigned to a group of schools for which two classes (non-tablet classes) in grade seven did not get any tablet computers. Teachers in tablet classes were asked to integrate the tablet computers as educational technology into their classroom practices. All teachers teaching in the classes participating in the school trial (tablet and non-tablet classes) were asked to participate in the study. For more information see (Backfisch et al., submitted) or (Q9). Demographic data (e.g., age, gender), performance measures (e.g., technological pedagogical knowledge), self-regulation (e.g., regulatory focus), occupational data (e.g., subjective stress, quality of teaching), computer and tablet use in and outside the classroom (e.g., frequency of use) and the use of tablets in class (e.g., self-efficacy in using tablets) were surveyed.

Q6: Specify whether this data is open or publicly available.
A6: It's complicated. The longitudinal assessment of the project *tabletBW* is still ongoing. At the end of data collection in the project (year 2022) it is planned to make all project data publicly available, as soon as it has been cleaned and prepared. However, independent of the overall data of the project, we are going to store the data which is used for this study online (see Q8).

Q7: How can the data be accessed? Provide a persistent identifier or link if the data are available online, or give a description of how you obtained the dataset.
A7: As already written in Q6, the data is currently not publicly available. It is planned to publish the data. Further information and announcements on the data will otherwise be available on the following homepage: http://tablet-tuebingen.de/. Access to the data used in this study will be given (see Q8).

Q8: Specify the date of download and/or access.
A8: Although the dataset of the whole project *tabletBW* is not yet publicly available, we will archive the dataset used for the study internally in an anonymous version (https://www.psycharchives.org/). The storage of the data provides both, a content and a time stamp. All syntaxes for further processing of the data of our study and of the analyses as well as all potential new dataset versions will also be archived (https://www.psycharchives.org/).

Q9: If the data collection procedure is well documented, provide a link to that information. If the data collection procedure is not well documented, describe, to the best of your ability, how data were collected.
A9: Three measuring points have already passed, one measuring point still lies ahead. As already mentioned, all teachers teaching in the classes participating in the school trial *tabletBW* were asked to participate in the study. For this purpose, letters of invitation, information letters and declarations of agreement were sent to the contact persons of the participating schools. The contact persons forwarded these letters to all potential teachers. If the teachers wanted to participate in the study, they signed the declaration of agreement. The declarations of agreement were sent back to us by the contact person. A link to an online survey was sent by e-mail to those teachers for whom a declaration of agreement was available. The teachers' data on demographics, personality, teaching and personal attitudes were collected through online questionnaires. Except of personality which is only measured at the first time of participation, almost all constructs were assessed at all measurement points. In most cases, Likert scales or open response formats were used. Technological pedagogical knowledge (TPK) was tested with an online test. This test was also edited online and could be accessed via the same link. In addition, teachers were asked to participate in a paper pencil technological knowledge test (TILT) consisting of 29 multiple choice items. The test was sent to the contact persons of the schools. They distributed the paper pencil tests to the teachers and returned the filled tests to us. Both tests (TPK and TILT) are applied at the first time of participation. During the survey phases, teachers had between one and three months to answer the questionnaires. For the data collection plan of the project see the following Table 1. All data was collected pseudonymously.

Table 1
Data Collection Plan of the tabletBW Project

Measurement point	t_0	t_1	t_2
Period of time	spring 2018	summer 2018	summer 2019

Q10: Some studies offer codebooks to describe their data. If such a codebook is publicly available, link to it here or upload the document. If not, provide other available documentation. Also provide guidance on what parts of the codebook or other documentation are most relevant.
A10: We will prepare a codebook of all variables of interest. We will upload this codebook and the data for this pre-registration on https://www.psycharchives.org/.

Part 3: Variables

Q11: If you are going to use any manipulated variables, identify them here. Describe the variables and the levels or treatment arms of each variable (note that this is not applicable for observational studies and meta-analyses). If you are collapsing groups across variables this should be explicitly stated, including the relevant formula.
A11: We do have manipulated data in our study. The data originate from the accompanying research of a school trial. Therefore, it was only possible to randomize on school level: schools either got tablet classes (students getting one-to-one tablets) or schools got non-tablet classes. The variable to distinguish teachers teaching in either tablet or non-tablet classes is included in the analyses. However, there is no real experimental setting in which teachers were randomly assigned to the respective conditions.

Q12: If you are going to use any measured variables, identify them here. Describe both outcome measures as well as predictors and covariates and label them accordingly. If you are using a scale (a set of items that have an underlying latent construct) or an index (a set of items that directly indicate a value or quantity), state the construct the scale/index represents, which items the scale/index will consist of, how these items will be aggregated, and whether this aggregation is based on a recommendation from the study codebook or validation research. If you are using any categorical variables, state how you will code them in the statistical analyses.
A12:
We will include two central dependent variables. First, teachers' tendency to participate in educational technology-related/tablet-related PD. We will use a variable which indicates whether a teacher did participate in educational technology-related/tablet-related PD (= 1) or did not (= 0). Second, we will use the adapted scale *Willingness for Professional Development* (Ehmke et al., 2004) which consists of 4 items. Teachers rated the four items on a 4-point Likert scale ranging from 1 (*do not agree at all*) to (*totally agree*).

As predictors we include motivation, knowledge test scores, conscientiousness and control variables.

Motivation:
Utility-value. We will measure the perceived social and personal utility of educational technology in the classroom with 4 items (Backfisch et al., in press). Teachers rated each item on a 4-point Likert scale ranging from 1 (*do not agree at all*) to (*totally agree*). Originally the scale consisted of five items and was called *Technological Innovativeness Scale* (TIS; van Braak et al., 2004). However, we will use the four items scale based on work of Backfisch et al. (in press), because the focus of the selected four items is more in line with typical utility measures (see Eccles & Wigfield, 2002; Wigfield & Eccles, 2000).

Ability test scores:
We will use weighted likelihood estimation (WLE; Warm, 1989) to estimate personal ability (estimation of ability in item response theory (IRT)). The scaling will be done according to the specifications of the test manual in ConQuest (Wu et al., 2007) or R (TAM package; Robitzsch et al., 2020).

Technological Pedagogical Knowledge (TPK). In order to assess TPK, we use scores from an online version of a TPK test, which comprises 18 multiple-choice items (Lachner et al., 2019). The test covers two dimensions of TPK: conceptual TPK (8 items) and situational TPK (10 items). Sum scores were formed during the test development. In this study, we will also perform IRT scaling (if possible) and use WLE scores as estimators of personal abilities.

Technological Knowledge (TK). We will use scores of the paper-and-pencil version of the test of technological and information Literacy (TILT) to assess TK (Senkbeil et al., 2013; Senkbeil & Ihme, 2015; see also Lachner et al., 2019). The TILT is conceptualized as a one-dimensional construct, comprises 29 multiple choice items and is Rasch scaled (partial credit model).

Personality:
Conscientiousness. We will assess conscientiousness with 3 Items of the BFI-2-XS (Soto & John, 2017) measured at the first measurement point (t0) on a 5-point Likert scale ranging from 1 (*do not agree at all*) to 5 (*totally agree*).

Control variables:
Additional measures are demographic variables like *gender*, *age* and *time in profession* of the teachers. We may also include additional control variables to obtain more robust results like *school ID*.

Note: The codebook also gives an overview of all variables.

Q13: Which units of analysis (respondents, cases, etc.) will be included or excluded in your study? Taking these inclusion/exclusion criteria into account, indicate the (expected) sample size of the data you'll be using for your statistical analyses (to the best of your knowledge). In the next few questions, you will be asked to refine this sample size estimation based on your judgments about missing data and outliers.
A13: In a first step, we are going to include all teachers available in the dataset in the analyses. In Q24 we describe further steps to deal with missing values concerning the sample for the analyses.

Q14: What do you know about missing data in the data set (e.g., overall missingness rate, information about differential dropout)? How will you deal with incomplete or missing data? Based on this information, provide a new expected sample size.
A14: We do not currently know how many values are missing for the variables considered in this study. However, we assume that individual values will be missing. Current research shows that approaches in which missing values are estimated like full information maximum likelihood (FIML) or multiple imputation (MI) provide a more unbiased estimation and robustness in case of violating assumptions like missing at random than traditional approaches such as listwise deletion (Enders, 2001; Graham, 2009, 2012; Newman, 2003; Schafer & Graham, 2002). Because the statistical power of MI depends on the number of imputations and is worse relative to FIML for small numbers of imputations (≤ 20), we will treat missing values with the FIML estimation.

For this reason, we are not assuming a smaller sample size than teachers available. We will use FIML for both independent and dependent variables. To ensure the robustness of the results, we will repeat the analyses and not apply FIML to the dependent variable.

Q15: How will you define what a statistical outlier is in your data and what will you do when you encounter them? If you plan to remove outliers, provide a new expected sample size. Note that this will be the definitive expected sample size for your study and you will use this number to do any power analyses.
A15: Since almost all items were set in a closed answer format (e.g., Likert scale, multiple choice), we do not expect any outliners. If outliners or implausible values are present (e.g., a 33 on a four-level Likert scale), then we try to correct them based on the raw data. We consider them to be implausible values, if a correction is not possible. We will therefore treat these values as missing values. As answered in question Q14, we do not expect any effects on our sample size, as we will treat missing values with the Full Information Maximum Likelihood (FIML) method.

Q16: Are there sampling weights available with this data set? If so, are you using them and how?
A16: There are no sampling weights available and we will not use any for this study.

Part 4: Knowledge of data

Q17: List the publications, conference presentations (papers, posters), and working papers (in prep, unpublished, preprints) you have worked on that are based on the data set. Describe which variables you have previously analyzed and which information you used in these analyses. Limit yourself to variables that are relevant to the current study. If the dataset is longitudinal, include information about what wave of data was previously analyzed.
A17: The following papers has been published so far: (Backfisch et al., submitted; Lachner et al., 2019; Stürmer et al., 2020). Three of the authors of these papers (Andreas Lachner, Kathleen Stürmer and Katharina Scheiter) have already published with the variables and scales mentioned in this paper (e.g., TPK, TK) and therefore have previous experience with these variables. However, since the survey has been repeated in the meantime, a different sample will be used in the current study.

Q18: What prior knowledge do you have at the time of preregistration about trends in the data set you will be working with? For example, are you aware of summary statistics or the statistical distribution of variables, or do you know about correlations between variables? Your prior knowledge could stem from working with the data first-hand, from reading previously published research, or from codebooks. Also provide any relevant knowledge of different subsets of the data (e.g., a different wave than you will be using). Finally, provide information about your prior knowledge for every author separately.
A18: Two co-authors (Andreas Lachner and Kathleen Stürmer) have already worked with the teachers' data, but have not used the final data set which will be used for this study. In addition, both authors have not worked with the dependent variables used in this study.

Part 5: Analyses

Q19: For each hypothesis, describe the statistical model you will use to test the hypothesis. Include the type of model (e.g., ANOVA, multiple regression, SEM) and the specification of the model (this includes each variable that will be included as predictor, outcome, or covariate). Specify any interactions and post-hoc analyses and remember that any test not included here must be noted as an exploratory test in the final article.
A19: To answer all research questions, we will use stepwise multivariate multiple regression models (SEM, ANCOVA). We will build the models stepwise to determine the additional added value of each predictor (measured by the additional explained variance). In order to predict teachers' willingness for PD and teachers' tendency to participate in ICT-related PD, we will include the external boundary variable whether a teacher is teaching in a tablet class or not in a first step. However, we assume that the internal boundaries (personal variables) are more important. We assume especially scales of teachers' motivation to be most important predictors. Therefore, in a second step, we will include utility value in the regression model as the first construct of all intern boundaries. In a third step, we will include both ability scores TPK and TK as predictors. Finally, in a fourth step, we will integrate teachers' conscientiousness as a predictor.

Even very low intraclass correlations can lead to a significant bias in the results of significance tests in regression analyses if ignored (Cohen et al., 2003; Geiser, 2013). The multi-level structure (teachers nested within schools) will be taken into account by estimating clustered-robust standard errors. We will use the type = complex option in Mplus with school ID as the cluster variable to automatically take into account the multilevel structure when computing standard errors.

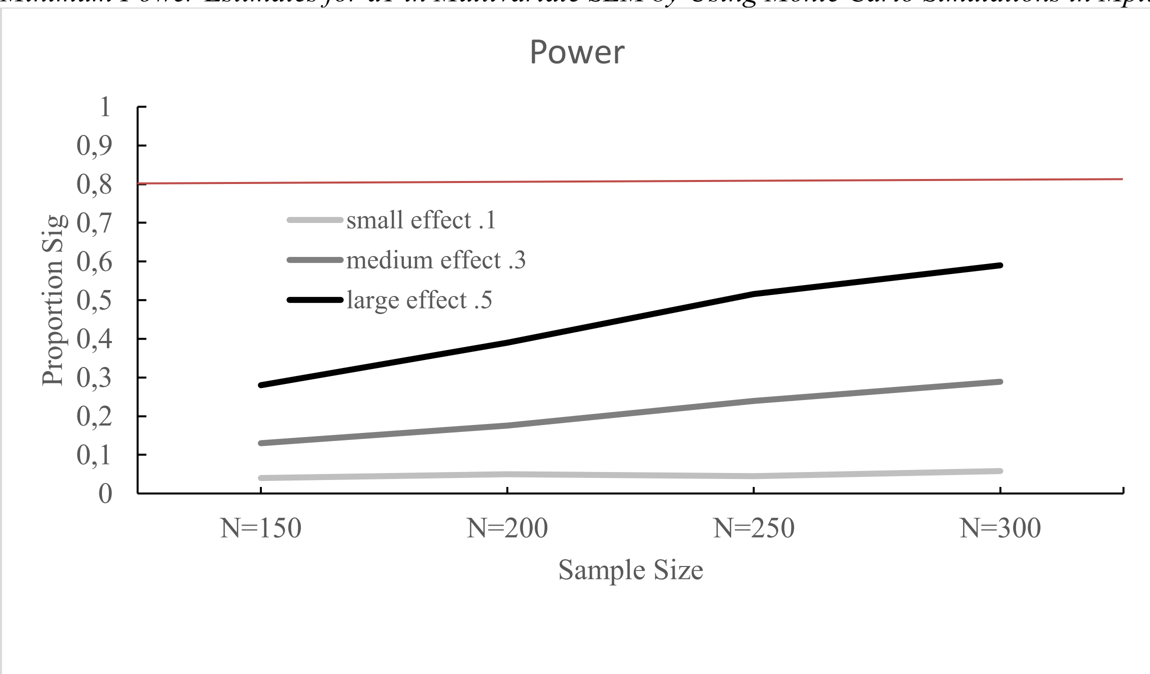
We will perform the analyses with the statistical programs R, Mplus and SPSS.

We are going to explore some interactions of the predictors (see Q25).

Q20: If applicable, specify a predicted effect size or a minimum effect size of interest for all the effects tested in your statistical analyses.
A20: Since no comparable studies are known to us at the moment, we are unable to state the expected effect sizes. Therefore, we calculated the power analyses (described in Q21) for different effect sizes (small, medium, large).

Q21: Present the statistical power available to detect the predicted effect size(s) or the smallest effect size(s) of interest. Use the sample size after updating for missing data and outliers.
A21: When performing the power analysis we followed the guidelines of Muthén and Muthén (2002). Because we assume that we do not have to exclude any cases from the analyses in first analyses steps, we calculated the power analyses for $N = 250$ teachers (approximately expected sample size). In order to get an impression of the distribution of power for different sample sizes and for different effect sizes, we performed power analyses for different scenarios. Results of these power analyses are presented in Figure 2 and Table 2. Figure 2 shows the smallest of the five calculated effect sizes (one effect size per predictor). The effect sizes of all regression weights are shown in Table 2. For all power analyses we included all information available to us (factor loadings, mean values and variances). All information about references, values and that had to be estimated as well as created datasets can be taken from the Mplus syntax in the Appendix and the supplementary pre-registered files. In the power analyses it was assumed that 15% of the values per item are missing. For medium and large effect sizes and at least a sample size of 250 teachers, the expected power for the dependent variable *Willingness for Professional Development* (d2) is almost 1-β=.80, whereas for participation in educational technology-related PD (d1) it is rather unlikely that effects can be detected with sufficient certainty.

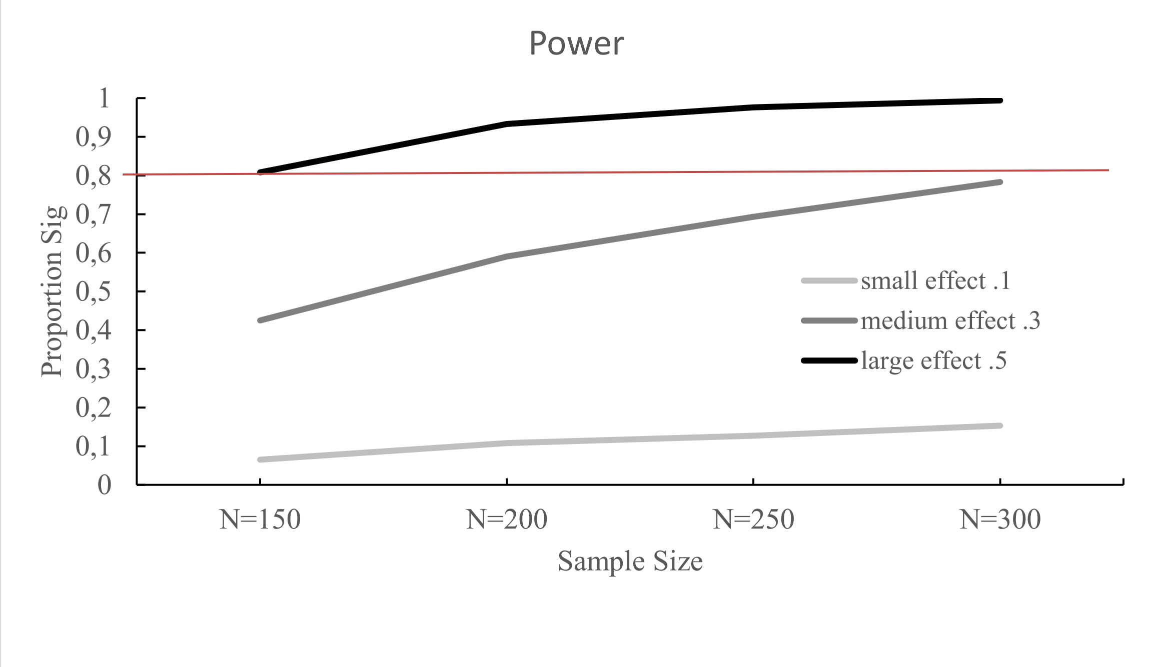
Figure 2
Minimum Power Estimates for d1 in Multivariate SEM by Using Monte Carlo Simulations in Mplus



Note. The figure shows the smallest of the five calculated effect sizes. The lowest power is always given for the regression weight of conscientiousness (see Table 2).

Figure 3

Minimum Power Estimates for d2 in Multivariate SEM by Using Monte Carlo Simulations in Mplus



Note. The figure shows the smallest of the five calculated effect sizes. The lowest power is always given for the regression weight of conscientiousness (see Table 3).

Table 2

Power (1-ß) for Regression Weights for d1 in Multivariate Structural Equation Models

	Small effect				Medium effect				Large effect			
N	150	200	250	300	150	200	250	300	150	200	250	300
Conscientiousness (i1)	.040	.050	.045	.058	.130	.176	.239	.289	.280	.390	.516	.590
Utility (i2)	.058	.071	.083	.099	.227	.266	.370	.397	.420	.559	.674	.740
TK(x8)	.082	.075	.089	.117	.291	.348	.439	.503	.550	.639	.765	.835
C TPK(x9)	.077	.094	.109	.132	.260	.341	.461	.501	.536	.684	.777	.841
S TPK(x10)	.078	.084	.098	.117	.283	.342	.438	.520	.550	.664	.775	.850

Note. i1, i2, x8, x9, x10 are the labels of the variables in the Mplus example syntax (cf. Appendix).

Table 3

Power (1-ß) for Regression Weights for d2 in Multivariate Structural Equation Models

	Small effect				Medium effect				Large effect			
N	150	200	250	300	150	200	250	300	150	200	250	300
Conscientiousness (i1)	.065	.108	.127	.153	.425	.590	.693	.783	.808	.933	.976	.994
Utility (i2)	.128	.161	.195	.223	.674	.797	.885	.923	.968	.996	.999	1.00
TK(x8)	.147	.170	.210	.234	.771	.872	.936	.972	.993	.999	1.00	1.00
C TPK(x9)	.165	.193	.241	.243	.758	.888	.938	.966	.987	1.00	1.00	1.00
S TPK(x10)	.179	.197	.236	.269	.795	.878	.927	.967	.990	.999	1.00	1.00

Note. i1, i2, x8, x9, x10 are the labels of the variables in the Mplus example syntax (cf. Appendix).

Note: The low power of conscientiousness is probably due to our assumption of low loadings of the items in the simulation studies. Our assumptions based on findings in questionnaire development studies (Soto & John, 2017). If the loadings in the current study data are better, we might expect a better test power.

Q22: What criteria will you use to make inferences? Describe the information you will use (e.g. specify the p-values, effect sizes, confidence intervals, Bayes factors, specific model fit indices), as

well as cut-off criteria, where appropriate. Will you be using one- or two-tailed tests for each of your analyses? If you are comparing multiple conditions or testing multiple hypotheses, will you account for this, and if so, how?
A22: The significance level for all tests used will set to $p = .05$. This means that we only consider results to be statistically significant if they have a p-value of less than .05. Effect sizes will be standardized regression weights and, where appropriate, mean differences (expressed in Cohen's d). If available in the literature, we base the classification of effect sizes on known and reported effect sizes. If no effect sizes can be found in the existing literature and when appropriate we follow the classification of Cohen (1988). We try to avoid multiple testing by using multiple multivariate linear regression models, where all predictors and all dependent variables are considered together in one model. Based on the results of the power analyses (Q21) we already discovered that the dependent dichotomous variable d1 has insufficient power. Therefore, we will plan to run separate models: Logistic regression models for the dichotomous dependent variable (d1) and linear regression models for the continuous dependent variable (d2). The interpretation of the model fits will be made according to the proposals of Schermelleh-Engel and colleagues (2003). The assessment of the reliability of scales will be based on the results of Taber (2018).

Q23: What will you do should your data violate assumptions, your model not converge, or some other analytic problem arises?
A23: We reserve the right to adapt statistical models in such a way that statistical calculations are possible despite warning and error messages.

1. If model fits are already insufficient for the individual latent variables, we reserve the right to parcel (Bandalos, 2002; Little et al., 2002, 2013; Matsunaga, 2008).
2. If model fits are insufficient, we try less complex models like separate multiple regression models instead of multivariate regression models.
3. In general, we will limit the variance in the structural equation models when including dichotomous variables that have missing values.
4. Should a warning message appear due to clustering (e.g., "THE STANDARD ERRORS OF THE MODEL PARAMETER ESTIMATES MAY NOT BE TRUSTWORTHY...THIS IS MOST LIKELY DUE TO HAVING MORE PARAMETERS THAN THE NUMBER OF CLUSTERS MINUS THE NUMBER OF STRATA WITH MORE THAN ONE CLUSTER".), we will check whether the error messages remain without clustering. If not, we will ignore this warning message. Similarly, we will deal with other warnings. If no plausible cause for the warning message can be found and we assume that the results are not strongly biased, we will ignore warnings if necessary. If models do not converge, we will increase the number of iterations.
5. If covariance coverage falls below the limits set by the statistics program, we will adjust the limits manually systematically.

Q24: Provide a series of decisions about evaluating the strength, reliability, or robustness of your focal hypothesis test. This may include within-study replication attempts, additional covariates, cross-validation efforts (out-of-sample replication, spilt/hold-out sample), applying weights, selectively applying constraints in an SEM context (e.g., comparing model fit statistics), overfitting adjustment techniques used (e.g., regularization approaches such as ridge regression), or some other simulation / sampling / bootstrapping method.
A24: In the regression analyses, we include demographic data (e.g., age, gender, time in profession, general school engagement, wish to be in tablet/non-tablet class) as control variables.

We always aim to perform the analyses with the largest possible data set. Therefore, we will use FIML. In order to check whether the results are robust with respect to the estimation of missing values, we will test the models (if possible) on smaller samples, for example by listwise deletion or without using FIML on the dependent variable. In detail, we will pursue the following strategy: We choose an inclusive approach. This means that in a first step we will include all teachers in the analyses who have valid values on at least one of the included variables. Because we assume that the estimates may become unreliable and coverage problems may occur, we will validate the analyses in a second step by excluding teachers who have 75% or more missing values on dependent and/or independent variables. In a third step, we check the results on an even smaller sample with teachers who have no missing values on the dichotomous dependent variable in addition to step two. In a last step, we check the results for the teachers who, in addition to step three, do not have complete missing values for all the independent variables included, but only a few missing values for each variable.

We also reserve the right to conduct models with different factor structures (bifactor/g-factor model) in order to test whether such models better represent the data and whether the results remain robust.

Q25: If you plan to explore your data set to look for unexpected differences or relationships, you can describe those tests here, or add them to the final paper under a heading that clearly differentiates this exploratory part of your study from the confirmatory part.
A25: We assume that there are additive, compensatory and/or synergetic effects of the predictors. Exploratively, we therefore examine these relationships with respect to the prediction of the dependent variables.

For example, studies on predicting students' effort (Song et al., 2020; Trautwein et al., 2015, 2019) suggest that there may be also compensatory interactions between motivation (Utility) and conscientiousness in predicting PD activity on teacher level. RQ: Are conscientiousness and utility compensatory as predictors of participation of teachers in PD on educational technology?

Furthermore, it can be assumed that there is an interaction between reform and conscientiousness. If a reform takes place, it can be assumed that especially teachers who are more conscientious are more likely to attend PD than teachers who are less conscientious. We likely going to explore such interactions.

Depending on the longitudinal availability of teachers and the existing patterns of missing values, we are going to explore whether the predictions are valid not only cross-sectional for t0 (first participation of teachers), but also longitudinal for t1 (second time of participation) and/or t2 (third time of participation). Whereby the predictors are always measured at t0, unless another measurement time makes more sense in terms of content.

References

Ainley, J., Enger, L., & Searle, D. (2008). Students in a Digital Age: Implications of ICT for Teaching and Learning. In J. Voogt & G. Knezek (Eds.), *International Handbook of Information Technology in Primary and Secondary Education* (pp. 63–80). Springer. https://doi.org/10.1007/978-0-387-73315-9_4

Backfisch, I., Lachner, A., Hische, C., Loose, F., & Scheiter, K. (in press). Professional knowledge or motivation? Investigating the role of teachers' expertise on the quality of technology-enhanced lesson plans. *Learning and Instruction*, *66*, 101300. https://doi.org/10.1016/j.learninstruc.2019.101300

Backfisch, I., Lachner, A., Stürmer, K., & Scheiter, K. (submitted). *Variability of Teachers' Technology Integration in the Classroom: A Matter of Utility!*

Bandalos, D. L. (2002). The Effects of Item Parceling on Goodness-of-Fit and Parameter Estimate Bias in Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, *9*(1), 78–102. https://doi.org/10.1207/S15328007SEM0901_5

Banister, S. (2010). Integrating the iPod Touch in K–12 Education: Visions and Vices. *Computers in the Schools*, *27*(2), 121–131. https://doi.org/10.1080/07380561003801590

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

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2.). Erlbaum.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Erlbaum. https://books.google.de/books?id=fAnSOgbdFXIC&printsec=frontcover&hl=de&source=gbs_ge_summary_r&cad=0#v=onepage&q=ICC&f=false

Eccles, J., & Wigfield, A. (2002). Motivational Beliefs, Values, and Goals. *Annual Review of Psychology*, *53*(1), 109–132. https://doi.org/10.1146/annurev.psych.53.100901.135153

Ehmke, T., Senkbeil, M., & Bleschke, M. (2004). Typen von Lehrkräften beim schulischen Einsatz von Neuen Medien. In F. Schumacher (Ed.), *Innovativer Unterricht mit neuen Medien: Ergebnisse wissenschaftlicher Begleitung von Semik-Einzelprojekten* (pp. 35–66). FWU Institut für Film und Bild in Wissenschaft und Unterricht.

Enders, C. K. (2001). The impact of nonnormality on full information maximum-likelihood estimation for structural equation models with missing data. *Psychological Methods*, *6*(4), 352–370. https://doi.org/10.1037/1082-989X.6.4.352

Falloon, G. (2013). Young students using iPads: App design and content influences on their learning pathways. *Computers & Education*, *68*, 505–521. https://doi.org/10.1016/j.compedu.2013.06.006

Fütterer, T., Cheng, X., Scheiter, K., & Stürmer, K. (in preparation). *Quality Beats Quantity: Investigating Students' Learning Related Effort When Introducing Educational Technology in Classrooms*.

Geiser, C. (2013). *Data Analysis with Mplus*. The Guilford Press.

Gerard, L. F., Varma, K., Corliss, S. B., & Linn, M. C. (2011). Professional Development for Technology-Enhanced Inquiry Science. *Review of Educational Research*, *81*(3), 408–448. https://doi.org/10.3102/0034654311415121

Graham, J. W. (2009). Missing Data Analysis: Making It Work in the Real World. *Annual Review of Psychology*, *60*(1), 549–576. https://doi.org/10.1146/annurev.psych.58.110405.085530

Graham, J. W. (2012). *Missing Data. Analysis and Design*. Springer. https://doi.org/10.1007/978-1-4614-4018-5

Haßler, B., Major, L., & Hennessy, S. (2016). Tablet use in schools: A critical review of the evidence for learning outcomes: Tablet use in schools: a critical review. *Journal of Computer Assisted Learning*, *32*(2), 139–156. https://doi.org/10.1111/jcal.12123
Hew, K. F., & Brush, T. (2007). Integrating technology into K-12 teaching and learning: Current knowledge gaps and recommendations for future research. *Educational Technology Research and Development*, *55*(3), 223–252. https://doi.org/10.1007/s11423-006-9022-5
Hogan, J., & Holland, B. (2003). Using theory to evaluate personality and job-performance relations: A socioanalytic perspective. *Journal of Applied Psychology*, *88*(1), 100–112. https://doi.org/10.1037/0021-9010.88.1.100
Ifenthaler, D., & Schweinbenz, V. (2016). Students' Acceptance of Tablet PCs in the Classroom. *Journal of Research on Technology in Education*, *48*(4), 306–321. https://doi.org/10.1080/15391523.2016.1215172
Jackson, J. J., & Hill, P. L. (2019). Lifespan development of conscientiousness. In D. P. McAdams, R. L. Shiner, & J. L. Tackett (Eds.), *Handbook of personality development* (pp. 153–170). The Guilford Press. https://books.google.de/books?id=2xx9DwAAQBAJ&lpg=PA159&ots=yh3y4cVnRG&dq=brant%20conscientiousness&hl=de&pg=PR4#v=onepage&q=brant%20conscientiousness&f=false
Jeno, L. M., Vandvik, V., Eliassen, S., & Grytnes, J.-A. (2019). Testing the novelty effect of an m-learning tool on internalization and achievement: A Self-Determination Theory approach. *Computers & Education*, *128*, 398–413. https://doi.org/10.1016/j.compedu.2018.10.008
Kell, H. J. (2019). Do Teachers' Personality Traits Predict Their Performance? A Comprehensive Review of the Empirical Literature From 1990 to 2018. *ETS Research Report Series*, *2019*(1), 1–27. https://doi.org/10.1002/ets2.12241
Kim, C., Kim, M. K., Lee, C., Spector, J. M., & DeMeester, K. (2013). Teacher beliefs and technology integration. *Teaching and Teacher Education*, *29*, 76–85. https://doi.org/10.1016/j.tate.2012.08.005
Kim, L. E., Jörg, V., & Klassen, R. M. (2019). A Meta-Analysis of the Effects of Teacher Personality on Teacher Effectiveness and Burnout. *Educational Psychology Review*, *31*(1), 163–195. https://doi.org/10.1007/s10648-018-9458-2
Klassen, R. M., & Tze, V. M. C. (2014). Teachers' self-efficacy, personality, and teaching effectiveness: A meta-analysis. *Educational Research Review*, *12*, 59–76. https://doi.org/10.1016/j.edurev.2014.06.001
Lachner, A., Backfisch, I., & Stürmer, K. (2019). A test-based approach of Modeling and Measuring Technological Pedagogical Knowledge. *Computers & Education*, *142*, 103645. https://doi.org/10.1016/j.compedu.2019.103645
Lawless, K. A., & Pellegrino, J. W. (2007). Professional Development in Integrating Technology Into Teaching and Learning: Knowns, Unknowns, and Ways to Pursue Better Questions and Answers. *Review of Educational Research*, *77*(4), 575–614. https://doi.org/10.3102/0034654307309921
Little, T. D., Cunningham, W. A., Shahar, G., & Widaman, K. F. (2002). To Parcel or Not to Parcel: Exploring the Question, Weighing the Merits. *Structural Equation Modeling: A Multidisciplinary Journal*, *9*(2), 151–173. https://doi.org/10.1207/S15328007SEM0902_1
Little, T. D., Rhemtulla, M., Gibson, K., & Schoemann, A. M. (2013). Why the items versus parcels controversy needn't be one. *Psychological Methods*, *18*(3), 285–300. https://doi.org/10.1037/a0033266

Matsunaga, M. (2008). Item Parceling in Structural Equation Modeling: A Primer. *Communication Methods and Measures*, *2*(4), 260–293. https://doi.org/10.1080/19312450802458935

Mishra, P., & Koehler, M. J. (2006). Technological Pedagogical Content Knowledge: A Framework for Teacher Knowledge. *Teachers College Record*, *108*(6), 1017–1054.

Muthén, L. K., & Muthén, B. O. (2002). How to Use a Monte Carlo Study to Decide on Sample Size and Determine Power. *Structural Equation Modeling: A Multidisciplinary Journal*, *9*(4), 599–620. https://doi.org/10.1207/S15328007SEM0904_8

Newman, D. A. (2003). Longitudinal Modeling with Randomly and Systematically Missing Data: A Simulation of Ad Hoc, Maximum Likelihood, and Multiple Imputation Techniques. *Organizational Research Methods*, *6*(3), 328–362. https://doi.org/10.1177/1094428103254673

OECD. (2015). *Schooling Redesigned: Towards Innovative Learning Systems*. OECD. https://doi.org/10.1787/9789264245914-en

Richter, D., Engelbert, M., Weirich, S., & Anand Pant, H. (2013). Differentielle Teilnahme an Lehrerfortbildungen und deren Zusammenhang mit professionsbezogenen Merkmalen von Lehrkräften. *Zeitschrift für Pädagogische Psychologie*, *27*(3), 193–207. https://doi.org/10.1024/1010-0652/a000104

Richter, D., Kunter, M., Klusmann, U., Lüdtke, O., & Baumert, J. (2011). Professional development across the teaching career: Teachers' uptake of formal and informal learning opportunities. *Teaching and Teacher Education*, *27*(1), 116–126. https://doi.org/10.1016/j.tate.2010.07.008

Roberts, B. W., Lejuez, C., Krueger, R. F., Richards, J. M., & Hill, P. L. (2014). What is conscientiousness and how can it be assessed? *Developmental Psychology*, *50*(5), 1315–1330. https://doi.org/10.1037/a0031109

Robitzsch, A., Kiefer, T., & Wu, M. (2020). *Package 'TAM'. Test Analysis Modules—Version: 3.4-26*.

Schafer, J. L., & Graham, J. W. (2002). Missing Data: Our View of the State of the Art. *Psychological Methods*, *7*(2), 147–177. https://doi.org/10.1037//1082-989X.7.2.147

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the Fit of Structural Equation Models: Tests of Significance and Descriptive Goodness-of-Fit Measures. *Methods of Psychological Research Online*, *8*(2), 23–74. https://doi.org/10.1.1.509.4258

Senkbeil, M., & Ihme, J. M. (2015). *NEPS Technical Report for Computer Literacy: Scaling Results of Starting Cohort 6—Adults* (Vol. 61). Leibniz Institute for Educational Trajectories, National Educational Panel Study.

Senkbeil, M., Ihme, J. M., & Wittwer, J. (2013). Entwicklung und erste Validierung eines Tests zur Erfassung technologischer und informationsbezogener Literacy (TILT) für Jugendliche am Ende der Sekundarstufe I. *Zeitschrift für Erziehungswissenschaft*, *16*(4), 671–691. https://doi.org/10.1007/s11618-013-0446-5

Song, J., Gaspard, H., Nagengast, B., & Trautwein, U. (2020). The Conscientiousness × Interest Compensation (CONIC) model: Generalizability across domains, outcomes, and predictors. *Journal of Educational Psychology*, *112*(2), 271–287. https://doi.org/10.1037/edu0000379

Soto, C. J., & John, O. P. (2017). Short and extra-short forms of the Big Five Inventory–2: The BFI-2-S and BFI-2-XS. *Journal of Research in Personality*, *68*, 69–81. https://doi.org/10.1016/j.jrp.2017.02.004

Stürmer, K., Fütterer, T., Lachner, A., Hoch, E., & Scheiter, K. (2020). Besser als gedacht? Individuelle Voraussetzungen von Schüler/innen sowie Lehrpersonen zum Lehren und Lernen mit digitalen Medien im Unterricht im tabletBW-Projekt. In N. Beck, T. Bohl,

& S. Meissner (Eds.), *Forschungs- und Entwicklungsfelder der Lehrerbildung auf dem Prüfstand. Ergebnisse der ersten Förderphase der Qualitätsoffensive Lehrerbildung an der Tübingen School of Education*. Tübingen University Press.

Sung, Y.-T., Chang, K.-E., & Liu, T.-C. (2016). The effects of integrating mobile devices with teaching and learning on students' learning performance: A meta-analysis and research synthesis. *Computers & Education*, *94*, 252–275. https://doi.org/10.1016/j.compedu.2015.11.008

Taber, K. S. (2018). The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. *Research in Science Education*, *48*(6), 1273–1296. https://doi.org/10.1007/s11165-016-9602-2

Trautwein, U., Lüdtke, O., Nagy, N., Lenski, A., Niggli, A., & Schnyder, I. (2015). Using Individual Interest and Conscientiousness to Predict Academic Effort: Additive, Synergistic, or Compensatory Effects? *Journal of Personality and Social Psychology*, *109*(1), 142–162. https://doi.org/10.1037/pspp0000034

Trautwein, U., Nagengast, B., Roberts, B., & Lüdtke, O. (2019). Predicting Academic Effort. In K. A. Renninger & S. E. Hidi (Eds.), *The Cambridge Handbook of Motivation and Learning* (1st ed., pp. 353–372). Cambridge University Press. https://doi.org/10.1017/9781316823279

van Braak, J., Tondeur, J., & Valcke, M. (2004). Explaining different types of computer use among primary school teachers. *European Journal of Psychology of Education*, *19*(4), 407–422.

Van den Akker, O., Weston, S. J., Campbell, L., Chopik, W. J., Damian, R. I., Davis-Kean, P., Hall, A. N., Kosie, J. E., Kruse, E. T., Olsen, J., Ritchie, S. J., Valentine, K. D., van 't Veer, A. E., & Bakker, M. (2019). *Preregistration of secondary data analysis: A template and tutorial* [Preprint]. PsyArXiv. https://doi.org/10.31234/osf.io/hvfmr

Warm, T. A. (1989). Weighted likelihood estimation of ability in item response theory. *Psychometrika*, *54*(3), 427–450. https://doi.org/10.1007/BF02294627

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. https://doi.org/10.1080/10665684.2014.866871

Wigfield, A., & Eccles, J. (2000). Expectancy–Value Theory of Achievement Motivation. *Contemporary Educational Psychology*, *25*(1), 68–81. https://doi.org/10.1006/ceps.1999.1015

Wu, M. L., Adams, R. J., Wilson, M. R., & Haldane, S. A. (2007). *ACER ConQuest Version 2.0: Generalised Item Response Modelling Software*. ACER Press.

Zhai, X., Zhang, M., & Li, M. (2018). One-to-one mobile technology in high school physics classrooms: Understanding its use and outcome: One-to-one mobile technology in physics. *British Journal of Educational Technology*, *49*(3), 516–532. https://doi.org/10.1111/bjet.12539

Appendix

Example of MPlus Syntax Power Analysis (Multivariate Model), N = 200, small effect size

```
TITLE:Power Analysis Montecarlo
          Multiple Regression
          Educational Technology PD
          SMALL EFFECT SIZE;

MONTECARLO: NAMES ARE x1-x14 d1;
          !d1 dependent variable (participated in educational
          !technology-related PD 0/1)
          !d2 dependent variable (Willingness for Professional
          !Development; Ehmke et al., 2004)
          NOBSERVATIONS = 200;
          NREPS = 1000;
          SEED = 53487;
          !Missing values, estimated 15% per item (no reference)
          PATMISS= x1 (.15) x2 (.15) x3 (.15) x4 (.15) x5 (.15)
                x6 (.15) x7 (.15) x8 (.15) x9 (.15)
                x10 (.15) x11 (.15) x12 (.15) x13 (.15) x14 (.15);
          PATPROB = 1;
          GENERATE = d1(1);
          CATEGORICAL = d1;
          REPSAVE = all; ! save data files for all replications
          SAVE = simsmall200_*.dat;

ANALYSIS:   !TYPE = GENREAL;
          ESTIMATOR = MLR;
          ALGORITHM = INTEGRATION;
          INTEGRATION = MONTECARLO;

          MODEL POPULATION:

          !%OVERALL%

          !Standardized loadings
          i1 BY x1*.70 x2*.45 x3*.40; !Conscientiousness;
          !Reference: Soto & John, 2017
          i2 BY x4*.59 x5*.73 x6*.72 x7*.52; !Utility;
          !Reference: Braak et al., 2004
          d2 BY x11*.75 x12*.7 x13*.8 x14*.65; !Willingness for
          !Professional Development;
          !Reference: Ehmke et al., 2004 (but values are estimated)

          x1*.51; !using 1-(loading)^2 for measurement residuals;
          x2*.7975;
          x3*.84;
          x4*.6519;
          x5*.4671;
          x6*.4816;
          x7*.2704;
          x11*.4375;
          x12*.36;
          x13*.61;
          x14*.51;
```

```
!Variance of factors (standardized SD)
i1@1 i2@1;

!Mean of items (M)
[x1-x3@3.20]; !Conscientiousness (estimated of scale mean;
!Rackoff et al., 2008)
[x4-x7@3.03]; !Utility (estimated of scale mean;
!Braak et al., 2004)
[x8@0]; !Technological Knowledge (TK)
!M=0, SD=1 (Senkbeil & Ihme, 2015)
[x9@0]; !Conceptual Technological Pedagogical
!Knowledge (TPK) (Lachner et al., 2019)
[x10@0]; !Situational Technological Pedagogical
!Knowledge (TPK) (Lachner et al., 2019)
[x11-x14@2.53]; !Willingness for Professional Development;
!(estimated of scale mean; Ehmke et al., 2004 ((3.76+2.82+1.90)/3))

!Variance of Competence Scores (standardized SD)
x8@1; !Technological Knowledge (TK)
!M=0, SD=1 (Senkbeil & Ihme, 2015)
x9@1; !Conceptual TPK (IRT scaling)
!M=0, SD=1 (Lachner et. al., 2019)
x10@1; !Situational TPK (IRT scaling)
!M=0, SD=1 (Lachner et. al., 2019)

!Dependent latent variable

!Standardized loadings (estimated, no reference)
!d2 BY x11@.8 x12@.7 x13@.7 x14@.6; !Willingness for
!Professional Development;
!x11*.36; !using (1-loading)^2 for measurement residuals;
!x12*.51;
!x13*.51;
!x14*.64;

!Mean of dependent latent variable
![x11@1.9 x12@2.82 x13@3.76 x14@2.80]; !Ehmke et al., 2004;
!(estimated of scale mean)
!last item estimated, no reference

!Variance of dependent latent variable (standardized,
!calculated from SD (VAR=SD^2))
!x11@1.35 x12@1.17 x13@.44 x14@1.10; !Ehmke et al., 2004;
!(estimated of scale mean)
!last item estimated, no reference

!Correlation of predictors (estimated, no reference)
i1 WITH i2@.25 x8@.25 x9@.25 x10@.25;
i2 WITH x8@.25 x9@.25 x10@.25;
x8 WITH x9@.25 x10@.25;
x9 WITH x10@.25;

!SEM, larg effect sizes
d1 ON i1*.1 i2*.1 x8*.1 x9*.1 x10*.1;
d2 ON i1*.1 i2*.1 x8*.1 x9*.1 x10*.1;
```

```
        d2@.99; !set disturbance to 1 - sqrt(beta=.1);

MODEL:  !%OVERALL%

        !Standardized loadings
        i1 BY x1*.70 x2*.45 x3*.40; !Conscientiousness;
        !Reference: Soto & John, 2017
        i2 BY x4*.59 x5*.73 x6*.72 x7*.52; !Utility;
        !Reference: Braak et al., 2004
        d2 BY x11*.75 x12*.7 x13*.8 x14*.65; !Willingness for
        !Professional Development;
        !Reference: Ehmke et al., 2004 (but values are estimated)

        x1*.51; !using 1-(loading)^2 for measurement residuals;
        x2*.7975;
        x3*.84;
        x4*.6519;
        x5*.4671;
        x6*.4816;
        x7*.2704;
        x11*.4375;
        x12*.36;
        x13*.61;
        x14*.51;

        !Variance of factors (standardized SD)
        i1@1 i2@1;

        !Mean of items (M)
        [x1-x3@3.20]; !Conscientiousness (estimated of scale mean;
        !Rackoff et al., 2008)
        [x4-x7@3.03]; !Utility (estimated of scale mean;
        !Braak et al., 2004)
        [x8@0]; !Technological Knowledge (TK)
        !M=0, SD=1 (Senkbeil & Ihme, 2015)
        [x9@0]; !Conceptual Technological Pedagogical
        !Knowledge (TPK) (Lachner et al., 2019)
        [x10@0]; !Situational Technological Pedagogical
        !Knowledge (TPK) (Lachner et al., 2019)
        [x11-x14@2.53]; !Willingness for Professional Development;
        !(estimated of scale mean; Ehmke et al., 2004 ((3.76+2.82+1.90)/3))

        !Variance of Competence Scores (standardized SD)
        x8@1; !Technological Knowledge (TK)
        !M=0, SD=1 (Senkbeil & Ihme, 2015)
        x9@1; !Conceptual TPK (IRT scaling)
        !M=0, SD=1 (Lachner et. al., 2019)
        x10@1; !Situational TPK (IRT scaling)
        !M=0, SD=1 (Lachner et. al., 2019)

        !Dependent latent variable

        !Standardized loadings (estimated, no reference)
        !d2 BY x11@.8 x12@.7 x13@.7 x14@.6; !Willingness for
        !Professional Development; no reference
```

```
!x11*.36; !using (1-loading)^2 for measurement residuals;
!x12*.51;
!x13*.51;
!x14*.64;

!Mean of dependent latent variable
![x11@1.9 x12@2.82 x13@3.76 x14@2.80]; !Ehmke et al., 2004;
!(estimated of scale mean)
!last item estimated, no reference

!Variance of dependent latent variable (standardized,
!calculated from SD (VAR=SD^2))
!x11@1.35 x12@1.17 x13@.44 x14@1.10; !Ehmke et al., 2004;
!(estimated of scale mean)
!last item estimated, no reference

!Correlation of predictors (estimated, no reference)
i1 WITH i2@.25 x8@.25 x9@.25 x10@.25;
i2 WITH x8@.25 x9@.25 x10@.25;
x8 WITH x9@.25 x10@.25;
x9 WITH x10@.25;

!SEM, larg effect sizes
d1 ON i1*.1 i2*.1 x8*.1 x9*.1 x10*.1;
d2 ON i1*.1 i2*.1 x8*.1 x9*.1 x10*.1;

d2@.99; !set disturbance to 1 - sqrt(beta=.1);
```