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Predicting secondary school teachers' acceptance and use of a digital learning environment: A cross-sectional study

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A R T I C L E I N F O

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A B S T R A C T

In this study, secondary school teachers' acceptance of a digital learning environment (DLE) was investigated. Questionnaires were taken on three times (T1/T2/T3) during the same school year, with the Unified Theory of Acceptance and Use of Technology (UTAUT) as theoretical framework. Next to questionnaires, user-logs were collected during the entire school year. A total of 72 teachers completed a questionnaire on at least one occasion: 64 teachers responded at T1, 41 at T2, and 55 at T3. We first investigated which factors influence teachers' acceptance of a DLE. The main predictors of DLE acceptance were performance expectancy and social influence by superiors to use the DLE. Effort expectancy and facilitating conditions were of minor importance. We then investigated how well the amount of final observed use could be predicted, and found that at T1 about one third, at T2 about one fourth and at T3 about half of the variance in observed use was predicted by attitude, behavioral intention and self-reported frequency of use. Our study showed that to maximize use of a DLE, its usefulness should be demonstrated, while school boards or principals should strongly encourage teachers to (start to) use the DLE.

1. Introduction

> *I've come up with a set of rules that describe our reactions to technologies:*
> *(1) Anything that is in the world when you're born is normal and ordinary and is just a natural part of the way the world works.*
> *(2) Anything that's invented between when you're fifteen and thirty-five is new and exciting and revolutionary and you can probably get a career in it.*
> *(3) Anything invented after you're thirty-five is against the natural order of things.*
>
> Douglas Adams (Adams, 2003), The Salmon of Doubt, p. 95.

In today's information society, computers and the Internet are omnipresent, and their importance is only likely to rise. This is also the case in education where there is an increased use of technology in the classroom. And although the use of computers in education is not a new issue (Eteokleous-Grigoriou, 2009) technology can be a challenge for teachers. In view of the fast rate of technological development, teachers constantly need to adapt to new technologies and refine their skills in order to integrate technology into the classroom. One such new technology is a digital learning environment (DLE). A DLE offers new learning and teaching opportunities and novel ways of interacting to both students and teachers. It is up to the teacher to explore and exploit these opportunities. In view of teachers' central role in students' attitude formation concerning technology (Hu, Clark, & Ma, 2003) and their central role in integrating technology in the classroom (Chen, Looi, & Chen, 2009), it is important to understand what factors drive teachers to accept and use a new technology. Moreover, from an implementer's or school board's point of view, it is interesting to know whether the future use of the technology by its users can be predicted as soon as the technology is introduced. A technology acceptance study can provide an answer to these questions.

1.1. Technology acceptance

The field of research on technology or information systems (IS) acceptance is very comprehensive. Building on the basis of social psychology and sociology theories like the Theory of Reasoned Ac-

Abbreviations: DLE, digital learning environment; EE, effort expectancy; FC, facilitating conditions; IS, information system; PE, performance expectancy; SI, social influence; TAM, technology acceptance model; TRA, theory of reasoned action; UTAUT, unified theory of acceptance and use of technology.

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tion (Fishbein & Ajzen, 1975), Social Cognitive Theory (Bandura, 1986), Innovation Diffusion Theory (Rogers & Shoemaker, 1971), or the Theory of Interpersonal Behavior (Triandis, 1980), several models were developed, with the Technology Acceptance Model (TAM) (Davis, Bagozzi, & Warshaw, 1989) as the most prominent model. TAM, building on the Theory of Reasoned Action, states that the acceptance of a technology depends on two types of beliefs: the technology's perceived usefulness and its perceived ease of use. TAM has been applied in several hundreds of studies in a wide range of settings, also in the field of education (e.g. Sanchez-Franco, 2010; Teo, Lee, & Chai, 2008). Typically no more than 40% of the variance in the dependent variable is explained, leaving room for additional antecedents of acceptance (Legris, Ingham, & Collerette, 2003), resulting in many follow-up studies focusing on model expansion or refinement. Ultimately, this led to a field of research in which the knowledge was dispersed and lacked structure, until Venkatesh, Morris, Davis, and Davis (2003) synthesized the available body of evidence. Eight widespread (technology) acceptance theories were taken into account, and through an empirical study, four recurrent constructs were withheld and form the base of the development of the Unified Theory of Acceptance and Use of Technology (UTAUT):

– *Performance expectancy (PE):* this encompasses perceived usefulness (Davis, 1989) and other constructs regarding the usefulness of the technology and is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003);
– *Effort expectancy (EE):* this encompasses constructs concerning the ease of use of the technology, such as perceived ease of use (Davis, 1989), and is defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2003);
– *Social influence (SI)*: encompassing constructs relating to norms in the social environment of the individual on his/her use of the technology, e.g. subjective norms (Fishbein & Ajzen, 1975). Social influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003);
– *Facilitating conditions (FC):* this construct is very broad as it encompasses training, support, infrastructure, and knowledge. This construct was distilled from perceived behavioral control (Ajzen, 1991), facilitating conditions (Thompson, Higgins, & Howell, 1991) and compatibility (Moore & Benbasat, 1991). It is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003).

Next to these four constructs, UTAUT also contains four variables that moderate the relationships between the predictors and intention or use: gender, age, experience with the technology and voluntariness of use. UTAUT was found to explain up to 70% of the variance in behavioral intention, thereby outperforming its originating models (Venkatesh et al., 2003).

1.2. Technology acceptance in education

The introduction and use of computers (or technology in general) in education attracted the attention of several researchers in the past. Two major lines of research can be discerned: on the one hand acceptance studies (e.g. Hu et al., 2003; Ma, Andersson, & Streith, 2005; Teo, 2009; Teo et al., 2008) and on the other hand more educational research in which computer attitudes, teacher beliefs and the integration of computers in the classroom are studied (e.g. Hermans, Tondeur, van Braak, & Valcke, 2008; Mueller, Wood, Willoughby, Ross, & Specht, 2008; Sang, Valcke, van Braak, & Tondeur, 2010; Shapka & Ferrari, 2003; van Braak, Tondeur, & Valcke, 2004).

Acceptance studies measure teachers' or student teachers' acceptance of computers operationalized as the intention to use (Hu et al., 2003; Ma et al., 2005; Teo, 2009) or attitudes towards computers (Teo et al., 2008). As in acceptance studies in settings other than education, usefulness was a consistently strong predictor of acceptance (Hu et al., 2003; Ma et al., 2005; Teo, 2009; Teo et al., 2008). In general, the effect of ease of use was not that strong (Teo et al., 2008) or only indirectly significant through usefulness (Hu et al., 2003; Ma et al., 2005; Teo, 2009). The effect of subjective norms on acceptance was inconsistent. Teo et al. (2008) identified it as a direct predictor of acceptance, while Hu et al. (2003) found it to be influential only in the beginning, and Ma et al. (2005) found no effect. Three studies found facilitating conditions (Teo, 2009; Teo et al., 2008) or the related construct compatibility (Hu et al., 2003) to influence acceptance indirectly through perceived ease of use and/or perceived usefulness. Other predictors of computer acceptance were attitude (Teo, 2009), (computer) self-efficacy (Hu et al., 2003; Kao & Tsai, 2009; Teo, 2009), job relevance (Hu et al., 2003) and technological complexity (Teo, 2009).

In educational sciences, several studies found that computer attitudes have a positive influence on the integration of computers in education. In these studies, the term (computer) attitudes may refer to very diverse constructs:

– General computer attitude: this encompasses confidence, anxiety and enjoyment/liking (Hermans et al., 2008; Shapka & Ferrari, 2003; van Braak et al., 2004);
– Attitude towards computers in the classroom (Mueller et al., 2008; Sang et al., 2010; van Braak et al., 2004) enclosing items related to the usefulness of a computer as a tool.

The importance of providing facilitating conditions is also a recurrent theme in this line of research. The following constructs that may be considered as categories of facilitating conditions were mentioned as important for integrating computers in education: equipment resources and support from school administrators (Smarkola, 2008), institutional support (Kadijevich, 2006), training, access to ICT resources and ongoing support (Williams, Coles, Wilson, Richardson, & Tuson, 2000), and computer training (van Braak et al., 2004). Other factors with a positive influence on the integration of computers in the classroom were self-efficacy (Sang et al., 2010; Shapka & Ferrari, 2003) and computer experience (Hermans et al., 2008; Mueller et al., 2008).

1.3. Operationalizing acceptance

Technology acceptance can be measured in several ways. Originally, models were devised for situations where users could choose to use (or not use) a technology, and this was reflected in the operationalization of acceptance: one accepts a technology if s/he uses (or intends to use) the technology. However, in many cases, users do not have a choice; they simply have to use the technology so that other conceptualizations of acceptance might be better (Warshaw & Davis, 1985b). Below, the most common operationalizations of acceptance are listed:

– *Use or use behavior* (Halawi & McCarthy, 2008; Landry, Griffeth, & Hartman, 2006; Venkatesh et al., 2003)*:* observed or self-reported. Observed use can be considered as the ultimate measure for acceptance: e.g. the duration of use computed from system logs (Venkatesh et al., 2003), recording the actions a subject undertakes while completing a task (Shapka & Ferrari, 2003). A problem with use (both observed and self-reported) is that it requires subjects to have some experience with the technology. When the implementation of a technology is still being planned, other measures of acceptance should be used;

– *Behavioral intention* (Marchewka, Liu, & Kostiwa, 2007; Venkatesh et al., 2003)*:* this measure can be used both for cases where the technology has already been introduced, and for cases where it is still under planning;
– *Behavioral expectation* (Davis, 1985; Venkatesh, Brown, Maruping, & Bala, 2008)*:* this measure is closely related to and has frequently been confounded in the past with behavioral intention (Warshaw & Davis, 1985a). Behavioral expectation takes into account that something might interfere between the intention and the actual performance of the behavior. Behavioral expectation has been found to correlate more strongly with behavior than behavioral intention (Warshaw & Davis, 1985b);
– *Attitude toward use of the technology:* attitude already appeared in the first version of TAM. Attitude has been used as a measure for acceptance in both mandatory (Brown, Massey, Montoya-Weiss, & Burkman, 2002; Pynoo et al., 2007) and voluntary (Teo et al., 2008) settings.

For this study, attitude, behavioral intention and use will be included as measures for acceptance. In view of the conceptual overlap with and dominance of behavioral intention in this field of research, behavioral expectation will not be taken into account. Use will be measured as self-reported frequency of use and observed frequency of use from log files.

1.4. Purpose

The purpose of this study is to scrutinize secondary school teachers' acceptance of a digital learning environment. Two research questions are put forward. We will first investigate which factors contribute to secondary school teachers' acceptance of a DLE. As we draw on UTAUT as theoretical framework, the first research question to be addressed in this study is:

> RQ1: To what degree can performance expectancy, effort expectancy, social influence and facilitating conditions predict the acceptance of a digital learning environment, measured as attitude, behavioral intention, self-reported frequency of use, and observed near-term use?

Second, we will also investigate if the amount of final observed use of the DLE can be predicted. As we dispose of both self-reported and observed measures, we will assess how well the self-reported measures of acceptance predict actual use. We hypothesize that these measures of acceptance have both a direct and indirect influence on the amount of observed use. A direct influence because attitude, behavioral intention and self-reported use all served in past research as measures for acceptance in the absence of a measure of observed use. An indirect influence because acceptance measures are interrelated: attitude influences intention (Davis et al., 1989), intention in its turn self-reported use (Venkatesh et al., 2003). Putting this together leads to the model as depicted in the research question 2 pane of Fig. 1, while the second research question is formulated as follows:

> RQ2: To what degree can attitude toward use of a DLE, behavioral intention to use the DLE and self-reported frequency of use of the DLE predict the final observed use of the DLE?

Combining the two research questions leads to the research model in Fig. 1. By combining the research questions, we will be able to distill the factors that lead to a maximal use of the DLE.

This study intends to add to the current literature on (educational) technology acceptance in three respects:

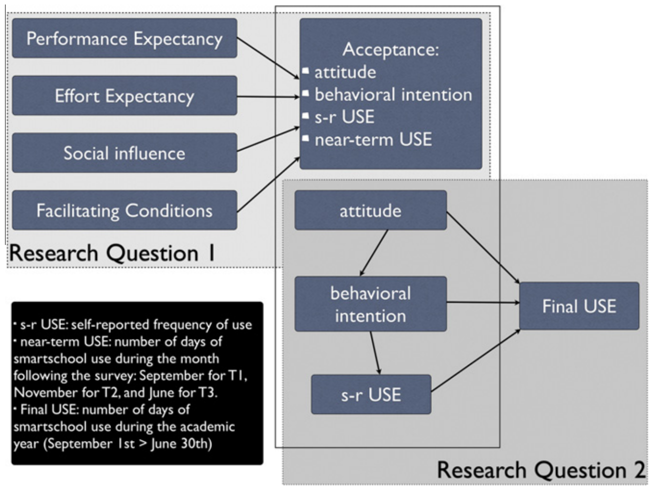

Fig. 1. Research model.

(1) by examining professional users (teachers);
(2) by administering questionnaires on three occasions during one school year. This way the evolution over time of the teachers' opinions concerning the technology can be revealed;
(3) by collecting, in addition to the questionnaires, use behavior from log files. This is a major strength of the study, as most studies in this field of research have to rely on self-reported measures of acceptance (Legris et al., 2003).

The combination of these three characteristics distinguishes this study from other (educational) technology acceptance studies.

2. Materials and methods

2.1. Technology

The digital learning environment under scrutiny is Smartschool (www.smartschool.be). Smartschool offers its users (administrative force, school board, teachers and pupils) both basic and very advanced opportunities. The three core functionalities of Smartschool are:

– digital learning environment consisting of 16 modules. In the DLE, teachers can set up learning paths, create exercises, take tests, collect and store tasks, etc.;
– *communication:* Smartschool has an internal messaging system for communication between users, public discussions can be conducted in forums, and users can read important messages from the school board on the bulletin board;
– *administration:* this comprises for example taking surveys, online timetables, and an intradesk where users can submit important documents.

Next to these core functionalities, extra features can be added to Smartschool, like an online scorecard, or linking the upload zone with Ephorus (www.ephorus.nl) to control for plagiarism in student papers.

2.2. Data collection

2.2.1. Study population

The participants were members of the teaching staff (total population of 90 teachers) of a secondary school. The school is situated in the Dutch-speaking part of Belgium. In this school, three streams of education are offered: general, technical and vocational education.

2.2.2. Instrument

The acceptance part of the questionnaire was made up of 21 items (22 at T2 and T3, see Section 3.1.). The items were adapted from Duyck et al. (2008), Moore and Benbasat (1991), and Venkatesh et al. (2003), and tweaked to an educational context. The following scales (number of items per scale between brackets), were included in the questionnaire survey: performance expectancy (four items), effort expectancy (three items at T1, four at T2 and T3, see Section 3.1.), social influence (four items), facilitating conditions (three items), attitude (three items), behavioral intention (two items), and self-reported frequency of use (two items). As the use of the digital learning environment was mandatory, we were only interested in social influence exerted by superiors and the SI-scale was adjusted in this way. All items had to be rated on a 7-point Likert scale ranging from "complete disagreement (1)" to "complete agreement (7)", except for self-reported use that ranged from "never (1)" to "daily (7)".

Next to these items, demographic information (gender, age, domain of teaching) was collected while the teachers could also indicate which of the 16 modules in the DLE part they used. At the end of the questionnaire, there was room for remarks or complaints.

For this study, use is derived from system logs containing date and time a user logged in into the system. Two measures were computed:

– *Near-term use:* number of days a teacher logged in into the system during the month following the survey, respectively, the use in September (T1), November (T2) and June (T3);
– *Final use:* number of days a teacher logged in into the system during the school year 2006–2007 (from September 1st to June 30th).

2.2.3. Procedure

The questionnaire was administered at three times during the same school year. The first questionnaire (T1) was taken during a plenary preparatory meeting at the end of August prior to the start of school year. At this meeting, Smartschool was formally introduced to the teaching staff, although it was accessible since May and already pretested. At the meeting, the principal strongly encouraged the teachers to use Smartschool during the lessons and for school tasks. He also announced that Smartschool would replace the official bulletin board, hence that use of Smartschool was mandatory. Teachers were given time to complete the questionnaire during the meeting, the responses were collected at the end, this way 64 usable responses were collected.

The second (T2) and third (T3) questionnaires were handed out to the teachers per their personal pigeonhole in the teachers' room. Completed responses could be posted in a sealed box in the teachers' room. The second questionnaire was handed out at the end of October, right before fall break, and 41 usable responses were collected. The last questionnaire was handed out at the end of May, and 55 usable responses were returned. A total of 72 (unique) teachers completed at least one questionnaire; user logs (showing data and time the user logged in into Smartschool) were collected for these 72 teachers.

2.3. Data-analysis

Prior to the analysis of the research questions, some preliminary analyses will be run. First, the reliability of the scales will be established using Cronbach α. Then descriptive statistics will be computed and the correlations between the constructs will be calculated.

For the first research question, we want to investigate which factors contribute to the acceptance of the DLE, if this changes over time, and how well the predictors predict the acceptance of the DLE. Hereto, ordinary least squares regression analyses will be run in SPSS 15, per measure of acceptance, pooled over the measurements and per measurement (T1, T2 or T3).

Path analysis using AMOS 6.0 will be applied to address the second research question, as we do not only want to investigate how well the self-reported measures of acceptance predict observed use, but also how the self-reported measures interrelate. To test the fit between our model and the data, the following fit-measures will be used: normed χ^2, root mean square error of approximation (RMSEA), comparative fit index (CFI), and adjusted goodness-of-fit index (AGFI). The recommendations of Hu and Bentler (1999) are used: below .05 for RMSEA and higher than .95 for CFI and AGFI, while for normed $\chi^2 < 3.0$ (Teo, Lee, Chai, & Wong, 2009).

3. Results

3.1. Preliminary analyses: Reliability, descriptive statistics, correlations

Table 1 displays the reliability and descriptive statistics of the scales and measures that were used throughout this study. The reliability of the FC-scale was below the threshold for acceptable reliability (.70) (Nunnally & Bernstein, 1994), however, by removing the item "Smartschool is not compatible with other systems I use" the reliability of this scale was drastically improved. For the EE-scale, there was a problem with one item ("I fear that learning to work with Smartschool will not go fast and will take a lot of time") at T1, therefore the item was replaced by "Learning to work

Table 1
Reliability and mean of the scales per measurement.

	Cronbach α	T1 ($n = 64$) *M* (*SD*)	T2 ($n = 41$) *M* (*SD*)	T3 ($n = 55$) *M* (*SD*)
PE	.84	3.52 (1.60)	3.54 (1.68)	3.76 (1.69)
EE	.72	4.15 (1.54)^{c}	4.00 (1.48)^{b}	4.81 (1.46)^{b,c}
SI	.73	6.03 (1.01)	5.99 (1.30)	6.24 (0.88)
FC	.84	4.10 (1.36)^{a}	4.80 (1.56)^{a}	4.28 (1.62)
BI	.84	5.22 (1.58)	5.39 (1.54)	5.42 (1.31)
ATT	.90	4.26 (1.57)	4.29 (1.79)	4.75 (1.50)
s-r USE	.96	4.26 (1.59)^{a,c}	6.01 (1.09)^{a}	6.02 (1.22)^{c}
Final use[d]		182.33 (62.94)	199.71 (54.05)	193.44 (57.56)
Near-term use[e]		21.34 (7.02)	22.20 (5.84)	20.85 (6.50)

Notes: [a,b,c] Values in the same line with the same superscript differ on $p < .05$ (independent samples *t*-test, two-sided); [d] number of days of Smartschool use during the school year; [e] number of days of Smartschool use during the month following the survey.

Table 2
Results of regression analysis.

Timing	Attitude			Behavioral intention			Self-reported use			Near-term use		
	T1	T2	T3	T1	T2	T3	T1	T2	T3	T1	T2	T3
PE[a]	.62***	.79***	.79***	.39**	.61**	.33°	.16	.11	.18	.36°	.57*	.29
EE[a]	.31***	.14	.18°	.11	−.14	.37*	.19	.07	.21	−.04	−.40°	.12
SI[a]	−.02	−.01	.00	.36**	.26°	.22*	.43***	.09	.27*	.31*	.23	.07
FC[a]	.04	.03	−.08	.08	.19	−.05	.12	.38°	−.03	−.17	.35°	.03
Adj. R^2	.78	.84	.76	.35	.31	.38	.29	.16	.12	.08	.26	.11
Model test[b]	***	***	***	***	**	***	***	*	*	°	**	*

Notes: [a] The values reported are standardized β regression coefficients; [b] *Model test:* significance level of the model test; ***$p < .001$; **$p < .01$; *$p < .05$; °$p < .10$.

with Smartschool did not go fast" and "Working with Smartschool costs me little trouble". In order to maximize comparability, only the two items that were measured on all three occasions were withheld for the EE-scale for the remainder of the analyses.

Five significant differences between the mean scale ratings were observed (Table 1). Perceptions of the ease of use of Smartschool (EE) were significantly higher at T3 compared to both T1 ($t(117) = 2.392$, $p = .018$) and T2 ($t(94) = 2.670$, $p = .009$). Mean scores on facilitating conditions increased significantly from T1 to T2 ($t(102) = 2.426$, $p = .017$). Finally, self-reported use (s-r use) on T1 was significantly lower compared to both T2 ($t(100.923) = 6.667$, $p < .001$) and T3 ($t(115.741) = 6.823$, $p < .001$).

The descriptive statistics show that the users rated performance expectancy of Smartschool low. Another remarkable, yet expected, finding is the high mean score on the SI-scale at all times.

The correlation analysis did not reveal unexpected findings, but we will highlight some results.

First, at all three times we observed a very high correlation between attitude and PE (r between .86 and .92, all $p < .001$) or EE (r between .72 and .77, all $p < .001$). FC correlated strongly at all times with PE (r between .57 and .64, all $p < .001$) and EE (r between .48 and .64, all $p < .001$).

Looking at the correlations between the dependent variables, we saw that the correlation between near-term and final use was very high at all times (r from .86 to .91). The correlations between the three measures of near-term use of the unique teachers ($n = 72$) were equally high: the correlation between use of Smartschool during September and during November was .65, between September and June .53, and between November and June .78. Apparently, users almost immediately adopt a base-rate of Smartschool use. This base-rate could be subjected to minor changes especially at the beginning of use (period between T1 and T2), while from T2 on only minimal shifts took place. One more trend deserves attention: we found that the correlation between attitude and the observed measures of use increased over time. For final use from $r = .25$, $p < .05$ at T1 to $r = .39$, $p < .01$, while for near-term use from $r = .16$, $p > .10$ at T1 to $r = .42$, $p < .01$ at T3.

3.2. Research question 1: Explaining and predicting acceptance

A regression analysis was performed to investigate which factors determine the acceptance of Smartschool. Separate regression analyses per operationalization of acceptance and per time were run, the results are reported in Table 2. To get a view on the changes over time, we also pooled the data over the three measurements and ran hierarchical regression analyses per dependent variable. The first block contained a time variable (T1/T2/T3) and the UTAUT-predictors, while the second block held the interaction terms. The results are displayed in Table 3.

Table 3
Results of hierarchical regression analysis, pooled over three measurements.

Pooled	ATT	BI	s-r USE	Near-term use
Time[a]	.04	−.04	.43***	−.07
PE[a]	.71***	.42***	.14	.36**
EE[a]	.24***	.13	.07	−.06
SI[a]	−.02	.28***	.23***	.20*
FC[a]	−.01	.08	.21*	.03
Time × PE[a]	.05	−.05	.03	−.02
Time × EE[a]	−.05	.08	−.05	.05
Time × SI[a]	.01	−.07	−.09	−.10
Time × FC[a]	−.05	−.07	−.10	.08
Adj. R^2	.80	.35	.38	.12
Sig. R^2 change[b]	$p = .60$	$p = .62$	$p = .29$	$p = .54$

Notes: [a] The values reported are standardized β regression coefficients; [b] this refers to the significance level of the change in R^2 after adding the interaction terms.

3.2.1. Predicting attitude

Performance expectancy is the primary predictor of attitude ($\beta = .62$), while effort expectancy was only significant for predicting attitude at T1 ($\beta = .31$) and marginally at T3 ($\beta = .18$, $p = .08$). At all three measurement moments, social influence and facilitating conditions did not have any direct effect on attitude. The amount of variance explained in attitude was very high, ranging from adjusted $R^2 = .77$ at T1 to .85 at T2. The pooled analysis revealed nothing new, and adding the interaction terms did not increase the proportion of variance explained.

3.2.2. Predicting behavioral intention

The primary predictor of behavioral intention at T1 was performance expectancy ($\beta = .39$), but the effect of social influence ($\beta = .36$) was also significant. The effect of effort expectancy ($\beta = .11$) and facilitating conditions ($\beta = .08$) was not significant at this time. At T2, when the teachers had acquired some experience with Smartschool, performance expectancy ($\beta = .61$) was the only significant predictor of intention, while the effect of social influence ($\beta = .26$, $p = .07$) appeared to be only marginal. At T3, when the teachers had acquired extensive experience with the use of Smartschool, the most significant predictor was effort expectancy ($\beta = .37$), together with social influence ($\beta = .22$). Performance expectancy ($\beta = .33$, $p = .06$) was only marginally significant. The proportion of variance explained appeared to be significantly lower compared to that in attitude, ranging from adjusted R^2 between .31 and .38. The pooled analysis showed that only performance expectancy ($\beta = .71$) and social influence ($\beta = .28$) predicted intention. Adding the interaction terms did not lead to any increase in the amount of variance explained.

3.2.3. Predicting self-reported use

At T1, social influence ($\beta = .43$) was the sole significant predictor of teachers' self-reported use of Smartschool. The effect of facilitating conditions ($\beta = .38$, $p = .06$) was marginally significant at T2, no other effects were found at this time. Just as at T1, social influence ($\beta = .27$) was the sole predictor of self-reported use at T3. Variance explained was low at T2 and T3 (.16 and .12), while at T1 about one third of the variance was explained. The pooled analysis provided more information. A main effect of time ($\beta = .43$) was found, indicating that self-reported use increased over time. Both facilitating conditions ($\beta = .21$) and social influence ($\beta = .23$) had a direct effect on self-reported use. Variance explained was a lot higher compared to the analyses per measurement. Adding interaction terms did not lead to any increase in the proportion of variance explained.

3.2.4. Predicting near-term use

At T1, performance expectancy, albeit marginally ($\beta = .36$, $p = .07$), and social influence ($\beta = .31$) predicted Smartschool use during the month of September. Variance explained in use was very low (Adj. $R^2 = .08$), and the model just failed to reach significance ($p = .06$). At T2, variance explained was considerably higher (Adj. $R^2 = .26$) but only performance expectancy ($\beta = .57$) was significant for predicting Smartschool use during November. The effects of effort expectancy ($\beta = -.40$, $p = .10$) and facilitating conditions ($\beta = .35$, $p = .05$) on use were marginally significant. At T3 none of the predictors were significant and variance explained was equally low (Adj. $R^2 = .11$). Performance expectancy appeared to be the most important factor ($\beta = .29$, $p = .16$). The pooled data analysis showed that performance expectancy ($\beta = .36$) and social influence ($\beta = .20$) were the only predictors of near-term use. Variance explained was low (Adj. $R^2 = .12$).

3.3. Research question 2: Explaining and predicting final use

The second research question concerned the prediction of the final use of Smartschool. The results of the path model are displayed in Fig. 2.

Per time, two models were analyzed: the original version as displayed in Fig. 1 (RQ2 pane) and a final model (Fig. 2) in which goodness-of-fit was maximized. Quality fit measures were very good for all three final models. At all times, normed χ^2 was lower than 1 (respectively .523, .987 and .333), CFI equaled 1 and RMSEA 0. Due to missing values AGFI could not be computed at T2, but at T1 and T3 AGFI also indicated a good measurement fit (.959 and .970, respectively). Already at T1, a substantive portion of the variance in "final use" could be explained (mcc = .31). Variance explained was slightly lower at T2 (mcc = .27), while at T3 variance explained was high as about half of the variance in observed use was explained (mcc = .46).

On all times, the same direction of influences was observed: attitude influences behavioral intention; behavioral intention self-reported use, and self-reported use observed use. There was one minor exception, the influence of attitude on observed use increased over time. While nonexistent at T1 ($\beta = -.02$) and T2 ($\beta = .07$), the influence of attitude on observed use was marginally significant at T3 ($\beta = .20$, $p < .10$).

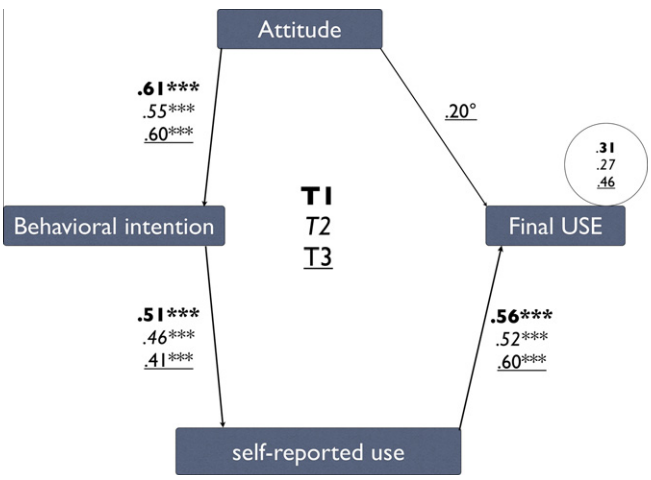

Fig. 2. *Path analysis:* final models. The values displayed are standardized regression coefficients and multiple correlation coefficients. *Notes:* values in bold refer to the analysis at T1, in italics to T2 and underlined to T3; ***$p < .001$; °$p < .10$.

4. Discussion

4.1. Predicting acceptance

The primary aim of this study was to assess which factors contribute to the acceptance of Smartschool. Hereto, acceptance was operationalized in four ways (attitude, behavioral intention, self-reported frequency of use and observed near-term use), and UTAUT was chosen as theoretical framework. This proved to be fruitful, as depending on the operationalization of acceptance, other predictors arose. To summarize: teachers hold a positive attitude of Smartschool because it is useful (PE) and easy to use (EE); they intend to use Smartschool because it is useful (PE) and their superiors expect them to use it (SI); they report that they use Smartschool more frequently the more they feel that their superiors expect them to use it (SI) and if the ideal conditions are created (FC); and their actual use of Smartschool depends on its usefulness (PE) and pressure from superiors to use Smartschool (SI).

4.1.1. Performance expectancy

Except for self-reported use, the usefulness of the technology (measured as performance expectancy) was the main predictor of DLE acceptance. This conforms to earlier TAM-studies in educational settings (Hu et al., 2003; Ma et al., 2005; Teo, 2009; Teo et al., 2008). In the case of self-reported use, performance expectancy was of no significance.

4.1.2. Effort expectancy

In studies involving professional users (Duyck et al., 2008; Hu et al., 2003), ease of use is often subordinate to usefulness and this is also what has been found in the current study. Effort expectancy was a predictor of attitude, especially in the beginning, and interestingly, it was also the strongest predictor of intention at T3.

4.1.3. Social influence

Although social influence in UTAUT and subjective norms in TAM2 are modeled as antecedents to behavioral intention and not to use, the construct was the main predictor of self-reported frequency of use. The regression analyses per measurement showed that the effect of social influence on acceptance (measured as behavioral intention, self-reported use and near-term use) was strongest at T1, slightly less strong at T3, while no effect was found at T2.

4.1.4. Facilitating conditions

According to Venkatesh et al. (2003), facilitating conditions should only have a direct influence on use. We also found a limited effect of facilitating conditions on acceptance: after pooling the data, the construct was, together with social influence, a predictor of self-reported use. The regression analyses per measurement revealed that facilitating conditions were only a marginally significant predictor of self-reported use at T2. This does not mean that facilitating conditions are of almost no importance, only that their influence is indirect rather than direct. A theoretical foundation hereto is provided by Venkatesh and Bala (2008). In their TAM3 model, facilitating conditions and social influence are modeled as antecedents to perceived usefulness and perceived ease of use, and they argued that constructs related to social influence determine usefulness, while facilitating conditions should load solely on ease of use. This is contrary to what we found. Inspecting the correlations, no relationship was observed between social influence and performance expectancy, while strong correlations were observed between facilitating conditions and both performance and effort expectancy. So, it seems that although the provision of facilitating conditions has no direct effect on acceptance (except marginally on self-reported and near-term use at T2, and pooled on self-reported use), facilitating conditions might have a significant indirect influence on acceptance through performance and effort expectancy.

4.2. Predicting observed final use

In order to address the second research question, we investigated to what extent self-reported measures of acceptance could predict the observed final use of Smartschool. Hereto, path analyses were run. Already at T1, we were able to predict about one third of the variance in the use that would be observed throughout the school year. Moreover, correlation analyses indicated that the users almost immediately adopted a base-rate of Smartschool use. This stresses the importance of preparing teachers to start using a new technology like a digital learning environment.

The path analyses showed that the only predictor of final use was self-reported frequency of use, while indirectly, attitude and intention played a role through self-reported use. As could be expected from Davis et al. (1989), a linear relationship was found between these constructs: attitude has an effect on intention, while intention has an effect on self-reported frequency of use, and the latter on observed use.

4.3. Maximizing use

Looking at the predictors of self-reported measures for acceptance we can conclude that in order to maximize the final use of the system, teachers should be urged to use the system right from the beginning, while stressing the usefulness of the system. Keeping in mind that the users rated the performance expectancy of Smartschool below four (on a 1–7 Likert scale), a lot of effort should have been invested in detailing the features of the system to maximize its use. Effort expectancy has in this case only a marginal influence through usefulness or attitude.

At T2, social influence becomes less important, but facilitating conditions comes into play, as the only (marginally significant) predictor of self-reported use. So after the technology is introduced, the necessary conditions should be created to facilitate use of the system. The usefulness of the system is also important at this time as it influences a teachers' intention to use the system and attitude toward the system.

At T3, social influence emerged again as sole predictor of self-reported use. Therefore urging teachers to use Smartschool remains important, even after several months of use. At T3, the importance of attitude for predicting final use also emerged. A teacher's attitude toward Smartschool was best explained by the system's usefulness and ease of use. On the other hand, teachers intend to keep using Smartschool, because it is easy to use and because they are urged to use it. So at T3, every factor is important as it can have a direct or indirect effect on the observed use.

4.4. Limitations

The main limitation of this study pertains to the sample size of our study. On top of this, the response rate at T2 was rather low. So future researchers should be careful in generalizing our results. Nonetheless, in view of reliability of the scales and as we collected information from two sources – questionnaires and user logs – we feel rather confident on the validity of our results.

5. Conclusion

In this study, secondary school teachers' acceptance and use of a digital learning environment was scrutinized by administering questionnaires drawing on UTAUT as theoretical framework, on three occasions during the same school year. In addition to the questionnaires, use behavior was extracted from log files. We first investigated which factors contributed to teachers' acceptance of the DLE. Acceptance was operationalized in four ways: attitude, intention, self-reported frequency of use and observed near-term use. The predictors differed depending on the operationalization of acceptance and on the timing of the measurement, but overall, we found that performance expectancy and social influence exerted by superiors to use the DLE were the main predictors of acceptance, while effort expectancy and the provision of facilitating conditions were of minor importance. Second, as we derived use behavior from log files, we investigated how well the amount of final observed use could be predicted during the school year. We found that at T1 about one third, at T2 about one fourth, and at T3 about half of the variance in final observed use was predicted by attitude, behavioral intention, and self-reported frequency of use. The user logs also showed that teachers seemed to adopt a base frequency of DLE-use almost from the beginning. Our results show that in order to maximize the use of a digital learning environment, its usefulness should be demonstrated and stressed, while school boards or principals should enforce teachers to (start to) use the DLE.

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