Jl. of Interactive Learning Research (2014) **25**(4), 509-529

Learner Characteristics predict Performance and Confidence in e-Learning: An Analysis of User Behaviour and Self-evaluation

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We examined the role of learner characteristics as predictors of four aspects of e-learning performance, including knowledge test performance, learning confidence, learning efficiency, and navigational effectiveness. We used both self-reports and log file records to compute the relevant statistics. Regression analyses showed that both need for cognition and serialist preference predicted test performance. Participants needed less time to complete the e-module when they had lower serialist and higher surface processing scores. Learners with higher deep strategy and need for cognition scores were more confident in their learning, whilst the reverse held true for learners who scored high on surface strategy use. Also, learners with higher surface strategy use showed less active navigation patterns. Age did not predict any outcome except performance efficiency. The results therefore support the importance of including self-reported learner characteristics and educational background in addition to log file information.

Adaptive e-learning systems have garnered growing research attention recently (e.g., Akbulut & Cardak, 2012; Desmarais & Baker, 2012). Many adaptation strategies, such as varying learner control or the complexity of information, are usually based on learner characteristics, for instance, cognitive styles, the level of prior knowledge and motivation (van Seters et al., 2012). There are several approaches to modelling learners on-line, such as automatic learner modelling (Özpolat & Akbar, 2009), trace analysis (Bousbia et al, 2010), data mining (Köck & Paramythis, 2011), or log file analysis (Cocea & Weibelzahl, 2009). These approaches are largely based on automatically collected user data, analysing series of user events to determine the learner's need for support (Ghazarian & Noorhosseini, 2010). Together with information about task difficulty and required user expertise (Horvitz et al., 1998), these inferences inform the subsequent user model and thus provide the basis for an instructional platform tailored to users' needs.

Whilst dynamic modelling might maximise the benefits of adaptation, large-scale use of dynamic systems (e.g., in work settings) might be difficult. As a learner's progress at any given point in time can only be measured in terms of the content accessed by that time, dynamic systems must be set up anew each time new content is introduced, which is rather time-consuming and costly. We therefore focus on a static approach that uses learners' self-ratings of their learning preferences.

Several performance measures are usually found in e-learning studies and relevant to our approach and study. Of interest here are performance on task, learning efficiency, navigation, and learning confidence. Performance in e-learning and similar online tasks frequently involves test performance (Ley, Kump, & Gerdenitsch, 2010), but performance is also often assessed by using error rates or the number of help requests (Recabarran & Nussbaum, 2010). Performance efficiency is computed from the time-on-task relative to performance achieved; more efficient learners attain the same level of test performance in less time than their less efficient counterparts (Corbalan, Kester, & van Merriënboer, 2006; Ley et al., 2010). Such a measure can help indicate how difficult the learning task was for particular learners, as learning time increases typically with complexity. This, in turn, may help indicate cognitive load or even overload (Corbalan et al., 2006). In addition to these variables, many of which are used in traditional learning situations, effective navigation of online websites and e-modules is another area of interest. Researchers frequently examine the frequency with which various navigation tools are selected (Chen & Ford, 1998). Such tools include the usage of links, navigation backwards and forwards on a site, and the number of pages visited (repeatedly).

These three sets of outcomes are usually effortlessly captured via log files. However, two things are frequently not considered in or only passively derived from log files. Firstly, they do not capture relevant constructs such as learner confidence. That is, the amount of confidence that learners have in terms of what they have just learned. The judgment of learning or judgment of confidence (Mengelkamp & Bannert, 2010) are either made prior to the participant seeing the test questions or after a test item is presented. They can add to the picture and increase self-reflection. The second aspect concerns the fact that log files frequently ignore the potential influence of learner diversity in terms of their age, background, and learner characteristics. Assessing and then addressing these variables would require the user models to become more user-focused and dynamic, which requires more resources and goes beyond log file analysis. However, moving into this direction is essential, especially when we consider the popularity of e-learning in the work place. These users tend to come from various different age groups, have different backgrounds and may vary significantly in terms of their learning strategies and preferences. Considering the role of age diversity, for example, is very relevant to the discussion of time on any given task, especially when the learners can be of any age. Age influences how effectively and how quickly we process information, given lower working memory capacity (Paas, Van Gerven, & Tabbers, 2005). Such changes go hand in hand with greater difficulty to inhibit irrelevant information coordination and integration of information (Van Gerven, Paas, & Tabbers, 2006). This suggests that e-learning features such as time stamping and graphics meant to aid learning in younger cohorts may actually inhibit learning for other user groups.

Our study sought to answer the following broad research questions. First, which learner characteristics predict e-learning performance? Second, what learning process variables (efficiency and navigation behaviours) do learner characteristics impinge upon? Third, are different learner characteristics associated with different levels of confidence assessed via a judgement of learning? Fourth, will learner characteristics effects differ as a function of age? In the subsequent section, we describe learner characteristics of interest for a process-related learner modelling approach and their relationship with learning outcomes.

Selected Learner Characteristics

A number of articles and reviews support the inclusion of various different cognitive and learning styles as predictors of learning in adaptive learning environments as well as assessments involving online learning performance, hypertext usage and web searches (e.g., Clewley, Chen, & Liu, 2010; Ellis, Ford, & Wood, 1993; Liu, Magjuka, & Lee, 2007; Palmquist & Kim, 2000; Sadler-Smith & Smith, 2004; Triantafillou et al., 2004; Vandewaetere, Desmet, & Clarebout, 2011). Accommodating individual learning styles but also developing learning strategies can be helpful to achieving learning outcomes and potentially even improving self-regulation (e.g., Rush & Moore, 1991). This suggests that learning styles may provide a starting point for research to develop personalized approaches in further development and work-based learning.

We use the term learning styles here to denote cognitive styles that are particularly relevant to a learning context (see Ford & Chen, 2000). The first two learning styles of interest concern serialist vs. holist learning preferences. Serialists can be labelled "operation learners" with a more pronounced bottom-up approach (Ford, 1985). These individuals tend to focus on the immediate or local aspects at a time. They learn in a linear and sequential fashion which goes hand in hand with an emphasis on memorising facts for reproduction, emphasising procedures in order to construe logical arguments and simple hypotheses (Ford, 2000). Merrill (2002, p. 103) suggested that "serialist learners learn better from content that is arranged in a logical sequence and prefer to learn each topic in order." Holists are "comprehension learners" with a clear top-down approach to tasks (Ford, 1985). They have a more global strategy and wider focus on several aspects. They aim to produce broader descriptions and use general illustrations such as analogies. As a result, they focus on gaining information first, which means procedural planning comes second.

A second style we were interested in concerns the depth of processing, that is, a surface and deep strategy approach. Those with a surface strategy approach to a task tend to focus on identifying and then memorising the main facts and ideas in order to reiterate these facts at the end of whatever exercise they are completing. The emphasis is therefore on learning by rote, with little attention paid to the structure and principles connecting the facts in the material (Fox, McManus, & Winder, 2001). In contrast, those learners who pursue a deep strategy actively seek to understand the wider meaning of materials, appraise information and try to relate this to prior knowledge and experience. Using Biggs, Kember, and Leung's, (2001) scales, Hua, Williams, and Hoi (2006) found that the surface approach was negatively associated with academic performance.

Finally, we studied the influence of learners' need for cognition, another cognitive style variable. Need for cognition describes an individual difference in terms of the degree to which individuals like to engage in and take pleasure in effortful cognitive activity (Cacioppo et al., 1996). Need for cognition has been demonstrated to play an important role when individuals process materials of varying textual and graphical complexity, which is also relevant in terms of content characteristics of e-learning materials. Cacioppo and Petty (1982) found that people with higher need for cognition are driven to understand their world by seeking more information and knowledge and subsequently reflecting on this newly gained material. Related to learning online, Jee and Lee (2002) examined perceived interactivity of websites and suggested that greater interactivity perceptions amongst those with higher need for cognition could be associated with their tendency to search for more information. Petty and Jarvis (1996) further noticed that learners with high need for cognition have a higher need for clarity and an aversion to ambiguity. They also prefer written or verbal information over visual information and are less influenced by non-content or peripheral cues (Carnaghi et al., 2007; Haugtvedt, Petty & Cacioppo, 1992).

These findings suggest that this variable will affect test performance, performance efficiency, and navigation. Individuals who rate higher on need for cognition are therefore expected to have higher test performance, spend more time in the e-modules (performance efficiency) and show more active navigation patterns. Since those with higher need for cognition further tend to have a significantly higher internal locus of control (Fletcher et al., 1986), they are also expected to be more confident about their learning progress.

In sum, we posit that serialists will need less time to complete the e-modules after controlling for test performance (performance efficiency) and make less jumps back and forward (navigation jumps). In contrast, individuals who rate higher on holist processing preference need more time to go through a learning unit (performance efficiency) and make more navigational jumps. No relationship is assumed in terms of their judgment of learning and test performance.

Based on these findings, we assume that individuals who rate higher on surface strategy processing have lower test performance, spend less time to go through the e-module (performance efficiency) and therefore show less active navigation patterns (page clicks, forward and backward jumps). No relationship is assumed in terms of their judgment of learning. And as a result, those individuals who rate higher in terms of deep strategy also have better test performance, spend more time in the e-modules (performance efficiency) and show more active navigation patterns. They are also more confident when they make the judgment of learning.

Hypotheses

H1: Deep and surface strategy as well as need for cognition are associated with different levels of test performance.

H2: Deep strategy and need for cognition are associated with different levels of confidence expressed in the one judgment of learning.

H3: Holist and serialist preference, deep and surface strategy, as well as need for cognition are associated with different levels of performance efficiency (time participants take to complete the e-module).

H4: Holist and serialist preference, need for cognition, as well as deep and surface strategy are hypothesized to predict different navigation patterns (number of page clicks, forward and backward jumps).

THE STUDY

Procedure

Participants were recruited using online announcements posted on a research site at a private University specializing in long-distance courses. All participants completed the module as part of a study requirement to earn research credits. Care was taken to separate the information collected from the e-module and the participants' personal information. The latter was collected via an intranet site which was inaccessible to the experimenters, thus separating personal information from the data collected in the survey.

Participants

851 participants agreed to participate in our research. We discarded data from 165 participants due to high numbers of outlier values or excessive times on page (120 sec/page). The final data set included 686 participants. 76.9% of participants (N=528) were female, mean age was 32.59 (SD=9.29, range 18-63 yrs). N=683). Two third were studying part-time (N=416) rather than fulltime (N=261). The large majority was working at the time (N=509), only a minority of students were not working (N=163).

Materials

The e-module content was split into three chapters and featured a site index, to enable participants to navigate to and fro. All pages in the e-module were structured similarly, including only 3 to five one-sentence bullet points and no graphical display. The language was kept simple and excluded difficult terminology. When accessing the e-module, the participants were first asked to rate themselves on the aforementioned learner characteristics (serialist/holist, surface/deep strategy, and need for cognition). Next, they were able to access a short e-learning module on team development, which also featured an index site for free navigational control. At the end of the e-module, participants made a judgement of learning by rating the likelihood that they would correctly answer questions on the module content. Following this judgment, they were then presented with four test questions about the e-module content. At the end of the follow-up questionnaire participants were given the opportunity to access the answers to the test questions. The follow-up questionnaire captured prior knowledge, perception of usefulness and ease of processing, as well as demographics.

Measures

Performance measures. Performance is captured with four test questions; each test response is coded as either right or wrong. The questions required participants to recall factual knowledge but were phrased so as to be broader and more comprehension-based. All test questions were presented on the same page, each featuring three answering options and only one correct answer. All data were checked to exclude the possibility of participants making subsequent corrections to their answers.

The judgment of learning is the second measure of performance based on one item and represented the confidence measure. Participants indicated their confidence in their ability to answer test questions by selecting a value between 0 and 100. We used a pre-diction paradigm, that is, participants were asked about their confidence prior to answering test questions.

Performance efficiency involved the time that individuals spend completing the entire and individual parts of the e-module. Data logs were utilized to capture this information.

The final outcome variable concerns navigational behaviour of participants, namely, the number of page jumps (forward and backward) within the e-module and the number of page visits in the e-module.

Personality and control variables. Five different personality characteristics are of interest. First, holist vs. serialist preferences, deep and surface strategy of information processing, and need for cognition.

Holist vs. serialist processing preference (learning style). In the present context, we utilized a revised and shortened measure developed by the authors and based on the work by Ford (1985). The serialist preference was examined using 7 items, the holist preference was examined using 4 items. An example item from the serialist scale is "I prefer to learn by concentrating on one aspect of a topic at a time." An example item from the holist scale is "I use several information sources at the same time." The response options ranged from (1) "strongly disagree" to (5) "strongly agree." The full scale is available from the authors.

Deep vs. surface processing. We included three items to measure deep vs. surface processing. The items were inspired by subscales produced by Biggs et al. (2001). We slightly changed the directionality of the surface strategy items to reduce socially desirable responding. All items were translated into German by the authors.

Need for cognition. This variable was measured using five items chosen from the German scale produced by Bless et al. (1994). The answering options were the same as those for deep and surface strategy.

Control variables. These included demographics such as age and sex, prior experience with the topic and e-learning. Three more covariates were relevant in this analysis to predict performance efficiency: average reading time (based on time needed to read instructions), number of page clicks and test performance.

Context variables. Context information was also collected. Of particular interest was the extent to which the content of the e-module was relevant to their studies and their jobs. Participants were also asked to indicate the extent to which the e-module allowed them to learn at their own pace. In addition, they were asked to indicate whether they found the texts easy to understand and the tasks easy to complete. The response options for all items ranged from (1) "strongly disagree" to (5) "strongly agree."

RESULTS

Descriptives and correlations

In the first step, the descriptives and scale characteristics were evaluated (see details in Table 1). One change was made to the holist subscale, where the first item was excluded due to its negligible contribution to the scale total overall. Excluding this item increased reliability from .76 to .86.

Table 1
Descriptives for scales

Construct	Items	Mean	SD	Skew	Kurtosis	α
Serialist subscale	7	3.57	.67	-.464	-.211	.73
Holist subscale	3	3.46	.95	-.443	-.693	.86
Deep strategy subscale	3	3.52	.85	-.413	-.260	.76
Need for cognition	5	3.27	.84	-.235	-.364	.85
Surface strategy subscale	3	2.98	.95	.038	-.614	.79

In the next step, the correlations amongst the scales were examined. Some of the correlations are worth mentioning briefly (for a complete summary see Table 2). Holist and serialist preferences were negatively correlated as expected (r= -.140, p < .001). Serialists were less likely to use surface strategies (r = -.154, p<.001), however, no difference was observed in terms of deep strategy use (r=-.029, ns). Holists did not use surface strategies (r= -.154, p<.001), but they did show a greater tendency towards using deep strategy (r= .202, p<.001). Holism also correlated weakly with need for cognition (r= .194, p<.001). Surface strategy scores were negatively associated with need for cognition (r = -.437, p <.001) and use of deep strategies (r = -.520, p <.001). Not surprisingly, deep strategies also correlated with greater need for cognition (r= .460, p <.001).

Table 2
Correlations amongst scales

	Holist	Serialist	Deep Strategy	Surface Strategy	NFC
Holist	1				
Serialist	-.140**	1			
Deep Strategy	.202**	.029	1		
Surface Strategy	-.154**	-.188**	-.520**	1	
Need for cognition (NFC)	.194**	-.012	.460**	-.437**	1

Note. * p<.05, ** p<.01.

As can be expected, the dependent measures also correlated with one another. For example, time spent in the e-module also correlated with better test performance (r=.270, p <.001), higher confidence in one's learning (r=.152, p <.001), a larger number of page visits (r=.294, p <.001), forward (r=.187, p <.001) and backward jumps (r=.266, p <.001).

Table 3

Correlations amongst dependent measures

	Test perform.	JOL	Time e-module	No. of page visits	Jumps forward	Jumps backward
Test performance	1					
Judgment of learning (JOL)	.222**	1				
Time e-module	.270**	.152**	1			
No. page visits	.034	-.005	.294**	1		
Jumps forward	-,020	.032	.187**	.520**	1	
Jumps backwards	.043	.002	.266**	.858**	.641**	1

Note. * p<.05, ** p<.01.

Hypothesis Testing

All hypotheses were tested using hierarchical multiple regression, including several covariates in each block. The covariates varied depending on the dependent measure in question. The role of the five scales as predictors were tested. This decision was taken in order to evaluate the relevance of each scale on its own. In addition, the correlations between the scales were weak to moderate, which suggest that they may each play an important role as individual predictors. In addition, age was also tested as a predictor of the dependent measures. Only the significant findings are reported here.

Hypothesis 1. H1 predicted that need for cognition, deep and surface strategy were associated with different levels of test performance. These predictors were entered separately following the entry of four covariates (age, sex, and prior knowledge of e-learning and the topic). The test variable was the combined score that participants obtained on all four questions (MN=2.75, SD=.96, N=686). The covariates explained 1.2% of the variance (R^2=.012, R^2_{adj} = .006, F(4,665)=2.008, p =.092). Only one of the four individual difference variables was a significant predictor of test performance. Need for cognition explained a significant proportion of variance ($R^2\Delta$=.007) and had a significant relationship with test performance (*b*=.100, β=.088, *t*=2.235, *p*=.026). Higher need for cognition predicted better test performance. The full model explained 1.9% of the variance (R^2=.019, R^2_{adj} = .012, *F*(5,664)=2.615, *p* =.024). As a result, research hypothesis 1 was only partially supported.

In addition, we tested for effects of serialist preference, which explained a marginally significant proportion of variance ($R^2\Delta$=.004) and had therefore a marginally significant relationship with test performance (*b*=.093, β =.064, *t*=1.672, *p*=.095). A stronger serialist preference was also associated with a slightly higher test performance. The full model explained 1.6% of the variance (R^2=.016, R^2adj = .009, *F*(5,664)=2.170, *p* =.056). We also examined the role of age in relation to test performance but did not find a significant relationship between age and test performance after controlling for the covariates sex, prior knowledge of e-learning and the topic.

Hypothesis 2. H2 predicted that deep strategy and need for cognition are associated with confidence expressed in the judgment of learning. These predictors were entered separately following the entry of four covariates (age, sex, and prior knowledge with e-learning and the topic). The test variable was the confidence judgment made by participants, presented before participants saw the test question (*MN*=62.87, *SD*=20.18, *N*=663). The covariates explained 1.7% of the variance (R^2=.017, R^2_{adj} = .011, *F*(4,628)=2.718, *p* =.029). As predicted, both individual difference variables were found to be significant predictors. Deep strategy explained a significant amount of variance ($R^2\Delta$=.014) and had a significant relationship with confidence (*b*=2.816, β =.120, *t*=3.041, *p*=.002). Higher deep strategy processing predicted greater confidence in learning. The full model explained 3.1% of the variance (R^2=.031, R^2_{adj} = .024, *F*(5,627)=4.050, *p* =.001).

Need for cognition explained a significant proportion of variance ($R^2\Delta$=.024) and had a significant relationship with confidence (*b*=3.714, β =.157, *t*=3.927, *p*<.001). Higher need for cognition predicted greater confidence in learning. The full model explained 4.1% of the variance (R^2=.041, R^2_{adj} = .033, *F*(5,627)=5.306, *p* <.001). As a result, the research hypothesis 2 was confirmed.

In addition, we examined the role of age in relation to confidence expressed in the one judgment of learning before we presented the test questions. Age was not a significant predictor of confidence after controlling for the covariates sex and prior knowledge. We also expanded the research to examine the relationship between the other three scales in relation to confidence. We observed another significant effect. However, surface strategy only explained a marginally significant amount of variance ($R^2\Delta$=.005) and had a marginally significant relationship with confidence (b=-1.482, β =-.071, t=-1.787, p=.074). Greater surface strategy processing was associated with lower confidence. The full model explained 2.2% of the variance (R^2=.022, R^2_{adj} = .014, F(5,627)=2.818, p =.016).

Hypothesis 3. H3 predicted that holist and serialist preference, deep and surface strategy, as well as need for cognition are associated with different levels of performance efficiency (time participants take to complete the e-module). These predictors were entered separately following the entry of seven covariates. In addition to the regular four covariates (age, sex, and prior knowledge with e-learning and the topic), we also wanted to control for individual reading time (using time records for the instruction page at the beginning of the e-module) and the total number of page clicks (as this would automatically be positively associated with more time needed). And finally, because efficiency could only be assessed in terms of it being independent of test performance, test performance itselfwas also entered as a covariate. The dependent variable in all analyses was the time that participants spend in the e-module (MN=415.02, SD=202.88, N=686). The covariates explained 32.2% of the variance (R^2=.322, R^2_{adj} = .314, F(7,662)=44.832, p <.001).

Three of the five predictors predicted time spent on the e-module. First, the serialist preference explained a significant proportion of variance ($R^2\Delta$=.009) and had a significant relationship with performance efficiency (b=29.123, β =.096, t=2.988, p=.003). The full model explained 33.1% of the variance (R^2=.331, R^2_{adj}= .323, F(8,661)=40.814, p =.001). The serialist preference was associated with more time needed to complete the e-module (and hence lower efficiency) even when we controlled for the seven covariates, including average reading time, page clicks, and test performance. Second, the scores on deep strategy also explained a significant amount of variance ($R^2\Delta$=.004) and had a marginally significant relationship with performance efficiency (b=14.238, β =.060, t=-1.866, p=.062). Third, those who pursued a deep strategy also tended to take more time, similar to the serialists. Not surprisingly, the results for those pursuing a surface strategy were the opposite to those pursuing a deep strategy. The scores on surface strategy also explained a significant amount of variance ($R^2\Delta$=.006) and had a significant relationship with performance efficiency (b=-16.624, β =-.078, t=-2.442, p=.015).

We also examined the role of age in relation to performance efficiency. When using age as a predictor, the remaining six covariates explained 24.3% of the variance (R^2=.316, R^2_{adj}= .310, F(6,663)=50.996, p <.001).

Even taking the covariates into account, age on its own further explained a significant proportion of variance ($R^2\Delta$=.006) and had a significant relationship with performance efficiency (*b*=1.691, β =.077, *t*=2.384, *p*=.017). The overall model therefore explained 32.2% of the variance (R^2=.322, R^2_{adj} = .314, *F*(7,662)=44.832, *p* <.001). Those participants who were older also took more time to complete the e-module, suggesting lower performance efficiency.

Hypothesis 4. H4 predicted that holist and serialist preference, need for cognition, as well as deep and surface strategy are hypothesized to predict different navigation patterns (number of page clicks, forward and backward jumps).

The first test variable was the combined number of page visits reported across the entire e-module by participants (*MN*=20.40, *SD*=4.30, *N*=686). An initial test showed that the selected covariates age, sex, and prior knowledge did not explain a significant amount of variance (only .3%) in the model (R^2=.003, R^2adj =-.003, *F*(4,665)=.530, *p* =.714). As a result, we ran all analyses without these four covariates. When regressing the test variable page visits separately onto the five variables, we observed two marginally significant effects. First, surface strategy explained a marginally significant amount of variance (R^2=.004) and had a very weak but significant negative relationship with number of pages visited (*b*=-.293, β =-.065, *t*=-1.702, *p*=.089). Those who pursued a surface strategy also spend less time browsing the e-module. Second, deep strategy explained a significant amount of variance (R^2=.005) and had a very weak but significant and positive relationship with number of pages visited (*b*=.343, β =.068, *t*=1.786, *p*=.075). Those who pursued a deep strategy also spend more time browsing the e-module.

The second test variable was the combined number of forwards jumps reported across the entire e-module by participants (*MN*=.28, *SD*=1.17, *N*=686). Forward jumps refer to forward movements through the e-module out of sequence, that is, jumps greater than one which could only be initiated by utilizing the site index. Again, the aforementioned covariates were excluded from the analysis as they did not explain a significant amount of variance in the model (R^2=.004, R^2adj =-.002, F(4,665)=.739, p =.565). We noted only one significant trend. Surface strategy explained a significant amount of variance (R^2=.007) and therefore had a significant relationship with forward navigation moves (*b*=-.100, β =-.082, *t*=-2.150, *p*=.032). Those who pursued a surface strategy were actually less likely to jump forward as much.

The third test variable was the combined number of backwards jumps reported across the entire e-module by participants. Backward jumps refer to backward movements through the e-module, that is, steps back or jumps greater than one. These could only be initiated by utilizing the site index or returning to the previous page using the browser (*MN*=.67, *SD*=1.91, *N*=685). As above, the covariates did not explain any significant variance (only .2%) in the model (R^2=.003, R^2adj =-.003, *F*(4,664)=.478, *p* =.752) and were thus excluded from the analysis. Similar to the trends observed for general number of page clicks, we observed two marginal effects for surface and deep strategy. First, surface strategy explained a marginally significant amount of variance (R^2=.005) and therefore had a significant but again negative relationship with forward navigation moves (*b*=-.140, β=-.070, *t*=-1.832, *p*=.067). Those who pursued a surface strategy were actually less likely to jump backward, a pattern very similar to those observed in terms of their forward jumps. These participants were clearly less likely to utilize the navigation options made available to them in terms of the site index and browser options to move back and forward. Second, deep strategy explained a significant amount of variance (R^2=.005) and had a very weak but significant and positive relationship with forward navigation (*b*=.154, β =.069, *t*=1.800, *p*=.072). Those who pursued the deep strategy approach also spend more time jumping forward and clicked on more links within the e-module overall. As a result, the research hypothesis 4 can only be partially supported. We only found evidence of surface and deep strategy as (marginally) significant predictors amongst the five hypothesized predictors in the hierarchical regressions.

We also considered the possibility that participant choices can be informative about the learners' characteristics. The participants were also given the option to choose whether or not they wished to see the results. A number of differences arose in terms of learning characteristics for need for cognition (*F*(1,681)=7.880, *MS*=5.590, *p* =.005), deep strategy (*F*(1,681)=3.467, *MS*=2.510, *p* =.063) and test performance (*F*(1,681)=38.612, *MS*=34.082, *p*<.001). Those who wanted the results had higher need for cognition (*MN*=3.29, *SD*=.85) than those who did not (*MN*=2.89, *SD*=.62). Similarly, those who wanted the results also reported more deep strategy use (*MN*=3.54, *SD*=.86) than those who did not (*MN*=3.27, *SD*=.72). In line with the hypotheses tests, test performance was higher amongst those who wanted to see results (*MN*=281, *SD*=.93) compared those who did not (*MN*=1.81, *SD*=1.14).

Those who wanted the results (*MN*=107.06, *SD*=64.43) spent more time choosing their answers than those who did not want to see the results (*MN*=52.69, *SD*=42.75). Those who wanted the results were more confident (*F*(1,681)=17.565, *MS*=7038.593, *p*<.001) about their learning progress (*MN*=63.42, *SD*=19.70) than those who did not want to see the results (*MN*=47.73, *SD*=25.76).

DISCUSSION

The purpose of our study was to examine the benefits of including both self-reported and log file analysis when examining a variety of different performance indicators in e-learning modules. The combination of both sources of data demonstrated that self-reported learning characteristics can add an important perspective on why and how different participants show different patterns of performance, confidence, and behaviour while learning online.

When reviewing the findings, the following trends can be summarized thus. Even when we controlled for the influence of age, sex, and prior knowledge, individual differences continued to play a significant role. Higher need for cognition and (marginally) serialist preference were significant and positive predictors of test performance. Deep strategy, need for cognition and (marginally) surface strategy were all significant predictors of confidence of learning. Those with higher deep strategy processing and need for cognition scores were more confident in terms of their learning, with the reverse being the case for those who rated higher on surface strategy.

Additional performance indicators were based on log file records. Here we noted that participants with a serialist preference took longer in the e-module while those with higher surface strategy scores took less time. Finally, we only observed marginally significant effects of surface strategy use with navigation. Individuals with higher scores exhibited less active navigation in terms of page visits, forward and backward jumps.

These findings suggest that learning characteristics influence judgements of learning more so than test performance. Furthermore, over- and underconfidence may not align with participants' performance outcomes. These findings suggest that the assessment of judgments of learning represents a starting point to gauge potential barriers to learning other than those that are motivational or based on personal learning characteristics. We were thus able to demonstrate how important learning characteristics are over and above the various potential covariates and confounds such as prior knowledge, sample differences, and behaviour online.

An additional area of interest was the extent to which the performance indicators were also subject to age differences in the sample, which included an age range of almost fifty years. We therefore also examined the extent to which age predicted test performance, performance efficiency, confidence in one's judgment of learning, and navigation in its own right. The only significant relationship was between age and performance efficiency. Participants took more time completing the e-module when they were older. This is in line with the evidence by Van Gerven and colleagues (2005, 2006).

However, we also contradicted some of the findings by these authors because our sample did not show reduced coordination or poorer integration of information (as measured in navigational behaviour patterns). That is, the younger and older participants in the sample showed equal levels of performance, confidence, and navigational patterns. In other words, older participants were just as likely to perform as well on the test sections. They are just as confident about their learning and exhibit similar navigation patterns as younger participants. This may, in part, be due to the fact that this sample was well-versed with online learning, having chosen to study using distance learning. As a result, the level of technological familiarity and similar intellectual engagement across the sample may have reduced the effects usually found when examining performance amongst older and younger participants. In our case, our older participants were actually more experienced; indeed, controlling for prior knowledge may actually have benefited the younger e-learners.

Limitations

A number of general limitations should be mentioned that concern the design of the e-module, the selection of learner characteristics, and psychometric decision-making.

First, the design of the e-module required largely sequential processing, which may have fostered performance effects for those who rank higher on serialist preferences. As a result, the performance results may be the effect of the design catering to those with a serialist preference, rather than an actual difference in learning preference. Another issue concerns the short nature of the e-module and the presentation of the test section at the end of the e-module. All test questions were presented together. This may have reduced the need for participants to revisit pages. As a result, the participants may not have seen the need to move back and forward, thus reducing the navigation patterns that we expected. In addition, all test questions were presented on the same page, which may have made it easier for the participants to compare the questions one to another.

The second potential limitation of our approach is that we made certain assumptions, both about the e-learning material and the likely users. This means that our approach will not necessarily be effective for all learners. By using a directive instructional style the focus on the type of strategies employed in the module is more restricted. It is quite possible, that some of the experienced learners would prefer and actually perform better if they had instructional materials that involved guided discovery or an exploratory design (Merrill, 2002)

At a methodological level, we should note a few well-known issues. To reduce the burden on e-learners, we shortened several scales to reduce the length of the study and keep participants engaged. Shorter scales also mean lower reliability (see also same approach used by Cress & Friedrich, 2000). Unfortunately, making only one judgment about the text that participants have learned does not give the participants the opportunity to indicate what they have versus have not learned (Dunlosky & Lipko, 2007). This is one aspect we changed in subsequent studies.

Concluding Remarks

Our study findings indicate that the measurement of learner characteristics (such as preferences, strategies and cognitive style) can provide a useful tool to interpret why participants' performance, time on task, and navigation patterns may vary – even after controlling for differences due to age, sex and prior knowledge. More research is needed to examine whether or not there are other learner and sample differences that should be included in the analyses of various performance measures. User modelling in the future will have to capture the varying types of e-learners we found in our sample: e-learners that include teens to individuals close to retirement, those with and without work experience, different levels of prior knowledge about the topic of choice, various degrees of technological familiarity and different learning styles.

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Financial Support

Work on this article was sponsored through grant 01PF07044 from the German Ministry of Education and Research (BMBF) to the second author.

Acknowledgements

We would like to thank Dirk Schulte am Hülse for his support.