Self-regulation during e-learning: using behavioural evidence from navigation log files

D. Jeske, J. Backhaus & C. Stamov Roßnagel
Jacobs Center on Lifelong Learning and Institutional Development, Jacobs University Bremen, Bremen, Germany

Abstract

The current paper examined the relationship between perceived characteristics of the learning environment in an e-module in relation to test performance among a group of e-learners. Using structural equation modelling, the relationship between these variables is further explored in terms of the proposed double mediation as outlined by Ning and Downing. These authors initially proposed that motivation and self-regulation strategies are mediators between the perception of the learning environment and performance. In our replication and extension study, we substituted self-reported self-regulation with behavioural indicators of self-regulation using navigation log files and focused on test-taking rather than general motivation. We proposed that navigational patterns captured using log files can also help deduce self-regulation in e-modules and provide information in the absence of self-reports. Path analyses provide partial support for our navigational hypotheses and the model. Implications of our results for the use of e-module data and conclusions based on navigation are discussed.

Keywords


Self-regulated learning and learner performance

Self-regulation can be described as a process that helps learners to structure their learning activities by making the appropriate and reciprocally related cognitive, affective and behavioural adjustments (Boekaerts, 1999; Karoly, 1993). Self-regulation is linked to how learners utilize materials, that is, how effectively the learners set goals, activate prior knowledge, monitor their learning and select strategies (Bol & Garner, 2011). Good instructional design of e-learning modules will include features that support self-regulation of learners (Abrami, Bernard, Bures, Borokhovski, & Tamim, 2011), in terms of helping the learners to orientate themselves on an online platform, access support and provide a structured overview of contents to the learners (Narciss, Proiske, & Koerndle, 2007). These features then enable learners to learn tasks in a self-directed manner at their own pace (Fisher, Wasserman, & Orvis, 2010; Paas, Van Gerven, & Tabbers, 2005), using the navigation options to select and construct their knowledge (Cunningham, Duffy, & Knuth, 1993).

Good self-regulators tend to pay more attention to planning their learning, revisiting their goals, engage in more self-monitoring and other cognitive strategies (Azevedo, Guthrie, & Seibert, 2004; Greene & Azevedo, 2007). Learners who are employing effective self-regulation also tend to have better performance (Pressley & Ghatala, 1990; Pressley & Harris, 2006; White & Frederiksen, 2005). Poorer self-regulators struggle with distractors, dwell on their mistakes, and are less organized when solving tasks (Zimmerman, 1998) as they spend less time assessing how the new information links to prior knowledge (Greene & Azevedo, 2009).
Navigation as behavioural evidence of self-regulation

Learners’ navigation patterns provide an important insight into self-regulation during e-learning. To date, few papers focus on non-cognitive self-regulation indicators (Devolder, van Braak, & Tondeur, 2012). A number of studies have already examined the usefulness of log files in exploring self-regulation while studying online (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007; Jamieson-Noel & Winne, 2003; Sullivan, Gnesdilow, & Puntambekar, 2011; Thillmann, Künsting, Wirth, & Leutner, 2009). Log files enable instructors and experimenters to observe how learners move through an e-learning unit and examine their navigation, and therefore also self-regulation in action. These files capture navigation patterns (Berendt & Brenstein, 2001) and provide information about frequency counts of sites visited, timing of actions, sequences, adaptive tactics (Greene, Costa, Robertson, Pan, & Deekens, 2010; Hadwin et al., 2007), selection of strategies, navigational paths, choices and learner actions during learning, pages visited, navigation across a platform, and features accessed (Barab, Bowdish, Young, & Owen, 1996; Berendt & Brenstein, 2001; Hadwin et al., 2007; Paganelli & Paternò, 2003; Richter, Naumann, & Noller, 2003). Furthermore, this information can be collected in a less intrusive fashion than self-report data (Barab et al., 1996).

Log file information reveals the micro-level processes associated with learning, which can then serve as indicators of macro-level self-regulation (Greene, Muis, & Pieschl, 2010). This means log files capture the behavioural components of self-regulation in process (Muis, Winne, & Jamieson-Noel, 2007) and thus provide researchers with the means to investigate successful and ineffective self-regulation behaviours in different contexts (Greene et al., 2010). Information about reading speed and page changes provide information about the learner’s engagement. Excessive movements between different areas while learning online also can be seen as indicators of poor self-regulation; such movements are also associated with poorer performance outcomes (Greene & Azevedo, 2007). Log files can similarly provide information on which to infer learner intentions, without having to intrude or disturb the learner during the process (Barab et al., 1996). These pieces of information can then be used to evaluate these activities in relation to learning outcomes (Mogus, Djurdjevic, & Suvak, 2012) and examine strategy use (Jamieson-Noel & Winne, 2003; Thillmann et al., 2009).

Navigation, and hence behavioural self-regulation, is influenced by design variables as outlined earlier. There is also some evidence that motivation plays a role in terms of the online activity and performance in collaborative learning (Nokelainen, Miettinen, Kurhila, Florén, & Tirri, 2005). Greater prior knowledge tends to lead to more planning and monitoring on behalf of learners (Moos & Azevedo, 2008) and better performance (Lawless, Schrader, & Mayall, 2007; MacGregor, 1999). Navigation is also influenced by prior knowledge in terms of the learning strategies individuals adopt (Lawless et al., 2007). Less experienced learners are more likely to become disoriented, struggle with navigation (Dillon, 1991; Hammond, 1989; Last, O’Donnell, & Kelly, 2001), and select fewer resources or links (Lawless et al., 2007).

Our extension and replication study

Using log files and self-reports, we intend to replicate and extend the model proposed by Ning and Downing (2012). This model had four major components and features one independent construct, two mediators, one outcome variable and a moderator. Moving from left to right, the learning experience (composed of appropriate workload, clear goals and standards, appropriate assessment, good teaching, and generic skills) was expected to influence student motivation and self-regulation strategies. Self-regulation strategies included time management, self-testing, study aids, concentration, information processing, selecting main ideas and test strategies. Motivation and self-regulation predicted academic performance [cumulative grade point average (GPA)]. The link between the learning experience and performance in the original model was separately mediated by both motivation and self-regulation. The relationship between all four components is further moderated by prior academic achievement. We deviate from the model by including different measures to assess learning experience, motivation, self-regulation and test performance.

Our first amendment involves the substitution of self-reported self-regulation with navigational indicators of self-regulation. We propose that our navigation indicators can provide information about self-
regulation. There are several advantages to using these data. Log files information is collected automatically in educational and work-related learning contexts. Using this information reduces time needed by learners. As a result, using such data makes practical and economic sense. During the learning process, the learners try to make sense of the material, selecting, activating and monitoring their learning strategies (Narciss et al., 2007). Moving forward and out of sequence in an e-learning module can be interpreted as a means by which the learners ascertain what they already know and what they want to know about the material (enabling them to set goals); it helps them to get an overview of the content (supporting planning), and a process that helps them to organize the learning activity (by scanning, exploring and structuring their learning; Narciss et al., 2007). At the other extreme, such jumps could indicate disengagement and disinterest, poor planning and self-monitoring. Backward jumps may capture these activities effectively and therefore be negatively related to test performance (see also Zimmerman, 1998). Those who backtrack may also not self-monitor as effectively, which serves as an explanation for their frequent returns to previous sections. Navigation patterns may consequently be important indicators of task disengagement, that is, the persistence of e-learners in the face of a challenging e-module and topic (Liem, Lau, & Nie, 2008). This is in line with Wecker, Kohnle, and Fischer (2007) who suggested that browsing through websites may be associated with shallow processing which is not functional for learning. This may then increase the number of links and pages visited but lead to poor task completion and performance (Berendt & Brenstein, 2001).

The second amendment concerns the exclusion of prior knowledge from the model. The rationale for including prior knowledge as a central variable presupposes all variables to be linked to prior knowledge. In the model by Ning and Downing (2012), prior knowledge had the smallest path coefficients. In our case, prior knowledge required was minimal, thus making this variable redundant. Some research further indicates that there is no relationship between prior content knowledge and performance (Barab et al., 1996; Berendt & Brenstein, 2001), which leads us to expect that if we would include prior knowledge, it would only have minimal relationships to the other model components (see note on additional analyses).

This research therefore addresses a number of gaps in the literature. Given the importance of using quantifiable and objective indicators of learning, we add to the limited research on navigation and self-regulation. Moreover, our research represents an example of self-regulation research in a non-traditional learning context and addresses the call for more work on how students interact with content during e-learning (Bol & Garner, 2011). The current study will further test the model by Ning and Downing (2012) in an e-learning context and consider implications of testing self-regulation via behavioural indicators.

Hypotheses

The research therefore reiterates the propositions by Cunningham et al. (1993), as well as Ning and Downing (2012) by proposing that both navigation behaviour and motivation are process variables. Our navigation variables include the number of backward and forward jumps that occur out of sequence and time in the e-module. These navigation variables have also been examined in other research by Chen and Ford (1998).

Based on the literature review mentioned earlier, we propose one overarching general as well as several specific hypotheses.

Hypothesis 1: Navigation behaviours are significant mediators between learning experience and test performance.

Hypothesis 2: A positive learning experience reduces the number of forward jumps. Here the implication is that the learning experience can influence the degree to which individuals are approaching the task with more thought, planning and effort.

Hypothesis 3: More forward jumps reduce test performance. The implication here is that limited content engagement leads to lower performance on test questions.

Hypothesis 4: A positive learning experience reduces the number of backward jumps. Here the implication is that the learning experience can influence the degree to which learners focus on their task, reducing disorientation.

Hypothesis 5: More backward jumps reduce test performance. The implication here is that more backward jumps may indicate more disorientation and poor self-monitoring.
Method

Materials

Learning materials and characteristics
In order to capture learner behaviour and navigation, the authors produced two short e-modules on health effects of shift work and team development. These common topics were chosen to keep age and familiarity effects to a minimum. The e-modules were developed specifically for the project, had a similar format, length and layout. All test questions, while involving participants to recall factual knowledge were phrased so as to be broader and more comprehension based. The materials were presented in a sequential and highly structured format with simple phrasing and sentence structure/length to compensate for potential differences in prior knowledge (Clark & Feldon, 2005). Pages were designed to minimize loading time (13 kb/page) across different browsers. The participants were able to self-pace through the e-module, providing them with maximal control (van Merriënboer & Kester, 2005). Participants did not need to log in; they only needed to access a specific link. All participant data were cross-checked to ensure they came from the right classes before their data was included in the final dataset.

Data collection, procedure and participants

Processes
Log files recorded all navigation behaviours and time on all pages within the e-module. A log file script enabled us to extract specific log file information about interactions of the learners with the e-module content (as the information would have been overwhelming otherwise). This information was compiled into a table listing each user’s interactions. We extracted a list of pages that were visited, number of visits per page and time per page. Further information enabled us to compute jumps of users as well as the time a learner spend in the e-module overall. We also collected participant demographics, the answers to test questions (at the end of each of the five chapters), test-taking motivation and participants’ perception of the learning experience upon completion of the e-module.

Procedure
Participants were recruited in two ways. The first group included students participating for extra credit. The second group included voluntary research participants who also had the option to participate in a lottery scheme to win vouchers for an online book store. The student participants were recruited via their instructors, the online participants via an online announcement posted on two research websites.

Participants
We originally had 360 participants; however, following data screening, we excluded a number of cases (final \( N = 332 \)). Student recruits made up the majority (\( n = 271 \)) of participants, Internet participants just a minority (\( n = 51 \)). Two-thirds of participants were women (\( n = 218, 67.7\% \)) and one-third men (\( n = 93, 28.9\% \)), which may be due to the fact that participants were recruited primarily in psychology classes (11 missing values). Participants were aged 18–68 (average 24 years, mode indicated that the most common age was 21 years old). Half of the participants were aged 18–21 (55.4%). Another third of participants were aged between 22 and 30 years old (34.1 %). The remainder of the sample were between 31 and 40 years old (5.1%) or older than 41 years old (5.4%). In terms of education, 19.3% (\( n = 62 \)) had a high school diploma, 31.7% had some vocational training or some college (\( n = 102 \)). Another 18.8% had an associate’s or Bachelor’s degree (\( n = 67 \)), Masters or PhD (\( n = 12 \)). No information was available for 79 participants.

Measures
As we wished to replicate the findings of Ning and Downing (2012), we also used similar measures.

Learning experience
This was measured using three items that assessed participants’ perception of the relevance, interestedness and difficulty of the e-module. All items had a 5-point response scale. The first item asked: ‘On a scale from 1 (very uninteresting) to 5 (very interesting), how interesting was this module for you?’ The second item asked: ‘On a scale of 1 (very irrelevant to me) to 5 (very relevant to me), how relevant was this module for you?’ The third item asked: ‘On a scale of 1 (very difficult to learn) to 5 (very easy to learn the material), how difficult did you find the content of this module?’ We used the three items as separate indicators of learning experience.
experience. All three items were positively correlated with one another (coefficients ranging from 0.1 to 0.4, \( p < 0.05 \)).

**Test-taking motivation**
Motivation to do well was assessed using four items to measure test-taking motivation put forward by Arvey, Strickland, Drauden, and Martin (1990). An example item is ‘Doing well on the test questions was important to me.’ The response options ranged from (1) ‘strongly disagree’ to (5) ‘strongly agree.’ A composite was created and then mean-centred. The English items were translated into German by the authors \( \alpha = 0.84, \text{mean} (MN) = 3.74, \text{standard deviation} (sd) = 0.79 \).

**Navigation behaviours**
The site index enabled participants to navigate back and forth (besides to using back and forward buttons). We used log files to collect the following indicators: time spent in the e-module (MN = 12.94 min, sd = 5.35 min). This variable was centralized for subsequent analyses. Jumps were moves made out of sequence. Forward jumps ranged from 0 to 15 (exhibited by a quarter of participants, \( n = 79 \)). Backward jumps ranged from 0 to 7 (exhibited by a third of participants, \( n = 100 \)). Forward and backward jump data were transformed using square-root transformation to correct positive skew.

**Test performance**
All participants were asked five test questions embedded into the e-module, the maximum score participants could obtain were 15 points. Each chapter of the module featured one test question. We also considered error and computed test performance by deducting points for selecting the wrong options (MN = 9.48, mode = 12, sd = 3.08).

**Demographics**
Demographical information included sex, education and age.

**Results**
**Correlations and preliminary analyses**
We first examined the descriptive characteristics and correlations between model components (Table 1). The items used to measure learning experience all correlated as expected. As expected, motivation correlated with all variables.

The next step was the preliminary analysis of variable relationships that support the idea of mediation via motivation and navigation variables. We followed the steps of Baron and Kenny (1986) to test the direct paths between our predictor, mediators and outcome variable. As expected, learning experience as a construct was a significant and positive predictor of motivation \( (\beta = 0.66, p < 0.001) \) and time in e-module \( (\beta = 0.22, p < 0.01) \). Learning experience was negatively related to forward \( (\beta = -0.15, p < 0.01) \) and backward navigation \( (\beta = -0.10, p = 0.10) \). The relationship with backward navigation was not significant. This suggests that when users found the e-module more interesting, simple and relevant, they also spend more time studying and did not disengage as easily by jumping ahead. Backward jumps had a marginally significant impact on individual performance \( (\beta = -0.13, p < 0.05) \) while the path from forward jumps to individual performance

### Table 1. Correlations between Model Components and Indicators

<table>
<thead>
<tr>
<th></th>
<th>Interesting</th>
<th>Relevant</th>
<th>Easy</th>
<th>Motivation</th>
<th>Time in e-module</th>
<th>Backward</th>
<th>Forward</th>
<th>Test score</th>
</tr>
</thead>
<tbody>
<tr>
<td>LE (Interesting)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LE (relevant)</td>
<td>0.460**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LE (easy)</td>
<td>0.258**</td>
<td>0.125*</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M (motivation)</td>
<td>0.504**</td>
<td>0.312**</td>
<td>0.243**</td>
<td></td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M (time in e-module)</td>
<td>0.185**</td>
<td>0.123*</td>
<td>0.141*</td>
<td>0.200**</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M (backward jumps)</td>
<td>-0.085</td>
<td>-0.016</td>
<td>-0.038</td>
<td>-0.018</td>
<td>0.043</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M (forward jumps)</td>
<td>-0.172**</td>
<td>-0.004</td>
<td>-0.016</td>
<td>-0.141*</td>
<td>-0.166**</td>
<td>0.184**</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>O (test score)</td>
<td>0.314**</td>
<td>0.122*</td>
<td>0.268**</td>
<td>0.282**</td>
<td>0.331**</td>
<td>-0.132*</td>
<td>-0.206**</td>
<td>1</td>
</tr>
</tbody>
</table>

*Note. * \( p < 0.05 \), ** \( p < 0.01 \). LE = learning experience variables. M = mediators. O = outcome variable. Backward and forward jumps were transformed using square root.*
was highly significant ($\beta = -0.21$, $p < 0.001$). Time in e-module was a significant predictor of test performance ($\beta = 0.33$, $p < 0.01$).

Testing the model

We tested our model using structural equation modeling (LISREL 8.8, cross-referencing these with MPlus results; Jöreskog & Sörbom, 2006). We used three different navigation variables, resulting in three models, which were examined in terms of full and partial mediation (motivation remained the constant mediator in all these three reiterations). This was necessary as each of the three variables were based on a different scale than the others (transformed frequency data for forward and backward navigation, time in e-module was assessed using a centred average time in minutes).

Adequate model fit was assessed by examining if comparative fit index (CFI; Bentler, 1990) exceeded 0.95, root mean square error of approximation (RMSEA; Browne & Cudeck, 1993) was below 0.08 and standardized root mean square residual (SRMR; Jöreskog & Sörbom, 1989) was below 0.05 (see also Hu & Bentler, 1999).

All full and partial mediation models had a significant $\chi^2$ value ($p < 0.05$). $\chi^2$/degrees of freedom (d.f.) values all fell below 5, which further suggest acceptable fit (Marsh & Hocevar, 1985). Model fit was better for the partial mediation models with CFI $\leq 0.96$, RMSEA $\geq 0.08$ and SRMR $\geq 0.05$ (Table 2). In case of mediation, adding the direct path should not improve model fit (Holmbeck, 1997). Model fit deteriorated when we included the direct path. This is in line with what we expected.

The results for the paths changed in terms of both magnitude and significance from one model to the next (Table 3). While motivation was a significant predictor of test performance in the full mediation models ($\beta_F = 0.26–0.31$, $p < 0.001$), this relationship became not significant in the presence of a direct path ($\beta_P = 0.06–0.11$, $p > 0.05$). The path coefficient between learning experience and backward jumps was also not significant in the full nor the partial mediation model ($\beta_F = -0.08$, $\beta_P = -0.08$, $p > 0.05$). This suggests an immediate problem with both motivation and backward navigation as full mediators. This was also confirmed in terms of the indirect effects. In the presence of both motivation and backward navigation, no significant mediation is observed ($\beta_F = -0.08$, $p > 0.05$).

The only marginally significant mediator was time in the e-module ($\beta_F = 0.10$, $p < 0.10$). As a result, we obtained support for partial mediation for time in e-module.$^3$

Figure 1 outlines the findings of the partial mediation model. The standardized path coefficients are also included. We exclude indicators to increase the clarity of the presentation (all indicators loaded as expected to each of the latent variables). All paths are significant ($p < 0.05$) except for the path between motivation and test performance. Learning experience accounted for 2.3% of the variance in navigation (forward navigation) and 15.9% of the variance in test performance.

Table 2. Model Fit Indices (Including Both Mediators)

<table>
<thead>
<tr>
<th>Navig. variable</th>
<th>Mediation model</th>
<th>$\chi^2$</th>
<th>d.f.</th>
<th>$p$</th>
<th>RMSEA (CI)</th>
<th>CFI</th>
<th>SRMR</th>
<th>$\Delta \chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>EFFEM</td>
<td>Full</td>
<td>25.56</td>
<td>8</td>
<td>0.00</td>
<td>0.081 (0.046–0.118)</td>
<td>0.95</td>
<td>0.054</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Partial</td>
<td>16.21</td>
<td>7</td>
<td>0.02</td>
<td>0.066 (0.026–0.107)</td>
<td>0.97</td>
<td>0.042</td>
<td>9.35**</td>
</tr>
<tr>
<td>Forward</td>
<td>Full</td>
<td>30.46</td>
<td>8</td>
<td>0.00</td>
<td>0.090 (0.056–0.126)</td>
<td>0.93</td>
<td>0.059</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Partial</td>
<td>20.05</td>
<td>7</td>
<td>0.00</td>
<td>0.076 (0.038–0.116)</td>
<td>0.96</td>
<td>0.045</td>
<td>10.41**</td>
</tr>
<tr>
<td>Backward</td>
<td>Full</td>
<td>25.72</td>
<td>8</td>
<td>0.00</td>
<td>0.079 (0.044–0.117)</td>
<td>0.94</td>
<td>0.056</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Partial</td>
<td>15.05</td>
<td>7</td>
<td>0.03</td>
<td>0.061 (0.017–0.103)</td>
<td>0.97</td>
<td>0.040</td>
<td>10.67**</td>
</tr>
</tbody>
</table>

Note: The first row lists the full mediation model (relationship between learning experience and test performance completely mediated by selected navigation variable and motivation). The second row lists the partial mediation model (allowing for a direct path between learning experience and test performance). $**p < 0.01$, $***p < 0.001$. CI = confidence interval; CFI = comparative fit index; d.f. = degrees of freedom; EFFEM = time in e-module; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

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Model revision

Based on the fact that these initial findings were all obtained in models that also included motivation as a mediator, we therefore decided to rerun the partial mediation model with only navigation as mediator (Table 4). All full and partial mediation models had a significant $\chi^2$ value ($p < 0.05$). The fit indicators suggest that the new models were similar if not as original models that included motivation (CFI $\geq 0.93$, RMSEA $\leq 0.10$ and SRMR $\leq 0.06$; Table 2). Learning experience was not a significant predictor of backward navigation ($\beta_p = -0.09$, $p > 0.10$) as observed in the previous analysis; however, we obtained two significant small indirect effects for time in e-module ($\beta_p = 0.06$, $p < 0.01$) and forward navigation ($\beta_p = 0.03$, $p < 0.05$).

Figures 2 and 3 outline the standardized path coefficients of the revised model without motivation. Figure 2 includes time in the e-module as a mediator and Figure 3 includes forward jumps. All paths are significant ($p < 0.05$). For Figure 2, learning experience accounted for 5.4% of the variance in navigation (time in e-module) and 19.6% of the variance in test performance. For Figure 3, learning experience accounted for

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**Table 3. Standardized Effects in Full ($\beta_f$) and Partial Mediation Model ($\beta_p$)**

<table>
<thead>
<tr>
<th>Navigation variable</th>
<th>Predictor</th>
<th>Criterion</th>
<th>Direct effect $\beta_f$</th>
<th>Direct effect $\beta_p$</th>
<th>Indirect effect $\beta_p$</th>
<th>Total effect $\beta_p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>EFFEM</td>
<td>Learn. exp. MOT</td>
<td>Test</td>
<td>0.67***</td>
<td>0.66***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Learn. exp. EFFEM</td>
<td>Test</td>
<td>0.25***</td>
<td>0.25***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MOT</td>
<td>Test</td>
<td>Test</td>
<td>0.26***</td>
<td>0.06</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EFFEM</td>
<td>Test</td>
<td>Test</td>
<td>0.28***</td>
<td>0.25*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Learn. exp.</td>
<td>Test</td>
<td>Test</td>
<td>-</td>
<td>0.28**</td>
<td>0.10t</td>
<td>0.38***</td>
</tr>
<tr>
<td>Forward</td>
<td>Learn. exp. MOT</td>
<td>Test</td>
<td>0.64***</td>
<td>0.64***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Learn. exp. Forward</td>
<td>Test</td>
<td>-0.18**</td>
<td>-0.18**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MOT</td>
<td>Test</td>
<td>Test</td>
<td>0.29***</td>
<td>0.10</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forward</td>
<td>Test</td>
<td>Test</td>
<td>-0.16**</td>
<td>-0.14*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Learn. exp.</td>
<td>Test</td>
<td>Test</td>
<td>-</td>
<td>0.28**</td>
<td>0.09</td>
<td>0.37***</td>
</tr>
<tr>
<td>Backward</td>
<td>Learn. exp. MOT</td>
<td>Test</td>
<td>0.64***</td>
<td>0.64*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Learn. exp. Backward</td>
<td>Test</td>
<td>-0.08</td>
<td>-0.08</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MOT</td>
<td>Test</td>
<td>Test</td>
<td>0.31***</td>
<td>0.11</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Backward</td>
<td>Test</td>
<td>Test</td>
<td>-0.12*</td>
<td>-0.10*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Learn. exp.</td>
<td>Test</td>
<td>Test</td>
<td>-</td>
<td>0.29**</td>
<td>0.08</td>
<td>0.37***</td>
</tr>
</tbody>
</table>

Note. The table lists the direct, indirect and total effects in the model. $t$ significant $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. $f$ indicates a result from full mediation models. $p$ indicates a result from partial mediation models. EFFEM = time in e-module; MOT = motivation.

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**Figure 1** Time in E-Module as Mediator (in Combination with Motivation). ns = not significant

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3.1% of the variance in navigation (forward navigation) and 13.5% of the variance in test performance.

The results of the revised model suggest the following. First, we have evidence for partial mediation in terms of time in e-module and forward navigation, thus providing some support for our mediation hypothesis for behavioural self-regulation measured via log files (partial support for Hypothesis 1). A more positive learning experience led to fewer forward jumps as predicted (confirming Hypothesis 2). This suggests that the learning experience plays a central role in that a positive experience may encourage learners to increase

<table>
<thead>
<tr>
<th>Navig. variable</th>
<th>Mediation model</th>
<th>$\chi^2$</th>
<th>d.f.</th>
<th>$p$</th>
<th>RMSEA (CI)</th>
<th>CFI</th>
<th>SRMR</th>
<th>$\Delta \chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>EFFEM</td>
<td>Full</td>
<td>39.28</td>
<td>5</td>
<td>0.00</td>
<td>0.141 (0.101–0.185)</td>
<td>0.83</td>
<td>0.096</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Partial</td>
<td>13.71</td>
<td>4</td>
<td>0.01</td>
<td>0.087 (0.040–0.140)</td>
<td>0.95</td>
<td>0.049</td>
<td>25.57***</td>
</tr>
<tr>
<td>Forward</td>
<td>Full</td>
<td>44.73</td>
<td>5</td>
<td>0.00</td>
<td>0.153 (0.112–0.196)</td>
<td>0.76</td>
<td>0.104</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Partial</td>
<td>17.19</td>
<td>4</td>
<td>0.00</td>
<td>0.100 (0.054–0.152)</td>
<td>0.92</td>
<td>0.051</td>
<td>27.54***</td>
</tr>
<tr>
<td>Backward</td>
<td>Full</td>
<td>45.91</td>
<td>5</td>
<td>0.00</td>
<td>0.153 (0.113–0.197)</td>
<td>0.73</td>
<td>0.109</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Partial</td>
<td>13.13</td>
<td>4</td>
<td>0.01</td>
<td>0.084 (0.037–0.137)</td>
<td>0.94</td>
<td>0.046</td>
<td>32.78***</td>
</tr>
</tbody>
</table>

Note. The first row lists the full mediation model (relationship between learning experience and test performance completely mediated by selected navigation variable and motivation). The second row lists the partial mediation model (allowing for a direct path between learning experience and test performance) *** $p < 0.001$. CI = confidence interval; CFI = comparative fit index; d.f. = degrees of freedom; EFFEM = time in e-module; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.
their self-regulatory efforts and moving through an e-module more consistently rather than jumping ahead. We also observed a negative relationship between forward navigation and test performance (confirming Hypothesis 3). This suggests that when participants cover all areas of the e-module, they also had better test performance than those individuals who skipped sections. While the relationship between learning experience and backward navigation was also negative, this relationship was not significant, which suggests that backtracking in an e-module may not necessarily be linked to the learning experience (failing to confirm Hypothesis 4). It is possible that other factors may have played a role in this relationship. While the learning experience did not influence backward navigation in the expected manner, backward navigation was a significant predictor of test performance as expected (confirming Hypothesis 5). This is in line with our suggestion that backward jumps may be indicators of poor self-regulation, specifically, poorer self-monitoring, which requires the learner to revisit sections.

Discussion

Our goal was to attempt and replicate the model by Ning and Downing (2012) in a slightly modified form using similar constructs and behavioural self-regulation indicators in the form of navigation behaviour. When we consider navigational patterns as behavioural self-regulation indicators, we see small, but significant partial mediation effects. The learning experience as assessed in our e-modules was a significant predictor of motivation, behavioural self-regulation (in the revised model) and test performance. This is also in line with other studies that reported a relationship between learning experience and motivation (Christophel, 1990; Richardson & Swan, 2003).

Our results regarding learning experience, self-regulation and performance are consistent with other studies as well. For example, learning experiences that are also more interesting and useful may influence navigation of hypertext (Lawless & Brown, 1997) and help to keep learners on task (Peacock, 1997). These effects may increase the effort invested by the learner during the learning process, thus increase self-regulation as recorded in log files. Previous research has further shown that the learning experience may be influenced by the characteristics of the learning environment, which in turn improves performance (Boekaerts, 1999). As expected, behavioural self-regulation also influenced test performance. This is in line with the research by Bol and Garner (2011) who suggested that maladaptive navigational patterns are due to deficits in self-regulation, hence impairing subsequent performance as observed in our study.

While these results support our argument to include log files when examining online learning, we need to revisit some of the results we obtained for motivation. We found no evidence that test-taking motivation mediated the relationship between learning experience and test performance in our e-modules (see also Little, Card, Bovaird, Preacher, & Crandall, 2007). This has also been observed in other studies which examined the relationship between test-taking as well as intrinsic motivation and test performance (Eklöf, 2007, Martens, Gulikers, & Bastiaens, 2004). It appears that greater intrinsic motivation and higher learning performance are not necessarily always associated with each other (Martens, Gulikers, & Bastiaens, 2004). Our findings may also be due to other circumstances. We believe that the results we obtained in our full mediation models are due to the fact that motivation shared a large portion of variance with learning experience (around 40% across various models), which may have weakened the influence of the learning experience on performance (see example by Farrell, 2010). Another explanation might be that the consequences of performing poorly on a test are not necessarily comparable with the consequences of poor overall academic performance (as in GPA tested by Ning & Downing, 2012). This means that motivation may only relate to a performance variable when performance on this variable is potentially personally meaningful and has long-term consequences. Furthermore, we measured only one specific facet of motivation (test-taking motivation rather than general motivation). It is therefore possible that we might have obtained a different effect if we had measured motivation as a broader construct.

Implications

These findings have several implications for the design of learning environments. The strong path between
learning experience and motivation suggests that the learning environment may be an important antecedent to consider when the goal is to increase motivation. Especially for individuals who lack confidence about their progress and abilities, increasing motivation might actually attenuate the effect of the learning environment.

Our study contributes to the exploration of behavioural self-regulation research via log files. Furthermore, our research also identified the need to expand the number of navigational variables that are collected and analysed so as to capture all the behaviours that reflect self-regulated learning. We only examined three aspects here. Other options to explore self-regulation strategies are to examine the routes taken, the number of help options utilized, and time spend on different pages. By learning how the pursuit of different strategies is expressed in log files (a starting point could be the early work by Canter, Rivers, & Storrs, 1985), we may be able to close the gap between self-reported and actual self-regulation (Hadwin et al., 2007; Winne & Jamieson-Noel, 2002).

**Limitations and future research**

In the following section, we would like to outline some of the possible limitations and address these where appropriate, either by suggesting potential research opportunities or outlining our procedures to reduce the influence that certain limitations may have had for our results.

We believe it is adequate to use navigational patterns as proxies for self-regulation because of the discrepancy often noted in self-reported self-regulation and actual self-regulation during learning. In our case, the mediator in question (self-regulation behaviour in an e-module) was not readily measurable via other means than log files, nor did the two mediators overlap either conceptually or measurement-wise with the other variables in the models (see also Little et al., 2007).

One limitation is that our study looked at navigation during one learning episode. Bucklin and Sismeiro (2003) found that the data collected about users who visit certain websites repeatedly differ from data collected from users who only visit websites once. That is, aggregate information about site visits diverge from models computed on individual browsing patterns and possibly cross-sectional heterogeneity in the sample. Further research examining navigation across a number of site visits would provide another perspective on self-regulation during repeated learning episodes. The combination of self-report and log file analyses could provide a more longitudinal picture of how efficient behavioural self-regulation develops.

**Final words**

Our research demonstrated the utility of using behavioural self-regulation indicators when exploring the relationship between learning experience and test performance. Using a modified model based on the work from Ning and Downing (2012), we were able to demonstrate with relatively simple indicators of navigation that log files can provide a vital source of information about self-regulation. We therefore hope that our very simplistic approach will encourage other researchers as well as practitioners to consider the merits of log files in combination with self-reports to expand and learn more about the overlap and reliability of cognitive, affective and behavioural indicators of self-regulation in relation to performance outcomes during learning.

**Acknowledgements**

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**Notes**

1. As a precaution, we did examine the role of prior knowledge as predictor of navigation (in addition to learning experience) in follow-up analysis. The strength of the mediation (full and partial) did not change significantly when we included prior knowledge.
2. We ensured that all variables met the requirements for multivariate normality in terms of skew and kurtosis in order to use maximum likelihood (Anderson & Gerbing, 1988). Please note that the two mediators (motivation and navigation) were conceptually distinct as required (Kenny, Kashy, & Bolger, 1998).
3. We also considered the influence of various covariates (such as data source) where appropriate in multiple regression analyses. The standardized coefficients were largely identical in magnitude and significance as the direct effects listed in Tables 3 and 5.
Table 5. Standardized Effects in Full ($\beta_F$) and Partial Mediation Model ($\beta_P$)

<table>
<thead>
<tr>
<th>Navigation variable</th>
<th>Predictor</th>
<th>Criterion</th>
<th>Direct effect $\beta_F$</th>
<th>Direct effect $\beta_P$</th>
<th>Indirect effect $\beta_P$</th>
<th>Total effect $\beta_P$</th>
</tr>
</thead>
<tbody>
<tr>
<td>EFFEM</td>
<td>Learn. exp.</td>
<td>EFFEM</td>
<td>0.22**</td>
<td>0.22**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>EFFEM</td>
<td>Test</td>
<td>0.33***</td>
<td>0.26***</td>
<td>0.06**</td>
<td>0.36***</td>
</tr>
<tr>
<td></td>
<td>Learn. exp.</td>
<td>Test</td>
<td>–</td>
<td>0.30***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forward</td>
<td>Learn. exp.</td>
<td>Forward</td>
<td>–0.15*</td>
<td>–0.17*</td>
<td>0.03*</td>
<td>0.34***</td>
</tr>
<tr>
<td></td>
<td>Forward</td>
<td>Test</td>
<td>–0.21***</td>
<td>–0.15*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Learn. exp.</td>
<td>Test</td>
<td>–</td>
<td>0.31*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Backward</td>
<td>Learn. exp.</td>
<td>Backward</td>
<td>–0.08</td>
<td>–0.09</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Backward</td>
<td>Test</td>
<td>–0.13*</td>
<td>–0.10*</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Learn. exp.</td>
<td>Test</td>
<td>–0.34*</td>
<td>0.01</td>
<td></td>
<td>0.35***</td>
</tr>
</tbody>
</table>

Note. The table lists the direct, indirect and total effects in the model. * significant $p < 0.05$, ** significant $p < 0.01$, *** significant $p < 0.001$. _f_ indicates a result from full mediation models, _p_ indicates a result from partial mediation models.

EFFEM = time in e-module.

References


