Transactions on Human – Computer Interaction

Research Paper

How Do Learners Interact with E-learning? Examining Patterns of Learner Control Behaviors

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Abstract:

There has been significant debate in the literature on technology-mediated training about the appropriate role of learner control. We define learner control as giving trainees the ability to make choices about how they proceed through the learning environment. We explore two perspectives. First, we consider learners' stated preferences for the extent of control in the learning environment. Second, we analyze the actual online learning behaviors of 518 trainees in a Fortune 500 organization. We compare a measure of learner control preferences to the most commonly used framework of learner control that comprises five dimensions: pace of instruction, sequence of topics, specific content covered, amount of advice/feedback provided, and type of media. We also compare the dimensionality of learner behaviors to this framework and examine the relationship between learner preferences and learner behaviors. Results suggest that fewer dimensions can capture both learner preferences and behaviors than what the literature currently suggests. Specifically, media control aligned with both pace and content control. The relationship between stated learner control preferences and learner control behaviors was relatively weak. However, we found support for the recently identified dimension of scheduling control and suggest a new learner control dimension of performance control, consistent with the importance of practice retrieval for learning.

Keywords: Learner Control, E-learning, Pace, Sequence, Content, Advice/Feedback, Scheduling, Performance.

The manuscript was received 12/15/2015 and was with the authors 6 months for 2 revisions.

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1 Introduction

As more and more learning resources have moved to the Internet over the past decades, interface design has become a critical component of overall e-learning design (Chou, 2003; Santhanam, Yi, Sasidharan, & Park, 2013). Design choices in the training software and interface can enhance or inhibit the learning experience and learning outcomes. These choices include micro features of the interface such as colors, shapes, and fonts and more macro issues such as multimedia availability, interactivity, and communication functionality. One key feature of interface design for e-learning is choice in how learners interact with the interface, the instructors, the content, and even other learners (Chou, 2003). The e-learning field has, driven by technological change, evolved toward learner-focused delivery methodologies that allow increased individual control over the training environment (Kraiger & Culbertson, 2012). New technologies (e.g., mobile, improved communication tools, new programming tools) and individual shifts in preferences (e.g., when and where to engage in e-learning, choice among laptop/tablet/smartphone) have combined to shift learner decisions and attitudes.

Research in the organizational training literature has often examined the notion of choice through a set of constructs identified as learner control. Learner control is “a constellation of both learner and instruction-centric constructs describing a general situation in which learners are given increased discretion over behaviors regarding formal learning events” (Brown, Howardson, & Fisher, 2016, p. 268). Aspects of learner control can be present in nearly any type of learning environment. Learner control has become a critical component of research and practice in e-learning in particular, with the idea that learner control may hold part of the key to how e-learning might offer advantages over more traditional face-to-face learning. From the instructional perspective, an e-learning program can allow learners control over a wide variety of features in the learning environment. Kraiger and Jerden (2007) reviewed the learner control literature in detail and identified four dimensions of learner control: 1) pace of instruction, 2) sequence of topics, 3) specific content covered, and 4) amount of advice/feedback on learning progress provided.

Pace of instruction represents the ways in which learners are offered control over how quickly or how slowly they move through a training program. Programs that require a learner to read text on a page and then click when ready to move onto the next page offer a basic level of learner control. A pre-recorded video lecture offers much less pace control such that learners may be allowed only to click on a pause button to periodically stop the program. **Sequence** control allows learners to determine the order in which they move through training topics. Consider a training program that a large organization offers on its code of conduct. Employees may be allowed to choose the order in which they complete sections on conflicts of interests, gifts, related laws, and reporting procedures. Other training programs may need to proceed in a specified manner such that one needs to learn the material in the first module in order to understand the second. **Content** control allows learners to choose which content they will learn. This type of control may be offered when trainees have a wide variety of backgrounds and the training designer wants to allow more experienced trainees to skip introductory material. For example, with the code of conduct training or other kinds of mandatory training repeated annually, new employees may have to complete the entire program, while experienced employees can choose a shorter version that focuses only on new aspects of the code. Control over **advice/feedback** allows trainees to determine if, and to what extent, they want to receive feedback about their progress through the training or how well they are learning the material. The training could offer periodic optional assessments that would allow learners to test their knowledge. After taking the assessment, the training could then offer advice on where the trainee had scored poorly and needed to review some material. The training program could even offer to take the trainee right to the section where that material was found.

In addition to the four learner control dimensions that Kraiger and Jerden (2007) describe, other researchers have identified the option of **media control** or the extent to which learners can choose which media format is used to display information in e-learning (Randolph & Orvis, 2013). For example, learners may be able to read descriptive information on the screen or listen to an audio recording of the same information. They may be able to view a video or read a transcript of the video (Orvis, Fisher, & Wasserman, 2009). Brown (2005) found that learners react differently to various types of media, which impacts their learning through attitudes toward the course. Media control is a more peripheral type of learner control than other types such as content or pace control and, thus, not as directly related to learning (Brown et al., 2016). However, making choices about media may help provide learners with more perceived control and make them more engaged in the training. Media control is also important from a universal design perspective where presenting information with multiple media types allows people with different learning preferences and disabilities to access the material (CAST, 2011). Thus, we include media control in the present study.

In the human-computer interaction (HCI) literature, researchers have examined similar training methods that offer learners greater control over their learning experiences, such as exploration-based training, self-paced training, and passive versus active training (Santhanam et al., 2013), to make training more effective. Exploration-based training typically combines several of the control dimensions described above and allows trainees to make choices about pace, sequence, and content as they work their way through the training material. Self-paced training focuses on pace control, while active training encourages trainee participation and engagement through a variety of mechanisms. Santhanam et al. (2013) identify research on these and other training methods and strategies and conclude that, despite extensive research activity in this domain, we do not yet know how to make e-learning interesting and effective across a range of learning outcomes.

From the learner perspective, we need to consider the extent to which learners actually use the learner control features designed into the training (Kraiger & Jerden, 2007; Brown et al., 2016). One interesting aspect of the nature of the learner control construct is that one cannot (by definition) require learners to use any of these training features even if the use of these features may enhance learning outcomes. Quite simply, not all learners want to use the learner control features or use them to the same extent. They may believe that using learner control will make the training take longer or that it will cause them to make mistakes they would rather avoid. Other learners may not be able to use the learner control features effectively. When given choices about content control, learners may overestimate their own level of competence in a particular area and skip too much of the content. Similarly, when given control over pace, learners may move through the training too quickly and not take the time to carefully read the text provided, which reduces the amount of knowledge they absorb.

While early work in this area suggested that high learner control was optimal, more recent work suggests mixed findings. The presence of learner control features in an e-learning interface offers learners the option of using them (i.e., the objective level of learner control) but does not guarantee that they will actually use that control (i.e., actual learner control) (Skinner, 1996; Kraiger & Jerden, 2007). Further, the presence of learner control features does not always improve learning outcomes and can even reduce learning (Brown, 2001; DeRouin, Fritzsche & Salas, 2004, 2005; Granger & Levine, 2010). Recent research findings suggest that we need to take an interactive view of the role of learner control in e-learning by looking at features of the training, characteristics of the trainee, and the match between them to draw conclusions about the role of learner control (Howardson, Orvis, Wasserman, & Fisher, 2017; Kraiger & Jerden, 2007; Orvis, Brusso, Wasserman, & Fisher, 2011; Santhanam et al., 2013).

Some research has examined ways to understand the best match between learner preferences and training design features in e-learning environments. Hornik, Johnson, and Wu (2009) examined learner beliefs about the appropriate learning model (e.g., objectivist learning where the expert transmits knowledge to the novice versus constructivist learning where learners play a more active role) in an online course and how they related to learning processes and outcomes. They found that learners had more positive outcomes when their beliefs about the best way to learn matched the training design, which suggests that mismatches cause friction. More specific to learner control, Freitag and Sullivan (1995) investigated the match between individual and training on one feature of learner control: the amount of content covered. They found that learners who were placed in a training environment that matched their preferences showed more positive outcomes, including training satisfaction and short-term knowledge gain. Orvis et al. (2011) investigated the matching hypothesis using the Big Five personality characteristics as "proxies for the 'innate preference' for learner control" (p. 63). They found that learners higher in openness and extraversion performed better in a training program that offered higher learner control, whereas those lower in these traits performed better with lower learner control. This type of research may allow avenues for personalizing user interfaces based on personality profiles, which Arazy, Nov, and Kumar (2015) call "personalityization".

2 Research Questions

While we have seen significant advances in learner control research, researchers have identified some methodological limitations. First, while researchers have been interested in preferences for learner control as an individual difference predicting use of learner control tools (e.g., Kraiger & Jerden, 2007; Orvis et al., 2011), to our knowledge, no prior published work has directly measured this construct. Theoretically, we have reason to believe that this individual difference affects behavior in the learning environment, but to date, published research that has examined preference for learner control has relied on proxies such as personality (e.g., Orvis et al., 2011) rather than directly measuring the construct of interest. Second, researchers have typically measured the use of learner control functionality through self-report or assumed in cases of learner control experimental manipulations. Learners may not be able to accurately report their own behaviors after the fact or may be motivated to report behaviors different from what they actually performed.

Our study contributes to this extant literature in two specific ways. First, we address both of the aforementioned methodological issues present in the majority of prior e-learning work. That is, we explicitly measure learners' preferences for learner control and their actual learner control behaviors when faced with actual opportunities to exercise control during an online training program. Second, we investigate the relationships between learners' stated preferences for control, how these learners actually interact with the learning environment (i.e., their actual learner behaviors), and the impact on subsequent learning. Understanding these relationships more clearly should allow training designers to create more effective training programs that maximize learning. Related to these contributions, we address three broad research questions:

RQ1: Is the five dimensional view of learner control used in the literature consistent with how learners think about their own preferences for learner control?

RQ2: When presented with a user interface that allows learners to substantially control the learning environment, which learner control features do they actually use? Are there different patterns of learner behaviors, and how are these patterns (if they exist) associated with learning?

RQ3: What is the relationship between learner control preferences and actual learner control behaviors exhibited during an online training program?

3 Method

3.1 Research Setting and Procedure

We conducted this study using a training program that included a four-module sequence of online courses at a Fortune 500 corporation. The program was part of an organizational effort to encourage more effective knowledge sharing among internal experts on an important internal process. Thus, the overall topic of the training was how to be an effective internal trainer. The first module addressed foundational training concepts. Subsequent modules addressed instructional systems design, on-the-job training, and instructor-led training. The median time to complete the modules was 123.3, 65.88, 50.58, and 36.52 minutes, respectively. The organization designed all modules to allow aspects of media control (e.g., viewing optional videos), content control (e.g., using internal links to view additional information about a training topic), and pace control (e.g., adjusting how long they spend on sections of the training). Each module also included an assessment of declarative knowledge (with multiple choice and true/false questions) related to the content covered in that module. Trainees had to obtain a 100 percent score to pass the training. If they did not pass on their first attempt, they were provided with feedback about which questions they missed. Trainees could simply choose another option or could review training content before attempting the missed questions again. The program did not specifically tell them where to find the relevant training material or provide them with links to return them to the relevant material. Questions on subsequent attempts were exactly the same as on the original assessment. Trainees only had to correct the answers on the questions they had missed; they did not have to re-take the entire assessment.

All members of a work unit in the organization had to take Module 1 (n = 518). A subset of the sample then completed Module 2 (n = 182), Module 3 (n = 328) and Module 4 (n = 233) based on their job requirements. Module 1 was a pre-requisite for the other modules, but Modules 2-4 could be completed in any order. Trainees had several different job categories, such as floor operator, laboratory technician, office worker, and supervisor. All of the training modules included a user interface that incorporated several learner control tools, which we describe in greater detail below. Trainees completed the modules over a six-month period. Several months after the training finished, one of the company's training managers asked participants to complete a self-report survey on their learner control preferences through an online survey link. The manager sent the survey to all 518 trainees, and 132 responded for an initial response rate of 25.5 percent. We included one attention check item in the survey to detect careless responses (Meade & Craig, 2012). We removed respondents who answered this item incorrectly from further analyses using the PLC measure. Thus, the usable sample size for all analyses using the PLC scale was 78 for a final response rate of 15 percent. We used a unique trainee identification number to link the training data to the learner control preference data.

3.2 Measures

The front-end training interface was connected to a SQL database backend that contained several tables that corresponded to the control actions we describe above. In real time, the training interface captured and stored information about relevant learner actions corresponding to these tables. It recorded some of the actions (e.g., clicking on a link) simply as present or absent. It recorded other actions in elapsed time (e.g., amount of time to choose the answer to an assessment question). Modules 1-4 contained a declarative knowledge assessment with seven, six, five, and four items, respectively, for a total of 22 assessment items. The training program automatically scored the assessments and returned feedback to the trainee about which items were completed correctly. For this analysis, we used the score of the first attempt at the assessment. Because learners were ultimately required to answer all items correctly, there was no variance in their final scores.

We developed the preferences for learner control (PLC) scale based on the literature and on work done by Randolph and Orvis (2013). We created the scale to measure individual learner preferences for having control over the pace of training, sequence of topics, advisory features or feedback offered, content covered, and media used during online training. The scale contained 15 items (three for each of the learner control dimensions). Participants used a five-point Likert scale (5 = "I definitely want to decide this" and 1 = "I definitely want the training to decide this") to evaluate each item. Sample items include: "The order that topics are presented during the training" (sequence control), "Which specific training topics and activities I complete during the training program" (content control), and "The amount of time I spend on the different training topics and activities" (pace control). Reliability of the 15-item scale was .82. The mean was 2.65 and the standard deviation was .65.

3.3 Analytic Strategy

We used specific learner behaviors as input for our empirical analyses, and each behavior corresponded to a specific feature of the training platform. The granularity of these behaviors, however, was particularly fine, which presented a challenge for drawing more abstract and generalizable conclusions from such data. Consequently, we employed data-reduction techniques to help answer our research questions above. Specifically, we first used a theory-driven or top-down approach where we used our substantive expertise to review the database of learner behaviors and identify specific combinations of behaviors related to the learner control dimensions that we describe above. Second, given that we focus less on mapping learner behaviors to extant conceptual dimensions and more on identifying empirically how learners appropriate control afforded, we also employed two empirically driven or bottom-up data-reduction techniques: principal components analyses and model-based information cluster analyses. We describe both our top-down and bottom-up data-reduction techniques in greater detail below.

3.3.1 Top-Down, Theory-driven Data Reduction

First, we reviewed the training platform's technical documentation, which included a detailed description of the SQL relational database that stored learner behaviors. Second, we completed each of the four training modules several times while taking detailed notes about relevant learner control features. Combining these notes with the database documentation, the second author (who has a computer science degree and Web-development and interface-design experience) explored the raw data contained in the SQL database to identify specific behaviors to extract and aggregate them into more theoretically substantive behavioral measures. Table A1 lists the extracted behaviors. Given our research questions and that learner behaviors numbered in the thousands for any specific module, we aggregated all measures to the overall training level. That is, we aggregated behaviors across the four separate modules[1]. The specific

[1] An alternative approach to aggregation, as noted by an anonymous reviewer, would be to account for the number of modules taken by each trainee. We conducted an additional set of analyses where we aggregated learner behaviors within training modules, then taking the average of their summed raw scores divided by the number of modules completed to produce total training scores. We found no significant differences in the principle component analyses and cluster analyses between the two aggregation methods. More detailed results of this analysis are available from the first author.

method of aggregation differed slightly according to the behaviors in question. Below, we present some examples that illustrate the aggregation strategies.

The training program recorded the date and time learners logged into the system. Learners could log out of the system and return at a later date, so each learner could have multiple dates for each module depending if they completed the module in one sitting or spaced out their sessions. To arrive at an overall number of sessions taken to complete the training, we summed the number of unique login dates and times in a module and then summed this number across modules to arrive at an overall score for “sessions to complete”. Another aggregation example involves media use behaviors. Given that learners could complete the training in as many sessions as they desired, we examined the number of actions taken in one specific session without logging out and back in, such as viewing a training video a second time in the same session. As with the sessions variable, the training program tracked the date, time, and session in which participants started each video. Thus, we summed the unique start dates and times for each video in one specific session and then summed those values across all videos in the module and then across all modules to arrive at an overall media review score for each learner.

The program also tracked learners’ actions during the end of module assessments. For example, the program tracked the total time spent on the quizzes and the number of times a learner navigated backwards to review a page as a result of a failed quiz. As with the above, we summed the total minutes spent across all four modules assessments to arrive at an overall score for each learner. For the backwards navigation behavior, the training program tracked from which page each learner came when viewing another page. We summed the number of backwards navigation instances in each module and then across all modules to arrive at an overall score. Consistent with how we aggregated all of the learner control behaviors, we summed the scores across assessments to create a total assessment score for each learner.

Many of the features that we describe above map onto the common dimensions of learner control features that we discuss in Section 1: content, pace, sequence, media, and advisory (Kraiger & Jerden, 2007). For example, some features were clearly related to *content* control. Each module contained several optional internal hyperlinks that, if selected, presented learners with additional information about the topic while they remained in the training program. Learners could click on a “helpful hints” button to obtain more detail about the content on some pages, and they could print these helpful hints for use later outside the training environment. The training also contained several content-related instructional features designed to encourage learner interaction with the training material (e.g., clicking on images to obtain more information about a training topic, dragging and dropping a term into its correct bucket, answering opinion-based questions about the training topic). Further, learners could choose how much they relied on videos (total time spent watching and rewatching videos), which corresponds to *media* control. Many of the videos included in these training modules repeated verbatim text presented on the screen. Other videos expanded somewhat on concepts presented in the text or presented examples of the concepts, but none of the videos were completely new content. In line with *advisory* control, learners also had the option to complete practice questions and receive information about the correct answers. Related to *pace* control, learners could complete each module in as many sessions as they desired. That is, learners could log out of a training module and the program would remember their location in the training when they started their next session.

The mappings above notwithstanding, other tools did not clearly fit into one of the learner control categories. For example, the training captured several learner behaviors during the end of module declarative knowledge assessments. The training captured how long a learner waited before selecting an answer, whether learners changed answers, and whether learners changed from an incorrect to a correct answer or from an incorrect to a correct answer. After each declarative knowledge assessment, the program gave learners feedback about their performance and the option to re-visit training content if their performance was less than satisfactory. The program tracked whether or not learners did indeed revisit content even though they were not presented with easy links to return to the relevant content. Although the features above do have some similarities with advisory control, they do not neatly fit one of the established categories.

Overall, through our top-down, theory-driven approach, we identified 18 relevant measures of learner behavior (see Table A1). The table includes descriptive statistics for these measures. However, as we note above, we focus not on mapping learner control features to extant conceptual dimensions but on identifying empirically how learners use such features. To do so, we employed two bottom-up or empirically driven data-reduction procedures: principal components analysis and model-based cluster analysis, each of which we describe in greater detail below. Both of the bottom up reduction strategies were implemented on the full set of 518 learners across all modules.

3.3.2 Bottom-up, Empirically Driven Data Reduction

Next, we applied empirical data-reduction techniques to further combine the 18 aggregated behaviors. Specifically, we used principal components analysis and cluster analyses, the latter of which we discuss in greater detail immediately below. In the case of learner control use behaviors, principal components analysis is more appropriate than the common factor model because we examined the latent patterns that emerged from several specific behaviors (i.e., formative) rather than how specific behaviors manifested as observations of pre-existing latent patterns (i.e., reflective; Edwards & Bagozzi, 2000). We determined the specific number of components to extract using parallel analysis (O'Connor, 2000) and we used the scree plots to determine the number of components to extract. Parallel analysis generates random data and extracts, for example, one factor. Then, one factor is extracted from the observed data and the results of the random and observed models are compared. Researchers determine the number of factors to extract by finding the number of factors at which the observed data results do not greatly fit better than the random data and extracting one less than that number of factors (O'Connor, 2000).

Although parallel analysis is effective for identifying the maximal number of components that would occur beyond chance, the method often results in extracting more components than actually exist in the data (O'Connor, 2000). Consequently, researchers who employ parallel analysis should further explore the structure of their data before deciding on the number of factors to extract. Specifically, researchers should examine the scree plots for the initial extraction and the pattern of loadings to determine if the results are theoretically interpretable (O'Connor, 2000). Thus, we subsequently conducted principal component analyses, extracting the number of the components identified from parallel analysis and examining both the scree plot and pattern of loadings for this solution. Based on the interpretability of these results, we then conducted subsequent principal component analyses before deciding on the specific number of components to extract.

Once we identified the appropriate number of components to extract, we used the loadings of the behavioral scores on each component to create scale scores such that learners had one score for each of the components identified from the parallel analysis. Specifically, we multiplied each learner's raw score for the behavioral measures by the behavioral measure's loading on its respective principal component, and, after repeating this process for each of the measures in a given component, we summed the results to form an overall composite score for each learner on each of the principal components extracted. This strategy is similar to the multiple-regression-based methods used in personnel selection to create a single, weighted composite score from several different predictors (e.g., personality test, cognitive ability test; Gatewood, Feild, & Barrick, 2011).

We then used these composite scores to determine if we could identify distinct patterns of learner behaviors. To do so, we conducted model-based cluster analyses (Fraley & Raftery, 1998). Researchers have criticized conventional cluster analysis methods for their subjectivity in choosing the number of clusters. Model-based procedures, however, empirically compare different clustering solutions using the expectation maximization (EM) algorithm and the Bayesian information criteria (BIC; Fraley & Raftery, 1998). This procedure contains two steps. First, traditional clustering methods are used to create a number of initial sub-clusters (i.e., one cluster less than the number of variables). These sub-clusters are then used as input for the EM algorithm. This algorithm maximizes the probability that an individual belongs to one of these sub-clusters but not the others. The BIC for this model is then calculated based on how well the EM algorithm could allocate individuals to clusters. The initial set of sub-clusters is then subsequently reduced (i.e., two clusters less than the number of variables) and the EM procedure is repeated. This procedure continues until only one cluster exists. Second, the BIC values for all models are compared and the model with the largest value is retained. This model contains the appropriate number of clusters and correct assignment of individuals to these clusters (Fraley & Raferty, 1998). The cluster assignment variable can then be saved and used in subsequent analyses.

To help interpret the clusters, we employed two strategies. First, we included the learners' overall score on the post-module declarative knowledge assessments in the cluster analysis, which helps identify between-cluster differences on external variables that may be theoretically meaningful. Second, we examined effect size differences across clusters on the learner control preferences items to further interpret the clusters. We discuss the results of these analyses below.

3.3.3 Identifying Preferences for Learner Control Dimensions

To answer Q1, we first conducted an exploratory factor analysis of the PLC measure to examine the dimensionality, including only those participants who answered the attention check item correctly (n = 78). To determine the number of factors to extract, we conducted parallel analysis as we describe above (O'Connor, 2000). Our parallel analysis results indicated that we should extract two, or possibly three, factors. As O'Connor (2000) notes, researchers should then conduct additional analyses to determine the specific number of factors to extract, such as examining the scree plot and item-factor pattern matrix to see if the solution is theoretically interpretable. As such, we fit both two- and three-factor solutions to the data, extracting factors with principal axis factoring within the common factor model and employing oblique factor rotation. The common factor model is more appropriate in this case because we conceptualize preferences for learner control as a reflective latent construct within each learner that should similarly affect like preferences items (e.g., Edwards & Bagozzi, 2000). The scree plot (see Figure 1) suggested that two factors captured the bulk of the variability in items and that solutions with three factors and beyond were relatively less informative.

Although the item loadings for the three-factor solution were somewhat interpretable, several item loadings were less interpretable. As such, we decided to extract two factors from the preferences for learner control data. In this solution, however, two of the original items (one measuring content control and one measuring feedback control) did not load highly on either factor, and so we removed them. Table A2 shows the final factor loadings for the two factor solution. The first factor, called time control, contained the six items intended to measure pace and media and had a coefficient alpha reliability of .86. The second factor, called information control, contained seven items intended to measure sequence, content, and feedback and had a coefficient alpha reliability of .83. The two subscales were correlated ($r = .29$, $p < .05$).

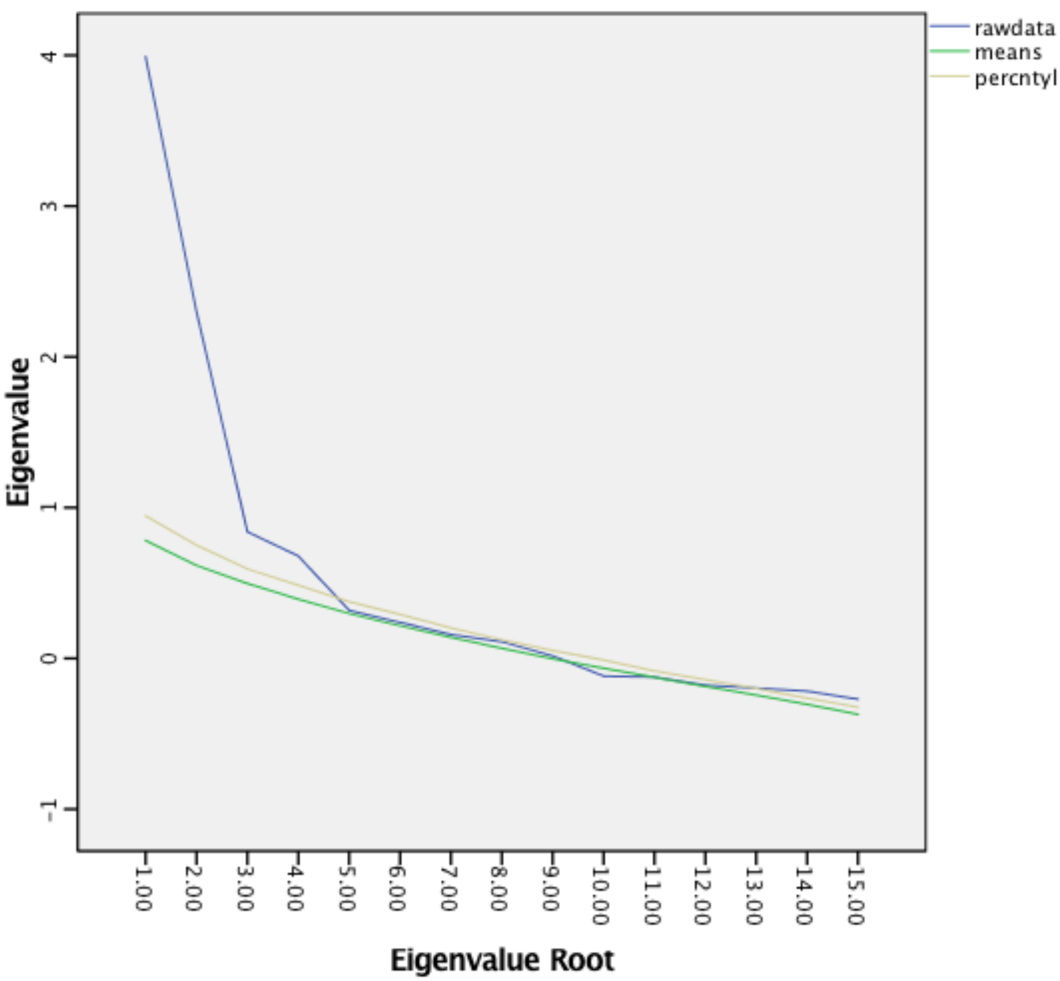


Figure 1. Scree Plot from Parallel Analysis for PLC Data

3.4 Results

3.4.1 Principal Components Results for Behavioral Data

The parallel analysis results for the behavioral data suggested that we should extract eight components. After extracting these eight components, however, we examined the pattern of learner behavior loadings on the eight components and concluded that this solution was not interpretable. Consequently, we rejected the eight-component solution. Closer examination of the parallel analysis scree plot shown in Figure 2 indicates that the observed data eigenvalues only barely exceeded the random data eigenvalues for the sixth, seventh, and eight components, which suggests that, at most, we should extract five components.

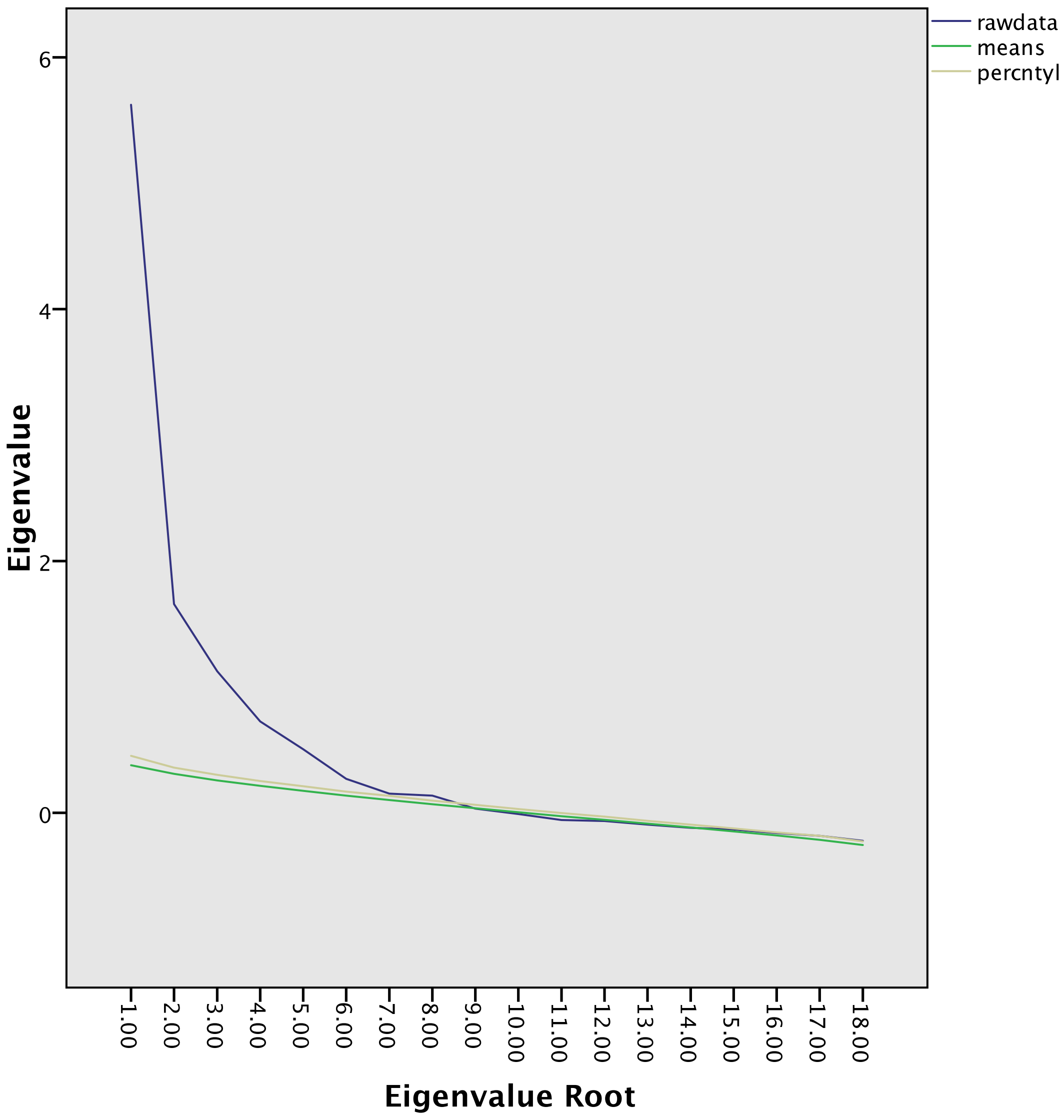


Figure 2. Scree Plot from Parallel Analysis for Behavioral Data

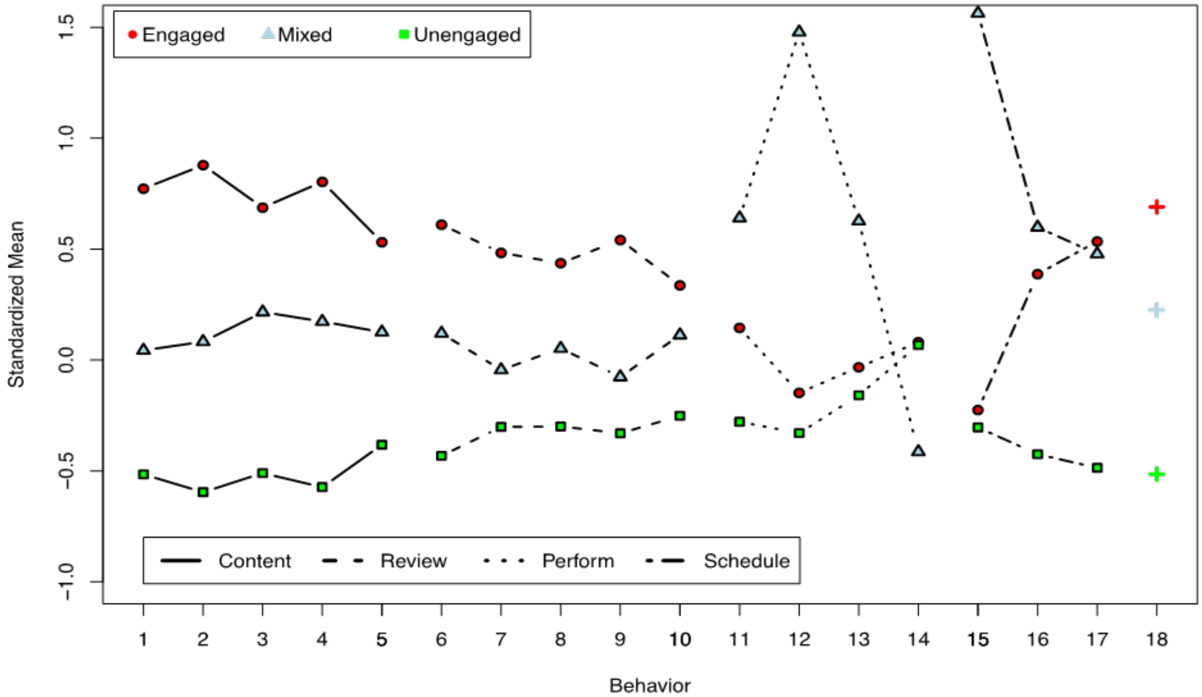
We next extracted five components and examined the pattern of learner behavior loadings on these components. Although more interpretable than the eight-component solution, the five-component solution was still difficult to interpret given the presence of multiple items loading greater than the absolute value of .50 (Hinkin, 1998). Consequently, we decided to extract four components and examined the pattern of learner behaviors' loadings on the extracted components. With the exception of one behavior with a low component loading (off-task behaviors), all remaining behaviors loaded highly on one and only one component and the pattern of loadings was interpretable. As such, we decided to extract four components and drop the off-task behavior (item 18), which resulted in a final set of 17 learner behaviors that each loaded onto one of four components. Table A1 presents the final pattern of loadings.

In response to Q2, we see that the final pattern of loadings for the behavioral data suggested four components of learner control: content, review, scheduling, and performance control use. Examples of content control use included clicking on optional training elements and viewing and restarting videos. Examples of review control use included reviewing material multiple times without being prompted by the training and using the helpful hints options. Scheduling control use examples included the number of times a learner logged out and logged back into the training and the total number of pages the learner viewed. Finally, performance control use examples included changing answers on quizzes, reviewing course material due to failing a quiz, and total time spent on post-module declarative knowledge assessments. In line with our analytic strategy, we created composite scores for content, review, schedule, and performance control use, which we then subjected to model-based cluster analyses that also included learners' overall declarative knowledge scores.

3.4.2 Model-based Cluster Analysis Results for Behavioral Data

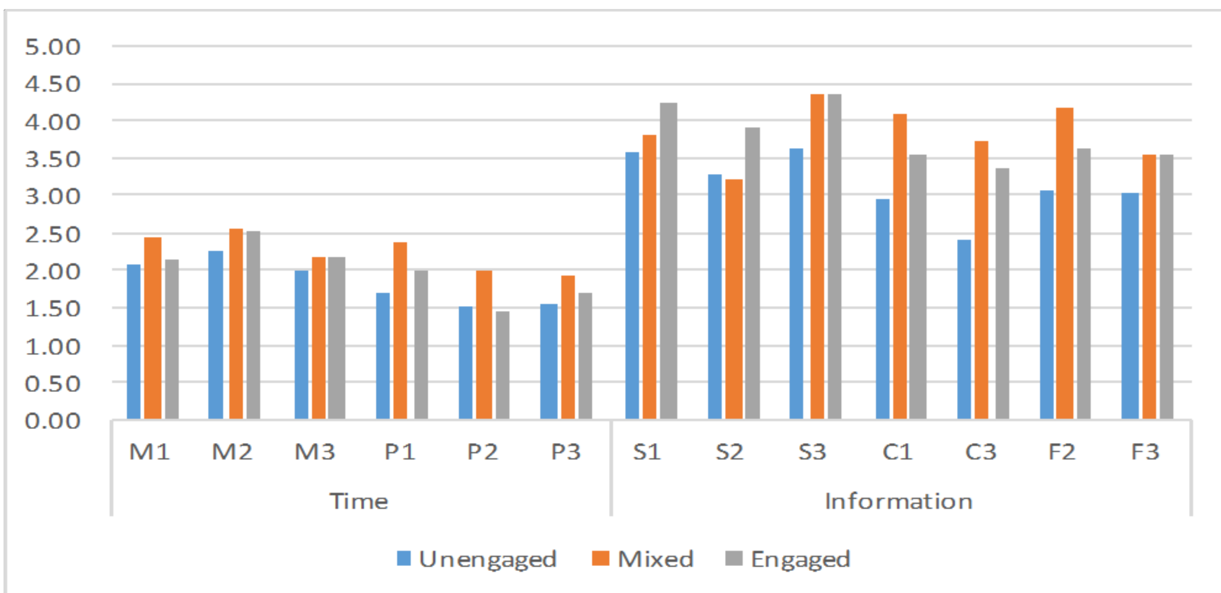
The model-based cluster analysis results suggested that a three-cluster solution fit the data best. To interpret the clusters, we standardized behavioral scores across the entire sample (n = 518) and plotted cluster means for each of the learner control behavior items. Figure 3 presents these results, which we organize by the four dimensions of learner behaviors: content (behaviors 1-5 along the x-axis), review (behaviors 6-10), perform (behaviors 11-14), and schedule (behaviors 15-17). We named the first cluster, represented by the red circles in Figure 3, the "engaged" trainees. The trainees in this group (n = 174, 33.6%) were most active in the more traditional learner control behaviors of content and review. They used less control over the scheduling and performance features, but their activity levels during the training still resulted in positive assessment scores (mean assessment score = 15.3). We named the second cluster, represented by the green squares in Figure 3, the "unengaged" trainees. These were trainees (n = 267, 51.5%) who performed few of the learner control behaviors across all four dimensions and, consequently, scored poorly on the learning assessment (mean assessment score = 8.4). We named the third cluster, represented by blue triangles in Figure 3, the "mixed" trainees. These trainees (n = 77, 14.9%) started out more like the unengaged trainees in that they used few of the learner control features related to content and review. However, once they reached the performance assessment, many of them performed poorly on the first attempt (mean assessment score = 12.6) and they then used most of the scheduling and performance control features to obtain passing scores on the assessment.

To further interpret the clusters, we examined mean differences across the clusters on the 13 individual learner control preference items retained in the factor analysis. Table A3 presents the results, which Figure 4 shows graphically. The first six items, M1 to P3, represent the time control factor (media and pace) and, the last seven items, C1 to S3, represent the information control factor (content, feedback and sequence). Overall, the engaged trainees stated higher control preferences than unengaged trainees on 11 of the 13 PLC items. Unengaged trainees expressed slightly more of a preference to control how quickly or slowly they went through the training (item P2 on the time factor), although the mean was still quite low (1.53). In contrast, trainees in the mixed category stated higher control preferences than engaged trainees on seven of the PLC items. The only two items on which engaged trainees expressed a higher preference for control were S1 and S2, which addressed sequencing or the order in which the program presented topics in the training (see Table A3).



Note: total n = 518; $n_{engaged}$ = 174, $n_{unengaged}$ = 267, n_{mixed} = 77

Figure 3. Analysis of Trainee Clusters by Behavioral Items and Dimensions



Note: M = media control items, P = pace control items, S = sequence control items, C = content control items, and F = feedback control items.

Figure 4. Mean Differences on PLC Items by Trainee Grouping

3.4.3 Correlations between Preferences and Behavioral Data

To answer Q3, we examined correlations among the two PLC dimensions (information and time), the four behavioral control dimensions (content, review, performance and scheduling), and the declarative knowledge score. The sample size for these correlations was 67 because we could not match some of the survey respondents with behavioral training data. Table A4 presents the results. The two PLC dimensions were positively correlated ($r = .23$, $p = .06$), but these variables were not significantly correlated with any of the behavioral control dimensions. The correlation between the PLC time dimension and performance control behaviors was marginally significant ($r = .20$, $p =.10$). In the behavioral dimensions, use of the content control features and the review control features were positively correlated ($r = .40$, $p < .01$). Two of the behavioral dimensions (content and review) were positively correlated with trainee scores on the knowledge assessment measures, which suggests that trainees who engaged in various learner control behaviors did perform better in the training. Because of the small sample size on the PLC measure, we also show correlations among the learner control behaviors and the knowledge score for the large training sample of 518. We see that the overall pattern of correlations was quite similar, and all four of the learner control behaviors were significantly correlated with knowledge scores (see Table A5)

4 Discussion

In this study conducted with a sample of 518 employees in a Fortune 500 company, we found several interesting results related to trainee learner control preferences and objectively measured learner control behaviors in an online learning environment. For our first research question on learner control preferences, a two-factor solution (information and time) emerged from our PLC data rather than the five dimensions traditionally discussed in the literature (pace, media, sequence, content, feedback; Kraiger & Jerden, 2007). The information component contained items related to sequence, content, and feedback, while the time component had items related to pace and media. We developed the PLC measure to reflect the five traditional dimensions, and it did not contain items that tapped into scheduling or performance control. Researchers have recently suggested scheduling control (choices about when and where to complete the training) as an additional dimension that one should regularly consider when designing training interfaces (Karim & Behrend, 2014) based on evidence that scheduling control has a positive relationship with both reactions to training and to learning. This dimension is less central to the core pedagogical decisions about training design (Brown et al., 2016) but clearly a feature that trainees in our study used. Similar to Karim and Behrend, we found a significant relationship between scheduling control and learning performance. Providing appropriate opportunities for scheduling control could be an important factor in enhancing both learning and completion rates in online training.

We believe that the two categories of learner control preference (information and time) augment the original categorizations as we show in Table A4 and could serve as higher-order factors that help us understand learner control in a different way. This categorization is consistent with the arguments of Karim and Behrend (2014) because they distinguish between high-level categories of instructional control (choices about learning behaviors during the training, such as pace, sequence, and content) and scheduling control. From the learner preferences perspective, the five original categories relate to each other through these higher-order ideas of time and information control. One may view control actions related to sequence, content, and feedback as ways to control the flow of information obtained from the training. Content control concerns how much information about the training topic that the trainee receives, while feedback control focuses on information regarding the trainee's performance in the training. Sequence control addresses the order in which a learner receives information. Looking at the time component, pace control fits logically here because of the direct impact that pace has on how long it takes to complete the training. Media choice was initially a surprising fit here, although this may reflect the low perceived utility of much audio and video content in online training. Choosing to view a video or hear an audio clip in a training session often takes longer than simply reviewing printed text on the same material. To the extent that video and audio components of online training repeat and reinforce concepts already introduced in the training, considering media choice as a component of time-based control makes sense and is consistent with the training used in our study. The optional video either reinforced concepts already covered or provided additional examples of the concepts. If a video component introduced completely new content, it is unlikely that designers would make it optional.

From the user interface perspective, the lower level dimensions are still how training designers and programmers would implement learner control at the operational level. But we argue that designers also need to think about learner motivations, when the learners might use the different tools, and why they might not use the tools. To this end, interface designers might find the goals, operators, methods, and selection rules or GOMS model (Card, Moran, & Newell, 1983) of interface design helpful in identifying the specific task-level learner controls (e.g., pace, sequence) that are associated with specific learner goals. Such guidance might be found in, for example, Schneiderman, Plaisant, Cohen, and Jacobs (2009) and the work they cite. Indeed, it is quite possible that the information and time preference factors identified above might serve as high-level guidance for identifying specific learner goals through a GOMS task analysis. That is, some learners may have strong goals to finish quickly (i.e., time preference) while also having low goals for information (i.e., information preference) in which case developing expensive supplemental videos may be less than ideal.

Regarding our second research question about learner behaviors, our data showed that four factors captured learner control behaviors in this study: content, review, scheduling, and performance control use. We then found three primary behavioral patterns among the trainees; engaged, unengaged, and mixed. Not surprisingly, the engaged behavioral pattern was most effective. Many previous studies (e.g., Orvis et al., 2011) relied on trainees to retroactively report their learner control behaviors in a training program. By using the training interface we did in this study, we could directly capture actual trainee behaviors during the training. Thus, the behavioral measures we used in this study were not subject to effects of trainee memory or biased recall that could create inaccurate self-reports of trainee behavior. We did not explicitly examine the relationship between learner control behaviors and knowledge gained from the training, but, in contrast to much earlier work on learner control, we found evidence that all four of the learner control behaviors were related to scores on the knowledge assessment. These effects possibly relate to the measurement technique; with our enhanced measurement accuracy, we could see relationships that memory effects have previously obscured.

One tradeoff of the objective measurement technique for learner control behaviors is that, while we do know exactly what the trainees did, we do not know why they exhibited various patterns of behaviors. For example, we observed that trainees in the mixed cluster had by far the highest levels of navigating backwards to review content after failing a quiz (perform item 2) and spreading the training out over a larger number of discreet sessions (schedule item 1). We do not know if those trainees chose to log out and back in frequently because they were bored or because their supervisor kept assigning them new tasks that they had to complete immediately (or some other unknown reason). Laboratory research using probed verbal protocols could help answer some of these questions.

Our results support the value of including pace control (as expressed through schedule-related behaviors) as a learner control feature. We observed that time spent on the training was not necessarily a good indicator of learning. Some of the trainees (those in the engaged group) completed the training relatively quickly and performed well on the knowledge assessment the first time through. Others (generally the unengaged learners) who went through quickly did poorly on the knowledge assessment. However, some learners in the mixed group who spent a relatively long time on the training performed as well as the engaged learners. Thus, unless training efficiency is an important outcome for the organization, allowing learners to make decisions about pace appears to be appropriate. It would be interesting to compare time spent and relative pace indicators to longer-term transfer measures of knowledge (Blume, Ford, Baldwin & Huang, 2010). If learners space their learning events out further or learn certain concepts in more depth because they take more time, they may better maintain knowledge.

The learner control literature has not previously discussed the performance control dimension. The range of behaviors we observed in this factor is similar to recommendations in the retrieval practice literature (e.g., Karpicke & Blunt, 2011; Roediger, Agarwal, McDaniel, & McDermott, 2011) in which students demonstrate better learning outcomes on declarative knowledge tests when they have taken other quizzes or sample tests to help them learn the material. In fact, Roediger et al. (2011) used a learner control intervention in one of their studies in which they instructed students to use an online game platform at home to practice retaining the material before an exam. This intervention was associated with improved declarative knowledge test performance. From an interface design perspective, such interventions help individuals develop stronger schemas for recognizing and retrieving important information in their environment at appropriate times. In other words, such designs reduce learners' cognitive burden by allowing the external environment to store more information and not forcing them to use their internal resources (e.g., Norman, 1998).

It is generally an effective strategy to present learners with some type of control during training for the positive motivational effects (Brown et al., 2016). However, one pattern of behaviors we observed in this training was a group of trainees who simply used the control functions to skip through as much of the training as quickly as possible (i.e., the unengaged). Ideally, training designers could use information available about the trainees to present them with the optimal set of learner control tools (e.g., Arazy et al., 2015), which would prevent trainees from using learner controls to be unengaged. In other words, one could perhaps use the GOMS model (Card, Moran, & Newell, 1983) to individualize which specific sets of operational controls specific learners receive. If one cannot do so in advance and trainees ineffectively use learner control in ways that hamper their learning, training designers could create interfaces that gradually remove control options. However, this strategy runs the risk that trainees could have negative reactions to losing control during the training program. Another option that might be more palatable to trainees would be to offer adaptive guidance on how to more effectively use the learner control tools through self-regulatory prompting such as that used by Sitzmann and Ely (2010).

Finally, in response to Q3, we found little evidence to suggest a relationship between stated preferences for learner control and the behaviors that trainees actually exhibited in the training. However, we did find a positive, marginally significant correlation between the PLC dimensions and the trainee knowledge scores (information: $r = .22$, $p = .08$; time: $r = .21$, $p =.09$). We know that preference for learner control is just one of many learner control motives, including constructs such as goal orientation, action-state orientation, and locus of control (Howardson et al., 2017) that drive learner behavior. Our results suggest that preference was not the strongest such motive at work in this situation. Other attributes of the learners or the situation must have been driving their choice to use the various learner control features and their subsequent higher performance on the knowledge tests, but we did not measure these other possible learner control motives in this study. Another possible explanation for the low correlations is the relatively low mean and standard deviation of the total PLC scale (mean = 2.65, SD = 0.65). The low variance in this sample may be partially responsible for the low correlations. It would be interesting to see if, in a sample that had stronger preferences for controlling learning features in the program, one would find different results[2].

When we compare our findings about learner control preferences to our findings about trainee behavior, we draw some interesting parallels. First, as we note above, the factor structures we observed in this study differed from the commonly used five-dimension model of learner control. Second, from what we observed in both the preference and behavioral datasets, media control seems to be conceptually embedded in other types of control. In the behavioral data, media control appeared to be a form of content control during the learner event. Traditionally, content control focuses on the actual concepts learned and media control focuses on the type of media used to present that content. From this perspective, one could imagine that within a training module the same content on a single topic (e.g., leadership theories) could be covered in a video and as pure text. However, in practice, it appears that these control factors may actually blend. An optional video tends to supply a different media interface and some additional content, such as additional context about the leadership theories or information about one leader's experience using a theory. Similarly, in the preferences data, pace and media loaded on the same factor. Certain types of media (e.g., video, audio) require the learner to give up some control over pace. Learners who seek to get through the training as quickly as possible may want to make all of their own choices over media to maximize efficiency. Thus, while media is an important factor to consider in training design, from the learner perspective it appears to be inextricably linked to questions of control over content and pace.

4.1 Future Research Directions

Future research should continue to examine the dimensionality and meaning of various learner control features to help move the field forward both in theory and in practice. While the definitions sound clear, in practice, we found it challenging to neatly sort training features or trainee behaviors into one category: several potentially fit into multiple categories. For example, one could categorize choosing to view a video as media control (a trainee wanting to use a different type of media), content control (a way to view more content), or pace control (a way to slow down the training). As Howardson et al. (2017) discuss, we need to better understand the motivations of learners and what their learner control choices actually represent.

While we examined relationships between learner behaviors and learning outcomes, the question of how learner control impacts learning merits further study. We found that learner control behaviors around content and review were positively related to short-term declarative knowledge outcomes in both samples, and all four learner control behaviors were related to knowledge in the larger sample. These findings are

[2] We thank an anonymous reviewer for suggesting this interpretation.

in contrast with other studies (e.g., Karim & Behrend, 2014) that have found lower learning performance under conditions of control due to reduced on-task attention. However, these differences may be due to differences in the training environment such that use of content and review control in the present training enhanced attention paid to the training and, thus, lead to improved learning outcomes. Alternatively, it could be related to measurement issues as we note above. We also found inconclusive results for the use of scheduling control. We found a small, positive correlation between scheduling control and knowledge in our full sample; however, we also found that it was a relatively effective strategy for the mixed group but unnecessary for the engaged group to obtain a passing score on the module assessments. While we do have some evidence to support Karim and Behrend's (2014) finding that scheduling control is associated with better learning outcomes, we need to further investigate the mechanism for effectiveness of scheduling control.

Another potential direction for future research is to examine the role of training valence and utility in predicting learner control behaviors. Consistent with the psychological interactionist framework (e.g., Mischel & Shoda, 1995), these factors might be strong enough to override control preferences under certain conditions. If trainees believe that a particular training program has high utility and will be useful for their job or if they are highly interested in the training content (Brown, 2005), they may be more motivated to apply control to enhance learning. If valence or utility perceptions are low, on the other hand, they may be motivated to use control to move through the training as quickly as possible. Essentially, trainees may have general preferences about learner control, but these preferences may interact with aspects of the situation or initial trainee reactions to learning to ultimately predict behavioral outcomes.

Another potential direction for future research is to use these findings to study learner control in the mobile learning space. Wasserman and Fisher (2017) developed a mobile learning framework that suggests two key dimensions of mobile learning are accessibility and distractability. Mobile learning generally enhances accessibility but often at the risk of greater distraction because learners are attempting to learn on devices that are full of distractions through social media, message alerts, and so on. It may be more difficult to make effective choices about content control, scheduling control, and performance control in a distracting environment. From a control perspective, designers could perhaps take control over aspects of the mobile device interface by blocking certain messages temporarily while the training runs. Future research in this area should investigate elements of interface design that allow users to focus on the aspects of control that will help them learn while trying to minimize the distractions that interrupt learning.

4.2 Implications for Practice

One important direction for designing future online training programs concerns how to effectively use information about the learners to create an optimally effective learning interface (Kalyuga & Sweller, 2005; Orvis et al., 2011; Arazy et al., 2015). Given the weak relationships we found between learner control preferences and behaviors and the general findings in the literature that learner control does not always lead to improved performance, we cannot assume that learners will make effective choices on their own. Human factors and HCI task analytic methods (e.g., GOMS, cognitive task analysis) are quite effective at identifying structural features of the learning environment that stimulate certain information processing mechanisms. On the other hand, organizational psychologists excel in identifying the psychological characteristics important for inducing effective learning states (e.g., Bell & Kozlowski, 2008). However, we lack a direct link between task analytic methods and learner motivation. That is, how specifically can training designers use task-specific behaviors to identify learners' current psychological states, and which states require the learning environment to adapt appropriately with more or less learner choice (Arazy et al., 2015)? We believe this area is ripe for future research.

We also encourage training designers to recognize the importance of learner control during assessments in terms of pace and review control that the interface provides. Our results suggest that some learners may need or simply prefer to take more time. They may also need to revisit content related to those assessments. Eventually, though, many will achieve a similar score as the more efficient, engaged learners. Basically, the mixed learners in our sample used the assessments as a trial-and-error opportunity that appeared to result in acceptable learning results, at least in the short term. As we note above, it would be interesting to see the relationships between pace, review, and transfer outcomes. Given this importance of repeated testing for learning, we suggest that the training interface should control when learners must take assessments rather than making them optional. Consistent with the practice retrieval literature (Karpicke & Blunt, 2011; Roediger et al., 2011), assessments should be regularly required throughout online training programs.

4.3 Limitations

Our study has several noteworthy limitations. First, because we used a real in-use training system in a major global corporation, we had no opportunity to influence the design of the training program and the learner control features offered. Thus, one strength of the study (the large sample of employees as learners) comes at a cost of limited experimental control over the research setting and measures. While the learner control tools are imperfect representations of the five learner control dimensions one can find in the literature, we believe that there are behaviors that do match up to each of the dimensions. However, the specific characteristics of this training program are likely to limit the generalizability of these findings to other organizations and training contexts. This limitation is, unfortunately, common in the training literature.

Second, because trainees could complete Modules 2-4 in any order they chose, we could not trace potential development or changes in learner control behaviors across time in a systematic way. It would be interesting to examine a similar training program where trainees had to proceed through the modules in the same order so we could examine within-person effects. We might expect that, if a trainee used a learner control strategy in Module 1 that turned out to be ineffective, the trainee would try a different approach in subsequent modules.

Third, we measured learner control preferences after the trainees completed the modules. While some evidence suggests stated learning preferences are generally stable (Pashler, McDaniel, Rohrer, & Bjork, 2009), we do not have test-retest reliability data on the PLC scale used in this study. Thus, the trainees' experiences with the training could have affected their PLC scores rather than their preferences' affecting behavioral choices during the training, which could be another reason we did not find strong relationships between PLC and behavior. Finally, we had a reduced sample size for the PLC analyses due to both the delayed administration of the survey and the participants removed from the analysis for incorrect responses to the attention item. However, it is better to have the smaller sample size with greater confidence in the quality of the data (Meade & Craig, 2012).

4.4 Conclusion

In this paper, we examine relationships between stated learner control preferences and learner behaviors with data from a unique training environment in which a training interface captured learner behaviors. We also examined the dimensionality of learner control preferences and learner control behaviors compared to theoretical models developed in the literature and found that each resulted in different dimensionality. We identified a unique learner control dimension of performance control, which refers to behaviors related to repeated testing, and found three distinct patterns of learner behaviors in the online training: engaged, unengaged, and mixed. We need additional research to identify a broader range of specific learner motivations and determine how best to help learners use control. However, this study enhances our understanding of how learners interact with e-learning.

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Appendix. Expanded Results

Table A1. Behavioral Data Definitions, Descriptive Statistics, and Component Loadings

						Component loadings			
Item	Behavior	Description	Mean	Median	*SD*	Cont.	Rev.	Perf.	Sched.
1	Content 1	Number of optional content windows opened linking to internal training material	9.32	9.0	6.32	.809			
2	Content 2	Number of interactive elements clicked overall	27.21	28.00	20.07	.804			
3	Content 3	Number of optional opinion items answered	16.06	17.07	6.00	.777			
4	Content 4	Total time spent viewing videos	50.92	39.94	44.32	.726			
5	Content 5	Total number of times a learner re-visited and re-viewed a training video	1.72	2.00	1.11	.628			
6	Review 1	Number of times a learner went backward in the training to re-visit content	2.60	1.00	4.75		0.760		
7	Review 2	Number of optional content windows opened to external sites	2.04	1.00	2.71		.711		
8	Review 3	Number of characters entered for optional practices	74.01	0.00	219.15		.688		
9	Review 4	Number of helpful hints/printable guides clicked	0.64	0.00	1.55		.607		
10	Review 5	Total time spent viewing practice items	14.18	2.57	37.17		.536		
11	Perform 1	Number of times learner changed a quiz answer before submitting	22.95	9.00	41.35			.851	
12	Perform 2	Number of times a learner navigated backward to review a page as a result of a failed quiz	2.82	2.82	2.34			.751	
13	Perform 3	The number of points gained or lost by changing answers on quiz	-0.18	0.00	4.07			-.688	
14	Perform 4	Total time spent on the quizzes	114.26	52.97	183.40			.609	
15	Schedule 1	The number of sessions in which learners completed the training	3.43	3.00	2.08				.839
16	Schedule 2	The total number of pages viewed across all sessions	323.26	249.00	281.66				.762
17	Schedule 3	Total minutes spent in the training	3181.18	204.81	9398.13				.677
18	Off-task	The number of times a learner changed focus to unrelated browser or program	64.75	42.00	75.97		—	—	—

Table A2. Factor Loadings for Preference for Learner Control (PLC) Items

Retained PLC Items	Time	Information
M3. Whether the training material is presented via text or audio at different points of the training.	.890	
M2. Which type of media is used to present the training information (e.g., audio vs. text).	.887	
M1. The different media I use during the training program, such as listening to or reading the training information.	.861	
P1. The pace at which the training material is presented.	.558	
P3. The amount of time I spend on the different training topics and activities.	.467	
P2. How quickly or slowly I go through the training material.	.428	
S2. The order in which I complete the training material.		.784
S3. The best sequence for covering the training topics.		.777
S1. The order that topics are presented during the training.		.688
C1. Which specific training topics and activities I complete during the training program.		.601
C3. What information I view about each training topic.		.556
F2. If I receive tips or suggestions during the program for how to best complete the training (for example, the training program suggests I review and earlier training topic again).		.548
F3. How much feedback I receive during the program on my mastery of the training material.		.485

Table A3. Cohen's d Results for Preference for Learner Control (PLC) Items

	Unengaged (3)		Mixed (2)		Engaged (1)		Cohen's d	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**1:3**	**1:2**
S1. The order that topics are presented during the training.	3.59	1.41	3.82	1.25	4.23	.77	.56	.40
P1. The pace at which the training material is presented.	1.72	1.02	2.36	1.57	2.00	1.07	.27	-.27
M1. The different media I use during the training program, such as listening to or reading the training information.	2.06	1.46	2.45	1.37	2.14	1.24	.06	-.24
C1. Which specific training topics and activities I complete during the training program.	2.97	1.47	4.09	.94	3.53	1.38	.39	-.48
P2. How quickly or slowly I go through the training material.	1.53	.80	2.00	1.34	1.44	.79	-.11	-.51
M2. Which type of media is used to present the training information (e.g., audio vs. text).	2.25	1.34	2.55	1.29	2.51	1.34	.20	-.02
S2. The order in which I complete the training material.	3.28	1.44	3.20	1.54	3.91	.98	.51	.55
F2. If I receive tips or suggestions during the program for how to best complete the training (for example, the training program suggests I review an earlier training topic again).	3.06	1.1	4.18	.41	3.63	1.19	.48	-.62
M3. Whether the training material is presented via text or audio at different points of the training.	2.00	1.27	2.18	1.25	2.17	1.34	.13	-.01
P3. The amount of time I spend on the different training topics and activities.	1.56	.80	1.91	1.22	1.71	1.05	.16	-.17
S3. The best sequence for covering the training topics.	3.63	1.29	4.36	.51	4.34	.64	.71	-.04
F3. How much feedback I receive during the program on my mastery of the training material.	3.03	1.26	3.55	1.29	3.54	1.09	.43	.00
C3. What information I view about each training topic.	2.42	1.43	3.73	1.27	3.34	1.24	.69	-.31

Note: C = content control items, F = feedback control items, S = sequence control items, M = media control items, and P = pace control items.

Table A4. Correlations between Learner Control and Knowledge Score

	1	2	3	4	5	6	7
1. PLC info	(.83)	.23	.12	-.06	.18	-.01	.22
2. PLC time		(.86)	.03	-.10	-.05	.20	.21
3. Behavioral content			---	.40*	.12	.10	.60*
4. Behavioral review				---	.06	.10	.52*
5. Behavioral scheduling					---	.06	.13
6. Behavioral performance						---	.18
7. Declarative knowledge							---
Note: *p < .05, n = 67							

Table A5. Correlations between Learner Control Behaviors and Knowledge Score (Full Sample)

	1	2	3	4	5
1. Behavioral content	---	.36**	.09*	.15**	.50**
2. Behavioral review		---	.05	.02	.37**
3. Behavioral scheduling			---	.00	.11*
4. Behavioral performance				---	.19**
5. Declarative knowledge					---
Note: *p < .05, **p < .01; n = 518.					

Table A6. Key Definitions of Learner Control and its Components

Term	Definition	Source
Learner control	A set of constructs describing a situation where learners are provided with discretion over behaviors related to formal learning activities.	Brown, Howardson & Fisher (2016)
Pace control	Learners can manipulate the pace (speed or tempo) in which learning activities are delivered to them.	Kraiger & Jerden (2007)
Content control	Learners can choose which specific content they learn.	
Sequence control	Learners can choose the order in which they learn program material.	
Advice/feedback control	Learners can determine if and to what extent they want to receive feedback on their program progress and learning outcomes.	
Media control	Learners can choose the media format used to display information delivered to them.	Randolph & Orvis (2013)
Scheduling control	Learners can control the temporal nature of their learning experience (e.g., time spent, number of sessions).	Karim & Behrend (2014)
Instructional control	Learners have control over pace, sequence, and content during the training session.	
Review control	Learners can choose to review materials as needed during a training session.	Present Study
Performance control	Learners can choose to control their experience during a knowledge assessment.	
Information control preference	Learners have a stated preference to have control over training elements that impact the amount of information they receive (e.g., sequence, content, and feedback).	
Time control preference	Learners have a stated preference to have control over training elements that impact the amount of time spent (e.g., pace, type of media).	

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