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ORIGINAL RESEARCH

# Toward a Definition of Learning Experience Design

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**Abstract**
Various theories and models have implicitly discussed the role of interaction when using learning technologies. Indeed, interaction is described as being important as it relates to technology adoption, cognitive load, and usability. While each of these perspectives describe elements of interaction, they fail to comprehensively detail how educators should design for both usability and learning with an interface. To address this gap, this work-in-progress study seeks to describe the broader interaction when using learning technology, which we define as learning experience design. Using grounded theory and related eye-tracking data, we asked participants to engage in a cognitive think-aloud as they utilized an adaptive tutoring system. When triangulated, the researchers identified the following broad constructs: interaction with the learning environment and interaction with the learning space. The former includes the following codes: customization, expectation of content placement, functionality of component parts, interface terms aligned with existing mental models, and navigation. Alternatively, the interaction with the learning space included the following: engagement with the modality of content, dynamic interaction, perceived value of technology feature to support learning, and scaffolding. Implications for both theory and practice are discussed.

**Keywords** Learning experience design · Human-computer interaction · Interaction design · Usability · User-experience design

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## 1 Introduction

Learning technologies must be designed in a way that facilitates meaningful interaction. In the human-computer interaction literature, Barzdell (2011) argues that interaction is the intersection between (a) the interface design and (b) the user experience (UX). The former mediates the technology, whereas the latter is defined as "the meanings, behaviors, perceptions, affects, insights, and social sensibilities that arise in the context of interaction and its outcomes" (p. 606). From an end-user perspective, interaction is imperative because it shapes the learner's perceived usability and usefulness of a technology toward one's learning goals (Kaptelinin and Nardi 2018). Moreover, the interaction with learning technology includes additional elements, such as affect and facilitation of cognitive processes. Indeed, Graesser et al. (2019) argue that the affective component of interaction is "the experiential glue of learning environments in the twenty-first century" (p. 2) and impacts an array of learning outcomes, including engagement and higher-order thinking. In this way, interaction becomes an imperative gateway to learning with technology. Alternatively, technologies with challenging interactions that create frustration, anxiety, confusion, and boredom are problematic for meaningful learning (Graesser et al. 2019, p. 2).

Although interaction is important, it is merely an implicit construct embedded within various theories and models to explain diverse phenomena, such as technology adoption and cognitive processing. For example, the Universal Theory of Acceptance and Use of Technology (UTAUT) predicts how interaction influences one's desire to adopt technology (Venkatesh et al. 2003). Specifically, one direct determinant of intention to use includes effort expectancy, where interaction is the degree of expended energy to employ the technology. Theorists describe how the interaction of effort expectancy is important for adoption because it relates to a learner's affective domain, often triggering reactions that lead to anxiety or engagement when utilizing new technology (Baki et al. 2018). Other theories and models make implicit reference to interaction in learning technology research. From a processing perspective, cognitive load considers the impact of interaction on one's ability to process new information in working memory (Mayer and Moreno 2003). Therefore, poorly designed interaction can "increase extraneous cognitive load too highly, leading to navigation and comprehension problems and to impairment in reading performance" (Madrid et al. 2009, p. 67). Finally, pedagogical usability focuses on interaction from a utility perspective (Nokelainen 2006). Pedagogical usability distinguishes itself from technical usability by examining its two primary metrics—readability and ease of use—in relation to their enhancement or depression of learning outcomes (Hadjerrouit 2010; Kenttälä et al. 2017; Nokelainen 2006).

The aforementioned theories and models underscore that interaction is a multifaceted concept that includes usability, learning, cognition, and other constructs. Although specific constructs within the theories help educators to understand the impacts of interaction on learning, it is less clear how these constructs *intersect* as learners interact with an educational technology. To date, no single comprehensive model has emperically defined the critical elements of learning experience design. Furthermore, research has yet to explore how design decisions for these technologies may facilitate or inhibit learning. To mediate this gap, a definition derived from data is needed to understand how interaction facilitates meaningful learning and supports user experience with technology. First, we examine the relevant research associated with interaction from the viewpoints of technology acceptance, cognitive load, and pedagogical usability. We then discuss the theoretical merits of each approach and what they have contributed to our understanding of interaction in learning environments. Finally, we apply grounded theory to define users' learning experience design when using a technology that incorporates knowledge visualization tools, multimedia, artificial intelligence, and other resources for STEM learning. We then present the results on their learning experience design through constructs synthesized from think-aloud protocol and eye-tracking data.

## 2 Literature Review

### 2.1 Interaction as Effort Expectancy

In prior research, interaction has been described as a key determinant as to why a user adopts technology. As technology became more commonplace, the Technology Acceptance Model (TAM) was created as a mechanism to predict user acceptance of information technology (Davis et al. 1989). The original TAM is a five-component model, starting with *perceived usefulness* and *perceived ease of use* as two determinants of user attitude toward and intention to use a new technology (Baki et al. 2018). The former describes how learners view the utility of the tool, while the latter describes if the perceived interaction is free of cognitive burden (Saadé and Bahli 2005). Perceived ease of use, thus denotes how interaction is an important part of one's decision to adopt a technology. Over time, the UTAUT reimagined *perceived ease of use* as *effort expectancy*, defining it as "the degree of ease associated with the use of the system during interaction with the technology" (Venkatesh et al. 2003). Studies highlight the importance of interaction within perceived ease of use/performance expectancy for digital textbooks and e-books (Joo et al. 2017; Tri-Agif et al. 2016; Verkijika 2019), e-portfolios (Abdullah et al. 2016), learning management systems (Revythi and Tselios 2019), multimedia and cloud-based learning tools (Hariguna and Akmal 2019; Sheppard and Vibert 2019; Wang et al. 2019), and even mobile learning (Althunibat 2015). When this theory is applied to e-learning, interaction helps elucidate factors that impact a learner's decision to use a tool for learning.

### 2.2 Interaction as Extraneous Cognitive Load

In addition to theories that explain technology adoption, interaction has also been analyzed from a cognitive-driven approach as learners employ technology. Cognitive load describes the amount of mental resources expended to complete a given task, including interaction with an interface (Mayer and Moreno 2003). Cognitive load theory is parsed into three broad constructs: intrinsic load, germane load, and extraneous load. Intrinsic cognitive load refers to the complexity of content tasks, while germane load details the effort it takes to integrate new material onto existing mental schemas. Finally, extraneous load refers to the strain when confusing material is presented (van Merriënboer and Sluijsmans 2009). Although interaction has been explored through these constructs, the majority of research regarding interactions with an interface focuses on intrinsic load and extraneous load. For example, Wang et al. (2014) explored the effects of extraneous cognitive load (e.g., website complexity) in regards to visual attention and website exploration behavior. They found that if participants' necessary interaction to complete a task is high, working memory is unduly taxed, and the learning process is compromised. Inversely, if task complexity is high and website complexity is low, participants may not spend time interacting with the site due to attention being solely focused on the task (Wang et al. 2014). Oviatt

(2006) proposed a further alignment between human-centered design and cognitive load theory. Her research suggested that when interactions mimic learners' natural behaviors and existing schemas, the interaction minimizes extraneous load. Oviatt (2006), therefore, recommended that designers adapt their interfaces to the user as part of the design process. Additionally, Oviatt advised designers to "accommodate user's existing work practice, minimize extraneous complexity due to unnecessary interface features, minimize the interruptions and distractions features generate" (p. 873).

### 2.3 Interaction as Pedagogical Usability

The above theories and models provide some clarity of interaction from a technology adoption and cognitive processing perspective. Pedagogical usability provides yet another lens through which to explore how learners interact with educational technologies. In contrast to UTAUT/TAM and cognitive load theory, pedagogical usability was conceptualized as a way to specifically explicate ease-of-use for learning technologies (Nokelainen 2006). Nokelainen (2006) recognized that extant studies of digital learning materials focused only on technical usability, or the extent to which the materials are easy, efficient, convenient, and user-friendly (p. 178). Hence, pedagogical usability was offered as a way to evaluate interaction design in learning technologies based on the interface ease-of-use (Nokelainen 2006).

To date, researchers have applied pedagogical usability to different learning technologies, whether it be an LMS for elementary students (Nokelainen 2006), web-based learning resources for language learning, mathematics, or science (Akayuure and Apawu 2015; Hadjerrouit 2010; Nokelainen 2006; Shield and Kukulska-Hulme 2006), wikis in pre-service teacher education (Hadjerrouit 2012), or virtual labs for university engineering students (Kumar et al. 2018). Over time, Nokelainen (2006) developed ten dimensions of pedagogical usability: "1. Learner control, 2. Learner activity, 3. Cooperative/Collaborative learning, 4. Goal orientation, 5. Applicability, 6. Added value, 7. Motivation, 8. Valuation of previous knowledge, 9. Flexibility, and 10. Feedback" (p. 181). In the same year, Shield and Kukulska-Hulme (2006) presented their own definition and research agenda for studying pedagogical usability in learning websites as they added technical usability, the academic content and context, and intercultural context. Years later, Hadjerrouit (2010) expanded on Nokelainen's work to create a conceptual framework that included technical usability, contextual considerations, and features inherent to the web-based learning resources themselves. Collectively, these studies of pedagogical usability move beyond the designer realm of making a learning technology functional and begin to also incorporate the expertise of various stakeholders to ensure the interaction is designed to facilitate meaningful learning.

## 3 Research Questions

The three views described above (user acceptance, cognitive load, and pedagogical usability) elaborate on elements of interaction as an individual utilizes a learning technology. Although various theories and models describe different elements of interaction, there is no comprehensive way to describe the requisite interaction needed to support meaningful learning experience design. For example, the UTAUT leverages empirical data to identify interaction as a determinant of user acceptance. These studies highlight the importance of interaction to explain a technology's perceived ease of use, especially as a source of positive and negative emotions and its impact on adoption. Meanwhile, cognitive load describes how interactions with technology impacts learners' ability to process new information and navigate the interface. From cognitive load studies, designers understand that certain interactions may contribute to effective intrinsic processing, while others may create extraneous processing that impede learning. Finally, pedagogical usability explains interaction from the standpoint of ease of use when using learning technologies. Together these perspectives contribute to ways practitioners and educators should consider interaction during the design and implementation of learning technologies. That said, none of the theories completely addresses the interaction from an overall user-experience perspective. To address this gap, this study explores the various perspectives and constructs of interaction as users employ a learning technology, which we describe as "learning experience design". We therefore proffer the following research question in this work-in-progress study:

1. What are the constructs that define learning experience design?

## 4 Method

### 4.1 Overview

The study was conducted using a cognitive think-aloud and associated data included (a) participant comments and (b) eye-tracking data (described below). To conduct the cognitive think-aloud, participants were asked to complete learning tasks on a website that teaches electricity and electronics fundamentals (*ElectronixTutor*). The protocol was designed to elucidate perceptions of aesthetics and learning processes. Upon completion, they engaged in a semi-structured, retrospective interview (Ericsson and Simon 1993) with a researcher to further elaborate on their interactions. Qualitative data were explored using grounded theory and later triangulated with eye-tracking data.

### 4.2 Procedure

Using the cognitive think-aloud method, participants were asked to navigate to specific functions on the website corresponding to realistic tasks that an instructor would assign. A cognitive think-aloud was used for several reasons. First, this methodology is especially helpful when the goal is to "elicit insights into their thought processes that are hard to obtain from mere observation" (Fan et al. 2020, p. 86). As such, it has been used in various studies that seek to understand a user's cognitive processes when interacting with technology (Elbabour et al. 2017; Ferguson et al. 2012). In a learning context, this approach has been used to describe the cognition and reasoning processes of diverse user groups (Ertmer et al. 2008; Tawfik et al. 2019). Given our focus on the learner's cognitive processes in terms of learning and interface usage, the literature suggests that the cognitive think-aloud was an appropriate means to employ for this study. The tasks employed during the think-aloud focused on the learner's interaction toward documenting their understanding (e.g., submit an answer), communicating with the artificial intelligence (e.g., ask a question), assessing their progress, and providing feedback about the embedded multimedia.

Before beginning their tasks, participants were provided with a brief summary of the system and testing apparatus, which included (a) a minimal conceptual introduction to the software; (b) the intended uses of the system; (c) and explanation of the eye-tracking hardware (Tobii Eye-Tracking). Participants were further instructed that there were no incorrect answers for this study and to provide think-aloud feedback as they worked through each assigned learning task. Following this initial briefing, the research assistant guided participants through the calibration of the eye-tracking system. Tobii Eye-Tracking was used to record audio and eye-tracking data for each task as the participants completed it. Prior to the semi-structured interview, the participants calibrated their eye gaze by following a red light on the screen. The software then provided a reading as to how well the hardware was able to calibrate with the eye gaze. If it was a poor reading, the participant repeated the task until proper alignment was achieved. The eye-tracking data provided several important research advantages. As user-experience research has expanded, researchers have increasingly employed eye-tracking to assess how learners interact with the system, including assessing usability (Elbabour et al. 2017) and cognitive processes (Ariasi and Mason 2011; Jarodzka et al. 2012; Wolff et al. 2016). Thus, the eye-tracking helps measure specific interaction patterns of overall learning experience design not captured by the cognitive think-aloud.

Upon completion of all the interviews, two graduate research assistants transcribed each audio recording. Research assistants then segmented participant responses into idea units (Weinberger and Fischer 2006). Given the focus of the research on defining constructs of learning experience design, idea units were broken down when (a) the participants detailed an interaction within the interface design, and (b) the participants discussed a learning process. The idea units were further divided by response to the completion of each UX task. Additionally, when possible, time codes were used to further aid in data analysis. Time for completion ranged from 30 minutes to one hour for each interview.

### 4.3 Participants

Participants were undergraduate electrical and computer engineering students from a large regional university in the Southeastern portion of the United States. A total of nine students took part in the evaluation of an adaptive tutoring system called ElectronixTutor. To minimize confounds, (a) all participants had completed at least one introduction to engineering class within the same institution and (b) none of the participants had interacted with the system before. The results of two participants were excluded from the data analysis—one due to communication challenges and the other due to corruption of the audio file. Nielsen and Loranger (2006) argued that five usability participants are enough to identify 80% of the issues in a system—a threshold exceeded in this study.

### 4.4 Materials

#### 4.4.1 Software

ElectronixTutor is an educational technology platform known as a hybrid tutor (Graesser et al. 2018; Hampton and Graesser 2019). It incorporates several learning resources, both intelligently adaptive and conventional (static), into a single interface. This includes artificial intelligence, multimedia resources, worked examples, and others. Further, a unified learning record store enables intelligent recommendations for proximal exercises based on past performance, derived user characteristics, and current affective state. Designed for use in conjunction with formal coursework, instructors can enroll their students and issue assignments based on time spent, specific problems, or level of mastery attained within a topic. Instructors can also view detailed progress reports that allow examination at the level of individual, class, topic, and time. Each of the federated learning resources has individual empirical support for its pedagogical effectiveness, but the novelty of combining them into a single website required substantial design and engineering configuration decisions that may not immediately reveal themselves to the learner.

### 4.4.2 Protocol

Upon completion of informed consent procedures, the researchers provided a brief conceptual overview of ElectronixTutor, its intended uses, and the eye-tracking system. Participants were encouraged to think-aloud throughout the study, and occasionally prompted to do so if silent or idle for too long (e.g., “What are you thinking right now?”). From there, participants viewed the website’s “Roadmap” that laid out the key features, recommendations, content navigation, and learner statistics pages (see Fig. 1).

Participants received a series of brief scenarios with embedded instructions that systematically progressed through the different aspects of ElectronixTutor, including methods for selecting proximal learning content (“Topic of the Day” controlled by the instructor, “Recommendations” controlled by artificially intelligent selection criteria, and self-regulation where participants select from an unconstrained list of all available content). Complementing the content selection tasks were similar scenario-based instructions for each of the federated learning resources, including feedback-enhanced questions (Dzikovska et al. 2014), adaptive formulaic workthroughs (*LearnForm*), dynamic circuit model construction and manipulation (VanLehn et al. 2016), hyperlink-reinforced textual topic summaries, and static manuals (Navy Electricity and Electronics Training Series—the original instructional material from U.S. Navy electrical engineering courses).

Special attention went to conversational reasoning questions presented in AutoTutor (Graesser 2016), as the free-form nature of conversational interaction provides ample opportunities for exploration. Initially, we allowed participants to complete an AutoTutor problem with no additional instruction. This typically involved several conversational turns designed to extract a complete answer to a multi-part question, and referring to an

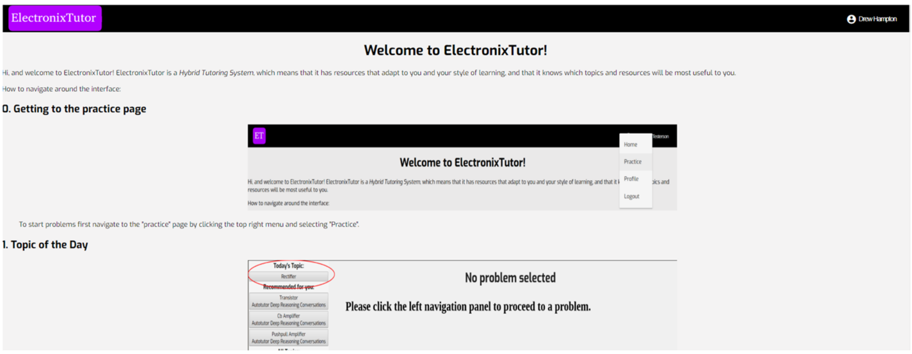


Fig. 1 ElectronixTutor “Roadmap” page, designed to orient new users to essential features

interactive diagram that displays common questions and answers when learners "mouse-over" hotspots (called Point & Query; Graesser et al. 2018; see Fig. 2). Next, participants were presented with a second AutoTutor problem and instructed to provide an incorrect answer, which may or may not have been accepted as correct depending on the phrasing that participants used. This follows from a design choice necessary in any imperfect natural language processing, where the system avoids rejecting correct answers by lowering thresholds for correctness, creating an acceptable fault in response patterns. Following the intentionally incorrect answer, participants posed their own questions to the system, gave metacognitive input (e.g., "I don't know"), and interacted with Point & Query, with think-aloud protocol throughout and follow-up questions at each stage. The final scenario-based task involved navigating to the learning records page, where learner scores and diagnostic information resides.

Following the scenario-based instruction phase, participants proceeded to the debrief. Here, researchers asked questions regarding their overall thoughts of ElectronixTutor. Questions were also posed about how they might employ the tool to improve their learning, along with any recommendations. At the end of every task, participants answered three questions from the semi-structured interview: How clear were the instructions in this section? Did you have any confusion on what you were supposed to do, or to where you were supposed to navigate? Do you have any suggestions for improvement of the interface or instructions? Finally, participants were thanked and received instructions for remuneration and where to follow up with any additional questions.

## 4.5 Data Coding

During the first round of coding, two graduate research assistants worked in Nvivo to individually to code line item utterances for every idea unit. To answer the research question, the specific approach employed grounded theory to analyze participants' comments.

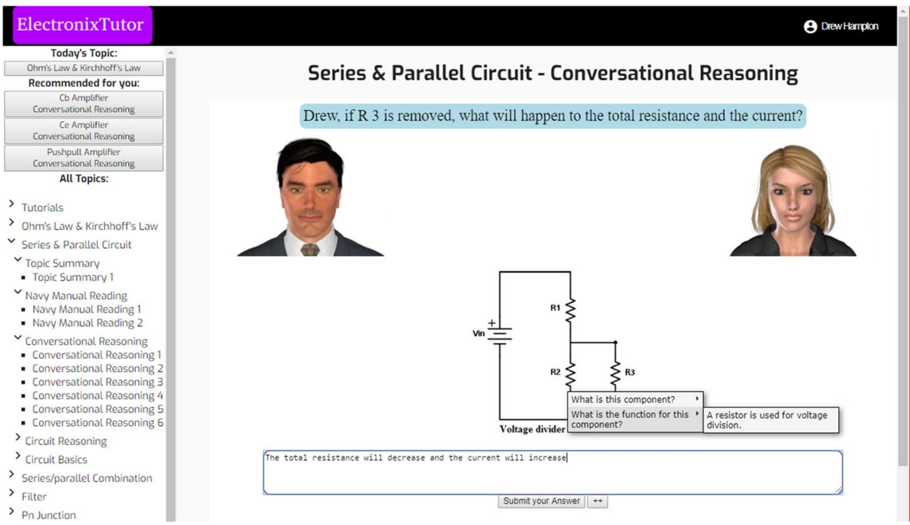


Fig. 2 An AutoTutor conversational interaction, demonstrating a point and query interactive diagram

**Table 1** Interaction within learning environment codes and definitions

| Interaction within learning environment (UX) | Definitions |
|---|---|
| 1. Customization of the interface | User autonomy to control elements of the interface as needed (e.g., closed captions, tutorial; search bar; other learning tools) |
| 2. Expectation of content placement | Where the user expects items to be; suggestions for new sections |
| 3. Functionality of component parts | Functionality of the items that are present |
| 4. Interface terms aligned with existing mental models | Labels are consistent with previous learning interactions (e.g., ebook, learning websites, etc.) |
| 5. Navigation | How users move from one location to another on the site |

**Table 2** Interaction within learning space codes and definitions

| Interaction within learning space | Definitions |
|---|---|
| 1. Engagement with modality of content | Thoughts on learning design format, aesthetics, and users' desire to engage with element used on learning interface |
| 2. Dynamic Interaction | Interaction that engenders learners' desire to continue or discontinue in their self-directed learning |
| 3. Perceived value of technology feature to support learning | Perceived value of a specific technology feature impacted one's learning |
| 4. Scaffolding | Cues, hints, etc. that expanded learners' prior knowledge |

Grounded theory is a systematic way to support theory development, especially for qualitative data. This approach calls for the "creation of analytic codes and categories developed from data, not from preconceived hypotheses" (Charmaz 1996, p. 28). Given that no established theory existed for the term "learning experience design" based on emperical data, grounded theory allows this research to develop associated constructs for the learning phenomenon (Creswell 2011).

First, research assistants independently read the participant transcripts in full to become familiar with the data. The research assistants then created line items based on patterns of the data that emerged. Specifically, research assistants independently grouped similar line items together in Nvivo and assigned those items to nodes they generated. In the first round, the researcher assistants identified 22 unique codes. Generally speaking, the initial codes focused on suggestions for improvement, distractions, frustration, and interaction with the content. The research team (faculty member, two graduate assistants) met to discuss the emerging themes, ensure the data aligned with the gap, and discuss whether saturation had been met to answer the research question.

After the meeting with the primary investigator, the second round of analysis focused on refining and clarifying themes from the initial 22 codes. It was concluded that the nine final themes could be segmented into two overarching themes (a) interaction within the learning environment and (b) interaction within the learning space (see Tables 1, 2). The former includes the following codes: customization of the interface, expectation of content placement, functionality of component parts, interface terms aligned with existing mental models, and navigation. Alternatively, the interaction with the learning space included the following: engagement with modality of content, dynamic interaction, perceived value of technology feature to support learning, and scaffolding.

At the conclusion of this round of coding, codes for each line item were compared and an initial percentage of interrater reliability was calculated (62%). After this comparison, research assistants decided to exclude extraneous comments that did not describe the interface from the coding (e.g., "yes","no"). After this exclusion, the percentage of agreement between raters was 73%. In a third round, raters met once again and added line item quotes to each code as to provide concrete examples. Once in agreement on these quotes, the raters again coded the line item utterances. Following this round of coding, the percentage of agreement between the two coders reached 100%.

## 5 Results

Initial independent attempts at coding resulted in 22 codes from researchers. After two rounds of discussion, the researchers came to mutually agree upon nine axial codes defining learning experience design, as can be seen in Tables 1 and 2. The nine codes were categorized into two broader themes: (a) interaction with the learning environment and (b) interaction with the learning space. 'Interaction with the learning environment' codes were conceptualized as comments of the user-experience and functionality of the interface. The following five codes fell under the purview of interaction with the learner environment: customization of the interface, expectation of content placement, functionality of component parts, interface terms aligned with existing mental models, and navigation. Alternatively, 'Interaction with the learning space' comments were unified by the respondents' description of occurrence or non-occurrence of learning as supported by the system. Interaction with the learning space contained four additional codes: engagement with modality of content, dynamic interaction, perceived value of technology feature to support learning, and scaffolding.

In addition to the participant comments, the code definitions were triangulated using Tobii eye-tracking data in the form of heat maps and gaze clustering data. The heat maps show fixation of the participants' gaze, with green representing quick glances and yellow, orange, and red indicating ever increasing fixation on one aspect of the site. The size of each circle corresponds to the length of fixation, similar to the heat map color representation. However, the lines superimposed on the site track the path of the eye, while the number in each circle reveals the order in which the eye traveled to each spot. The eye-tracking data provides additional input for the research team about how a learner interacts with a learning technology.

## 6 Interaction with the Learning Environment (UX)

### 6.1 Customization of the Interface

Participants' comments about their ability to manipulate the system were coded under *customization of the interface*. Their comments pointed to desired user-driven changes that would enable them to control and transform aspects of the system that met particular learning needs. For example, participant suggestions like "*if you could just increase the size of the font, like if that was an option for the viewer*" (P1) and comments such as "*that would* *bother me with the image being in between the sentence*" (P1) denoted how the ability to make seemingly simple changes to the design impacted the overall learner experience. Participants also commented on how the presence or lack of certain customizable tools impacted their learning. For example, one common complaint was a lack of closed captions to accompany the AutoTutor's conversations, as exemplified by P1′s comments:

> One thing that was really tough for me was that there aren't closed captions. Like, I can't understand what this man is saying and I know he's trying to give me valuable information, but it's not getting through. And I was looking for a place to turn on closed captions, but I didn't see anything. I don't know if that's an option, but that would help me a lot. (P1).

In reality, closed captions were available on the learning site, but the learners often spent considerable time trying to find this customizable option without success. A heat map taken with the eye-tracking software appears to support the need for more salient closed captions options. For example, Fig. 3 shows a red spot over the leftmost AutoTutor agent (the tutor agent, as opposed to the peer agent on the right) who was providing an explanation of the circuit displayed in the center of the page. Ideally, participant fixation should be on the circuit and not the agent. Based on participant comments, the researchers can attribute the misplaced attention to the fact that participants are assigning too much effort to understanding the agent and not enough on the learning task. Customizing the learning environment to make closed captions a more obvious option would help to better balance the participant's attention.

## 6.2 Functionality of Components

In a similar vein, the research team cataloged participant perceptions of how well site features worked under *functionality of components*. Whereas customization comments were generally focused on the learner's ability to control the functions of the environment, *functionality of components* described the degree to which the features worked as expected. When this did not happen, the data indicated this was a significant source of frustration

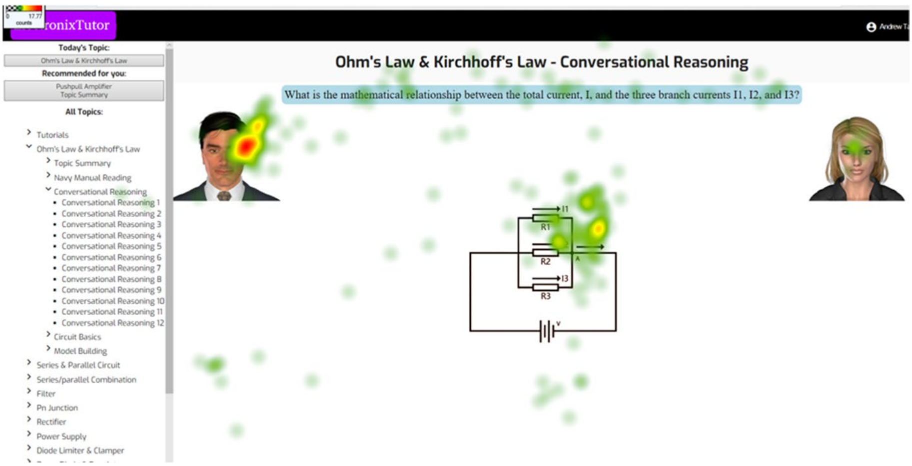


Fig. 3 Eye tracking heat map represents fixation on AutoTutor versus circuit

and diminishing of the learning experience. For instance, phrases like "*that would bother me*" and "*it's driving me crazy*" were directed at components that participants perceived as preventing learning when not operating properly. Additionally, participant suggestions lent more clarity to the value users place on component functionality. The eye-tracking cluster map in Fig. 4 supports the expression of frustration that ensues when functionality of components is not met. The cluster of fixation spots on the left sidebar are both more numerous and larger than the cluster on the learning task in the center of the screen. The map shows that a disproportionate amount of time was spent on the sidebar that was blocking the question rather than on answering the question itself.

## 6.3 Expectation of Content Placement

The next code, *expectation of content placement*, is characterized by how well the placement of content on the learning site met the participants' mental model of where it should be placed. Here the researchers noted expressions of confusion like *"it confused me*" (P5), and *"that threw me off at first*" (P1) when the interface was located in sections that they did not originally expect. Participant comments helped to further illuminate their mental model as one that more closely resembles an e-book, as noted by P1:

> I know some online textbooks have it to where you can have the texts, like the sidebar is a part of the text or whatever. So that doesn't happen, but that would probably be better. (P1).

P3 expressed a similar sentiment when he said:

> Yeah, they're showing okay, but shouldn't they have a section where like a book… where it says content and then tells you with the 'This is a book'? I feel like I like the book better, but now not sure. (P3).

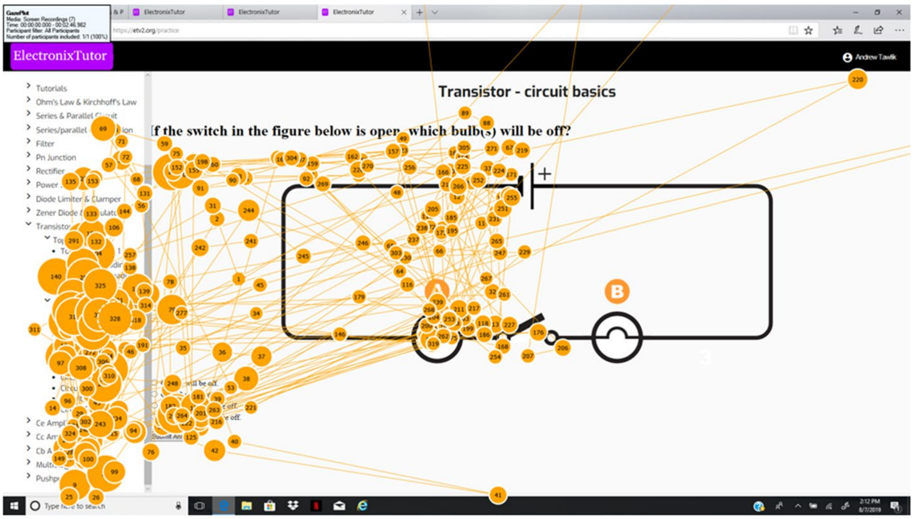


**Fig. 4** Eye-tracking cluster map showing participant attention disproportionately spent on the side navigation bar versus the central learning task

In the above quote, the user had a specific mental model and expectation that the presentation would follow a function similar to an e-book, which impacted where he expected the content placement. Eye-tracking data illustrates the learning experience as users attempted to locate content. The heat map in Fig. 5 can be interpreted as confirming participants' confusion about content placement. The red fixation spots on the sidebar indicate a great deal of time and attention are dedicated to understanding where the content is placed in the larger organization of the site.

## 6.4 Expectation of Interface Terms

Participant confusion about content and content placement was exacerbated by a disconnect between the expectation and the reality of *interface terms* utilized by the learning site. That is, once the participants acclimated to the organization of the site content, they were still uncertain about what each section represented. Participants expected to see literal labels like "readings", "formulas", "practice", and "multiple-choice problems." Participants instead expressed confusion with quotes like *"I'd rather it be labeled something different*" (P1), *"I was looking for something that said…*", (P3) "*It's not clearly mentioned…*" (P4), and simply "*so why don't you just call it 'practice'*?" (P6). As in the case above, the unmet expectations of interface terms in the design led to disruption of the learner experience. For example, a few participants commented on the verbiage for the button "Submit Your Answer" and how that impacted their subsequent interaction. The learning task associated with the button was for the learner to ask AutoTutor a question, which then would be submitted via the aforementioned button. This comment from P1 expounds upon the feelings of anxiety stemming from the button label:

> Another thing is submitting a question under the button 'Submit Your Answer' was anxiety inducing. Because you don't know if it's going to accept it as an answer and then you're wrong on this problem. I had that sorta interaction in my physics class for

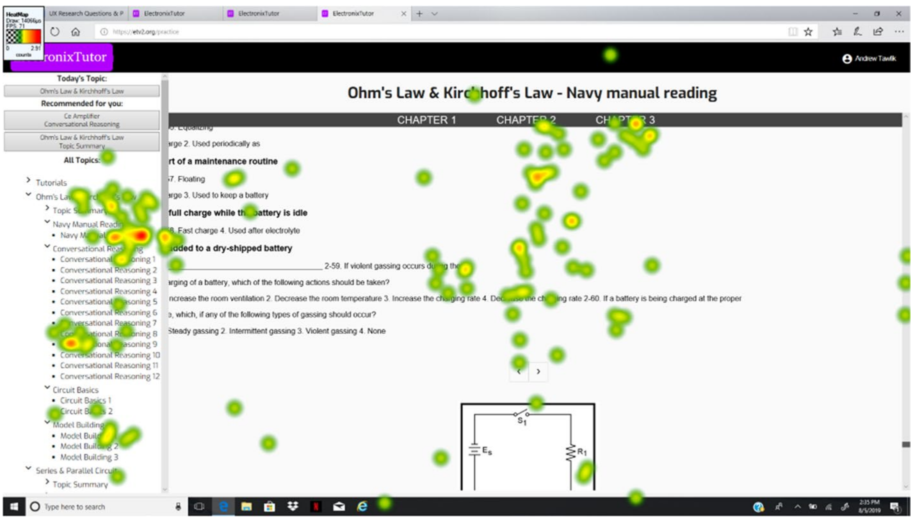


**Fig. 5** Eye-tracking heat map shows participant concentration focused on the sidebar in an apparent attempt to understand content placement

> the software we use for that, for our homework. Like, you thought it was going to end up one way and then it ended up a different way and it counted against you. So if I was trying to get feedback, I would want a different button where I could say 'this is a question' rather than this is not an answer to this problem. I'm asking a question to the tutors. (P1).

In the aforementioned example, the eye-tracking cluster map appears to substantiate the participants' comments related to the "Submit Your Answer" button. Figure 6 shows a large cluster of learner gazes right over the spot where the button appears at the bottom center of the screen. If the interface term used for this button more closely met the mental model of the learner, this map would certainly show less attention on the button and more on the task at hand.

## 6.5 Navigation

The fifth and final component of the Interaction with the Learning Environment construct of learning experience includes *navigation*. The navigation sub-construct is similar to the previous codes *content placement* and *interface terms*, but more specifically relates to the ability to orient oneself and travel efficiently within the environment during their learning. Participant comments related to site navigation were characterized by phrases like "*I had a hard time finding where to go*" (P6) and *"I don't know where I would go to…*" (P9). For example, one task asked participants where they would go to check their progress. Given how the interface was designed, this task proved particularly difficult for learners, which resulted in additional time and effort as they clicked around to different spots to find their progress. The eye-tracking cluster map in Fig. 7 confirms this difficulty and impact on the overall learning experience. Participant attention was focused on the left side of the screen, while the progress bar was actually located in the upper right corner under a drop-down

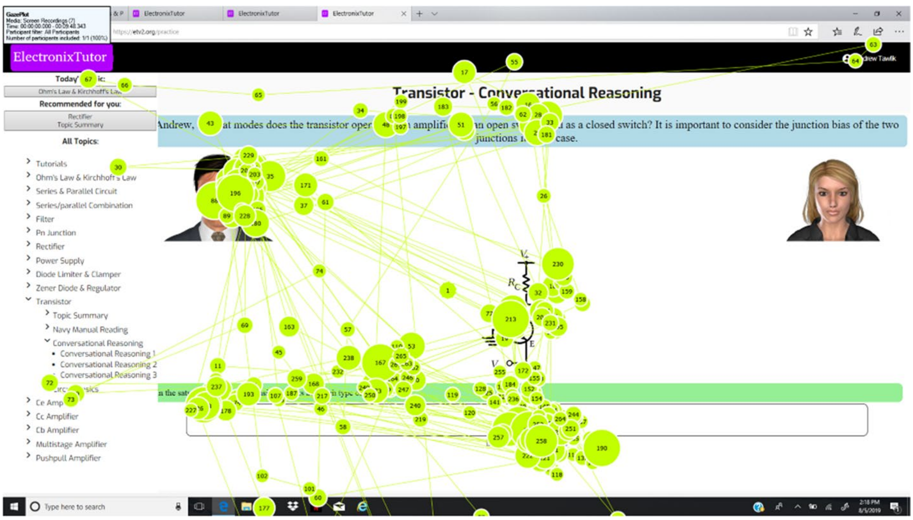


**Fig. 6** Eye-tracking cluster map shows excess learner attention on the "Submit Your Answer" button at the bottom center of the screen

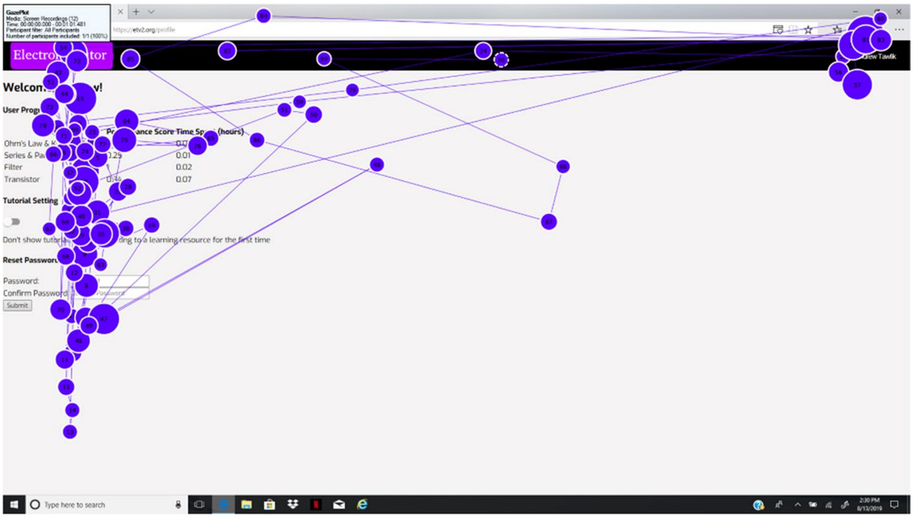


**Fig. 7** Eye-tracking cluster map demonstrates participant difficulty in navigating to their progress

menu. The cluster on the correct spot has higher numbers in the gaze spots, indicating that this was among the last places that the participants thought to look in their search.

## 7 Interaction with Learning Space

### 7.1 Engagement with Modality

The research team found several quotes from the participants that depicted either engagement or non-engagement with the modality of the content. Engagement as a construct is framed as an emotional or affective response to the way in which learning content appears on the screen. That is, this construct seeks to define the degree to which learners espouse the materials and its presented format. Most participant comments falling under *engagement with modality* focused on the agents within the AutoTutor feature. Overall, the participants appeared to like the idea of the feature but were distracted by the execution, especially with regards to the audio and animation quality. These comments from P1 and P2 respectively expound upon the nature of the learning experience as it relates to modality:

> It sounded like two AI, two artificial intelligences talking to [each other] Like it was making a conversation on its own. It sounded very robotic. Not even like the way they said it, not the audio quality, but also the nature, like the content of the conversation sounded really robotic. But as it applied to the problem, like I understood it, but that wasn't my focus. (P1).
> They're kind of distracting 'cause I was like, I was trying to focus on the circuit, but I know at least the guy, his mouth is a little bit more choppier. So it kept like, I tried to see what was going on over there [on the agent] other than the circuit. (P2).

Most participants conceded that the AutoTutor, despite needing some superficial tweaking, could facilitate engagement with their learning. This conclusion is supported by requests in the *customization of the interface* section for more accessible closed captions to compensate for distracting audio and animation. The eye-tracking data in Fig. 8 illustrate this point with clear and appropriate participant fixation on the center circuit and with minimal glances to the on-screen avatars.

## 7.2 Dynamic Interaction

Participant quotes that illuminate how the learning site either sustained or interrupted their learning interaction were categorized as *dynamic interaction*. As in the previous code, *engagement with modality*, the participant lines coded for *dynamic interaction* were seemingly concentrated on interaction with the AutoTutor feature. Whereas the participants were sometimes able to maintain engagement in the face of distracting design elements, dynamic interaction was difficult to sustain. Participant comments zeroed in specifically on two aspects that were programmed into AutoTutor. First, AutoTutor was designed to answer questions with a subsequent question. This adaptive programming was intended to engender a follow-up interaction that leveraged the learner's critical thinking and problem-solving skills using probing questions. Comments from P2 and P5 demonstrate challenges of the dynamic interaction when he said:

> I feel like I ended up more confused at the end because every time I'd ask it a question it just kind of ignored it and asked me a different question. And I eventually just gave up and went through it, but it wasn't really leading me anywhere. (P2).

Similarly, P5 described the following as it related to dynamic interaction with the learning environment.

> It didn't directly answer my question. It answered my question with a question, which I guess is fine if it makes you want to think more. But, yeah, like if it had an answer along with a question to give you some type of reference to back it off of, that

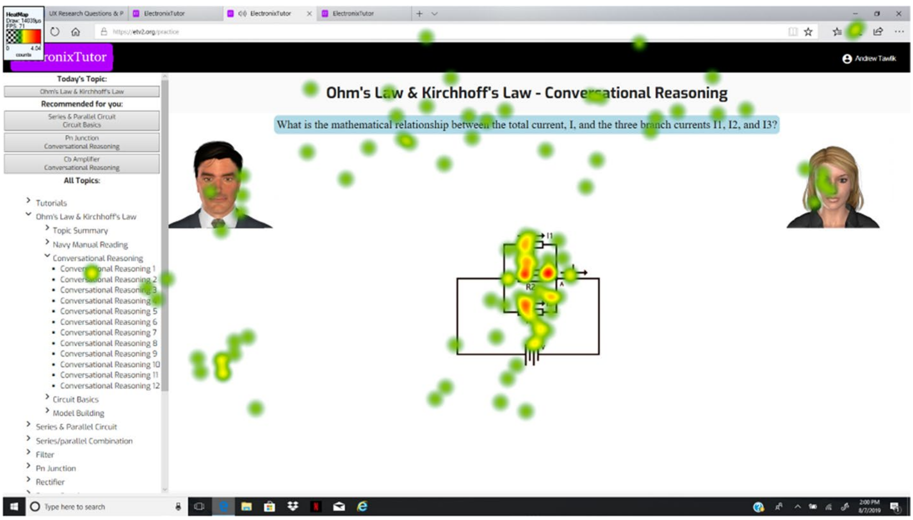


**Fig. 8** Eye-tracking heat map demonstrates appropriate learner engagement with the learning task (central circuit) as opposed to the avatars

> would've made it a little bit more intuitive. You know, just answering the question with another question is kind of repetitive. (P5).

While P2′s comment demonstrates frustration and a desire to discontinue interaction, P5′s comment suggests that despite understanding the intention of the interaction, he was still unsatisfied. Figure 9 captures participants' fixation on the textbox where he was prompted to ask the tutor a question. The fixation can be interpreted as hesitation stemming from uncertainty about how to properly continue his interaction with AutoTutor.

In the follow-up interaction, AutoTutor was made to provide an incorrect answer to a question. The intention here was to determine how participants would react to unanticipated feedback. Six of seven participants commented on the incorrect feedback, most perceiving it as a mistake in the program. Some expressed confusion, especially when the tutor later corrected itself without explanation, as in P2′s comment:

> Because it told me to put in that wrong answer, but then instead of correcting it afterwards and explaining it, instead it straight up just changed from being multiplied to, it says the sum of the three. (P2).

This and other comments seem to question the credibility of the program as a source for learning. As in the case of P5, they may turn inward and question their own expertise:

> It really made me question whether or not I truly know electrical engineering or not, because last time I checked if the sum of all currents going into this one node is going to be equal to that output current… But, uh, I guess that's, that's false. (P5).

### 7.3 Perceived Value of Technology Feature to Support Learning

The code *perceived value of technology feature to support learning* (Jonassen et al. 1998) covered participant thoughts about what they found valuable in the learning site

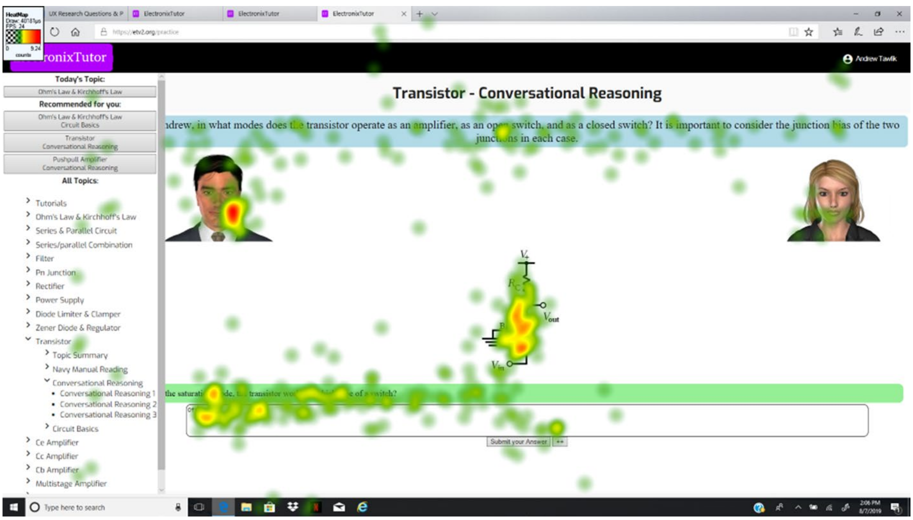


**Fig. 9** Eye-tracking heat map shows participation fixation on the textbox where they were to ask the AutoTutor a question

and how they predicted their learning gains based on that judgment. In this context of this study, the feature is similar to 'mindtools' and defined as: "computer applications that, when used by learners to represent what they know, necessarily engage them in critical thinking about the content they are studying" (Jonassen et al. 1998, page 24). Participant phrases such as "*It's a great way to learn by yourself*"(P6) signaled a value judgment from the participant for the tools embedded within the system. Additional participant comments in this regard were shaped by their perceptions of unmet expectations or difficulties encountered in the aforementioned *content placement* and *interface terms*. Participant 1, for example, stated that she would use the site for studying theory, but not for practice. She explained that "*it seems like it had a lot of theory that I could get from practice problems, not so much for the reasons that I said before.*". As such, Participant 1 found value in the site's theory presentation, but less so in the opportunities for practice because she could not easily navigate to that portion of the site. In contrast, some participants reported finding value in the adaptive systems inherent in the system. For instance, P3 commented on the "Recommended For You" section of the site, which uses intelligent technology to select materials and activities for the learner based on previous interactions:

> I also liked the recommended section that you have. If you're working on like some type of exercise and would they recognize which one you need I help on? (P3).

Participant 3′s comment is supported by the eye-tracking cluster map in Fig. 10. When participants were asked how they would direct their own learning using the site, they fixated early and often on the "Recommended for You" section. The research team deduced that this section was easy to find and intuitive for the participants.

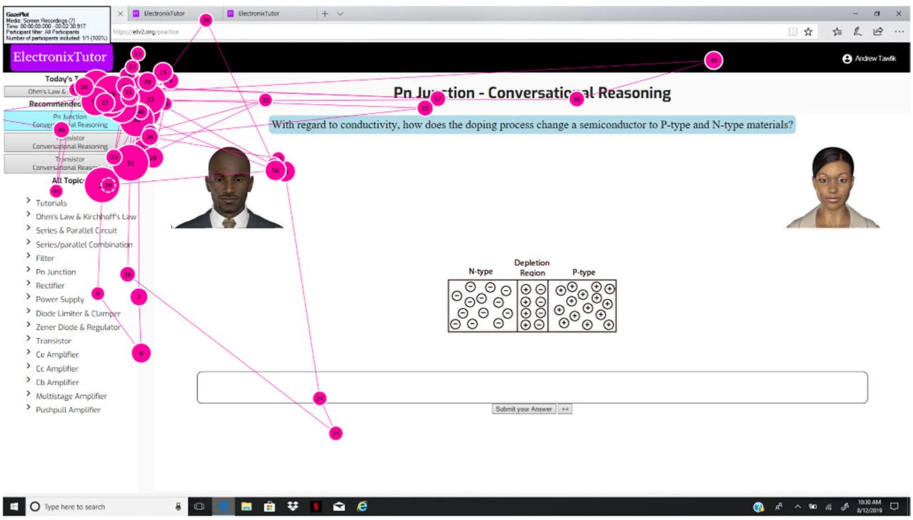


**Fig. 10** Eye-tracking cluster map demonstrates participant concentration on the "Recommended For You" section of the site

### 7.4 Scaffolding

In contrast to the *engagement with modality* constructs capturing affective reactions and preference for the modality, the *scaffolding* construct describes how participants felt their knowledge construction was or was not supported by the site. Participants responded positively, for example, when they felt the site provided feedback. Alternatively, if participants felt the absence of support, they used phrases like "*it might would be helpful if…*" (P4) or "*I like the idea of having…*" (P1) about ways to scaffold their learning. Suggestions beginning with these phrases generally alluded to the need for immediate feedback that would guide their self-directed learning and help them address their knowledge gap, as in the case with P1′s comment:

> I like the idea of having, you know, something where you can see where you went wrong and then study that theory again and build up on it. But as with two and three, if I got those wrong, then I'm kind of still stuck. (P1).

A comment from P2 echoed this need for informative feedback, while also emphasizing a need for a systematic and sequenced approach to knowledge building:

> Because if you get confused, they don't send you anywhere. But this one is kind of simple and you can get the basics and build up through some, assuming that they actually go through these, they get a little harder. So you can go one by one and slowly addressed the topic more and more rather than just being thrown into seeing a transistor. (P2).

Participants at times moved beyond requests for feedback and the structure of instruction to suggest entirely new content areas for the site based on their knowledge gaps. For example, Participant 4 commented that:

> The equations for those components would be helpful in starting because it goes from theorems straight to components. It needs a basic overview of those components. (P4).

Participant 4 had two additional comments requesting scaffolding through specific support features that would aid his learning:

> I'm not sure what kind of function expression it requires for this function. If some examples are given and this pop-up bubble were viewable, that would be [helpful]. And a little more hint about what to type in the those answer boxes, like what format. That would be helpful. (P4).

The need for such support figures is reinforced by the heat map in Fig. 11 and similar to the construct of *dynamic interaction* (Fig. 9). For Fig. 9, the research team attributed disproportionate learner attention on the question and textbox area to learner hesitation about how to proceed with the next steps. Alternatively, the patterns in Fig. 11 might be explained by a need for additional scaffolding. Participant 4′s suggestion for pop-up bubbles with examples and just-in-time hints might resolve this issue.

## 8 Discussion

In the context of learning technologies, Novak et al. (2018) cautioned that: "Despite a growing body of research in the area of digital learning and information processing, the literature on how people process and interact with information on electronic devices and

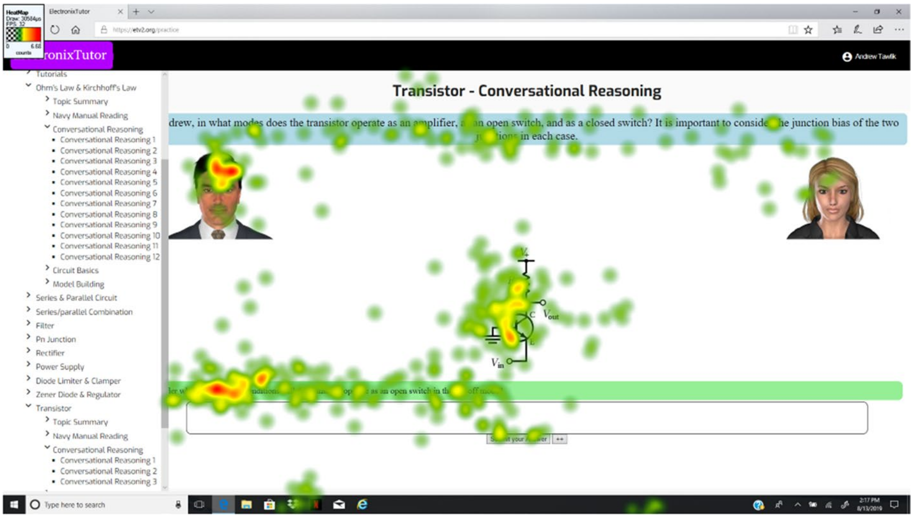


**Fig. 11** Eye-tracking heat map showing a possible need for additional scaffolding to support learner interaction

computers is still very scarce" (p. 151). One of the reasons is that extant theories and models from various perspectives have only implicitly referenced the role of interaction as individuals utilize learning technologies. For example, the literature on UTAUT describes the degree to which effort expectancy during an interaction impacts one's desire to adopt the technology (Davis et al. 1989; Venkatesh et al. 2003). Alternatively, cognitive load theory often describes the interaction as a source of extraneous cognitive load if not designed correctly (Mayer and Moreno 2003; Oviatt 2006; van Merriënboer and Sluijsmans 2009; Wang et al. 2014). Finally, pedagogical usability provides specific ways to think about the design, but often from an interface utility perspective (Hadjerrouit 2012; Nokelainen 2006). These theories and models, therefore, underscore that interaction is an important element of design; however, the specific constructs of the overall learning experience design is ill-defined and need of an emperical basis.

Given the critical role of interaction, theorists have underscored the importance of exploring human-computer interaction within a learning technology context (Chung et al. 2013; de Leeuw et al. 2019; Gray et al. 2020; Hollender et al. 2010). This work-in-progress study sought to move towards empirically defining constructs of "learning experience design" that accounts for both cognitive process and user-experience for learning technologies. In doing so, it builds on Bardzell (2011) emphasis on interface design and user experience, while also contextualizing it for learning technology interaction. The results of the grounded theory broadly define the confluence of the following constructs: (a) interaction with the learning environment and (b) interaction with the learning space. The former largely entails specific usability components that learners described as important, including the customization of the interface, functionality of components, expectations of content placement, expectation of interface terms, and navigation. Alternatively, interaction with the learning space described the ability to engage with the modality, dynamic interaction, perceived value added of the technology tools, and scaffolding.

The first broad construct in this work-in-progress study includes interaction with the learning environment and largely focused on needs from a usability and UX perspective.

Therefore, this study builds on studies that find that user experience is an increasingly important element when employing a learning technology (Chyung and Vachon 2013; Davids et al. 2014; DeStefano and LeFevre 2007; Hsu and Chen 2018). As in the case of prior research that focuses on the usability of learning technologies (Bakki et al. 2020; Swanson 2020), participants identified areas of the interface that either facilitated or detracted from their learning experience. Interestingly, learners wanted the ability to customize areas of the interface and described it as important to facilitating their self-directed learning. Additional codes focused on expectations of the interface: functionality of components, expectations of content placement, and expectation of interface terms. Functionality of components was important to their learning experience because learners expressed wanting to understand how the tools within the learning environment operated as to not expend too many cognitive resources trying to understand their functionality. When this was problematic, they described how the design disrupted their learning experience. The study aligns with prior literature that finds that a user's frustration to employ features of technology are problematic for the overall user experience (Eltahir et al. 2019; Novak et al. 2018) and one's ability to self-direct their learning (Madrid et al. 2009; Schmidt and Tawfik 2018; Schroeder et al. 2019).

Expectations of content placement and expectation of interface terms described how it was important for the location of interface components and the terminology to be oriented with their mental model. When this was done, the user could focus on learning and expended more cognitive resources on the content. If not, the learning would be disrupted and they would be focused on trying to reconcile the interface components. This finding seems to especially relate to recent studies which have attempted to explicate how one utilizes an informational text (e.g—ebook, library site) that is mediated by an interface and how the placement influences interaction (Çakiroğlu and Aksoy 2017; DeStefano and LeFevre 2007; Mattis 2015; Novak et al. 2018; Stuijfzand et al. 2016). Finally, navigation was described as important for several reasons. Users described how navigation was important to understand where they were within the learning environment in order to revisit material or progress in their knowledge construction. If they were unable to understand their position, learners expressed frustration that ultimately detracted from their learning. This finding relates to other learning technology usability evaluations when they discuss how navigation plays a critical role in one's ability to effectively explore the environment and its impact on self-directed learning (Hsu and Chen 2018; Moos and Bonde 2016; Schmidt and Tawfik 2018; Stull et al. 2013).

Literature suggests that when learning technology is perceived to be user-friendly, learners are more likely to engage with the materials (Davids et al. 2014; Novak et al. 2018). While the above describe how the usability of the interface either facilitated or impeded their learning, the interaction with the learning space described the unique cognitive processes learners conduct as they employ learning technologies. The qualitative and supporting eye-tracking data identified the following as important to interaction with the learning space: engagement with modality of content, dynamic interaction, perceived value of technology feature to support learning, and scaffolding.

The first subconstruct (engagement with modality of content) identified learners' affective perception and espousal of how the content was conveyed. When learners felt as though the content was displayed in a way that was misaligned with their desired format, they described how this diminished their overall learning experience. This finding coincides with research on multimedia videos and artificial intelligence which finds that learners often want control not just in terms of navigation, but in how to engage in various representations of an idea as they address their knowledge gaps (Garofalo and Farenga 2019; Mattis 2015; Schroeder et al. 2019).

The second element identified in the grounded theory was dynamic interaction, which describes ones' ability to iterate their learning with the interface and subsequent interactions that progress their understanding. In some cases, the response provided by the AI was beneficial to the learner and engendered additional questions or exploration of the problem space. However, other data identified how learners were unclear about the content materials, which stunted their desire to continue their learning progression. A related code focused on the importance of scaffolding within the learning environment, which is one's ability to learn from the material presented and support their knowledge construction through cues, hints, and other supports. This required that the interface present elements that coincided with their existing mental model and align new information as they generated a new schema. Finally, perceived value of technology feature to support learning described how learners expressed the degree to which they felt the tools accurately allowed them to represent and advance their knowledge.

Millis et al. (2017) noted that "In order for designers of educational software to maximize learning, they need to understand the interactions among design features (e.g., competition, narratives), noncognitive states (e.g., emotions, motivation), and aspects of the learner (e.g., prior knowledge, interest)" (p. 19). Indeed, the above data highlight the challenge of designing for technology interaction that facilitates meaningful learning. The broad constructs of interaction with the learning environment and interaction with the learning space are closely tied together; rather than being mutually exclusive, the data indicate that learning experience design must constitute a convergence between the two and their related subconstructs. In terms of interaction with the learning space, the data align with emerging literature (Graesser et al. 2019; Hollender et al. 2010) suggesting that interaction with the learning space should consider both cognitive and affective elements. In addition, the interaction was non-linear, and different design strategies were needed as learners updated their understanding of the phenomenon. For instance, the dynamic interaction describes how learners continue to iterate their understanding as they interact with what is presented on the interface. From a theoretical perspective, this is important because it suggests designers should extend their approach beyond a content-only strategy (e.g., what the learner needs to know); rather, they must consider how learners will react to the material and thus design for the subsequent interactions (Madrid et al. 2009). However, if this is not done in conjunction with content placement, terminology, or seamless navigation, the data indicate this would inhibit their sustained interaction. Similarly, the users described how they ascribed value to a feature to support their understanding. This finding has multiple implications. First, this requires that designers consider when to make these features available as they outline a learner's potential interaction within the learning environment. Similar to the construct of perceived usefulness, our study aligns with prior research (Carey and Stefaniak 2018; Schmidt et al. 2020) that underscores that it must be clear as to how the feature will benefit users' learning at that stage of understanding for them to meaningfully leverage that resource.

## 9 Conclusion and Future Studies

Interaction is an important aspect in the design of learning technologies. Although the user perspective has been implicitly referenced in prior theories and models, the overall learning experience design has yet to be emperically defined within the literature. Using a grounded theory approach and corresponding eye-tracking data, we argue that learning experience design consists of the following: (a) interaction with the learning environment and (b) interaction with the learning space. The former is more focused on UX elements and includes learner's utility of the technology in terms of customization, expectation of content placement, functionality of component parts, interface terms aligned with existing mental models, and navigation. Interaction with the learning space describes how the student perceives the interface elements, including engagement with the modality of content, dynamic interaction, perceived value of technology feature to support learning, and scaffolding. Rather than see these as mutually exclusive, the results suggest that the design is a confluence of these design constructs.

Despite addressing this gap, there are multiple opportunities to build on this work-in-progress study. In the current study, participants were limited to undergraduate STEM students, who were predominantly male. Considering this limitation, it is unknown if the results of the current study would replicate in populations such as children or adult learners. Furthermore, the sample consisted of novice engineering students. Those with additional expertise and domain knowledge may have differing experiences as they employ the learning technology, especially as it relates to interaction with the learning space.

Although this research aligned with prior studies that utilized a think-aloud (Ertmer et al. 2008; Tawfik et al. 2019), future studies could apply the same method with a larger sample size. It is also possible that asking participants to verbalize their thought process delayed the completion of specific tasks, which would subsequently modify the heat gaze and other eye tracking metrics. One way to build on this study is through a validated and reliable survey instrument that measures the proposed constructs. Future studies could also triangulate the results through learning analytics that measure how users navigate a learning environment. These varying metrics could provide further clarity on what is needed to support learning experience design.

Additional studies could also explore the degree to which the study is similar or different across different types of technology. In the current research, participants only used desktop technology to interact with the learning environment. The target technology was a system that included knowledge representation tools, worked examples, artificial intelligence, multimedia resources, and others. However, using mobile devices or collaborative tools may influence the interaction participants experienced between themselves and the learning environment. Finally, this study is limited by the length of time in which participants interacted with the learning technology. The current study elucidates participants' initial reaction to the technology, which may skew the results more heavily toward difficulties in orienting to the program rather than learning from the program. A longitudinal study may reveal more about how a student's learning experience is sustained over time.

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